**London School of Economics
and Political Science**

# Essays in Economic Growth and Innovation

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A thesis submitted to the Department of Economics of the London School of Economics for the degree of Doctor of Philosophy.

# Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).



I declare that my thesis consists of approximately 114,000 words.

# Statement of co-authored work

I confirm that Chapter 2 is joint work with Professor Alessandro Gavazza and Professor Andrea Lanteri, and I contributed to 33% of this work.

# Statement of inclusion of previous work

I confirm that Chapter 3 is the result of previous study for the Master of Research in Economics I undertook at the London School of Economics in September 2017-August 2019.

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# Abstract

This thesis explores factors that influence firms' incentives to invest in R&D and innovate.

The first chapter examines the effect of patent term on innovation. Leveraging a US policy change that varied patent term across technological fields, I estimate that unanticipated adoption of a longer patent term stimulates R&D and innovation. However, if firms anticipate a longer patent term for future inventions, R&D and innovation decline, also due to technology disclosure externalities. A new structural model highlights that normative evaluation of patent term changes should consider both transitional dynamics and potential anticipation. Moreover, it shows that the unanticipated extension of US patent term to 26 years would increase US welfare compared to current policy.

The second chapter studies the role of new-product quality for the dynamics of durable-goods expenditures around the Great Recession. We assemble a rich dataset on US new-car markets during 2004-2012, combining data on transaction prices with detailed information about vehicles' technical characteristics. During the recession, a reallocation of expenditures away from high-quality new models accounts for a significant decline in the dispersion of expenditures. In turn, car manufacturers introduced new models of lower quality, which persistently depressed the technology embodied in vehicles.

The third chapter examines the interaction between innovation, productivity, and technological standards. The latter integrate firms' disclosures of standard-essential patents into documents that provide technical and informational coordination on how to combine technologies to achieve interoperability and overcome innovation complementarities that may harm growth. I empirically show that the number of disclosed patents negatively correlates with productivity growth across sectors. I develop a Schumpeterian growth model featuring complementarity, standards, and patents dis-

closures, and identify conditions under which more disclosures lead to slower productivity growth. Namely, when the degree of complementarity is strong enough. Lastly, I show that this prediction holds in the data.

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# Chapter 1

# Patent Term, Innovation, and Technology Disclosure Externalities

**Abstract**

This paper investigates the impact of *anticipated* quasi-experimental variation in US patent term across technological fields on R&D, innovation, and welfare. Through a difference-in-difference analysis, I find that R&D and innovation (i) decline after news and before adoption of a future extension in patent protection and (ii) remain lower for 5 years after implementation. At news, innovators reduce R&D as they wait for the more favorable upcoming policy. After implementation, this leads to lower aggregate creation of new projects due to the cumulative nature of innovation. The latter outweighs the positive direct effect of a longer patent term's implementation on R&D and invention, which I empirically identify once controlling for heterogeneous innovation patterns induced by the news shock. The paper develops and estimates a novel semi-endogenous growth model. Counterfactual policy experiments show that policy anticipation and transitional dynamics to patent term changes have sizable welfare implications.

## 1.1 Introduction

The patent term, i.e., the duration of legal monopoly granted by patents, is a crucial policy instrument for promoting innovation and long-term growth. However, there is limited empirical evidence on its impact on Research and Development (R&D), innovation, and welfare (Budish, Roin and Williams, 2016). Normative models prescribe a patent term range that varies from zero (Boldrin and Levine, 2013) to infinite protection (Gilbert and Shapiro, 1990), and in most jurisdictions, the official patent term is determined by a rule-of-thumb approach.[1]

This paper contributes to the literature in two ways. Firstly, it presents new quasi-experimental empirical evidence on the effects of patent term on R&D and innovation, emphasizing the impact of policy anticipation. While an unanticipated longer patent term leads to a significant increase in R&D and innovation, the same policy generates–perhaps surprisingly–a prolonged decline in these outcomes if firms anticipate the intervention. Secondly, the paper identifies theoretical channels that drive these results and formalizes them in a novel semi-endogenous growth model, which allows for the quantification of key welfare trade-offs. Negative news effects are driven by intertemporal substitution of costly innovative investment on existing projects. Amplification of these effects occurs due to a technology disclosure externality, wherein a decline in knowledge diffusion dampens the ability to create new projects.

The empirical analysis leverages quasi-experimental variation in effective patent term across technological fields resulting from an anticipated policy intervention, specifically the ratification of the international agreement on Trade-Related Aspects

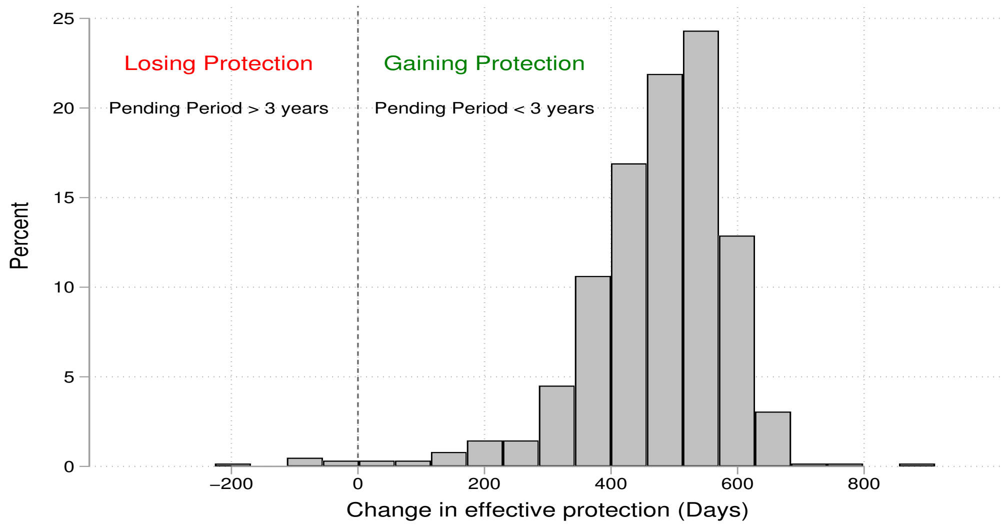
[1] US patent term was introduced in 1790 and set to 14 years after the grant date in line with English law. In turn, the English term was based on the expected training period of two sets of apprentices, as reported by Nordhaus (1969), and not on any welfare considerations. In 1861, the US patent term was changed to 17 years, and Nordhaus (1969) reports that this change was the result of a political compromise.

of Intellectual Property Rights (TRIPs) by the US.[2] TRIPs standardized US patent term from 17 years after the patent grant date to 20 years after the application day. As legal monopoly is only enforceable after grant, *effective* US patent term changed from 17 years to 20 years minus the pending period, i.e., the time between application and grant dates, when the US Patent and Trademarks Office (USPTO) examines application materials. Identification exploits two sources of variation: Cross-sectional variation in average pending period across technological fields due to heterogeneous congestion of technical units that within the USPTO examine distinct technologies, and time variation due to two policy shocks: the news shock at the of 1992 when US innovators learned of the future intervention, and the implementation shock in June 1995. Figure 1.1 shows the distribution of the change in *effective* patent term across technical fields. On average, most fields gained protection from the policy (positive values) but variation is wide.

A Difference-in-Difference (DiD) analysis compares R&D, patenting, and other innovative outcomes across fields with heterogeneous patent term changes over the two policy shocks. The results reveal three empirical facts. Firstly, Fact 1 demonstrates that news of a patent term extension on future patents leads to a contemporaneous decrease in patenting before policy implementation. Consistent effects on firm-level R&D expenditures and sectoral TFP suggest that this represents a change in actual innovation. This finding is interpreted as firms intertemporally substituting costly investments in ongoing projects until after the implementation of the longer patent term, when expected rewards are higher. Secondly, Fact 2 shows that the decline in R&D and innovation arising from the news persists for at least five years following policy implementation. This outcome results from the combined action of two forces

[2] TRIPs were part of the Uruguay Round of negotiations of the General Agreement on Trade and Tariffs (GATT), which laid the ground to the formation of the World Trade Organization (WTO). TRIPs set common intellectual property protection rules with which WTO members had to comply. As the 20-years-from-application patent term was the most common among initial members, it was taken as a standard.

Figure 1.1: Distribution of the expected change in effective protection time




The histogram shows the distribution of the TRIPs-induced change in average effective patent term across technical fields. The units on the x-axis are days and positive values denote an expected patent term extension. Subsection 1.2.3 reports additional details on measurement.

that are empirically documented. On the one hand, the implementation of the new, longer patent term *increases* R&D and innovation as a *direct* effect, which is Fact 3. On the other hand, the cumulative nature of the innovation process leads to a temporary decline in innovation after implementation because there are fewer novel technologies on which to build. Using backward citations among patents to capture technical links, the study provides suggestive evidence that this effect is due to a decline in the diffusion of new knowledge through patent documents, which is referred to as a technology disclosure externality, consistent with evidence from Hedge, Herkenhoff and Zhu (2022). Various analyses address the main endogeneity concerns, supporting a causal interpretation of these results.

The paper formalizes the intertemporal substitution of costly investment on ongoing projects and the technology disclosure externality in a novel semi-endogenous growth model, showing that both channels are key to replicate the empirical effect of an anticipated patent term extension. The model features two key ingredients. Firstly, it distinguishes Research and Development as separate activities, with research discovering abstract ideas whose value lies in obtaining a new product in the future. Development, on the other hand, transforms these ideas into actual patentable technologies at a cost. Firms trade off the cost of faster development with the value of obtaining a patented technology at different points in time, capturing the intertemporal substitution channel. Secondly, the model assumes that a faster average speed of development increases aggregate productivity of research through an externality because the diffusion of new knowledge is more frequent.

Upon receiving news of an upcoming increase in patent term, firms tend to reduce their development effort prior to policy implementation, as the value of future patents becomes higher relative to current ones. Although the incentive to slow down development terminates with the policy's implementation, the news effect leads to lower knowledge diffusion and aggregate research productivity for some time. As a result, research investment remains depressed even after implementation, despite longer protection enhances incentives to generate new ideas as a *direct* effect. In the long run, the latter dominates, increasing R&D and innovation.

Through a structural estimation, this study successfully matches the DiD empirical evidence and identifies key parameters of the innovation process. Specifically, it finds severe decreasing returns to discovering new ideas and mild cost convexity of developing existing projects at a faster pace. Furthermore, counterfactual policy experiments uncover two previously overlooked channels that impact the welfare effects of a patent term change. While most of the literature focuses on long-term outcomes, the model highlights that the transitional dynamics of the economy to the new long-run equilibrium can also significantly affect welfare. Additionally, the theory confirms that news effects are crucial, as even short anticipation can undermine the welfare gains that would result from an unanticipated implementation of a longer patent term (26 years) in the US.

**1.1.0.0.1 Structure of the paper** The remainder of the paper proceeds follows. Subsection 1.1.1 relates the contribution to existing literature. Section 1.2 presents the institutional setting of TRIPs and Section 1.3 data and measurement. Section 1.4 shows the main empirical facts and Section 1.5 empirically documents the externality. Section 1.6 presents the model, Section 1.7 its structural estimation, and Section 1.8 counterfactual policy scenarios and the quantification of normative trade-offs. Section 1.9 concludes.[3]

### 1.1.1 Connection to the literature

Evidence on the effect of patent term on innovation and R&D is limited, partly due to lack of variation in policy. The latest empirical contribution on the topic is by Budish, Roin and Williams (2015), who document that in the US pharmaceutical sector R&D is disproportionately directed towards treatments with shorter clinical trials, which implicitly offer longer effective protection time. However, the paper cannot disentangle the importance of the policy instrument, i.e. the finite patent term, relative to firms' preference for projects with faster return from investment. Other papers examine more comprehensive measures of patent protection strength (Lerner (2009), Moser (2005), Moser and Voena (2012), Sakakibara and Branstetter (2001), Schankerman and Schuett (2017), Moscona (2021), Kyle and McGahan (2012)), but not patent term specifically. This paper uses one source of variation due to a major policy change (TRIPs) and exploits the heterogeneity in its impact across fields.

Abrams (2009) uses the same quasi-experimental strategy but assumes that the policy intervention was *unanticipated*, which leads to different econometric specifications and divergent reduced-form results. Specifically, Abrams (2009) estimates a two-period DiD specification comparing patenting in a narrow window of data (6, 12, or 24 months) before and after the implementation shock of June 1995. In contrast,

[3] Appendix 1.A and 1.D describe the data, Appendix 1.B and 1.E report additional empirical results, and Appendix 1.C and 1.F include further theoretical results.

I provide documental evidence from several sources that US firms anticipated the TRIPs. In Appendix 1.B.1 I discuss at length that disregarding potential news effects may lead to an incorrect interpretation of implementation effects and I reconcile the results of the two papers. Moreover, Section 1.4 shows that an *anticipated* patent term extension leads to a decline in R&D and innovation, which is opposite to what would happen absent anticipation and contrary to conventional wisdom. Finally, this paper develops a novel structural semi-endogenous growth model and quantifies the key normative trade-offs of patent term.

To do so, it builds on Jones (1995) and it borrows the modelling of a finite patent term from Lin and Shampine (2018). However, it introduces significant modifications to the engine of growth, modeling distinct trade-offs of Research and Development activities and embedding a new externality. The two-step structure of the innovation process is similar to Comin and Gertler (2006*a*), but the interpretation of the two stages is different. Section 1.6 and Appendix 1.C.5 discuss that this departure is crucial for rationalizing the empirical evidence. In addition, differently from the several theoretical papers that study the normative consequences of patent term (Nordhaus (1967), Gilbert and Shapiro (1990), Klemperer (1990), Futagamia and Iwaisako (2007), Acemoglu and Akcigit (2012)), this paper tightly links the model to quasi-experimental empirical evidence that informs the key structural parameters used for normative analysis.

Finally, the paper contributes to the large empirical and theoretical literature on innovation related spillovers, which include: Knowledge accumulation spillovers, at the core of Romer (1990), and recently re-examined by Bloom et al. (2020) and Aghion and Jaravel (2015); spillovers from basic to applied research (Akcigit, Hanley and Serrano-Velarde (2020)); geographic spillovers (Moretti (2020), Lychagin et al. (2016), Lanahan and Myers (2022)); externalities at the inventor level (Bell et al. (2019), Akcigit et al. (2020)); and spillovers in the technological space (Bloom, Schankerman and Van Reenen (2013), Moretti, Steinwender and Van Reenen (2019)). This paper provides evidence of a technology disclosure externality acting through the diffusion of *novel* knowledge, which can be seen as a "standing on the shoulders of *young* giants" effect. This is close to evidence in Hedge, Herkenhoff and Zhu (2022), who document that a more timely publication of patent application increases the rate of follow-up innovation.

## 1.2 Nature and timing of the TRIPs policy change

### 1.2.1 Content of the policy change

The paper's empirical analysis utilizes quasi-experimental variation in the US effective patent term resulting from the adoption of *The Agreement on Trade-Related Aspects of Intellectual Property Rights* (TRIPs) in the US. TRIPs standardized intellectual property protection rules across trading partners as a part of the Uruguay Round of agreements that established the World Trade Organization (WTO). The US statutory patent was modified by the TRIPs, changing the expiry date of patents from *17 years after grant date* to *20 years after application date.* During the pending period, defined as the time between application and grant dates when the patent office examines applications, monopoly power is not legally enforceable. Thus, the policy modified the *effective* patent term from 17 years before the TRIPs to 20 years *minus* the pending period after the TRIPs. The paper's identification strategy, explained in Subsection 1.2.3, exploits the interaction between this time variation and pre-existing heterogeneity in the average pending period across technological fields. Additionally, the paper argues in the following subsection that US innovators anticipated the TRIPs adoption.

### 1.2.2 Timing: News and implementation shocks

The Uruguay Round Agreements Act (URAA) of December 8, 1994 officially ratifies the TRIPs provisions in the US, which came into full effect on June 8, 1995.[4] Despite this, various official documents and articles indicate that US firms were aware of the impending policy change well before its formal adoption.

First, the US business sector played a direct role in the TRIPs negotiation process from the beginning of the Uruguay Round in 1986. According to Morgese (2009) and Matthews (2002), the US Advisory Committee on Trade Policy and Negotiations (ACTPN), which included CEOs of companies like IBM and Pfizer, had significant influence on the US delegation's position. Second, the adjustment of the US patent term was first mentioned in a final draft for the whole Uruguay Round circulated by the GATT Director-General at the end of 1991.[5] Third, as Montalvo (1996) notes, the Advisory Committee on Patent Law Reform took the first step towards this change in August 1992 by issuing a report to the Secretary of Commerce recommending a twenty-year term from the filing date of the first complete United States application.[6] This report, jointly signed by several representatives of the business community, ex-

[4] The Uruguay Round Agreements Act (URAA), which ratified the TRIPs provisions in the US, brought four major changes to US patent law. The first change examined in this paper is the patent term change. The final version of the URAA included a retro-activity clause for patents filed before the June 1995 policy implementation that would have had longer effective protection under the new policy regime. This crucial implementation detail was unknown before the formal signing in December 1994, so innovators' incentives were not affected by the retro-activity clause before then. The second relevant policy change was a non-discrimination rule for foreign inventors. The third change was the introduction of provisional applications, which are preliminary applications that anticipate the official one but are not examined. While the data may be affected by substitution to the new type of applications, provisional applications must be turned into official ones within one year to avoid being considered abandoned, which limits potential measurement error to a one-year re-timing of innovation, at worst. The TRIPs also broadened the patentable subject matter in developing countries and increased protection for developed country innovators. The effects of this aspect of the policy are studied by Delgado, Kyle and McGahan (2013) and Kyle and McGahan (2012). Subsection 1.4.2 discusses the potential confounding effects arising from these concomitant changes, finding overall support for the validity of the results.

[5] *GATT doc. MTN.TNC/W/FA, Draft Final Act Embodying the Results of the Uruguay Round of Multilateral Trade Negotiations, 20/12/91*

[6] *The Implementation of the Uruguay Round Agreement on Trade-Related Aspects of Intellectual Property–the TRIPs Agreement: Hearings on S.2368 and H.R. 4894 before the Subcomm. on Patents, Copyrights and Trademarks of the Senate Judiciary Comm. and the Subcomm. on Intellectual Property and Judicial Administration of the House Judiciary Comm., 103rd Cong., 2d Sess.*

plicitly referred to the 1991 TRIPs draft.[7] Fourth, early academic articles in law journals, such as those by Reichman (1993), Martin and Amster (1994), and Doane (1994), examined various aspects of the TRIPs draft. Finally, an article in the New York Times also mentioned the policy change in September 1992.[8] Therefore, US innovators were aware of the negotiation content and could anticipate the policy change.

Moreover, according to historical records of the Uruguay Round negotiations, the Blair House Accord signing in November 1992 significantly reduced the uncertainty surrounding the adoption of the agreements, with the resolution of the agricultural trade dispute between European countries and the US being a key factor in this development.[9] Therefore, the paper considers two separate policy shocks: A news shock in November 1992 and an implementation shock in June 1995.[10]

In Appendix 1.B.1, I address the issue of neglecting anticipation, which can potentially result in biased inference on implementation effects. I also reconcile the empirical results of my paper with those of Abrams (2009), who studied the effects of patent term using TRIPs but assumed no anticipation.[11]

[7] Representatives of IBM, 3M, P&G, Motorola, and Garret&Dunner signed the report, among the others.

[8] *Panel Proposes Patent Changes*, New York Times, Late Edition (East Coast); New York, 15 Sep 1992.

[9] This is reported by Morgese (2009) and at `https://en.wikipedia.org/wiki/Uruguay_Round`, where it reads: *"The round was supposed to end in December 1990, but the US and EU disagreed on how to reform agricultural trade and decided to extend the talks. Finally, In November 1992, the US and EU settled most of their differences in a deal known informally as the "Blair House accord", and on 15 April 1994, the deal was signed [...]"*

[10] The URAA, signed on December 8th, 1994, allowed innovators filing patent applications between December 8th, 1994 and June 7th, 1995 to choose whichever policy regime was more favorable to them. All empirical results are unaffected by an additional anticipation of one or two quarters.

[11] When assuming the absence of policy anticipation, the effects of the news shock are essentially assumed to be zero. However, Appendix 1.B.1 demonstrates that if this assumption fails to hold, the difference-in-differences (DiD) comparison of R&D and innovation before and after policy implementation can result in confounded estimates of the policy's effect. In fact, if the news shock does indeed alter R&D and innovation before policy implementation, the pre-implementation levels of these outcomes, which are used as the reference for the pre-post comparison in the DiD exercise, can themselves become endogenous to the treatment. Section 1.4 presents evidence of anticipation effects, while Appendix 1.B.1 illustrates how these confound the DiD estimates of Abrams (2009).

### 1.2.3 Cross-sectional variation in patent term across technical fields

Subsection 1.2.1 explained that TRIPs modified the effective patent term from $T^{pre} = 17$ years to $T^{post} = 20$ years *minus* the pending period, the length of which was crucial in determining the sign and magnitude of the policy change. A shorter (longer) pending period than three years resulted in an extension (reduction) of the effective patent term. To identify the effects of the TRIPs policy change, my paper exploits the interaction of the TRIPs-induced time variation with pre-existing cross-sectional heterogeneity in the average pending period across technical fields, which are defined as the 621 4-digit patent classes of the International Patent Classification (IPC) scheme that categorizes patents based on their technological content.[12] The variation in the average pending period across fields is a result of the examination process within the US Patent and Trademark Office (USPTO), as patents in different fields are examined by distinct technical units that differ in congestion levels, due to staffing or intensity of foreign filings, and technical examination complexity.[13]

Therefore, I define the change in effective patent term for field $j$ as

$$\Delta T_j = 20 \text{ years} \times 365 \ - \ \overline{PP}_j \ - \ 17 \text{ years} \times 365 \tag{1.1}$$

[12]For example, the 4-digit IPC "A23" is "Edible Oils or Fats, e.g. Margarines Shortenings, Cooking Oils". It is included in the 3-digit IPC "A23", "Food or Foodstuffs; Their Treatment, not covered by other classes" and in the 1-digit IPC "A", "Human Necessities". It further includes two 8-digit IPCs: "A23D 7/00", "Edible oil or fat compositions containing an aqueous phase, e.g. margarines", and "A23D 9/00", "Other edible oils or fats, e.g. shortenings, cooking oils".

[13]Classification of patent applications into fields is made by the USPTO rather than by the applicant, but the pending period also depends on the responsiveness of patent applicants to the inquiries of the patent office during the examination process Lemus and Marshall (2018) document that applicants became strategically quicker after the TRIPs. This would constitute a concern for the validity of the empirical analysis of this paper if the strategic adjustment correlated with the pre-existing heterogeneity in the pending period across fields. Section 1.4 discusses that this is not the case. Moreover, Table 1.A.4 of Appendix 1.A.2 shows that the average pending period across technical fields does not correlate with the field-specific growth rate of patenting before the TRIPs news. However, it positively correlates with proxies of congestion–such as the share of patent filings by foreign applicants seeking to extend patent protection in the US—and of examination difficulty—i.e., the average pending period at the European Patent Office.

where $\overline{PP}_j$ is the average pending period, in number of days, for patents classified in field $j$ before the TRIPs news.[14] The interactions of $\Delta T_j$ with quarterly fixed effects constitute the treatment variables in the field-level DiD empirical analysis of Section 1.4.[15]

Figure 1.1 displays how $\Delta T_j$ is distributed across technical fields, revealing that most fields experienced an anticipated increase in the average effective patent term due to TRIPs, whereas a few fields saw a projected decrease. The mean of the distribution is roughly +473 days, or about 15 months, with a standard deviation of 177 days. As shown by Table 1.A.5 in Appendix 1.A.2, average $\Delta T_j$ varies across broad technical areas, with "Chemistry and Metallurgy" obtaining the shortest average extension and "Fixed Construction" the longest. Importantly for the empirical strategy, Subsection 1.4.2 discusses that this variation does not correlate with unobserved factors that may heterogeneously affect innovation across fields after policy shocks.

[14]As I describe in Section 1.3.1, I use PATSTAT to compute $\overline{PP}_j$ as the average of the pending period–i.e., the difference between grant date and application date–across all *granted* US patent applications that (i) belong to technical field $j$; (ii) whose earliest application is filed at the USPTO; and (iii) whose grant date is between January $1^{st}$, 1990 and May $31^{st}$, 1992. I impose the second restriction to capture the examination time of a novel patent, rather than that of applications already examined at another foreign patent office or at the USPTO itself. The third condition restricts the calculation of the average pending period to a time window that is both unaffected by the policy news and recent enough to be representative of applicants expectations. Moreover, the third condition implicitly requires that, for $\Delta T_j$ to be representative of the actual change in protection after news and implementation, the average pending period does not endogenously adjust to the policy change. I show that this is the case in subsection 1.4.1.

[15]Subsection 1.4.2 performs several checks to support the exogeneity of $\Delta T_j$ and its representativeness of the actual effective patent term after news and implementation shocks. First, it shows that post-TRIPs quarter-specific average pending period does not endogenously change with $\Delta T_j$. Second, it directly employs in the main DiD analysis a field- and quarter-specific version of $\Delta T_j$ based on the field- and quarter-specific average pending period, instrumented by the pre-news $\Delta T_j$. The instrument is strong and all the results are identical to using $\Delta T_j$ directly. Lastly, it shows that the raw correlation between the ex-ante and the ex-post average pending period is generally above 0.6.

## 1.3 Data and measurement

### 1.3.1 Data sources

The empirical investigation includes analyses by (i) technological field of patents, (ii) firm, and (iii) NAICS 6-digit industry. The analyses by technical field are primarily based on patent data from PATSTAT (EPO, 2017), which I complement with data from the NBER Patent database (Hall, Jaffe and Trajtenberg, 2001) and data on patent value from Kogan et al. (2017). The quarterly panel sample includes the universe of 621 4-digit International Patent Classes, which define technical fields in the paper, over the period 1985Q1-2000Q4, around the TRIPs shocks. I stop the sample period in 2000 due to additional changes to patent regulation.[16] The average quarterly number of patents and 5-year forward citations-weighted patents are 36 and 195, respectively, with standard deviations of 136 and 1,070. Table 1.A.1 in Appendix 1.A provides additional summary statistics.

The firm-level dataset is a yearly panel that includes 2,421 listed US firms from the NBER-Compustat matched dataset by Hall, Jaffe and Trajtenberg (2001) over the period 1985-2000, with balance-sheet data from Compustat (Standard&Poor's, 2022). The yearly average number of patents filed per firm is approximately 14, and the average yearly R&D expenditure is $61 million, with standard deviations of 95 and $359 million, respectively. Table 1.A.2 presents additional summary statistics at the firm level.

The sectoral analysis uses data on Total Factor Productivity (TFP), producer prices, and other aggregates from the NBER CES manufacturing database (Becker, Gray and Marvakov, 2021) for 428 6-digit NAICS industries from 1985-2000. Ad-

[16] In 2000, the American Inventors Protection Act (AIPA) introduced mandatory publication of patent applications after 18 months from the application date. The AIPA was signed on 11/29/1999 and entered into force for patents filed after 11/29/2000. Hedge, Herkenhoff and Zhu (2022) studies the effects of the AIPA on innovation and it suggests that the AIPA did not have effects on patenting behavior before actual policy implementation at the end of year 2000.

ditionally, it employs patent variables that I aggregate from the technical-field level sample using the "Algorithmic Links with Probabilities" crosswalks by Goldschlag, Lybbert and Zolas (2019), which map technological fields into industrial sectors. Table 1.A.3 presents summary statistics of sectoral aggregates.

### 1.3.2 Measurement

**1.3.2.0.1 Innovation** I primarily use patent-based measures to capture innovation outcomes, specifically (i) raw patent counts, (ii) patents weighted by the number of forward citations within five years of publication (which is a standard measure of scientific patent quality), and (iii) patents weighted by private economic value according to Kogan et al. (2017). However, patents may not fully capture genuine innovation, so I also examine how policy-induced variation in patenting affects Total Factor Productivity (TFP) and producers' prices at the sectoral level, which more directly reflect the real effects of successful innovation. This issue is especially important for the research question at hand because a change in patent term may affect both incentives to innovate and incentives to patent. Empirically, I find that changes in TFP and prices align with the estimated impact of patent term on patent-based innovation measures, indicating that the latter capture genuine innovation to some extent. I also examine this issue theoretically, proposing a simple extension of Section 1.6's model in Appendix 1.C.8 that incorporates both patenting and trade-secrecy.

**1.3.2.0.2 R&D** To measure field-level R&D effort, I use the headcount of researchers working in a field over time, which I estimate based on the number of inventors listed on patents while avoiding double-counting of individuals appearing on more than one patent in the same quarter-field combination. While this measure is admittedly imperfect, it relates to researcher payroll, a significant component of R&D expenditures, and is measurable by technical field. This approach enables me to avoid the coarseness of sectoral R&D investment data by the National Science Foundation, which would not capture the fine-grained policy variation I use for identification. In addition to field-level results, I also examine firm-level data using direct balance-sheet measures of yearly R&D expenditures from Compustat. Empirical findings are consistent across R&D proxies, and most importantly, align with estimated effects of patent term changes on patent-based innovation measures. These results suggest that the patent-based measures capture genuine changes to innovation rather than mere adjustments to patenting strategies.

Appendix 1.D reports construction details for all variables used in the paper.

## 1.4 Estimating the effects of a change in patent term

This section presents the primary empirical evidence of the paper. Subsection 1.4.1 outlines the difference-in-difference (DiD) strategy and presents the results. Subsection 1.4.2 addresses endogeneity concerns, while Subsection 1.4.3 establishes a link between changes in patenting outcomes and actual R&D expenditures and productivity. Subsection 1.4.4 isolates the direct effect of an unanticipated effective patent term extension, controlling for news effects. Subsection 1.4.5 estimates elasticities and examines their heterogeneity by broad technical areas. Finally, 1.4.6 summarizes and interprets the key takeaways.

### 1.4.1 Difference-in-Difference analysis by technical field

#### 1.4.1.1 Specification

The DiD strategy involves the comparison of innovation outcomes and R&D inputs (i) across different technical fields with heterogeneous $\Delta T_j$ and (ii) before and after the two policy shocks: News in 1992Q4 and implementation in 1995Q2. Specifically, I estimate the preferred linear specification (1.2) or the Poisson model for count variables

(1.3).[17]

$$Y_{j,t} = \alpha_j + \sum_{\substack{k=1985Q1\\k\neq 1992Q3}}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_{\substack{k=1985Q1\\k\neq 1992Q3}}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta T_j + \varepsilon_{j,t} \tag{1.2}$$

$$Y_{j,t} = \exp\left\{ \alpha_j + \sum_{\substack{k=1985Q1\\k\neq 1992Q3}}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_{\substack{k=1985Q1\\k\neq 1992Q3}}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta T_j + \varepsilon_{j,t} \right\} \tag{1.3}$$

where $Y_{j,t}$ is technical field-$j$ and application quarter-$t$ dependent variable in levels, i.e., number of patents, number of quality-adjusted patents, or number of inventors. $\alpha_j$ are technical field fixed effects. $\mathbf{1}_{(t=k)}$ are quarter-specific dummy variables, with the $\gamma_k$ coefficients capturing the effect of any quarter-specific factor common to all technical fields and unrelated to treatment. $\varepsilon_{j,t}$ is the field- and quarter-specific error term.

The $\beta_k$'s are the DiD coefficients of interest, whose interpretation depends on the specification and on the sub-sample to which $k$ refers. In the linear model (1.2) each $\beta_k$ represents quarter-$k$ effect of a one-day increase in effective patent term on the *level* of $Y$, in deviation from its baseline value in the pre-news quarter 1992Q3. In Poisson model (1.3), each $\beta_k$ represents quarter-$k$ effect of a one-day increase in effective patent term on the log-deviation (percentage deviation) of $Y$ from its baseline value in 1992Q3.

[17] In analyzing patent count data, it is important to consider models that account for the non-negativity, right-skewedness, and large probability mass at zero of the dependent variable. Mullahy and Norton (2022) discuss different classes of models and show that linear regression models that use log or inverse hyperbolic sine transformation of the dependent variable may estimate incorrect marginal effects. On the other hand, linear regressions with untransformed dependent variable or Poisson models yield the correct marginal effects. Thus, I choose specifications (1.2) and (1.3) for my analysis. To further justify my choice of specification, I conduct a time-series analysis of patenting behavior in the late 1980s and early 1990s. I find that arithmetic growth describes patenting by field more accurately than exponential growth. To demonstrate this, I fit a model with field-specific intercepts and a field-specific linear time-trend on (i) the levels of quarterly granted patent applications and (ii) a log-one-plus transformation of the same series over the period of 1985Q1-1989Q4. I then make out-of-sample predictions for the levels of quarterly patenting by field in 1990Q1-1992Q4 based on the two models, and I compute the mean-squared error. The level regression has a higher in-sample $R^2$ (0.97 vs. 0.93) and a 25% lower mean-squared prediction error. Therefore, I choose (1.2) as the preferred specification for my analysis.

Moreover, for $k \leq$1992Q3, $\widehat{\beta}_k$ measures the effect of a positive one-day change in patent term before any news about the policy, and values close to zero indicate the absence of pre-trends. For $k \in [1992Q4; 1995Q2]$, $\widehat{\beta}_k$ represents the quarter-specific marginal impact of the news that patent term will be one-day longer for future applications filed after 1995Q2. Finally, for $k \geq 1995Q3$, $\widehat{\beta}_k$ estimates the marginal impact of an anticipated one-day increase in patent term at different times after its implementation. These coefficients reflect both the direct effect of implementing a longer term and the dynamic impact of news on subsequent innovation, which is a cumulative process (Romer, 1990). To isolate the direct effect, I propose an empirical strategy in Subsection 1.4.4.

In Appendix 1.B.1, I show that multi-period specifications (1.2) and (1.3) can flexibly capture potential news effects. On the other hand, a standard two-period DiD analysis comparing outcomes before and after policy implementation would lead to biased treatment effect estimates.

#### 1.4.1.2 Reduced-form DiD results

**1.4.1.2.1 Innovation outcomes** Figure 1.2 presents the estimated marginal effects of a one-day anticipated increase in patent term on the number of granted patent applications ($P_{j,t}$) classified in field $j$ and *applied for* in quarter $t$. The figure consists of two panels: panel (a) shows OLS estimates of the $\beta_k$ coefficients of the linear specification (1.2), and panel (b) presents pseudo-maximum-likelihood estimates of the $\beta_k$'s in the Poisson model (1.3). The bands represent 95% confidence intervals, with standard errors clustered by technical field. The figure highlights three key takeaways.

First, the estimated $\widehat{\beta}_k$ $k \leq 1992Q2$ values are close to zero before the news shock, indicating the absence of pre-trends. In addition, formal tests based on Roth (2022) reveal that economically significant pre-trends are rejected with high power.[18]

[18] I examine several alternatives. A linear trend with a quarterly slope of -0.005 (equal to 2000Q4 point estimate divided by the number of post-news quarters) would be detected with a power of 1.

This suggests that there is no correlation between $\Delta T_j$ and unobserved heterogeneous innovation patterns pre-dating the policy news.[19] However, there may be endogeneity concerns arising from other confounding factors contemporaneous to policy shocks, which I discuss in Subsection 1.4.2.

Second, the $\widehat{\beta}_k$ $k \in [1992Q4; 1995Q2]$ coefficients are negative, indicating a contemporaneous decline in patenting resulting from the news that future patent applications filed after policy implementation will obtain a longer term of protection. This is referred to as **Fact 1**. The magnitude of the effect is small initially but grows significantly as implementation approaches. For example, one year after news and two years before implementation, an upcoming positive one-month change in patent term generates a decline in patent filings of 0.5 units per technical field×quarter, which is approximately -1.5% of the 1992Q3 baseline. The magnitude almost triples two years after news and one year before implementation and further increases by a factor of four in the pre-implementation quarter 1995Q2. Inspection of the raw data reveals that the latter effect is almost entirely driven by a dramatic rise in patenting in fields that are more exposed to a reduction in effective patent term. Intuitively, for innovators at risk of having a patent protection loss ($\Delta T_j < 0$) starting from June 1995, 1995Q2 represents the last chance to file an application under the old, more advantageous policy regime, which generates the strongly negative DiD estimate in 1995Q2.[20]

Third, the post-implementation $\widehat{\beta}_k$ $k \in [1995Q3; 200Q4]$ coefficients remain negative, which I refer to as **Fact 2**. The reduced-form impact of an *anticipated* patent

A linear trend with a quarterly slope of -0.001 (equal to the upper bound of 2000Q4's confidence interval divided by the number of post-news quarters) would be detected with a power of 0.92. A linear trend with a slope of -0.0008, which would be detected with power 0.5, would induce a downward bias as small as 10% in 2000Q4 DiD estimate.

[19] A natural concern is that the length of the pending period is negatively correlated with the maturity of the field. This would be the case if before the TRIPs more recent fields have both fast growth in innovation and a longer average pending period because of congestion. This would bias the DiD estimates, but pre-news coefficients would be negative and significant. Figure 1.2 shows that this is not the case.

[20] Appendix 1.B.2.1 investigates bunching in greater detail.

term extension is negative for at least five years after implementation. The average effect is significant, with a one-month patent term increase being related to -3.7 quarterly patents per field, which is around 12% of the baseline. However, a sample extension to 2010 (Appendix 1.B.2.6) suggests that this negative effect is temporary, as the estimated coefficients gradually revert to zero. It is important to note that the negative post-implementation estimates should not be interpreted as a direct causal effect of the implementation of a longer patent term on a decrease in patenting. The post-implementation estimates may also be influenced by the heterogeneous innovation patterns that were induced by the news shock.

Patent-based measures of innovation focusing on scientific value, measured by patents weighted by the number of forward citations received within 5 years from grant, or private economic value deliver consistent results with the main findings. Appendices 1.B.2.2 and 1.B.2.3 present evidence for these alternative measures, respectively. Additionally, I provide results for claims-weighted patents in Appendix 1.B.2.4. These findings suggest that the policy had null or mild effects on average patent quality.

Patent-based measures of innovation have limitations, and the policy change could lead to estimated DiD coefficients resulting from (i) a genuine effect of the policy on actual innovation, (ii) an effect on patenting choices as an alternative to trade secrecy, absent any changes in innovation, or (iii) a mix of both. However, I argue against case (ii) through several empirical analyses that reveal a tight connection between policy-induced variation in patenting and real variables. In Subsection 1.4.3, I show that the estimated policy-induced reduction in patenting outcomes corresponds to an economically significant decline in Total Factor Productivity and to a rise in producers' prices at the sectoral level. Additionally, firms with more exposure to fields anticipating a patent term extension reduced their balance-sheet R&D expenditures after both policy news and implementation. This evidence complements the field-level analysis of R&D effort, which I present next.

**1.4.1.2.2 R&D effort** I measure field-level R&D effort as the headcount of inventors who contributed to any patents classified in a given field-$j$ and quarter-$t$.[21] Results for R&D effort as an outcome of interest are presented in panels (a) and (b) of Figure 1.3, which display DiD estimates of specifications (1.2) and (1.3), respectively. The findings mirror those discussed earlier for patent-based innovation outcomes: R&D effort decreases after the announcement of a future patent term increase and remains lower after implementation. The magnitudes are similar as well: news of a one-month increase in patent term on future patents leads to a decline of 4.1 active inventors (roughly -7% of the 1992Q3 baseline) one year before implementation. Post-implementation estimates indicate a reduction of 9.2 inventors per field and quarter, which is equivalent to -15% of the baseline.

## 1.4.2 Identifying assumptions and endogeneity concerns

In this subsection, I first outline conditions necessary for a causal interpretation of the results. Subsequently, I address various endogeneity concerns.

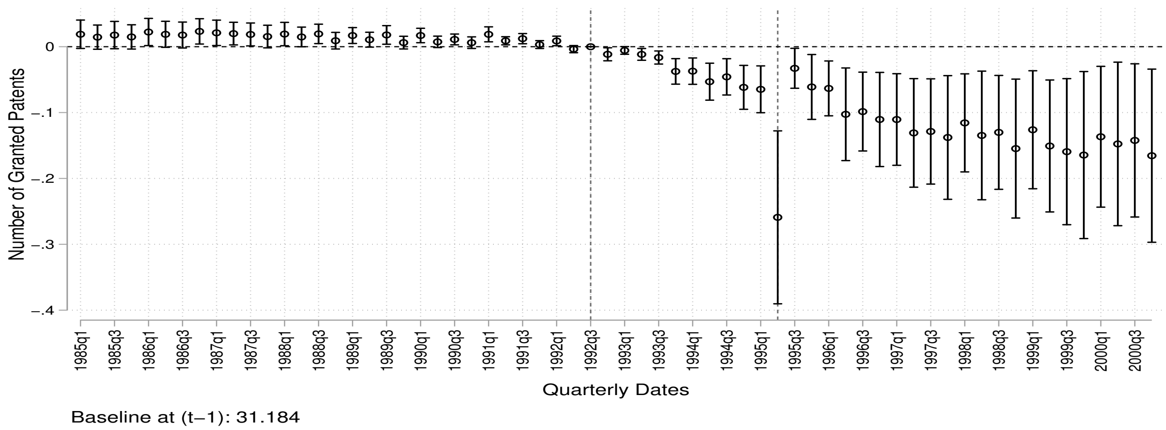
### 1.4.2.1 Identifying assumptions

To interpret the results of Subsection 1.4.1 causally, it is necessary to rule out reverse causation and omitted variable bias. Concerning the former, Section 1.2 explained the origin of the TRIPs-related patent term adjustment in the US, making it unlikely that technical fields experienced differential changes in effective patent term due to differences in future innovation outcomes. As for the latter, I need to ensure that, given the control variables, the change in patent term $\Delta T_j$ is not correlated with

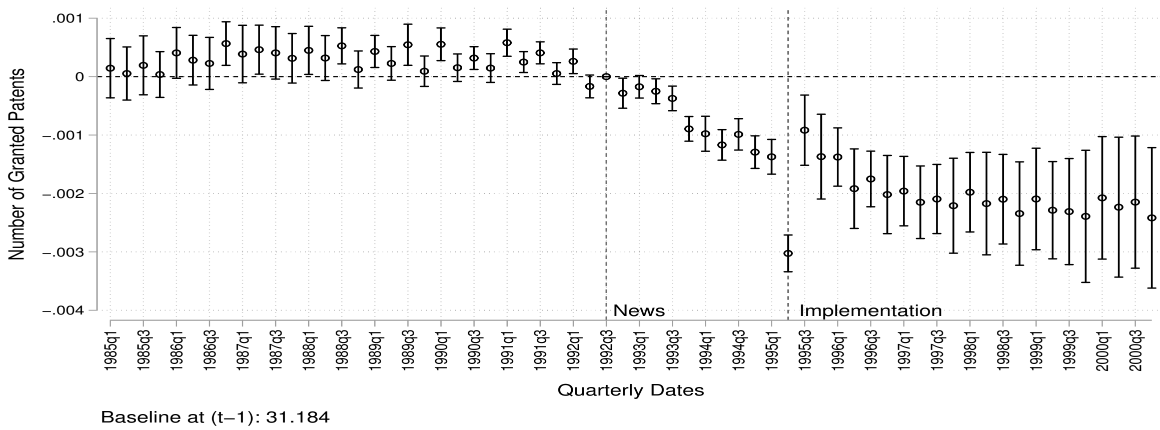
[21] To compute inventors count, I use disambiguated STAN harmonized identifiers by the EPO Worldwide Bibliographic Database, available in PATSTAT. I compute the number of inventors listed on field $j$ patents filed in quarter $t$. To avoid inflating the R&D proxy, I count inventors just once per field$\times$quarter if they appear on multiple patents.

Figure 1.2: Marginal effect of effective patent term on granted patents

(a) Linear model



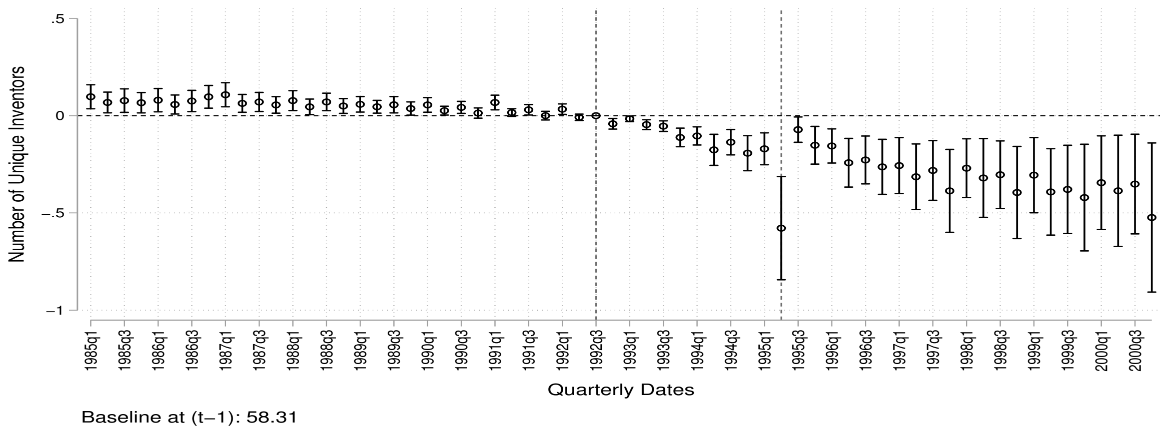

(b) Poisson model



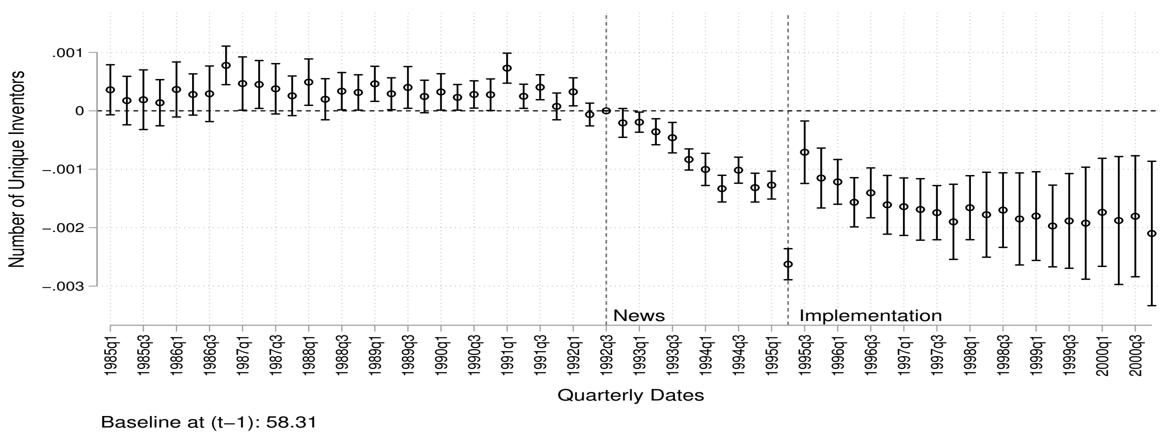

Panel (a) and panel (b) show the $\widehat{\beta}_k$ estimates of specifications (1.2) and (1.3), respectively, having as dependent variable the number of granted patent applications. The first (second) vertical line denotes the news (implementation) quarter 1992Q4 (1995Q3). In panel (a), each point-estimate represents the change in the number of granted patents filed in quarter-$k$, relative to the 1992Q3 baseline reported at the bottom of the plot, due to a one-day positive variation in $\Delta T_j$. In panel (b), each point-estimate represents the percentage deviation of the number of granted patents filed in quarter-$k$ from the 1992Q3 baseline due to a one-day positive variation in $\Delta T_j$. Standard errors are clustered by technical field and 95% confidence bands are plotted.

Figure 1.3: Marginal effect of effective patent term on the number of inventors

(a) Linear model




(b) Poisson model




Panel (a) and panel (b) show the $\widehat{\beta}_k$ estimates of specifications (1.2) and (1.3), respectively, having as dependent variable field- and quarter-specific inventors headcount. The first (second) vertical line denotes the news (implementation) quarter 1992Q4 (1995Q3). In panel (a), each point-estimate represents the change in quarter-$k$ inventors' headcount, relative to the 1992Q3 baseline reported at the bottom of the plot, due to a one-day positive variation in $\Delta T_j$. In panel (b), each point-estimate represents the percentage deviation of quarter-$k$ inventors' headcount from the 1992Q3 baseline due to a one-day positive variation in $\Delta T_j$. Standard errors are clustered by technical field and 95% confidence bands are plotted.

any unobserved factors that differentially affect R&D or innovation across fields at the same time or after the policy shocks. While field fixed effects account for time-invariant heterogeneity and a lack of significant pre-trends suggests a limited role for pre-existing omitted variables, in the following subsection, I discuss several time-varying confounders that may occur contemporaneously or subsequent to the policy shocks.[22]

#### 1.4.2.2 Discussion of endogeneity concerns

**1.4.2.2.1 Macroeconomic factors** To address potential bias from macroeconomic changes that may have affected innovation outcomes heterogeneously across technical fields, I add quarter-by-three-digit International Patent Class (IPC) fixed effects to specifications (1.2) and (1.3).[23] These fixed effects control for any quarter-specific unobserved factor whose effect is specific to a three-digit IPC and estimate $\widehat{\beta}_k$ using variation in innovative outcomes across four-digit fields within the same three-digit IPC. Given that the latter provide a relatively granular level of control, the approach effectively mitigates the influence of several macroeconomic confounders such as the rise of Information Technologies during the 1990s, the recovery from the 1991 recession, Clinton's tax increases, reductions in defense spending after the end of the Cold War, and changes to nominal interest rates. Figures 1.B.19 and 1.B.21 in Appendix 1.B.2.12 display DiD estimates of this enriched specification for granted patents as outcomes, using both linear and Poisson models. Results remain similar to those of Figure 1.2.

[22]For instance, field fixed effects control for time-invariant differences, such as average size or patent examination complexity, which could influence congestion and generate pending period heterogeneity that is crucial for the proposed identification strategy. Additionally, Table 1.A.4 indicates that $\Delta T_j$ does not correlate with variables such as the growth rate of patenting, which would suggest the existence of pre-trends.

[23]For example, a 3-digit IPC C21 is "Metallurgy of Iron", which includes three 4-digit IPCs among which C21B "Manufacture of Iron or Steel", C21C "Processing or Pig-Iron (...)", and C21D "Modifying the Physical Structure of Ferrous Metals (...)". Examples of other 3-digit IPCs are C25 "Electrolytic or Electrophoretic Procceses", A43 "Footwear", D03 "Weaving", etc.

#### 1.4.2.2.2 Additional factors related to TRIPs and Uruguay Round

The primary concern arises from alterations in maximum tariffs that occurred as a result of the Uruguay Round of agreements. As Coelli, Moxnes and Ulltveit-Moe (2022) shows that tariff reduction positively affected innovation in several countries, if trade-related factors have a correlation with $\Delta T_j$ across fields the estimates obtained using DiD would be biased for the effect of interest. To mitigate this issue, I leverage WTO data to measure the change in import tariff intensity by technical field between 1996 and 2001 for the US, European countries, and China. In specifications (1.2) and (1.3), I control for these variations, interacted with quarterly fixed effects.[24] Figures 1.B.28 and 1.B.29 in Appendix 1.B.2.15 present identical estimates to Figure 1.2. The reason being, Appendix 1.B.2.15 illustrates that tariff changes had a negligible correlation with $\Delta T_j$ across fields.

The second concern arises from the fact that patent protection in several Low- and Middle-Income countries (LMICs) was strengthened by TRIPs, thereby benefiting the US firms' access to these markets.[25] If a relation exists between enhanced patent protection in LMICs and $\Delta T_j$ across fields, the DiD estimates from specifications (1.2) and (1.3) could capture a biased effect of $\Delta T_j$. However, Appendix 1.B.2.7 argues against this possibility. Using specification (1.2), I test whether $\Delta T_j$ has any relation to the access of US innovators to LMICs' markets where TRIPs strengthened patent rights. I measure it by the field- and quarter-specific share of US patents for which applicants file additional applications in those jurisdictions, and I find no effect.

The third concern is that TRIPs may have increased applicants' responsiveness to

[24] The analysis uses WTO data on tariff intensity by HS-2002 product categories, a standard classification scheme for traded products. Using the crosswalks by Goldschlag, Lybbert and Zolas (2019), I compute exposure to tariffs by technical field as a weighted average of the share of HS-2002 product codes with a reported tariff on imports from WTO members above 5%.

[25] Kyle and McGahan (2012) argue that US pharmaceutical firms increased their innovation investment after TRIPs due to their ability to enforce patents in new developing markets. Appendix 1.B.2.16 shows that Subsection 1.4.1.2's results are robust to excluding from the sample fields related to the pharmaceutical products and bio-technologies. Bloomfield et al. (2022) shows that the introduction of stronger patents in LMICs favored scientific knowledge flows to developed countries.

USPTO's inquiries during examination, resulting in a reduction of the pending period ex-post.[26] If this responsiveness is correlated with $\Delta T_j$ across fields, it may bias DiD estimates. However, Appendix 1.B.2.5 indicates that $\Delta T_j$ does not correlate with variation in the field- and quarter-specific average pending period after TRIPs shocks. This finding suggests that changes in applicants' responsiveness do not impact DiD estimates.[27] Additionally, results in Appendix 1.B.2.8 show that the measurement error caused by using $\Delta T_j$ instead of $\Delta T_{j,t}$ (i.e., the patent term change computed using a pre-TRIPs average pending period instead of a quarter-specific one) is negligible.[28]

Lastly, to address potential endogeneity concerns arising from unobserved attributes of the US innovation environment, such as differential lobbying or political connections across fields, that could correlate with $\Delta T_j$ and lead to differential innovation outcomes after the TRIPs, an instrumental variable (IV) strategy is proposed. This IV strategy isolates variation in $\Delta T_j$ from two external instruments that measure (i) the field-specific complexity of patent examination, proxied by the pre-TRIPs field-specific average pending period at the European Patent Office (EPO), and (ii) the congestion of technical units, proxied by the field-specific share of USPTO applications by non-US applicants before the TRIPs.[29] The 2SLS DiD estimates for the

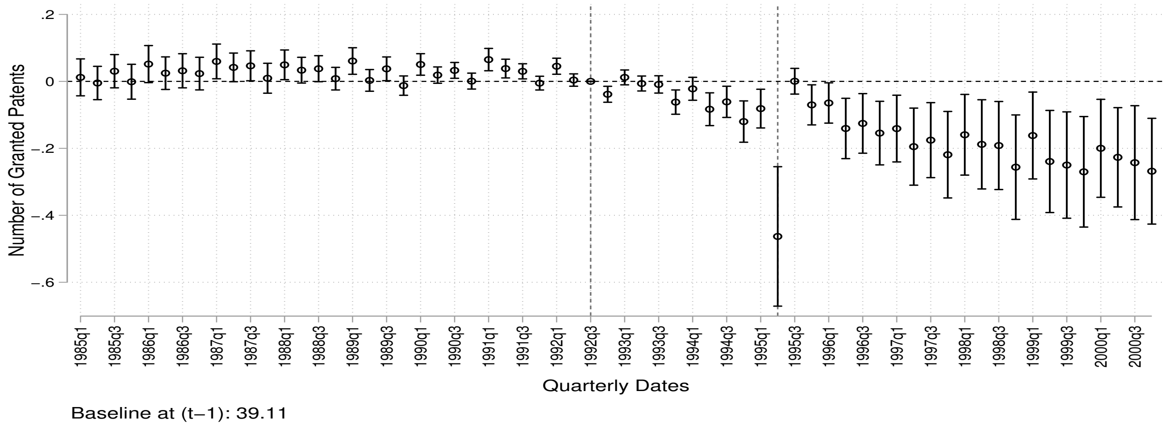
[26] Lemus and Marshall (2018) show this for the pharmaceutical sector.

[27] I replicate the analysis of specification (1.2) using the quarter- and field-specific average pending period as the dependent variable. The resulting $\beta_k$ estimates for the post-news and post-implementation periods capture the impact of $\Delta T_j$ on deviations of the outcome variable from the pre-TRIPs average pending period used to compute $\Delta T_j$. Figure 1.B.11 displays the findings, indicating that $\Delta T_j$ is not correlated with (i) field-specific heterogeneous trends in average pending period prior to the TRIPs news, or (ii) significant level- or trend-changes following the TRIPs shocks.

[28] In Appendix 1.B.2.8, I address measurement error concerns by using an instrumental variable specification. Specifically, I instrument the quarter- and field-specific policy-induced change in effective patent term ($\Delta T_{j,t}$) with $\Delta T_j$ interacted with quarterly dummy variables. This allows for a more accurate measurement of the treatment variable, while also reducing endogeneity concerns. The results are consistent with those reported in subsection 1.4.1.2, and the first-stage regressions confirm that $\Delta T_j$ is a statistically strong predictor of the ex-post average change in patent term. Additionally, the raw correlation between $\Delta T_j$ and $\Delta T_{j,t}$ is generally between 0.5 and 0.6.

[29] To minimize reverse causation concerns, both instruments are based on patents granted prior to the policy news in 1992Q4. For the IV strategy to be valid, it is necessary for confounding factors to be orthogonal to the excluded instruments, i.e., for US lobbying activity or political connections to be uncorrelated with the average patent examination time at the EPO and with foreign firms' decisions to seek patent protection in the US.

Figure 1.4: Marginal effect of effective patent term on granted patents – IV




The plot shows the 2SLS DiD estimates of $\beta_k$ coefficients in specification (1.2) when $\Delta T_j$ is instrumented by (i) congestion by non-US applicants and (ii) technical complexity of examination. Appendix 1.B.2.10 reports all the details of the analysis. The first (second) vertical line denotes the news (implementation) quarter 1992Q4 (1995Q3). Each point-estimate represents the change in the number of field-specific granted patents applied for in quarter-$k$, relative to the 1992Q3 baseline reported at the bottom of the plot, due to a one-day positive variation in $\Delta T_j$. Bands represent 95% confidence bands, with standard errors are clustered by technical field.

number of granted patents as an outcome are shown in Figure 1.4, which are analogous to the OLS DiD results of Figure 1.2. Further details and additional results are reported in Appendix 1.B.2.10.[30]

**1.4.2.2.3 Additional analyses** Appendices 1.E.1.1, 1.E.1.2, and 1.E.1.3 show that the change in patent term did not affect average patent quality. Appendices 1.B.2.13 and 1.B.2.9 demonstrate that the magnitude of DiD estimates is more pronounced in fields that are (i) expected to be more responsive to patent term changes, based on their higher rate of renewal fees payment up to the maximum term, and (ii) where the inference on the TRIPs-induced change in average patent term was more precise due to lower dispersion of patent-specific pending periods around field-average. Appendix 1.B.2.14 presents a placebo analysis supporting the validity of the results.

[30] Appendix 1.B.2.10 presents the 2SLS DiD regression specification and confirms the consistency of results for the R&D effort as an outcome variable with the OLS DiD evidence. In addition, Appendix 1.B.2.11 provides further evidence of consistency by demonstrating similar results obtained using an IV-control function approach in the Poisson model (1.3).

### 1.4.3 From patents to firm-level R&D and sectoral TFP

In this subsection, I demonstrate that the impact of the TRIPs patent term change on direct measures of R&D inputs and innovative output is in line with the observed effect of the policy on patenting and patent-based R&D measures. This indicates that the latter reflect, to some extent, actual changes in innovation rather than just adjustments in patenting strategies. To begin with, I conduct a firm-level analysis of R&D expenditures. I then establish a connection between patenting variations and Total Factor Productivity (TFP) as well as producers' prices.

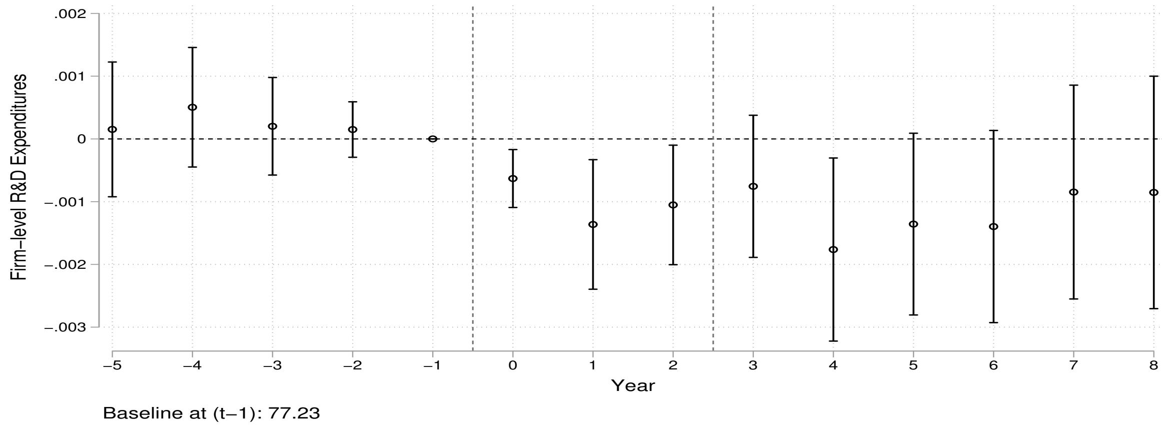
#### 1.4.3.1 Firm-level evidence on R&D

I compile a yearly panel sample comprising 2,421 listed US firms included in the NBER-Compustat matched dataset by Hall, Jaffe and Trajtenberg (2001) for the period 1985-2000. For each firm $i$, I calculate the TRIPs-induced change in patent term $\Delta T_i$ as a weighted average of field-specific effective patent term changes $\Delta T_j$, where the weights correspond to firm $i$'s technological exposure to field $j$ before the TRIPs. To compute weights, I use the fraction of firm $i$'s patents filed in field $j$ during 1971-1991. To supplement this information, I gather balance-sheet data on firm-level R&D expenditures (`xrd` in Compustat) and other relevant details from Compustat (Standard&Poor's, 2022). The firm-level Poisson DiD specification is

$$R\&D_{i,t} = \exp\left\{\alpha_i + \sum_{\substack{k=1987 \\ k\neq 1991}}^{2000} \gamma_k \mathbf{1}_{(t=k)} + \sum_{\substack{k=1987 \\ k\neq 1991}}^{2000} \beta_k \mathbf{1}_{(t=k)} \Delta T_i + \theta' \mathbf{X}_{i,t} + \varepsilon_{i,t}\right\} \tag{1.4}$$

and compares R&D investment between firms heterogeneously exposed to the TRIPs patent term change before and after the policy shocks. Model (1.4) includes firm fixed effects $\alpha_i$, year fixed effects, a vector of controls $\mathbf{X}_{i,t}$ comprising firm-age fixed effects, 3-digit SIC industry $\times$ year fixed effects, and a 3-digit-SIC-specific

Figure 1.5: Marginal effect of 1 more day of protection on firm-level R&D




The plot shows the $\beta_k$ coefficients of regression (1.4) having as dependent variable $R\&D_{i,t}$, i.e., year-$t$ and firm-$i$ R&D expenditure. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on *percent deviations* of the outcome variable from its baseline value in 1992Q3. Standard errors are clustered by firm and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

quadratic trend in age. The idiosyncratic error term is $\varepsilon_{i,t}$. Each DiD coefficient $\beta_k$ captures the impact of an expected one-day positive change $\Delta T_i = +1$ on the log-deviation (approximate percentage change) of R&D expenditures from their 1991 baseline level.

Figure 1.5 shows the pseudo-ML estimates $\widehat{\beta}_k$ of (1.4) with 95% confidence bands clustered by firm. The results are in agreement with those of Subsection 1.4.1.2 based on patent-based proxy of R&D effort. According to the findings, the announcement of a one-month increase in patent term to be implemented in 1.5 years leads to a contemporaneous decrease of 4% in yearly firm-level R&D expenditures (Fact 1). Additionally, the DiD estimates remain negative after implementation, which is consistent with the previous Fact 2.[31]

Appendix 1.B.4.2 reports consistent results for firm-level patenting, citations, and

[31] The magnitudes of the effects are smaller compared to the technical field analysis, possibly due to three reasons. Firstly, the effect estimated for patent-based R&D may include changes in patenting decisions that are not related to innovative effort. Secondly, firm-level results do not include net entry, which is present in aggregate innovation and R&D. Thirdly, balance sheet R&D data reflects policy effects more promptly than patent-based inventors headcount, which partly reflects past efforts.

patent value, and placebo analyses of firm-level variable costs, capital expenditures, and sales. Moreover, Appendix 1.B.4.5 shows consistent evidence of reallocation of innovation within firms between technical fields.

#### 1.4.3.2 Industry-level evidence on TFP and prices

This subsection presents evidence that changes in patenting due to the TRIPs patent term change led to consistent variation in sectoral Total Factor Productivity (TFP) and producers' prices, which are used as an inverse measure of consumer welfare.

To do so, I construct a yearly panel of 428 6-digit NAICS industries over 1985-2000. This involves observing TFP estimates, price deflators, and other aggregates from the NBER CES Manufacturing database (Becker, Gray and Marvakov, 2021), and using crosswalks by Goldschlag, Lybbert and Zolas (2019) to construct sectoral patenting outcomes and the sectoral patent term change $\Delta T_s$ from the technical-field measures. Appendix 1.B.6 provides additional details.

I conduct two analyses. Firstly, I estimate the effect of TRIPs-induced changes in patenting on TFP and prices through the following second-stage panel regression

$$\{tfp_{s,t} \quad ; \quad vsd_{s,t}\} = \alpha_s + \gamma_t + \beta \widehat{Pat}_{s,t} + \Xi \mathbf{X}_{s,t} + \varepsilon_{s,t} \tag{1.5}$$

Here, the dependent variables are the natural logarithm of either TFP or the value of shipments deflator in industry $s$ and year $t$. The model includes industry- and year-fixed effects, denoted by $\alpha_s$ and $\gamma_t$, respectively. Additionally, $\mathbf{X}_{s,t}$ comprises industry-specific time-varying controls, namely the (log of) energy inputs deflator and energy costs. Finally, $\varepsilon_{s,t}$ represents the idiosyncratic error term. $\widehat{Pat}_{s,t}$ represents the fitted values of the first stage regression

$$Pat_{s,t} = \kappa_s + \iota_t + \psi_t \times \Delta T_s + \Lambda \mathbf{X}_{s,t} + u_{s,t} \tag{1.6}$$

which is a sectoral version of (1.2) augmented by the second-stage controls $X_{s,t}$.

The coefficient $\beta$ in equation (1.5) represents the effect of policy-induced changes in patenting on TFP and producers' prices. In Appendix 1.B.6, Tables 1.B.9 and 1.B.8 report estimates for both outcomes and various patenting measures. The results show that a yearly and sectoral increase of 100 patents (36% of the sample average) induced by the patent term change leads to a 3.3% increase in TFP and a 2.7% decrease in prices. The implied pass-through of TFP gains into lower prices is approximately 0.83. These findings indicate that the estimated impact of patent term on patenting corresponds to economically significant effects on productivity and welfare.

In the second analysis, I examine the dynamics of the effects of TRIPs patent term change on TFP and prices. To do so, I estimate (1.6) with the natural logarithm of either TFP or the value of shipments deflator as the dependent variables. Figures 1.B.53 and 1.B.54 in Appendix 1.B.6.2 plot DiD estimates that are consistent with Facts 1-2, as TFP declines and producers' prices rise after both news and implementation of an anticipated patent term extension.

### 1.4.4 Direct effects of patent term *without* anticipation

I will now proceed to analyze the direct effects of an unexpected implementation of a patent term extension, which I discover increases both R&D and innovation. As discussed in Subsection 1.4.1.2, two factors potentially impact the post-implementation DiD estimates of specifications (1.2) and (1.3). The first is the direct effect of the policy implementation shock, while the second factor originates from any changes in innovation and R&D that occur as a result of the news shock. The baseline specifications do not directly account for the latter, and therefore rely on $\Delta T_j$ to indirectly capture the effects of any such changes.[32] Following Angrist and Pischke (2009), it seems therefore relevant to control for field-specific innovation histories through past

[32] This is the case because the post-implementation effects of news-driven changes in innovation patterns are mechanically correlated with $\Delta T_j$, which is responsible for heterogeneous news effects.

outcomes, which requires dropping field fixed effects because their inclusion would result in inconsistent DiD estimates (Nickell, 1981). Hence, I estimate the specification

$$\begin{aligned} Y_{j,t} = & \sum_{k \neq '92Q3} \mathbf{Z}_{pre,j} \mathbf{1}_{(t=k)} \eta_k + \sum_{k \neq '92Q3} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k \neq '92Q3} \phi_k \mathbf{1}_{(t=k)} \Delta T_j + \\ & + \sum_{k \neq '92Q3} \psi_k \mathbf{1}_{(t=k)} \underbrace{\overline{Y}_{j,k-\mathcal{A}-1:k-1}}_{\equiv \frac{1}{\mathcal{A}} \sum_{q=k-\mathcal{A}-1}^{k-1} Y_{j,q}} + \psi_0 \underbrace{\overline{Y}_{j,t-\mathcal{A}-1:t-1}}_{\equiv \frac{1}{\mathcal{A}} \sum_{q=t-\mathcal{A}-1}^{t-1} Y_{j,q}} + v_{j,t} \end{aligned} \tag{1.7}$$

To control for field-specific time-invariant characteristics, I introduce a vector $\mathbf{Z}_{pre,j}$ consisting of pre-determined attributes interacted with quarterly fixed effects, replacing the field-fixed effects. $\mathbf{Z}_{pre,j}$ includes data on field size, average forward citations per patent, and average inventors per patent from 1980-1985. Separate analyses confirm that substituting fixed effects with $\mathbf{Z}_{pre,j}$ controls does not alter the findings of Subsection 1.4.1.2. In addition, I account for the quarter-specific impact of lagged outcomes in the second line of equation (1.7), where $\overline{Y}_{j,k-\mathcal{A}-1:k-1}$ denotes the average outcome variable in the $\mathcal{A}$ quarters before $k$, and $\psi_k$ represents the deviation of its quarter-specific impact from $\psi_0$. I set $\mathcal{A}$ equal to 10, which corresponds to the number of TRIPs anticipation quarters.[33]

The DiD coefficients $\phi_k$ reflect the marginal effect of $\Delta T_j$ on quarter-$k$ outcome, conditional on field-specific innovation histories up to that point, which also includes the influence of policy shocks themselves on past outcomes. Thus, the $\widehat{\phi}_k$ estimates for the anticipation period 1992Q4-1995Q2 primarily capture the impact of the news shock, while the post-implementation $\widehat{\phi}_k$ estimates clean original DiD estimates' cumulative news effects and isolate the impact of the implementation shock only.

Figures 1.6a and 1.6b display OLS estimates of $\phi_k$ coefficients for the number of granted patent applications and patent-based R&D effort as the dependent variables, respectively.[34] Both figures confirm that the direct effect of a positive patent term

[33] Results are robust to choosing a smaller $\mathcal{A} = 8$ or larger $\mathcal{A} = 16$ number of quarters.

[34] In a robustness analysis shown in Appendix 1.B.2.17, I estimate (1.7) by 2SLS instrumenting lagged outcomes $\overline{Y}_{j,k-\mathcal{A}-1:k-1}$ by the fitted values of DiD specification (1.2) having $\overline{Y}_{j,k-\mathcal{A}-1:k-1}$ as

change on R&D and innovation is positive after implementation, denoted as **Fact 3**. This effect remains stable throughout the sample period, indicating that absent anticipation, the implementation of a patent term extension increases both R&D and innovation. On average, a one-month extension generates +0.64 patents per quarter, approximately 2% of the 1992Q3 baseline, while the average effect on R&D effort is +1.4 inventors per quarter, which is +2.7% of the baseline. Additionally, pre-implementation coefficients remain negative, consistent with **Fact 1**, which suggests that the news of the patent term increase on patents filed in the future results in a decline in current R&D and innovation until implementation.[35]

### 1.4.5 Key elasticity estimates and heterogeneity by broad technologies

To summarize results and investigate heterogeneity by broad technical area, I propose two elasticity measures of R&D and innovation to patent term news and implementation shocks.

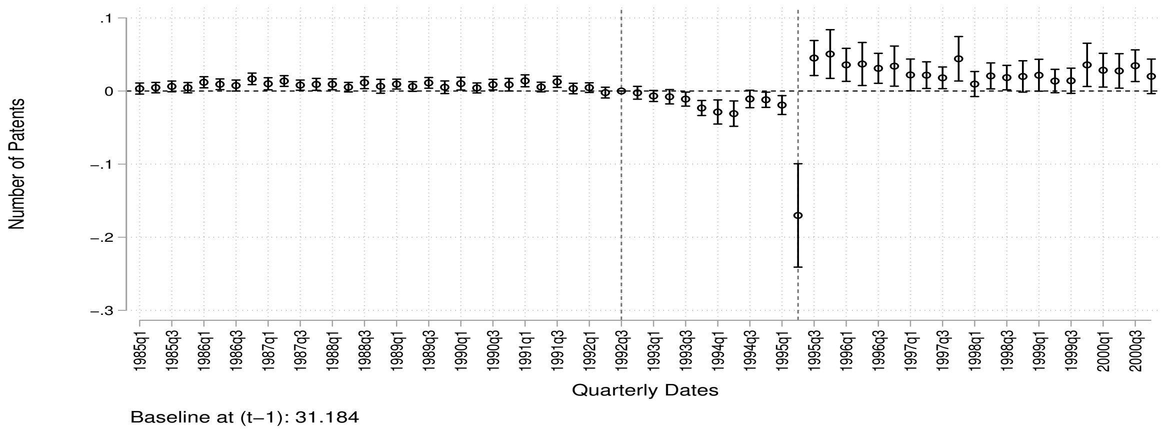
The first elasticity, denoted as $e^{news}_{y-1,T}$, captures the percentage change in outcome $y$ at time $t$ due to the news of a 1% increase in patent term $T$ for future patents filed after one year from $t$. To compute this measure, I use the estimate $\widehat{\beta}_{1994q2}$ of the marginal effect of a 1-day increase in $T_j$ on $y$, obtained from specification (1.2). Specifically, $e^{news}_{y-1,T}$ is calculated as $\frac{\widehat{\beta}_{1994Q2}/\overline{y}_{1994Q2}}{1/(365\times 17)}$, where the numerator is the ratio of the marginal variation in $y$ to the average outcome $\overline{y}_{1994Q2}$ across fields in the same quarter, and the denominator is the ratio of the 1-day change in $T_j$ to the pre-TRIPs effective patent term of 17 years. The results show that news of a 1% future increase

dependent variable. Therefore, I exploit variation in lagged outcomes $\overline{Y}_{j,k-\mathcal{A}-1:k-1}$ that originates from the policy change only. Results are fully consistent with OLS estimation of (1.7) presented in Figure 1.6.

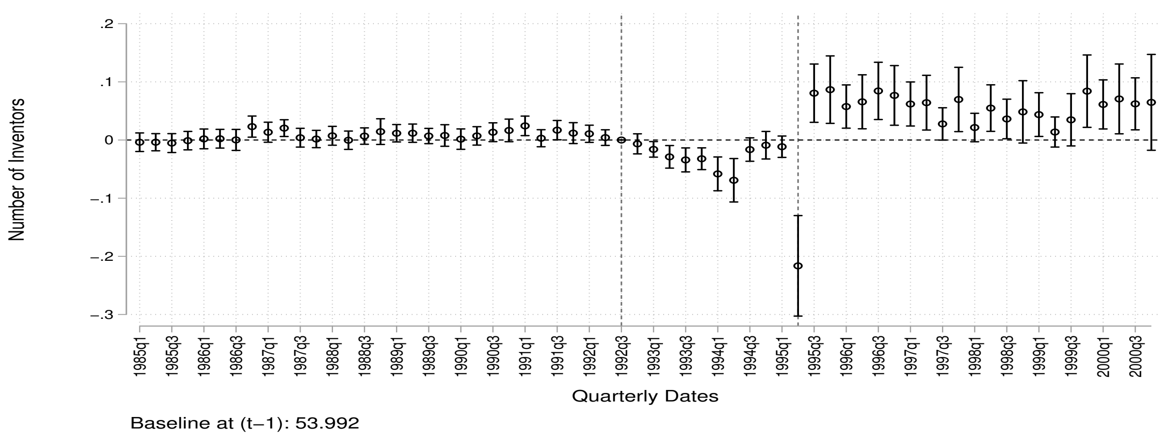
[35] Appendix 1.B.2.17 shows similar evidence for citations-weighted patents. Appendix 1.B.2.18 shows that innovation histories in other fields are quantitatively negligible for identifying the post-implementation direct effects of $\Delta T_j$. Appendix 1.B.2.19 extends the empirical strategy of this subsection to a Poisson specification.

Figure 1.6: Marginal effect of patent term controlling for anticipation

(a) Number of patents




(b) R&D effort




Panel (a) and panel (b) show the $\phi_k$ coefficients of OLS estimation of specification (1.7) with $Y$ being the raw count of patents or the number of inventors, respectively. Inventors count avoids multiple counting of the same individual appearing on more than one patent in the same field and quarter. The first (second) vertical line denotes the news (implementation) quarter 1992Q4 (1995Q3). Each point-estimate represents the change in the *level* of the outcome variable in quarter-$k$, relative to the 1992Q3 baseline reported at the bottom of the plots, due to a one-day positive variation in $\Delta T_j$. Standard errors are clustered by technical field and 95% confidence bands are plotted.

in effective patent term leads to a decline in R&D and patenting of approximately -12.1% and -8.6%, respectively, one year before policy implementation. These elasticity measures represent new findings in the innovation literature.[36]

The second elasticity of interest, denoted by $e^{post,d}_{y+5,T}$, measures the percentage change in outcome $y$ five years after the *unanticipated* implementation of a 1% patent term increase. To compute it, I use the estimate of the direct patent term effect $\widehat{\phi}_{2000Q3}$ from specification (1.7) for $k$ =2000Q3 divided by the average level of the outcome $y$ in the same quarter ($\overline{y}_{2000Q3}$) and re-scaled by the ratio of $\Delta T_j = +1$ day to 17 years. The resulting 5-year elasticity of R&D and innovation to an unanticipated 1% patent term extension is 4.2 for both outcomes, with standard errors of 1.34 and 1.54, respectively.[37] This estimate is a novel contribution to the literature and can be related to the elasticity of innovation to market size, which, similarly to a patent term extension, increases profits. Using Chinese manufacturing data, Beerli et al. (2020) find that the elasticity of firm-level productivity to market size is 0.46. Interestingly, this is remarkably close to the elasticity of sectoral TFP to patent term that I estimate to be 0.4 based on the results of Subsections 1.4.4 and 1.4.3.2.[38]

Table 1.B.3 reports considerable variation in both elasticity measures across broad technological areas. The largest values are found in "Chemistry, Metallurgy" (8.09 and 9.75 for patenting and R&D, respectively), which includes pharmaceutical technologies, consistent with Budish, Roin and Williams (2015)'s finding that drugs are highly sensitive to patent protection. Additionally, "Human necessities" and "Electric-

[36]In addition, standard errors reported in Table 1.B.3 in Appendix 1.B.3 demonstrate that the effect is not only economically but also statistically significant. I compute the latter based on the clustered standard errors of $\widehat{\beta}_k$ and $\widehat{\phi}_k$, re-scaled using the same formulae used to compute the elasticity.

[37]Estimates are similar using the coefficient estimates from Poisson model (1.3) in Appendix 1.B.2.19. The computation is analogous to the one used in the text but does not re-scale by $\bar{y}$, because Poisson model's coefficients already express approximate percentage deviations. $e^{news}_{y-1,T}$ is -7.3 for patenting and -8.3 for R&D effort. $e^{post,direct}_{y+5,T}$ is 2.9 for patenting and 1.8 for R&D effort.

[38]I compute this figure as follows. Subsection 1.4.3.2's results imply that +100 patents induce +3.3% yearly TFP increase, which corresponds to an elasticity of 0.0924. Moreover, this subsection infers that the direct elasticity of patenting to patent term is 4.2. Therefore, the elasticity of TFP to patent term is computed as $0.0924 \times 4.2$.

ity" also exhibit high responsiveness to patent term incentives (4.44 and 3.58 elasticity of patenting to patent term, respectively). Conversely, estimates for other fields are either close to zero ("Performing Operations; Transporting", "Mechanical Engineering; Lighting; Heating; Weapons; Blasting", "Physics") or imprecisely estimated.

### 1.4.6 Key takeaways and interpretation

This section presented three empirical facts. Fact 1 shows that the announcement of a future patent term extension leads to a contemporaneous reduction in patenting and R&D expenditures prior to the policy's implementation. This change in patenting implies a genuine effect on innovation, as indicated by consistent changes in firm-level R&D expenditures and sectoral TFP. I interpret this as a result of firms intertemporally substituting costly investments in ongoing projects until after the implementation of the longer patent term, when the expected rewards are higher. Fact 2 demonstrates that the decline in R&D and innovation observed after the announcement persists for at least five years following policy implementation. This is due to the combined effects of (i) the direct effect of the new patent term, which enhances innovation and R&D (Fact 3), and (ii) the dynamic impact of field-specific innovation patterns induced by the news shock across different sectors on subsequent R&D and inventive outcomes. As the latter effect dominates the former, Fact 2 emerges. In the next section, I present suggestive evidence on the transmission channel of dynamic news effects related to the cumulative nature of innovation and a technology disclosure externality, which is a key feature of the model presented in Section 1.6.

## 1.5 Transmission channel of news effects

In this section, I first discuss the technology disclosure externality and present suggestive evidence of its role in transmitting anticipation effects to post-implementation outcomes. In Subsection 1.5.2, I also explore alternative channels, including competition.

### 1.5.1 Cumulative innovation and technology disclosure externality

The cumulative nature of innovation has been a central focus in growth literature since Romer (1990). While standard "standing on the shoulders of giants" externality concerns the stock of knowledge, recent studies highlight the significance of *recent* inventions, indicating for instance that more timely publication of patent applications generates more follow-up innovation (Hedge, Herkenhoff and Zhu, 2022). As new technologies build upon previous ones, inventors learn about them through direct interaction or detailed technical descriptions disclosed by patent documents. This is particularly relevant in the context of transitory news shocks, which affect the flow of novel inventions and the disclosure and diffusion of their technological content.

To investigate whether patterns of technological dependence and knowledge disclosure drive the dynamic effect of the news shock on post-implementation outcomes, the empirical analysis leverages cross-field heterogeneity in the degree to which new inventions build on previous ones. Motivated by Subsection 1.4.4's results and technological proximity, attention is restricted to the reliance of field-$j$ advances on recent ones from the same field and technological links among inventions are proxied by patents backward citations.[39] The preferred measure is $\overline{B}_{jj}$, which represents the average number of backward citations made by field-$j$ citing patents to previous field-$j$

[39]Patent classes are useful for identifying inventions with similar technological contents. However, other measures of technological similarity exist, such as Jaffe (1986)'s distance. This measures the distance between two fields based on the cosine similarity of their patent citation vectors. An extension of the analysis in Appendix 1.B.2.18 distinguishes the effect of same-field past innovation and a weighted aggregation of innovation from other fields based on their distance from the focal field. I find that the within-field channel is the primary driver of the transmission of the news shock to post-implementation outcomes. This is likely because the impact of $\Delta T_j$ news on same-field innovation is clear, while the news effect on the weighted aggregation of other fields' innovation combines positive and negative changes across fields, which partially cancel each other out.

patents published within three years from the application date of the citing document.[40]

In equation (1.8), I interact the change in patent term $\Delta T_j$ with $\overline{B}_{jj}$ and quarterly fixed effects. I observe two empirical patterns. First, the negative triple difference estimates $\widehat{\theta}_k$ in Figure 1.7a suggest that in fields with stronger dependence, the initial drop in innovation due to anticipation is followed by a larger additional decline after implementation. Second, the positive DiD post-implementation estimates $\widehat{\beta}_k$ in Figure 1.7b show that with zero technological dependence ($\overline{B}_{jj} = 0$), a patent term extension ($\Delta T_j > 0$) increases innovation after implementation. Similar results hold for R&D effort and quality-adjusted patent measures (see Appendix 1.B.5.6). These findings imply that the post-implementation effect of the patent term change is negatively related to the reliance on recent technologies, and are positive in fields where technological dependence is sufficiently low.

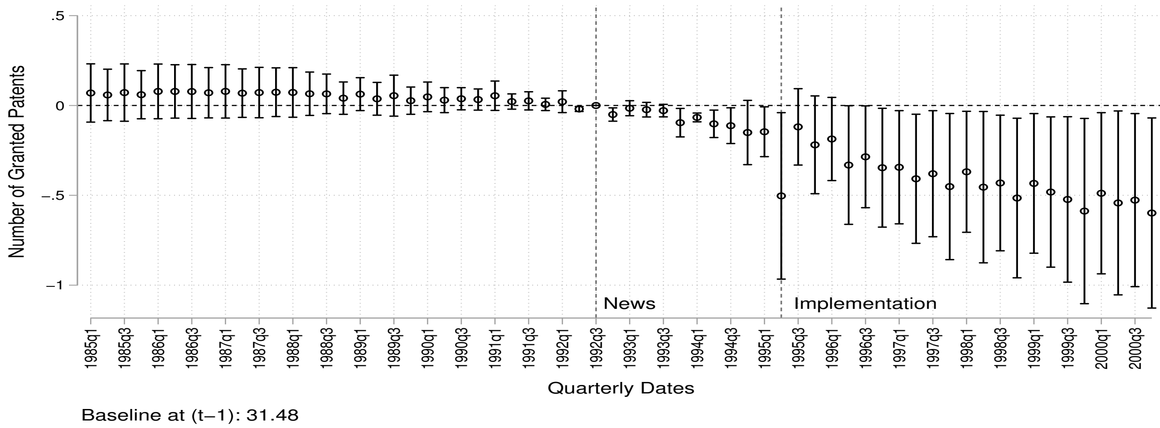
$$\begin{aligned} P_{j,t} = \alpha_j &+ \sum_{\substack{k=1985Q1 \\ k\neq 1992Q3}}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_{\substack{k=1985Q1 \\ k\neq 1992Q3}}^{2000Q4} \eta_k \mathbf{1}_{(t=k)} \overline{B}_{jj} \\ &+ \sum_{\substack{k=1985Q1 \\ k\neq 1992Q3}}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta T_j + \sum_{\substack{k=1985Q1 \\ k\neq 1992Q3}}^{2000Q4} \theta_k \mathbf{1}_{(t=k)} \Delta T_j \times \overline{B}_{jj} + \varepsilon_{j,t} \end{aligned} \tag{1.8}$$

Additionally, I present further empirical evidence highlighting the significance of the proposed transmission channel. Firstly, Appendix 1.B.5.7 demonstrates that time-varying measures of technological dependence decrease after implementation in fields that experience an average patent term extension. This implies that patents with high technological dependence contribute disproportionately to the negative DiD post-implementation effect in equation (1.2). The evidence also suggests that the technological disclosure externality has a half-life of four years, which I use in the model's

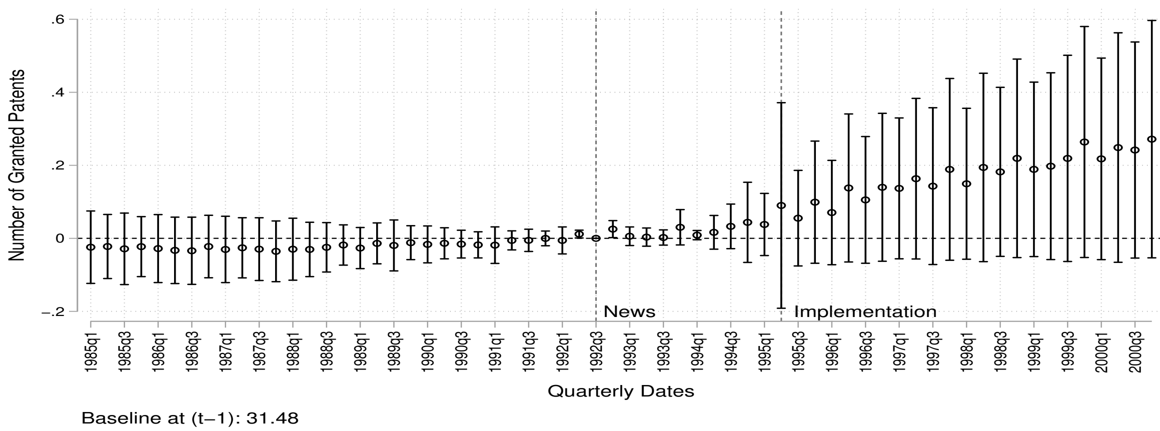
[40] The variable is computed using patents whose application is filed between 1980Q1 and 1989Q4, i.e., before the news shock of the policy.

Figure 1.7: Heterogeneity analysis based on within-field technological dependence

(a) Triple difference coefficients $\widehat{\theta}_k$




(b) Difference-in-Difference coefficients $\widehat{\beta}_k$




Panel (a) and panel (b) show the $\widehat{\theta}_k$ and $\widehat{\beta}_k$ coefficient OLS estimates of specification (1.8) with outcome of interest being the raw count of field- and quarter-specific patents. The former coefficients represent the change in the marginal effect of a one-day increase in patent term $\Delta T_j = +1$ on the number of patents corresponding to an increment of one in the average number of within-field backward citations per patent $\Delta \overline{B}_{jj} = +1$. The DiD estimates $\widehat{\beta}_k$ represent the marginal effect of a one-day increase in patent term $\Delta T_j = +1$ on the number of patents conditional on the average number of within-field backward citations per patent being zero $\overline{B}_{jj} = 0$. Standard errors are two-way clustered by technical field and treatment period (pre-news: 1985Q1-1992Q2; news: 199Q4-1995Q2; post-implementation: 1995Q3-2000Q4) and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

quantification.[41] Secondly, Appendix 1.B.5.8 shows a decrease in the intensity with which patents filed during the news period of 1992Q4-1995Q2 are cited by patents filed in the same field during the post-implementation phase. Thirdly, Appendix 1.B.5.9 finds that the proposed channel occurs entirely between firms, rather than within them, supporting its interpretation as an externality.[42] The magnitude of this channel is measured by the elasticity of future innovation to current innovation shocks, estimated to be 2.1 in Appendix 1.B.5.11. Finally, Appendix 1.B.5.10 utilizes firm-level balance-sheet data to demonstrate that R&D expenditure is relatively lower after implementation for firms more exposed to technological fields where aggregate R&D has fallen more during the news period.

### 1.5.2 Alternative channels

This subsection presents evidence on alternative channels through which patent term changes may impact innovation. Two potential channels are considered: Manipulation of patenting strategies and quality, and competition.

As to the former, for instance, a patent term loss may lead to breakup of applications and staggered filing thereof, inducing a downward bias in DiD estimates. However, this should result in a decline in measures of patent quality, such as average citations, originality, and generality, which I do not find in the data.[43]

[41] I calculate field- and quarter-specific technological dependence $\overline{B}_{jj,t}$ using applicant-made citations from field-$j$ patents applied for in quarter-$t$. To capture technical knowledge flows, I use $\overline{B}_{jj,t}$ as the outcome of interest in the DiD specification (1.2). The negative estimates of $\widehat{\beta}_k$ in Figure 1.B.52 indicate a decline in within-field technological dependence in fields with a patent term extension, which experienced a decrease in innovation during the anticipation period. This effect is strongest about four years after implementation, which I interpret as the half-life of the effect. The timing is consistent with a knowledge diffusion lag of two years, which is the approximate average time between invention and patent publication before TRIPs, and R&D gestation of two years. The estimate of 1.5 years by Pakes and Schankerman (1984) is close to the latter.

[42] The exercise involves (i) replicating the analysis from Subsection 1.4.4 on aggregated firm-level data, and (ii) taking advantage of the observation that new entrants in the post-implementation period do not experience a within-firm technological dependence effect upon entry. This implies that any innovation generated by these entrants cannot depend on their own past innovation.

[43] In addition, changes in patent term may affect incentives to patent irrespective of actual inventive activity. Subsection 1.4.3 already discussed that estimated effects on patenting correspond to

Competition is another potential channel, as competitive pressure may affect the desirability of patent protection and, thus, the effects of the policy change. Longer patent terms may affect the degree of competition by better shielding past innovators from new entrants and favoring the adoption of anti-competitive foreclosure practices, which could reduce further innovation. However, the analysis finds that higher ex-ante competitive pressure enhances the response of innovators to the patent term change, but it does not affect the degree of competition at the field level, suggesting that this is not the prevalent source of transmission.[44]

## 1.6 Model

This section introduces a semi-endogenous growth model with two novel features. Firstly, it distinguishes between research of new abstract ideas and the costly development of actual technologies, which allows for a representation of the intertemporal trade-off underlying the observed effects of the news shock on patenting and R&D. Secondly, it formalizes the technology disclosure externality underlying post-implementation effects by assuming that a faster aggregate speed of development enhances knowledge diffusion, thus increasing research productivity.

The new model is related to the workhorse semi-endogenous growth framework of Jones (1995) and to the two-stage R&D model of Comin and Gertler (2006*a*). In Appendix 1.C.5, I discuss the effects of an anticipated patent term change in these models and argue that the new theoretical elements are jointly crucial to correctly

consistent changes in R&D and TFP rather than reflecting bad measurement.

[44]Appendix 1.B.5.3 and 1.B.5.4 indicate that the policy treatment $\Delta T_j$ has no effect on the concentration of patents across innovators, as measured by the field-specific Herfindahl-Hirschman Index of quarterly patents flow, or on the field- and quarter-specific entry rate of new applicants, which is the percentage of patents granted to applicants that file for the first time in the field. For disambiguation, I use STAN harmonized applicant's identifiers from the EPO Worldwide Bibliographic Database, available in PATSTAT. Appendix 1.B.5.1 and 1.B.5.2 suggest that the effect of $\Delta T_j$ on innovation outcomes may be stronger with higher competitive pressure. Furthermore, Appendix 1.B.5.5 shows that the average quality of incumbents' patents does not decline with $\Delta T_j > 0$, and Appendix 1.E.1.4 documents that the renewal rate of patents up to the maximum term does not increase with $\Delta T_j > 0$. For the details of variables' construction, refer to Appendix 1.D.

infer the policy effects documented in Section 1.4.

The remainder of the section is organized as follows. Subsection 1.6.1 outlines the environment and the standard parts of the model. Subsection 1.6.2 describes research and development activities, which are distinct and determine the endogenous growth rate of the economy. Subsection 1.6.3 defines the competitive equilibrium, and Subsection 1.6.4 provides a qualitative description of the economic forces shaping the response of R&D and innovation to an anticipated patent term increase in the model. Appendices 1.C.1-1.C.4 contain derivations, computational and estimation details, and the analysis of key channels. Appendix 1.C.7 extends the model to a multi-field environment that closely matches the empirical setting of Section 1.4 and estimates it. Finally, Appendix 1.C.8 theoretically examines the role of trade-secrecy.

### 1.6.1 Environment

Time is continuous. and the economy is populated by a measure $L(t)$ of identical individuals. These individuals consume and invest out of a homogeneous final good, which is produced competitively using labor and intermediate capital varieties. Productivity growth is driven by research, which generates abstract ideas for new varieties, and development, which transforms these ideas into actual technologies. Innovators obtain patents on their inventions, and earn profits over the finite patent term $T$. As a result, only an endogenous fraction $\zeta$ of varieties is monopolistic, while the rest are competitively produced because their patents have expired. The representative consumer inelastically supplies labor and owns all the firms in the economy.

**1.6.1.0.1 Consumers** The representative consumer is characterized by linear utility $u(c(t)) = c(t)$ in per-capita consumption and inelastic labor supply. The consumer discounts the future at rate $\rho$, saves in real assets at interest rate $r(t)$, and its aggregate labor supply coincides with population $L(t)$, which exogenously grows at a rate of $n$.[45] Appendix 1.C.1.1 presents the household's maximization problem and shows that the Euler equation is $r(t) = \rho$ for all $t$.

**1.6.1.0.2 Final good production** Identical firms competitively produce the homogeneous final good solving the profit-maximization problem

$$\max_{L(t),\{X_{(i,t)}\}_i} \left\{ (h(t)L(t))^{1-\alpha} \int_0^{V(t)} X(i,t)^{\alpha} di - w(t)L(t) - \int_0^{V(t)} z(i,t)X(i,t)di \right\} \quad (1.9)$$

where $Y(t) = (h(t)L(t))^{1-\alpha} \int_0^{V(t)} X(i,t)^{\alpha} di$ is the production function of the final good, $h(t)$ is an exogenous productivity term, $L(t)$ is labor, $i$ indexes the measure $V(t)$ of intermediate capital varieties, $X(i,t)$ is the amount of $i$ used in production, $z(i,t)$ is its price, and $w(t)$ is the wage rate. Final good producers take input prices as given.

**1.6.1.0.3 Intermediate capital varieties production** Firms produce intermediate capital varieties using a linear technology in raw capital $K(t)$, which they rent from households at a competitive rate $r(t) + \delta$, where $\delta$ is capital depreciation rate. As the patent term is finite, the production of intermediate varieties can be either monopolistic or competitive. In the former case, producers maximize profits by taking the inverse demand for each variety as given and solve

$$\begin{aligned} &\max_{X(i,t),z(i,t)} \left\{ z(i,t)X(i,t) - (r(t)+\delta)X(i,t) \right\} \\ &\text{s.t.} \quad z(i,t) = \alpha h(t)^{1-\alpha} L(t)^{1-\alpha} X^{\alpha-1}(i,t) \end{aligned} \quad (1.10)$$

where the constraint equals the price $z(i,t)$ of intermediate variety $i$ to final good producers' inverse demand. The value of problem (1.10) represents the equilibrium flow of profits that new varieties guarantee over the finite patent term $T$.

[45]The economy features multiple assets, such as physical capital and firms' stocks. No arbitrage conditions ensure that, in the absence of uncertainty in this economy, the real rate of return is equal across assets. Appendix 1.C.1.1 precisely defines total assets for the household.

When it expires, production of the intermediate variety becomes perfectly competitive. Therefore, in maximization problem (1.10), the inverse-demand constraint is replaced by $z(i,t) = r(t) + \delta$, as perfect competition drives the price to marginal cost, resulting in zero profits.

**1.6.1.0.4 Capital market** Capital market clearing requires that the stock of capital supplied by households, $K(t)$, equals the quantity demanded for production of the $V(t)$ existing varieties, i.e., $K(t) = \int_0^{V(t)} X(i,t)di$. Furthermore, aggregate capital stock evolves according to $\dot{K}(t) = I_K(t) - \delta K(t)$, where capital growth $\dot{K}(t)$ is determined by the flow of new investment $I_K(t)$ and by depreciation $\delta K(t)$.

### 1.6.2 Research and Development

R&D activity generates new varieties through costly investments in units of the final good.[46] Identical firms engage in research activity to originate abstract ideas for new varieties, and those that successfully obtain a new idea have the exclusive possibility to develop it into a new patentable technology.

**1.6.2.0.1 Research** A unit measure of atomistic identical firms invest $I_R(t)$ units of the final good to discover new ideas, with the stock of ideas in the economy denoted as $N(t)$ and their price as $P(t)$, reflecting the option value of exclusively developing a new variety from the idea at a future date, net of development costs. The research investment problem is

$$\max_{I_R(t)} \left\{ P(t) \left[ E(t)^\chi V(t)^{\phi_1} I_R(t)^{\phi_2} \right] - I_R(t) \right\} \tag{1.11}$$

where $E(t)^\chi V(t)^{\phi_1} I_R(t)^{\phi_2}$ is the production function of ideas and the last term is the cost of research investment.[47] The production function assumes that new ideas

[46] Appendix 1.F.1 proposes an equivalent model where R&D uses labor rather than final good.

[47] In an extension of the model used for welfare analysis, the production function of projects is transformed into $(1-\zeta(t))^{\phi_1\eta} E(t)^\chi V(t)^{\phi_1} I_R(t)^{\phi_2}$, where $(1-\zeta(t))^{\phi_1\eta}$ is a distortion term that

increase with: (i) research investment $I_R(t)$, subject to decreasing returns governed by $\phi_2$; (ii) the mass of existing varieties $V(t)$, which represents the standard "standing on the shoulders of giants" externality of the *stock* of existing knowledge on the creation of new ideas, with decreasing returns governed by $\phi_1 < 1$; and (iii) the new technology disclosure externality term $E(t)^\chi$. $E(t)$ represents the average speed of development in the economy in the recent past and it is formally defined by $E(t) \equiv d^{-1} \int_{t-d}^{t} N(s)^{-1} \int_0^{N(s)} \iota_D(j,s) \mathrm{d}j \mathrm{d}s$, where $d$ is the maximum memory of externality calibrated to $d = 8$ years, in line with Section 1.5's evidence, $\iota_D(j,s)$ is the speed of development on project $j \in [0, N(s)]$ at instant $s$, and $N(s)$ is the total number of projects. A faster average pace of development increases the frequency with which *novel* technical knowledge diffuses to innovators, enhancing learning and inspiration for new ideas. This highlights a separate role of *recent* advances compared to standard "standing on the shoulders of giants effect" that relates to the stock $V(t)$.

**1.6.2.0.2 Development** Once firms originate new ideas, they must decide how quickly to develop them into patented intermediate varieties of value $\upsilon(t)$. Consistent with Lin and Shampine (2018), I assume that a patent's life is finite and that a firm's monopoly power over a variety lasts *at most* $T$ years. Therefore, the value of a new patent issued at $t$ is given by the equation:

$$\upsilon(t) = \int_t^{t+T} e^{-\int_t^s (r(t')+\lambda(t'))dt'} \pi(s) ds \tag{1.12}$$

where $\pi(s)$ is the equilibrium profit stream of the patented technology over its life, discounted by the real interest rate $r(t')$ and the endogenous instantaneous probability of creative destruction $\lambda(t')$. This probability is assumed to be proportional to the percentage growth rate of novel technologies $\frac{\dot{V}(t)}{V(t)}$ and defined as $\lambda(t) \equiv \psi \frac{\dot{V}(t)}{V(t)}$, where

represents the probability of *not* having an idea blocked by an existing monopoly. It is decreasing in the share of varieties that are monopolistic and in the parameter $\eta$, which captures the severity of the distortion.

$\psi$ is a parameter.[48] Development problem is symmetric and independent across ideas, and defined by the value function

$$r(t)P(t) - \dot{P}(t) = \max_{\iota_D(t)} \left\{ \iota_D(t) \left[ \upsilon(t) - P(t) \right] - \mu \iota_D(t)^\theta \upsilon(t) \right\} \tag{1.13}$$

where $\iota_D(t)$ represents the pace of development, or the instantaneous probability of transforming a project into a product. To achieve a given development pace, total investment required is assumed to be proportional to the value of the innovation $\upsilon(t)$, and can be expressed as $I_D(t) = \mu \iota_D(t)^\theta \upsilon(t)$. Here, $\mu$ is a scaling parameter, while $\theta > 1$ reflects the convex costs of increasing development pace. The expression within square brackets highlights that a successful firm generates a new variety valued at $\upsilon(t)$ but forfeits the worth $P(t)$ of the initial idea or project, which terminates. Crucially, firms do not account for the beneficial impact of an accelerated pace of development on the overall research productivity through $E(t)^\chi$.

**1.6.2.0.3 Evolution of innovation state variables** Total varieties $V(t)$ evolve according to

$$\dot{V}(t) = \iota_D(t)N(t) - \psi \dot{V}(t) \tag{1.14}$$

The first addend represents the increase in varieties due the successful development of ideas. As they are symmetric and independent, the mass of new inventions equals the common instantaneous success probability $\iota_D(t)$ times the measure of projects $N(t)$. The second addend represents creative destruction, with $\psi \dot{V}(t)$ varieties destroyed by the new ones.

The evolution of the stock of ideas $N(t)$ follows satisfies

$$\dot{N}(t) = \left[ d^{-1} \int_{t-d}^{t} \iota_D(s) ds \right]^\chi V(t)^{\phi_1} I_R(t)^{\phi_2} - \iota_D(t)N(t) \tag{1.15}$$

[48]t is worth noting that the effective patent term can be shorter than the maximum statutory patent term $T$, as evident from (1.12). Along the balanced growth path equilibrium, the expected patent duration is given by $T^e \equiv \frac{1}{\lambda^*}(1 - e^{-\lambda^* T})$, where $\lambda^*$ denotes the endogenous rate of creative destruction.

The first addend represents the mass of new ideas generated by research in equilibrium, where $\left[d^{-1}\int_{t-d}^{t}\iota_D^*(s)ds\right]^{\chi}$ replaces the externality term $E(t)^{\chi}$ in ideas' production function using its definition. The second term is the mass of ideas turned into varieties at instant $t$.

The share of monopolistic varieties $\zeta(t)$ endogenously evolves over time due to new patented innovations and to the expiration of patent rights on old ones after $T$ periods. The law of motion is

$$\dot{\zeta}(t) = (1-\zeta(t))\frac{\dot{V}(t)}{V(t)} - (1+\psi)\frac{\dot{V}(t-T)}{V(t)}e^{-\int_{t-T}^{t}\lambda(t')\mathrm{d}t'} \tag{1.16}$$

The first term captures the positive net contribution of new inventions produced at time $t$, i.e., $\dot{V}(t)$, to the growth of patent-protected varieties. The second term captures the fall of monopolistic varieties due to the expiration of patent protection on the fraction $e^{-\int_{t-T}^{t}\lambda(t')\mathrm{d}t'}$ of intermediates generated at $t-T$, i.e., $(1+\psi)\dot{V}(t-T)$, that have survived creative destruction until $t$. Appendix 1.C.1.8 derives expression (1.16) in detail.

### 1.6.3 Definition of the competitive equilibrium

*A competitive equilibrium equilibrium for this economy is a sequence of quantities* $\{V^*(t), N^*(t), \{X^*(i,t)\}_{i=0}^{V^*(t)}, \{\iota_D^*(j,t)\}_{j=0}^{N^*(t)}, I_R^*(t), I_K^*(t), C^*(t), K^*(t), \pi^*(t), \zeta^*(t)\}_{t=0}^{\infty}$*, prices* $\{r^*(t), w^*(t), \{z^*(i,t)\}_{i=0}^{V^*(t)}\}_{t=0}^{\infty}$*, and values* $\{P^*(t), \upsilon^*(t)\}_{t=0}^{\infty}$*, such that, given the exogenous evolution of* $\{h(t), L(t)\}_{t=0}^{\infty}$*, (i)* $r^*(t) = \rho$ *(ii)* $C^*(t)$ *and* $I_K^*(t)$ *solve consumer's utility maximization problem; (iii)* $L(t)$ *and* $\{X^*(i,t)\}_{i=0}^{V^*(t)}$ *solve problem (1.9); (iv)* $X^*(i,t)$ *and* $z^*(i,t)$ *solve problem (1.10)* $\forall i \in [0, V^*(t)]$*; (v)* $I_R^*(t)$ *solves problem (1.11); (vi)* $\iota_D^*(t)$ *solves problem (1.13) for all* $j \in [0, N^*(t)]$*; (vii)* $\upsilon^*(t)$ *satisfies equation (1.12); (viii)* $\pi^*(t) = (\rho+\delta)^{-\frac{\alpha}{1-\alpha}}\left(\alpha^{\frac{1+\alpha}{1-\alpha}} - \alpha^{\frac{2}{1-\alpha}}\right)h(t)L(t)$ *from the* *solution of problem (1.10); (ix) $P^*(t)$ satisfies*

$$P^*(t) = \int_t^{\infty} e^{-\int_t^s [\rho + \iota_D^*(t')]dt'} [\iota_D^*(s) - \mu \iota_D^*(s)^{\theta}] \upsilon^*(s) ds \tag{1.17}$$

*(x) $\zeta^*(t)$ satisfies equation (1.16), (xi) $K^*(t)$ satisfies $K^*(t) = \int_0^{V^*(t)} X^*(i,t)di$ and $\dot{K}^*(t) = I_K^*(t) - \delta K^*(t)$;(xii) the aggregate resource constraint (1.18) holds*

$$Y(t) = C(t) + I_K(t) + I_R(t) + \mu \upsilon(t) \iota_D(t)^{\theta} N(t) \tag{1.18}$$

*(xiii) $V^*(t)$ satisfies (1.14); and(xiv) $N^*(t)$ satisfies (1.15).*

*Along the balanced growth path (b.g.p.) equilibrium, each variable $x(t)$ grows at a constant rate $g_x$, so that $x(t) = e^{g_x t}\tilde{x}(t)$, where $\tilde{x}(t)$ is the stationary version of $x(t)$.*

Appendix 1.C.1 derives the solution, shows that the economy admits a balanced growth path, and pins down equilibrium growth rates.

### 1.6.4 Model's response to an anticipated patent term change

In this subsection, I explore the fundamental economic mechanisms that underlie the model's ability to reproduce the observed effects of an anticipated extension of patent term. Specifically, I consider a scenario where at time $t = \tau$, innovators receive information that patent term will increase from $T_o$ to $T' > T_o$ beginning at $\tau + A$. I examine the response of R&D and patenting in three sub-periods: the news period $t \in [\tau, \tau + A)$, the implementation period $t \geq \tau + A$, and the long run $t \to \infty$. Additional discussion and a graphical illustration of key variables' responses can be found in Appendix 1.C.4.

**1.6.4.0.1 News** During the news period $t \in [\tau, \tau + A)$, the model predicts a decline in total R&D and innovation as firms reduce costly development efforts prior to implementation. This response stems from the different reaction of the patent value $\upsilon^*(t)$ and idea value $P^*(t)$ during the anticipation phase. Specifically, the value of patent in equation (1.12) remains unchanged because the profits associated with a new variety obtained in the news stage are discounted according to the old patent term $T_o$ until implementation. In contrast, equilibrium value of ideas $P^*(t) = \int_t^{\infty} e^{-\int_t^s [\rho + \iota_D^*(t')]dt'} [\iota_D^*(s) - \mu \iota_D^*(s)^{\theta}] \upsilon^*(s) ds$ increases on impact as it reflects higher expected value of obtaining an innovation in the future, net of development costs, i.e., a higher $\upsilon^*(s)$ for $s \geq \tau + A$ in the integral expression of $P^*(t)$. Contemporaneous changes in patent and idea values influence optimal development intensity and optimal research investment according to equations (1.19) and (1.20), respectively.

$$\iota_D^*(t) = \left[ \frac{(\upsilon^*(t) - P^*(t))}{\theta \mu \upsilon^*(t)} \right]^{\frac{1}{\theta - 1}} \tag{1.19}$$

$$I_R^*(t) = \left( P^*(t) \left[ d^{-1} \int_{t-d}^{t} \iota_D^*(s) ds \right]^{\chi} V^*(t)^{\phi_1} \right)^{\frac{1}{1-\phi_2}} \tag{1.20}$$

As the value of holding and transforming ideas in the future increases relative to the value of immediately developing them, it is optimal to slow down the pace of development and patenting. This decrease in development outweighs the positive impact of higher value of ideas on research investment. Consequently, aggregate R&D declines.

**1.6.4.0.2 Implementation** After the implementation of the new policy ($T' > T_o$), the incentive to substitute development effort intertemporally ends. This is because the value of a new variety $\upsilon^*(t)$ for $t \geq \tau + A$ increases and fully reflects the new patent term. Since $\upsilon(t)$ and $P(t)$ are proportional in the new equilibrium, the optimal speed of development $\iota_D(t)$ in equation (1.19) reverts to its previous level. However, the slowdown in development during the anticipation phase continues to reduce knowledge diffusion and depress research productivity through the externality term $E(t)^{\chi}$. This effect lasts for $d = 8$ years after policy implementation. Overall, this negative effect dominates the positive effect of the higher value of ideas on research investment, which remains temporarily lower.

**1.6.4.0.3 Long run** After the implementation of a longer patent term, R&D and innovation levels remain low until research productivity recovers. This recovery occurs when two conditions are met: (i) the technology disclosure externality forgets the initial drop in development pace, and (ii) the missing varieties caused by the news shock are gradually replenished.[49] However, over the long run, the increased value of ideas resulting from a longer patent term promotes greater investment in research, leading to higher total R&D and innovation. This occurs because the flow of new inventions, $\iota_D^*(t)N^*(t)$, increases with the larger stock of projects $N(t)$. Thus, while the long-run behavior of the model is similar to standard frameworks, the novel ingredients are essential for qualitatively replicating the empirical patterns of Section 1.4. The next section assesses the model's quantitative performance by estimating its structural parameters.

## 1.7 Model estimation

In this section, I describe the estimation strategy (Subsection 1.7.1) and illustrate the quantitative performance of the model and the key findings from estimated parameters (Subsection 1.7.2).

### 1.7.1 Estimation

I use a mix of estimation via generalized method of moments for eight parameters ($\phi_1$, $\phi_2$, $\theta$, $\mu$, $\psi$, $\chi$, $\alpha$, $\delta$) and calibration for $(\rho, n, g_h)$.

**1.7.1.0.1 Calibrated parameters** I calibrate $\rho = 0.04$ and fix population growth rate at $n = 1.1\%$, its yearly average in the US during the post-war period. The growth

[49]The importance of spillovers in generating persistence can be observed by comparing the responses of innovation and R&D flow in a model with the externality channel switched off. In such a scenario, innovation and R&D flow increase immediately after the implementation of the longer patent term. This point is illustrated in Figure 1.C.3 of Appendix 1.C.5.2.

rate $g_h$ of exogenous productivity is set to match a growth rate of output-per-capita equal to 2%.[50]

**1.7.1.0.2 GMM** To estimate the remaining structural parameters, I use generalized method of moments to minimize the loss function $(\mathbf{m}-\mathbf{m}^t)'W(\mathbf{m}-\mathbf{m}^t)$. Here, $\mathbf{m}^t$ is a vector of targets, $\mathbf{m}$ represents their counterparts in the model, and $W$ is a diagonal positive definite weighting matrix. $\mathbf{m}^t$ includes two sets of targets: (i) the quarterly empirical responses of patenting and R&D effort to a 100-day patent term extension anticipated by 2 years and 8 months, based on post-news and post-implementation DiD estimates of Poisson specification (1.3) plotted in Figures 1.2b and 1.3b (33+33 moments); and (ii) three restrictions that capture the characteristics of the US economy in the 1990s, namely a private R&D-output ratio equal to 0.017, a consumption-output ratio of 0.65, and a capital-output ratio of 3.

To match the first set of targets, I simulate the same policy change in the stationary model and derive the quarterly evolution of patenting and patent-based R&D effort, expressed as deviations from the pre-news steady state. I assume that the economy is at this steady state before the news shock. The model counterpart of patenting is $\iota_D^*(t)N^*(t)$, i.e., the symmetric probability that each project is successfully developed into a patented technology $\iota_D^*(t)$ times the number of projects $N(t)$. Moreover, I derive time-$t$ patent-based R&D effort as

$$R\&D(t) = \int_{-\infty}^{t} \underbrace{\left[I_R(\tau)/n(\tau,\tau) + \int_{\tau}^{t} \mu \iota_D^*(s)^{\theta} \upsilon^*(s) ds\right]}_{\equiv r\&d(t,\tau)} \times \Big(\iota_D^*(t) n(t,\tau)\Big) d\tau \tag{1.21}$$

The term $r\&d(t,\tau)$ represents the R&D expenditure on projects of vintage $\tau$, suc-

[50]In the extended model with blocking innovation, $\eta$ is calibrated so that the steady-state block probability $1-(1-\zeta_{ss})^{\eta\phi_1}$ is equal to 1%, which is computed by combining information on patent litigation rates (1.5%) and plaintiff win or voluntary settlement rates (65%). Patent litigation rates are taken from Figure S9 of WIPO report "Special theme - An overview of patent litigation systems across jurisdictions" (`https://www.wipo.int/edocs/pubdocs/en/wipo_pub_941_2018-chapter1.pdf`). Plaintiff win and settlement rates are taken from `https://law.stanford.edu/wp-content/uploads/2016/07/Revised-Stanford-August-4-2016-Class-Presentation.pdf`

cessfully developed at time $t$. It assumes that each of the $n(\tau, \tau)$ new ideas created at time $\tau$ absorbs an equal share of total research investment $I_R(\tau)$ and accumulates development costs $\mu \iota_D^*(s)^\theta \upsilon^*(s)$ over the development period $s \in [\tau, t]$. Total R&D in equation (1.21) is the integration of $r\&d(t, \tau)$ across vintages $\tau$, weighted by the measure of patents from that vintage that are successfully developed at $t$, i.e., $\iota_D^*(t) n(t, \tau)$. Since development activity is symmetric and independent across projects, the latter is the product of the common $\iota_D^*(t)$ and the measure of vintage-$\tau$ ideas still undeveloped at $t$ $(n(\tau, t))$.

**1.7.1.0.3 Identification of key parameters** The rich dynamics of reduced-form DiD estimates and long-run restrictions provide valuable insights into key structural parameters of the model, consistent with the economic forces discussed in Subsection 1.6.4. Firstly, the adjustment of R&D and innovation to the news shock informs the development cost convexity parameter $\theta$. When faced with news of a future patent term extension, innovators may slow down the pace of development on existing projects, and the extent of this adjustment informs the mildness of the cost convexity. Secondly, the research parameters ($\chi$, $\phi_1$, $\phi_2$) are determined by the post-implementation effects and the long-run R&D-output ratio. A stronger technology disclosure externality (higher $\chi$) results in a deeper post-implementation trough of R&D and innovation. A smaller "standing on the shoulders of giants" externality ($\phi_1$) results in a quicker recovery of R&D and innovation to the new long-run equilibrium. Finally, a higher $\phi_2$ parameter implies less severe decreasing returns to research investment, which results in a larger R&D-output ratio, given other R&D parameters, as returns to larger research investment decrease less quickly. Appendix 1.C.6 illustrates previous arguments graphically.

**1.7.1.0.4 Solution algorithm** To estimate the model, it is necessary to solve for the transitional dynamics of the stationary model to the anticipated policy. However, this is non-standard due to the presence of the delayed differential equation (1.16).

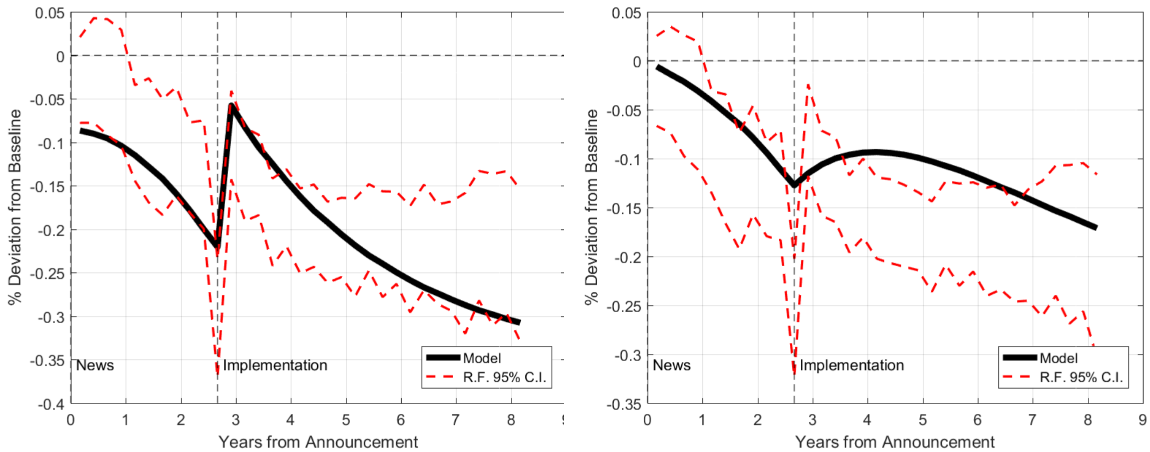
Appendix 1.C.2 describes the details of the solution algorithm, which guesses $\lambda(t)$ and iterates over its dynamics until convergence.

**1.7.1.0.5 Limitations and multi-field model** While Subsection 1.7.2 illustrates the effectiveness of the approach, there is a limitation in that it uses a one-field model to match empirical DiD estimates resulting from the comparison of R&D and patenting across fields. To address potential concerns regarding this limitation, an extended version of the model is proposed in Appendix 1.C.7, which includes 621 fields with varying sizes and pending periods. This extended model is then used to simulate an exact replication of the TRIPs patent term change, and the field-specific model-based responses are used to re-estimate the DiD Poisson model (1.3) on simulated data. The resulting estimates are then used as theoretical counterparts to the empirical DiD estimates in the proposed GMM setting. The performance of the extended model is reported in Appendix 1.C.7, and the results show remarkable similarity to those of the one-field model.

### 1.7.2 Quantitative performance and estimation results

Figure 1.8 illustrates the performance of the model in comparison to the targeted DiD empirical estimates of patenting (left panel) and R&D effort (right panel). The black solid lines represent the responses to an anticipated 100-day patent term increase as suggested by the model's optimal parameter estimates, while the red dashed lines display the 95% confidence bands of the DiD coefficients in Figures 1.2b and 1.3b. The model closely replicates both the initial decline in R&D and innovation observed upon news and the additional negative effect estimated after policy implementation. As discussed in 1.6.4, a reduction in the pace of development is responsible for news effects, while post-implementation dynamics are driven by research investment. Initially, research investment drops due to the technology disclosure externality, but it converges to a higher long-run level (not plotted) due to the longer patent term. Addi-

Figure 1.8: Model-based simulation of the policy and targeted reduced-form estimates




(a) New patents

(b) R&D Investment

The left panel of the figure shows the model-based responses of patenting, while the right panel shows the responses of R&D effort, both represented by black solid lines. The responses are in percentage deviation from the pre-news steady state, assumed to be at $t = 0$ when the news shock occurs. The shock considered is a 100-day patent term increase anticipated by 2 years and 8 months, similar to the TRIPs case. The second dashed blue vertical line represents the policy implementation. Parameter values are reported in Table 1.1. The red dashed lines show the 95% confidence bands of the DiD estimates of the Poisson model (1.3) in response to the same shock.

tionally, Figure 1.C.3 demonstrates that the model without the technology disclosure externality ($\chi = 0$) closely matches the (untargeted) positive post-implementation estimates of the augmented DiD specification in Subsection 1.4.4.

Table 1.1 presents the estimated parameters and their corresponding standard errors, which are computed in Appendix 1.C.2. These estimates reveal key characteristics of the innovation process. Firstly, the cost convexity of development pace is mild, with $\theta$ nearly equal to 1. The point estimate of $\theta = 1.06$ implies an optimal average project duration of approximately 3 years that is slightly longer than the two-year average research lag estimated by Pakes and Schankerman (1984), potentially reflecting the increased complexity of modern projects. Secondly, the estimated value of $\phi_2 = 0.12$ suggests that the returns to research investment decrease significantly as aggregate investment levels increase. In other words, the marginal dollar spent on finding new ideas becomes relatively unproductive for low levels of investment. Fi-

Table 1.1: Estimated and Calibrated Structural Parameters

| Symbol | Value | S.E. | Parameter | Target/Source |
|---|---|---|---|---|
| *A: Calibration* | | | | |
| $\rho$ | 0.04 | | Discount rate | |
| $g_h$ | 0.009 | | Exog. Prod, Growth | 2% p.c. Output Growth |
| $n$ | 0.011 | | Population Growth | World Bank |
| *B: Estimation* | | | | |
| $\alpha$ | 0.5089 | 0.0225 | Capital share | |
| $\delta$ | 0.0710 | 0.0010 | Capital Depreciation | |
| $\phi_1$ | 0.6475 | 0.0983 | Research $V$-Curvature | |
| $\phi_2$ | 0.1227 | 0.0146 | Research $I_R$-Curvature | |
| $\chi$ | 8.2937 | 1.7825 | Spillover Exponent | |
| $\theta$ | 1.0557 | 0.0437 | Dev.'t Curvature | |
| $\mu$ | 0.5310 | 0.1317 | Dev.'t M. Cost | |
| $\psi$ | 0.0001 | 0.2346 | Endog. Creative Destruction | |
| *C: Extension* | | | | |
| $\eta$ | 0.0846 | | Curv. Monopoly Distortion | 1% Block Probability |

The table presents the calibrated parameters ($\rho$, $n$, and $g_h$), along with the GMM estimates for the other parameters. The GMM estimation targets include two main objectives: (i) the reduced form DiD estimates of granted patents and R&D effort in the Poisson specification (1.3); and (ii) three long-run restrictions, namely a Capital-output ratio equal to 3, a consumption-output ratio equal to 0.65, and a private R&D investment-output ratio equal to 0.017. In addition, parameter $\eta$ of the model with blocking innovation is calibrated to match a 1% block probability of new projects. Subsection 1.7.1. reports details on estimation and calibration.

nally, the estimated value of $\phi_1 = 0.65$ implies strong "standing on the shoulders of giants" effects, meaning that marginal gains in research productivity slowly decline as the knowledge stock expands.[51]

Furthermore, the model allows for inference on the *long-run* elasticity of innovation and R&D to patent term, which could not be directly identified in the empirical estimates. Specifically, a 1% increase in patent term from the base of 17 years results in a +0.45% increase in patents and a +1.3% increase in total R&D in the new steady state. Additionally, I estimate that the elasticity of long-run aggregate TFP to patent term is 0.4, which is close to the elasticity of firm-level TFP to market size estimated by Beerli et al. (2020) using Chinese data.[52]

[51] Bloom et al. (2020) find similar evidence for some US sectors, but, differently from the present setting, they infer $\phi_1$ close to 0 for the aggregate US economy.

[52] In the steady state of the stationary model final output can be written as $Y_{ss} = V_{ss}(\alpha^\alpha \zeta_{ss} + (1-\zeta_{ss}))L_0^{1-\alpha} X_{nm,ss}^\alpha$, where $L_0$ is de-trended labor, $X_{nm,ss}$ is the amount of capital used for non-monopolistic varieties, and $V_{ss}(\alpha^\alpha \zeta_{ss} + (1-\zeta_{ss}))$ is TFP.

## 1.8 Policy simulations and normative analysis

In this section, I finally employ the estimated model to examine and quantify the normative trade-offs of patent term. The analysis proceeds in three steps. Firstly, in Subsection 1.8.1, the welfare effects of a change in patent term are examined by focusing on the steady state of the model. Previous literature has mostly focused on long-run outcomes of innovation policies, but this approach implicitly assumes that the economy immediately jumps to its new long-run equilibrium. Secondly, Subsection 1.8.2 studies welfare if the full transitional dynamics induced by the *unanticipated* adoption of a new patent term are considered. The optimal policy is derived in this case, and it is argued that the transition is as important as the long-run outcomes for normative considerations. Finally, Subsection 1.8.3 investigates the role of policy anticipation and shows how the impact of optimal patent term derived in Subsection 1.8.2 changes if news of it precedes implementation. Due to the action of the technology disclosure externality, even small anticipation offsets any welfare and output gains.

### 1.8.1 Steady-state trade off

The steady-state trade-off of patent term is similar to the one identified by Nordhaus (1967). A longer patent term $T$ leads to more varieties $V_{ss}$ in any steady-state equilibrium, but it also results in a larger share $\zeta_{ss}$ of sub-optimally produced varieties due to monopoly power granted by patents. While welfare considerations pertain to final consumption $C$, the expression of aggregate output in the steady-state highlights the two key forces that affect it:

$$Y_{ss} = \quad V_{ss} \quad \underbrace{\left(\alpha^{\alpha}\zeta_{ss} + (1-\zeta_{ss})\right)}_{\approx 0.95} \quad L_0^{1-\alpha} X_{nm,ss}^{\alpha} \tag{1.22}$$

The first force increases output by generating more varieties $V_{ss}$, while the second force depresses output. A higher share of monopolistic varieties $\zeta_{ss}$ reduces the distortion term $(\alpha^{\alpha}\zeta_{ss} + (1 - \zeta_{ss})) \in [\alpha^{\alpha}, 1]$ by placing greater weight on $\alpha^{\alpha} < 1$, which reflects the severity of the under-supply of intermediates. Because the distortions are small in the pre-TRIPs steady-state, the first positive force dominates the second. Therefore, in the benchmark model, the patent term that maximizes steady-state consumption (welfare) is 138 years.

The third column of Table 1.2 presents variations of the optimal steady-state patent term under alternative parameter values, with associated welfare change reported in brackets as percent deviations from the pre-TRIPs status quo of $T = 17$ years. Furthermore, the fifth column shows that in a model with "blocking innovations", where patent term leads to additional distortions by impeding with probability $1 - (1 - \zeta(t))^{\phi_1 \eta}$ the development of new ideas that infringe on patented technologies, the optimal policy is uniformly shorter.[53]

### 1.8.2 Transitional-dynamics trade off

The second trade-off concerns the transitional dynamics of the model following the *unanticipated* implementation of a new patent term. As discussed in the previous subsection, a longer patent term generates higher output and consumption in the long run due to an expanded stock of varieties. However, the transition to this new steady state requires a consumption sacrifice to finance R&D investment needed to increase productivity. Therefore, development lags that characterize the creation of new varieties are important not only from a positive perspective but also from a normative one.

[53] The block probability $1-(1-\zeta(t))^{\phi_1\eta}$ increases as the share of monopolistic varieties $\zeta(t)$ grows, which, in turn, is higher for longer patent terms $T$. The impact of this effect is determined by the value of parameter $\eta$, which I calibrate to ensure a block probability of 1%. As firms anticipate the possibility of being blocked, the production function of projects becomes $(1-\zeta(t))^{\phi_1\eta}E(t)^{\chi}V(t)^{\phi_1}I_R(t)^{\phi_2}$, where $(1 - \zeta(t))^{\phi_1\eta}$ represents the probability of *not* being blocked by an existing monopoly.

To balance short-run losses and long-run gains, I use the representative agent's time-zero utility expressed as

$$\Theta = \int_0^\infty e^{-(\rho - g_c^*)t}\tilde{c}(t)dt \tag{1.23}$$

where $\tilde{c}(t)$ is per-capita consumption in the stationary model, $g_c^*$ is its growth rate along the balanced growth path, and $\rho$ is the discount rate.

I estimate the patent term that would maximize (1.23) in the absence of anticipation, starting from a status quo of $T_0 = 17$ years. To do so, I assume that the economy is in the steady-state and simulate the *unanticipated* adoption of a new patent term $T' \geq 0$. For each $T'$, I compute the welfare index $\Theta^{(T')}$ along the transition to the new steady-state and express the welfare gain/loss in percentage deviation from $\Theta^{(T_0)} = \tilde{c}_{T_0,ss}/(\rho - g_c^*)$, which is index (1.23) if no policy change occurs, and the economy remains at the old steady-state.[54] I similarly compute output and innovation changes relative to the status quo.

My analysis reveals that in the absence of anticipation, the optimal patent term is 26 years, leading to a +0.3% increase in welfare and a +1.2% increase in output compared to the current status quo. This suggests that extending patent terms in the US would increase welfare. The second column of Table 1.2 shows that the optimal policy varies with key parameters, with the severity of decreasing returns to research investment (governed by $\phi_2$) being the most significant driver of optimal $T$. A lower $\phi_2$ leads to a significant reduction in the optimal patent term. This implies that protection is most beneficial in sectors with high returns to innovation. The optimal policy is not particularly sensitive to (i) the cost convexity $\theta$ of development pace, (ii) the "standing on the shoulders of giants" parameter $\phi_1$, and (iii) the technology disclosure externality parameter $\chi$ (not reported in Table 1.2).

[54] I simulate $T'$ on a yearly grid $[5, 50]$ and I compute the transition for 2,000 years, after which the economy is assumed to be at the new steady state.

Table 1.2: Optimal patent term - Transitional dynamics vs. steady state

| Specification | Benchmark | | Blocking innovation | |
|---|---|---|---|---|
| | Dynamic | Steady State | Dynamic | Steady State |
| **Baseline** | **26** (+0.3%) | 138 (+54.6%) | **22** (+0.1%) | 62 (+29.9%) |
| $\theta = 1.01$ | **26** (+0.3%) | 136 (+54.0%) | **22** (+0.2%) | 62 (+29.6%) |
| $\theta = 1.10$ | **27** (+0.3%) | 140 (+55.5%) | **23** (+0.1%) | 63 (+30.3%) |
| $\phi_2 = 0.07$ | **16** (+0.0%) | 109 (+21.7%) | **15** (+0.0%) | 61 (+13.1%) |
| $\phi_2 = 0.17$ | **37** (+1.7%) | 177 (+115.0%) | **29** (+0.9%) | 62 (+56.1%) |
| $\phi_1 = 0.55$ | **26** (+0.3%) | 121 (+35.1%) | **24** (+0.2%) | 71 (+23.9%) |
| $\phi_1 = 0.75$ | **26** (+0.4%) | 181 (+121.5%) | **20** (+0.1%) | 50 (+41.9%) |

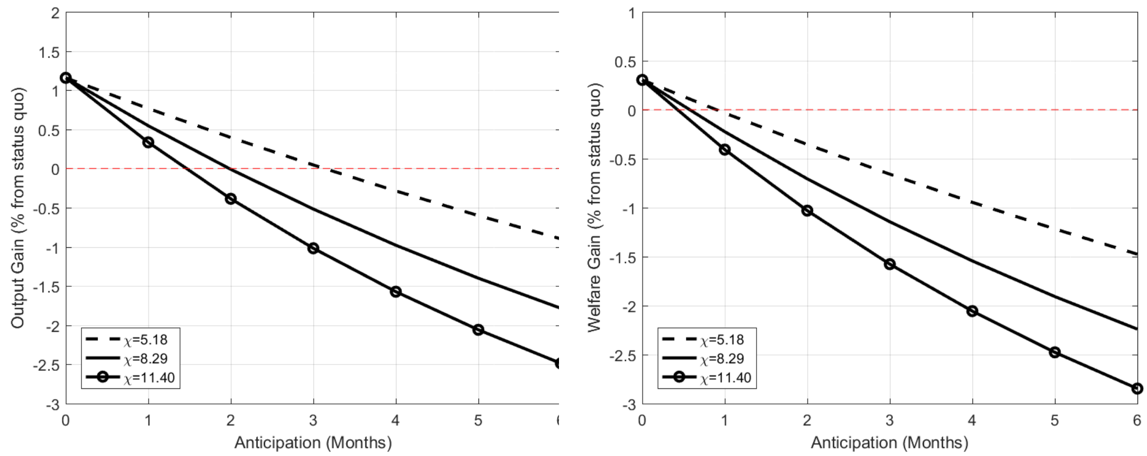
The table presents optimal patent terms under various conditions. Rows represent different model parameters. The first row uses the parameter values from Table 1.1. For subsequent rows, the first column shows which parameter is changed while keeping others constant. The second and third columns present results from the benchmark model. The second column shows the optimal patent term, accounting for transitional dynamics and unanticipated implementation, in bold. Figures in brackets indicate the percent change in welfare relative to the status quo. The third column reports the patent term that maximizes steady-state consumption, with figures in brackets indicating the percent change in consumption relative to the pre-TRIPs steady state. The fourth and fifth columns report the same figures as columns three and four but assume that existing patents block the development of 1% of new ideas in an extended model.

### 1.8.3 The role of anticipation

Finally, I examine the impact of news effects on the optimal patent term by simulating a policy change from $T_0 = 17$ years to $T' = 26$, derived in the previous subsection, with varying degrees of anticipation. Figure 1.9 shows the percent change in consumption (left panel) and output (right panel) relative to the status quo as anticipation changes. The role of the technology disclosure externality is highlighted in a comparative statics exercise with respect to $\chi$. Results indicate that even a slight anticipation completely dissipates the welfare and output gains estimated without news effects. A 6-month anticipation period results in a 1.75% welfare loss.[55] Furthermore, a stronger technology externality exacerbates the news effects, amplifying and prolonging the temporary decline in R&D and innovation. Therefore, this analysis emphasizes the importance of policy implementation details in determining output

[55] The change in welfare and output is computed as the utility index (1.23) under the simulated policy in percentage deviation from its value absent any policy change.

Figure 1.9: Change in output and welfare from $T$ =26 years by anticipation




(a) Output per capita

(b) Consumption per capita

The left (right) panel shows how the change in output-per-capita (consumption-per-capita) due to the *anticipated* implementation of a 26-year patent term varies with anticipation. The changes are expressed in percentage deviation from the pre-TRIPs status quo featuring a 17-year patent term.

and welfare consequences of patent term changes and other innovation policies. Using Appendix 1.C.7's multi-field model, I estimate that TRIPs led to 5.96% consumption loss and 6.78% output loss but its unanticipated adoption would have induced 0.21% higher output and negligible change in consumption.

## 1.9 Concluding remarks

This paper makes three important contributions to the innovation and growth literature. Firstly, it provides quasi-experimental evidence on the impact of anticipated patent term changes on R&D and innovation. Consistent with the literature, a direct positive effect of a +1% patent term extension is estimated to increase R&D and innovation by 4.2% in five years, but the paper demonstrates that policy anticipation overturns this result. Specifically, innovators initially reduce the pace at which existing projects are developed into patented technologies to file applications under the more profitable future policy, thus reducing R&D and innovation at news. As innovation is cumulative, this decline in knowledge diffusion reduces the ability to create new projects due to a technology disclosure externality, thus further depressing R&D and innovation for at least five years after implementation. This highlights the crucial role of news effects and externalities in the estimation of patent term changes or other innovation policy interventions.

Secondly, the paper develops a novel semi-endogenous growth model that formalizes the intertemporal substitution mechanism and the technology disclosure externality, and shows that both are necessary to match empirical evidence with the theory. The model distinguishes between research and development activities as two distinct steps and assumes that faster diffusion of new knowledge increases productivity in finding new ideas. A structural estimation reveals severe decreasing returns to discovering new ideas but mild cost convexity of developing existing projects at a faster pace.

Finally, the paper conducts counterfactual policy experiments that shed light on two overlooked channels that influence welfare effects of a patent term change. It shows that the transitional dynamics of the economy to the new long-run equilibrium can be equally important for welfare, and confirms that news effects are key. Even short anticipation dissipates the welfare gains that would occur with unanticipated implementation of a longer patent term in the US. These findings have important implications for policy design and suggest that the devil is in the implementation details.

# Appendices

## Appendix 1.A Data description

### 1.A.1 Data sources

I utilized six data sources for the empirical analysis. PATSTAT was used to build technical field-level innovation and treatment variables. The NBER Patent Database was used to obtain patent information and match applicants to firm identifiers in COMPUSTAT, which reports balance sheet and financials for selected subsample of innovating firms responsible for a relevant share of the aggregate US GDP, R&D, and innovation. The fourth data source was the economic value of patents, obtained from Kogan et al. (2017), which estimated the private economic value of patents by exploiting the stock market reaction to patent grants. For sectoral analyses, the fifth data source was the NBER CES manufacturing database, containing annual industry-level data for 1958-2011 by 6-digit NAICS industries. Finally, the 'Algorithmic Links with Probabilities' crosswalk by Goldschlag, Lybbert and Zolas (2019) was used to map technical field (4-digit IPC classes) into industries (6-digit NAICS) and vice versa, based on text-analysis of patents abstracts and descriptions of different sectors. For more information on variable construction, please refer to the additional materials in Appendix 1.D.

### 1.A.2 Summary Statistics

Summary statistics by technical field, firm, and industry are reported below.

Table 1.A.1: **Summary statistics by technical field and quarter**

| Variable | Mean | S.D. | 10th p. | 90th p. |
|---|---|---|---|---|
| Granted Patents | 36.09 | 136.35 | 0 | 78 |
| 5 years Citations | 195.15 | 1070.1 | 0 | 360 |
| Patent value (Million Dollars) | 351.01 | 3341.87 | 0 | 406.01 |
| Pending Days (days) | 1022.1 | 496.2 | 558.93 | 1660.94 |
| Change in patent length (days) | 472.66 | 117.42 | 343.55 | 590.79 |
| Standard dev. of $\Delta$ patent term (days) | 37.13 | 38.93 | 11.53 | 72.55 |
| Patents share w. p.p.>3y. | .06 | .08 | 0 | .12 |
| Share of patents renewed to max. term | .29 | .26 | 0 | .63 |
| Share of entrant applicants | .54 | .21 | .28 | .82 |
| Share of patents granted to entrants | .49 | .23 | .2 | .8 |
| Patents-based HHI | 1191.51 | 1982.33 | 116.35 | 2800 |
| N. Patent with w.-field bckwd. cit.s | 4.89 | 27.07 | 0 | 10 |
| Sh. Patent with w.-field bckwd. cit.s | .19 | .28 | 0 | .59 |
| Patents at EPO | 1.47 | 4.65 | 0 | 4 |
| Avg. Pending Period at EPO (days) | 1702.43 | 272.63 | 1386.5 | 2012.84 |
| Share of second filing applications | .56 | .15 | .37 | .73 |

The Table reports the summary statistics of different variables used in the paper by technical field (4-digit IPC class) and quarterly date

Table 1.A.2: **Summary statistics by firm and year**

| Variable | Mean | S.D. | 10th p. | 90th p. |
|---|---|---|---|---|
| Granted Patents | 13.57 | 94.75 | 0 | 12 |
| Citations-weighted Patents | 199.02 | 1589.75 | 0 | 173.72 |
| Patents value (Million Dollar) | 287.16 | 3434.04 | 0 | 74.8 |
| Expected change in protection time | 445.02 | 118.57 | 273.29 | 571.4 |
| Sales (Million Dollar) | 2337.66 | 9997.57 | 2.59 | 4456.27 |
| Age | 14.73 | 13.88 | 1 | 37 |
| Employment (Thousands) | 10.85 | 42.01 | .05 | 22.92 |
| R&D Expenditure (Million Dollar) | 60.87 | 359.06 | 0 | 58.78 |

The Table reports the summary statistics of different variables used in the paper by firm (COMPUSTAT firms) and year

Table 1.A.5: Patent term change and variation across technical areas

| Technical Section | Nb. Fields | $\overline{\Delta T_j}$ | S.D.($\Delta T_j$) | $\overline{\mathbf{Pr}(\Delta T_j < 0)}$ | S.D.($\mathbf{Pr}(\Delta T_j < 0)$) |
|---|---|---|---|---|---|
| A Human Necessities | 83 | 484.99 | 104.01 | .06 | .06 |
| B Operations, Transp. | 163 | 489.22 | 91.87 | .05 | .05 |
| C Chemistry, Metallurgy | 84 | 376.41 | 158.87 | .13 | .12 |
| D Textiles, Paper | 37 | 465.31 | 98.84 | .05 | .06 |
| E Fixed Constructions | 29 | 554.15 | 44.22 | .03 | .02 |
| F Mechanical Engineering | 98 | 531.53 | 94.48 | .04 | .03 |
| G Physics | 78 | 434.05 | 123.6 | .08 | .12 |
| H Electricity | 49 | 462.77 | 75.43 | .06 | .04 |

The table reports the number fields, i.e., 4-digit IPC classes (column 2), the average change in patent term (column 2), the standard deviation in average pending period (column 4), the average probability of losing protection time from TRIPs (column 5), and the standard deviation of this probability (column 6) across 1-digit IPC technical areas (column 1).

Table 1.A.3: **Summary statistics by industry and year**

| Variable | Mean | S.D. | 10th p. | 90th p. |
|---|---|---|---|---|
| Granted Patents | 199.23 | 591.3 | .44 | 491.7 |
| Citations-weighted Patents | 1433.73 | 6930.68 | 1.4 | 2656.01 |
| Patents value (Million Dollar) | 3015.86 | 16684.91 | .38 | 4595.21 |
| Expected change in protection time | 474.27 | 87.17 | 377.46 | 564.72 |
| Avg. TFP Growth (p.p.) | .39 | 6.43 | -6.09 | 6.86 |
| Avg. Inflation (p.p.) | 1.89 | 4.87 | -1.53 | 6.26 |

The Table reports the summary statistics of different variables used in the paper by industry (6-digit NAICS) and year

Table 1.A.4: **Correlation between Pending Period and Field Characteristics**

| Variable | Correlation | Weighted Corr. |
|---|---|---|
| Number of Applications | .13 | |
| Number of Second Filings | .18 | |
| Perc. Growth of Patents | -.02 | |
| Number of First Grants | .08 | |
| Patents at EPO | .14 | |
| Avg. Pending Period EPO | .27 | .44 |
| Share of Second Filings | .3 | .3 |

The first column reports the simple correlation between the average ex-ante pending period by field and several average characteristics of the field. The second column reports the same correlations, weighted by the field-specific number of patents.

# Appendix 1.B Additional empirical evidence

## 1.B.1 Anticipation and differences with Abrams (2009)

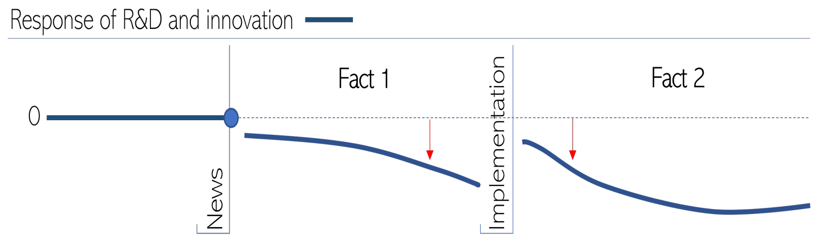
The objective of this subsection is to reconcile the divergent findings between Abrams (2009) and this paper by taking into account the fact that Abrams (2009) assumed the absence of policy anticipation, while I argue that firms were aware of the policy change approximately 2.5 years before its implementation. Abrams (2009) made three key assumptions: (i) no policy anticipation, (ii) a narrow sample window (6, 12, or 24 months) around the policy implementation, and (iii) a two-period DiD specification with a field-specific linear trend. I explain below how these assumptions led to the positive effect of patent term on innovation found in Abrams (2009) and the discrepancies with the current paper. To clarify the differences and facilitate comprehension, I first present a scheme. Next, I perform various analyses to demonstrate that Abrams (2009)'s assumptions are likely to result in a violation of the parallel trends assumption that underlies the DiD methodology.

### 1.B.1.1 Graphical scheme to build intuition

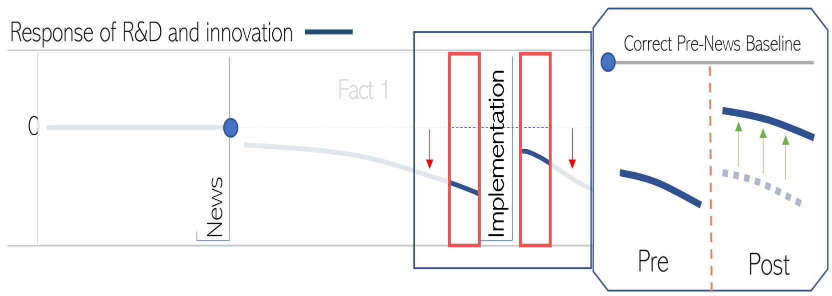
Panel (a) of Figure 1.B.1 presents a graphical representation of the DiD empirical findings of the current paper, while panel (b) provides a view of the conclusions that one can draw by focusing on a narrow window of data around policy implementation, as in Abrams (2009). In panel (a), two significant shocks from the policy change are highlighted: the news at the end of 1992 (first vertical line) and implementation in June 1995 (second vertical line). Section 1.4 of the paper demonstrates that the marginal effect of a relative *increase* in patent term, represented by the solid dark blue line in the scheme, is negative between news and implementation (Fact 1) and negative after implementation (Fact 2). The sign of the two effects is relative to the baseline innovation level just before the first news shock. Panel (b) narrows in on a

Figure 1.B.1: Graphical illustration of differences with Abrams (2009)

(a)




(b)




small window around implementation and illustrates that the difference between the post-implementation and pre-implementation policy effects is positive, even though both effects are negative relative to the pre-news baseline. This is because the magnitude of the post-implementation effect is initially weak. This pre-post comparison is similar to assuming no policy anticipation and using a traditional pre-post DiD comparison around the event, as in Abrams (2009). Hence, this provides a preliminary understanding of why Abrams (2009) finds a positive reduced-form DiD coefficient after implementation rather than a negative one.

The present paper suggests that a patent term increase has a direct positive effect on innovation and R&D, either in the long-run or in the short run if the policy is implemented without anticipation. However, Section 1.4 reveals that with anticipation, a patent term increase may lead to a protracted decline in innovation, while Section 1.8 demonstrates that anticipation is crucial not only from a positive standpoint but also from a normative perspective.

#### 1.B.1.2 Formal analyses

As an initial step, I begin by replicating the results of Abrams (2009) using my own data. Specifically, I estimate the two-period difference-in-difference (DiD) specification

$$Y_{j,t} = \alpha_j + Post_t + \delta \Delta T_j + \beta Post_t \Delta T_j + \chi_j t + \mathbf{X}_{j,t}\gamma + \varepsilon_{j,t} \tag{1.24}$$

which is equivalent to Specification (2) in Abrams (2009), and report the results in Table 1.B.1. In this specification, $j$ indexes technical fields–which are represented by 4-digit IPC classes in my setting–while $t$ identifies a specific month. The outcome variable $Y_{j,t}$ represents either the number of patents filed or the number of citations-weighted patents in month-$t$ and field-$j$. The field fixed effects $\alpha_j$ are included, and the dummy variable $Post_t$ takes a value of 1 if month-$t$ comes after the policy implementation of June 1995 and 0 otherwise. $\Delta T_j$ is the policy-induced change in patent term, and $\chi_j t$ represents a field-specific monthly linear trend. Additionally, $\mathbf{X}_{j,t}$ includes field-specific controls, such as the average number of inventors per patent and the average number of claims per patent. The difference-in-difference coefficient of interest is $\beta$, which is the coefficient of the interaction term between $\Delta T_j$ and the post-implementation dummy variable.

Columns (1) and (2) of Table 1.B.1 present the results for the number of granted patents as the outcome variable, and they are consistent with the sign of Abrams (2009)'s estimates. However, the magnitude of the estimates is smaller in my replication due to two reasons. First, Abrams (2009) restricts the sample to technical fields with at least thirty patents in every year, while I do not impose this restriction. Second, Abrams (2009) defines technical fields as USPC classes, which are slightly broader than the 4-digit IPC classes that I use. Consequently, the baseline average number of patents in each field is smaller in my sample than in Abrams (2009), leading to smaller marginal effects. When I impose the same restriction as Abrams (2009), I

Table 1.B.1: **Replication of Abrams (2009)'s results**

| | (1) Patents | (2) Patents | (3) Citations | (4) Citations |
|---|---|---|---|---|
| $Post_t$ | -12.238*** | -17.261*** | -55.151** | -76.602** |
| | (3.106) | (4.051) | (22.098) | (31.091) |
| $Post_t \times \Delta Tj$ | 0.020*** | 0.029*** | 0.072* | 0.109* |
| | (0.006) | (0.008) | (0.041) | (0.059) |
| Avg. Num. of Inventors | | 0.216*** | | 4.121*** |
| | | (0.048) | | (0.539) |
| Avg. Num. of Claims | | -0.005 | | 0.537*** |
| | | (0.004) | | (0.080) |
| Constant | 14.640*** | 16.980*** | 108.129*** | 111.448*** |
| | (0.200) | (0.235) | (1.763) | (2.372) |
| Field F.E. | Y | Y | Y | Y |
| Field-specific Trend | Y | Y | Y | Y |
| Observations | 14904 | 12603 | 14904 | 12603 |

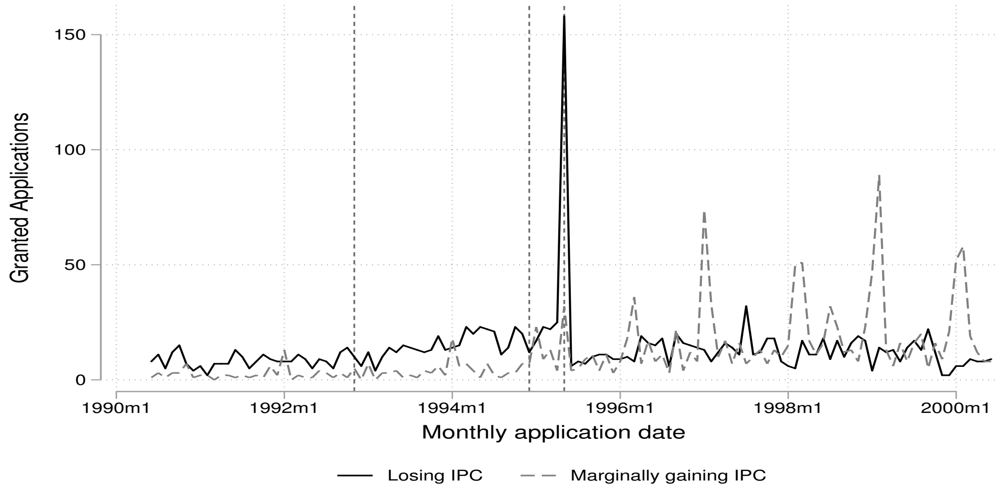
Columns (1) and (2) report the OLS estimates of specification (1.24) using granted patents filed in month-$t$ and classified in field-$j$ as dependent variable. Columns (3) and (4) report the OLS estimates of specification (1.24) using citations-weighted granted patents filed in month-$t$ and classified in field-$j$ as dependent variable. Standard errors are clustered by technical field. Statistical significance levels: $^{*}(p < 0.05),^{**}(p < 0.01),^{***}(p < 0.001)$

obtain estimates that are approximately four times larger than those in Table 1.B.1 and are in line with the original results. Columns (3) and (4) present the results for citations-weighted patents as the outcome variable.

In the second step of the analysis, it is demonstrated that assuming the absence of anticipation creates conflicts with the employed two-period DiD specification, leading to problems with the parallel trends assumption and causing upward bias in the estimates of $\beta$. To illustrate this, two technical fields, C12R and A01H, are taken as examples. The expected change in protection time for C12R is negative (-75 days), while A01H shows a slightly positive change in patent term (+50 days).

The number of granted patents in the two fields over the period 1990-2000 is plotted in Figure 1.B.2. The first vertical line represents the policy news of November 1992, the second refers to the formal ratification of TRIPs in the US in December 1994, and the third line represents the date of policy implementation in June 1995.

Figure 1.B.2: Number of monthly patents in a losing and a gaining field




The plot shows the time series of granted patents applied for in month-$t$ and classified in field C12R, the "losing field", and field A01H, the "marginally gaining field".

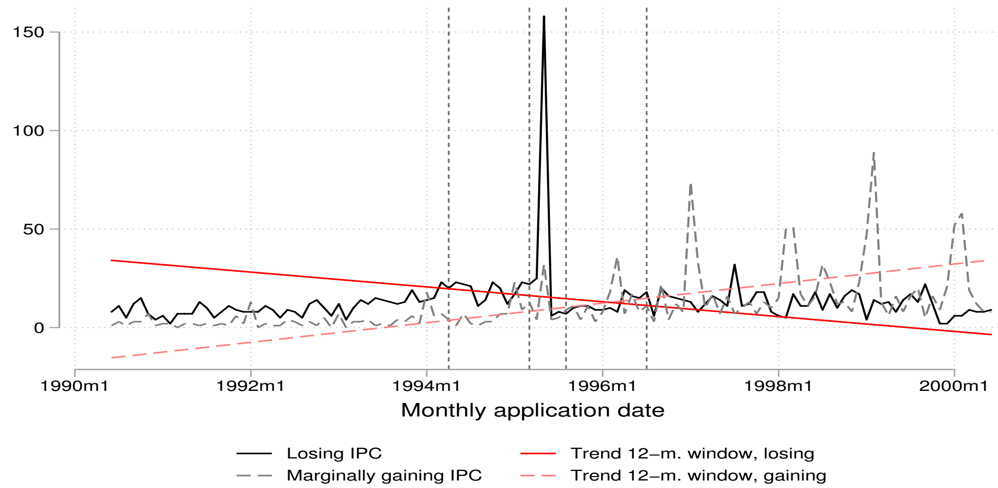
The figure shows that patenting in the field losing protection began to accelerate well before December 1994.

Figure 1.B.3 depicts the implications of this anticipation for the estimated field-specific time trend in Abrams (2009)'s specification. The vertical lines in the figure represent the bounds of the outer 12-month estimation window used in Abrams (2009), with an inner gap of 2 months before and after June 1995. The estimated trends for the field losing and gaining protection are represented by the red solid and dashed lines, respectively. As the figure shows, these trends do not accurately capture the long-run behavior of patenting in the two fields.

The interpretation of the $\beta$ DiD estimate of specification (1.24) is significantly impacted by these findings. According to the Frisch-Waugh-Lowell theorem, $\beta$ can be obtained from the residuals regression of the outcome variable and the regressors on a field-specific linear trend. In practice, it is important to confirm that the pre-trends assumption underlying the DiD exercise holds in the residuals of the patenting outcomes from the estimated linear trend.

Figure 1.B.4 shows the time series of these residuals for the two fields of interest. It is evident from the plot that while the parallel trend assumption appears to hold in the

Figure 1.B.3: Number of monthly patents in a losing and a gaining field - Fitted trends from Abrams (2009)

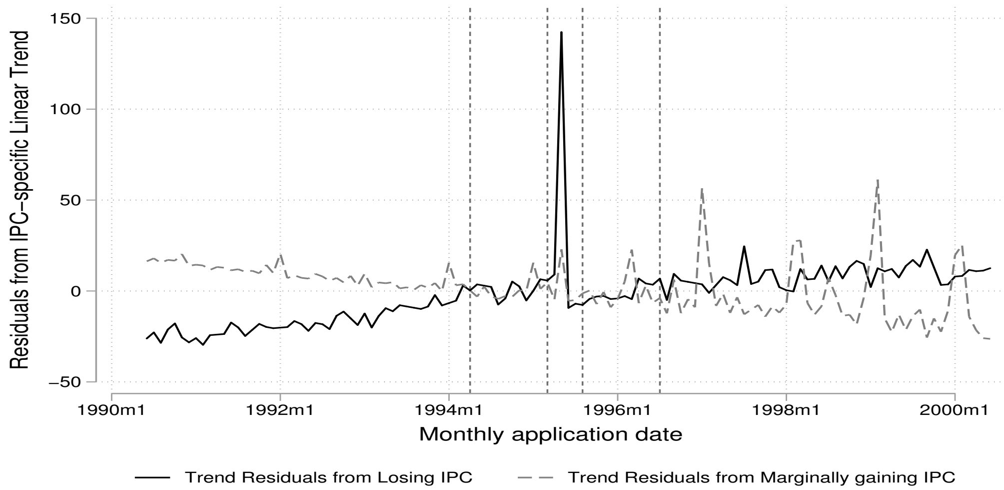



The plot shows the time series of granted patents applied for in month-$t$ and classified in field C12R, the "losing field", and field A01H, the "marginally gaining field". In red, it also plots the fitted field-specific time trends implied by Abrams (2009) specification and sample restriction.

raw data, as confirmed by section 1.4 of the paper, the same is not true when focusing on the trend-deviations. This significantly undermines any causal interpretation of the static difference-in-difference estimates in Abrams (2009).

The paper identifies two main issues with Abrams (2009)'s assumptions. Firstly, the assumption of no policy anticipation is overly restrictive, and the paper argues that assuming anticipation is a more conservative approach. A dynamic DiD specification like equation (1.2) can capture reactions to news or the absence thereof during the pre-implementation period. Secondly, the narrow time-window sample used in Abrams (2009) means that the fitted field-specific trend does not capture the overall behavior of the series, which leads to a violation of the parallel trends assumption in trend-deviations. This makes cross-field comparisons misleading because fields become bad counterfactuals of one another. The simplest solution is to extend the estimation window to improve the representation of the series and reduce concerns related to the violation of the parallel trends assumption. Therefore, Figure 1.B.5 replicates the plot of Figure 1.B.3 but extends the sample from June 1990 to November 1994 and

Figure 1.B.4: Number of monthly patents in a losing and a gaining field - Trend deviations

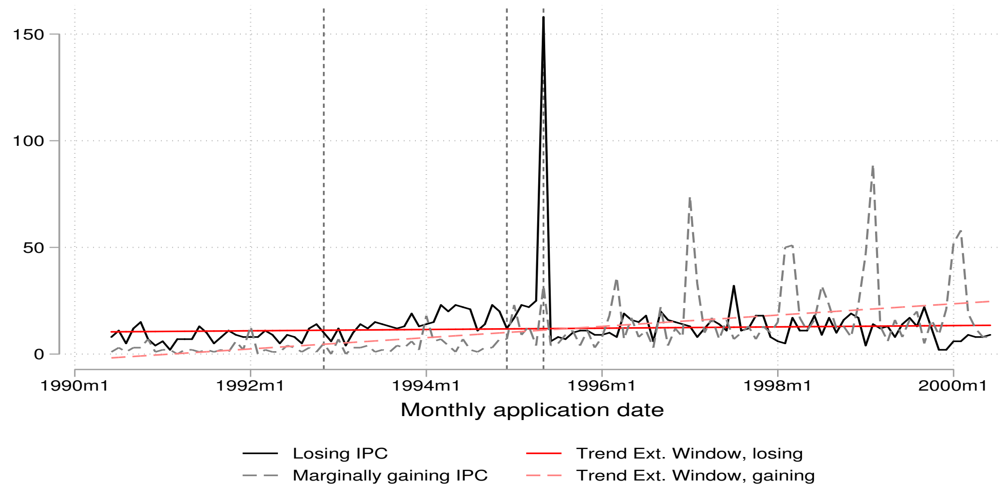



The plot shows the time series of the deviation of granted patents from a field-specific linear trend on a time-window of data corresponding to April 1994 to April 1995 and from August 1995 to July 1996. Field C12R is the "losing field" and field A01H is the "marginally gaining field". The fitted field-specific time trends are those implied by Abrams (2009) specification and sample restriction.

from December 1995 to June 2000, expanding both the outer and inner window. The rationale for expanding the inner window is to further reduce anticipation concerns by excluding the six months between the formal signing of the URAA (December 1994) and policy implementation. As shown in Figure 1.B.5, the fitted trends better represent the behavior of the series in the sample.

After observing the improvement in the representation of the behavior of the patenting series by extending the estimation window, I proceed to replicate the estimation of specification (1.24) used by Abrams (2009) on the extended sample of June 1990 - November 1994 and December 1995 - June 2000. The results of this exercise are reported in Table 1.B.2, which shows that after correcting for the problems discussed earlier, the DiD coefficient changes sign compared to Abrams (2009) analysis. These findings are consistent with the reduced-form estimates of Section 1.4 of the paper, providing further support for my argument.

Figure 1.B.5: Number of monthly patents in a losing and a gaining field - Fitted trends on extended sample




The plot shows the time series of granted patents applied for in month-$t$ and classified in field C12R, the "losing field", and field A01H, the "marginally gaining field". In red, it also plots the fitted field-specific time trends obtained on an extended sample compared to Abrams (2009). The new sample overs the periods June 1990 to November 1994 and December 1995 to June 2000.

Table 1.B.2: **Replication of Abrams (2009)'s results - Extended Sample**

| | (1) Patents | (2) Patents | (3) Citations | (4) Citations |
|---|---|---|---|---|
| $Post_t$ | 1.357*** | 1.975*** | 122.192*** | 170.237*** |
| | (0.440) | (0.568) | (8.691) | (11.239) |
| $Post_t \times \Delta T_j$ | -0.003*** | -0.005*** | -0.226*** | -0.320*** |
| | (0.001) | (0.001) | (0.018) | (0.023) |
| Avg. Num. of Inventors | | 0.152*** | | 3.489*** |
| | | (0.045) | | (0.900) |
| Avg. Num. of Claims | | 0.002 | | 0.649*** |
| | | (0.005) | | (0.093) |
| Constant | 13.444*** | 15.681*** | 110.019*** | 114.221*** |
| | (0.059) | (0.130) | (1.168) | (2.574) |
| Field F.E. | Y | Y | Y | Y |
| Field-specific Trend | Y | Y | Y | Y |
| Observations | 72657 | 60969 | 72657 | 60969 |

Columns (1) and (2) report the OLS estimates of specification (1.24) using granted patents filed in month-$t$ and classified in field-$j$ as dependent variable. Columns (3) and (4) report the OLS estimates of specification (1.24) using citations-weighted granted patents filed in month-$t$ and classified in field-$j$ as dependent variable. The sample is extended to the period June 1990 - November 1994 and December 1995 - June 2000. Standard errors are clustered by technical field. Statistical significance levels: $^{*}(p < 0.05),^{**}(p < 0.01),^{***}(p < 0.001)$

### 1.B.2 Technical field-level analyses

#### 1.B.2.1 Discussion of bunching in the pre-implementation quarter

In this subsection, I examine the bunching of patent applications in 1995Q2, the last quarter before policy implementation. As previously discussed in Subsection 1.4.1.2, I relate the bunching behavior to the policy implementation details of the policy. The URAA was formally signed in December 1994, and the new policy had full effectiveness in June 1995. However, until June 1995, innovators could benefit from the most favorable regime. This had a dual effect. Firstly, it encouraged all innovators at risk of receiving lower protection under the new regime to file their applications before implementation. Secondly, it allowed innovators in fields with a longer term to obtain the more favorable policy before the final implementation. Both groups had an incentive to file more, but the pressure to increase innovation intensity and file applications before implementation was stronger in fields about to lose protection from the policy. Section 1.4 shows a markedly negative DiD estimate in 1995Q2 for this reason.

To illustrate this point, Figure 1.B.6 presents the quarterly number of granted patents by quarter of applications in two fields with opposite exposure to the policy change. Panel (a) shows the 4-digit technical field C12N, related to microorganisms and enzymes (red solid line), and the 4-digit field F01B, related to internal combustion engines (green dashed line). Field C12N had a longer average pending period of approximately 3 years and 2 months before 1992, thus losing on average 2 months of effective patent term from the policy. In contrast, examination in field F02B was quicker, around 1.5 years. Therefore, the policy change induced an average increase in patent term of 1.5 years in this field. The figure demonstrates that patenting activity was remarkably similar in the two fields before the policy news (first vertical line) but diverged afterwards. Between the policy news and implementation (second vertical line), patenting in the field expected to lose protection time in the future experienced a marked acceleration, culminating in the pre-implementation quarter. This corresponds to incentives to file applications under the old policy regime, resulting in bunching in 1995Q2. On the contrary, patenting in the field expected to receive longer protection from the new policy declined slightly relative to the pre-news trend. After implementation, patenting in microorganisms and enzymes remained higher than in internal combustion engines for at least 5 years, despite a shorter effective patent term.

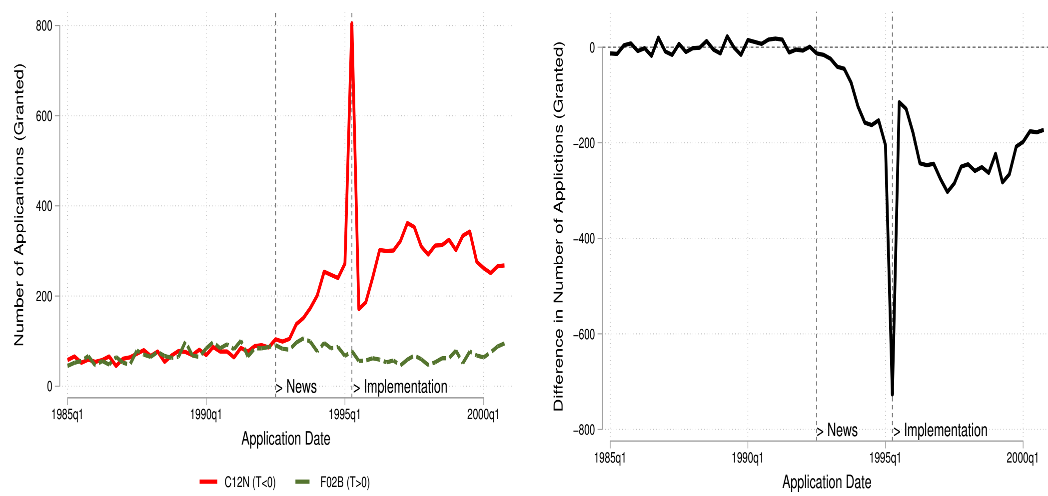
Panel (b) of the figure shows the difference between the green line (patenting in the field gaining protection) and the red line (patenting in the field losing protection). This represents what the difference-in-difference estimates of Section 1.4 capture, a relative comparison of fields with a larger versus smaller change in patent term. Since the increase in patenting rates in the losing field is considerably larger than in the gaining field, the DiD estimate of the pre-implementation quarter is significantly negative.

To expand on this idea for the other technical fields in the sample, I examine the excess mass of innovation in 1995Q2 for each field and its relationship to the policy-induced change in patent term. The excess mass is defined as the absolute difference between the actual number of granted applications applied for in 1995Q2 and the number predicted by a field-specific linear trend estimated from the quarterly patenting series prior to policy news. These findings are presented in Figure 1.B.7.

Panel (a) of the figure depicts the negative correlation between field-specific excess mass and the policy-induced change in average effective patent term. This result aligns with the discussion in the previous section, which suggested that fields with a worse patent term adjustment from the policy were more likely to experience stronger bunching before policy implementation. Panel (b) of the figure presents a complementary perspective by plotting the correlation between innovation excess mass and the field-specific share of patents filed before the policy news that experienced a pending period longer than three years, which is the critical threshold for losing vs. gaining

Figure 1.B.6: Patenting in fields with positive vs. negative change in patent term

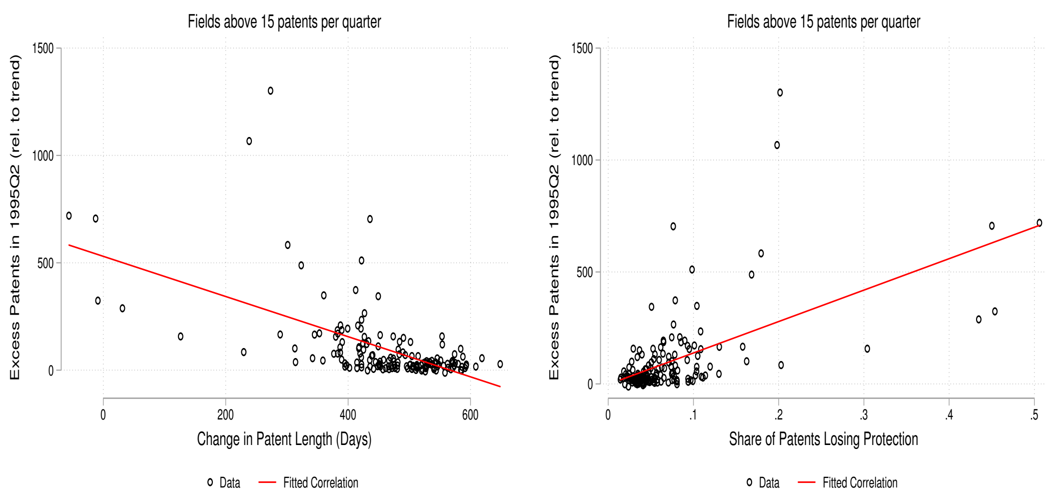
(a) Patents by application quarter (b) Difference in patenting




Panel (a) of the figure shows the number of granted patents by application quarter in the 4-digit IPC C12N “MICROORGANISMS OR ENZYMES; COMPOSITIONS THEREOF; PROPAGATING, PRESERVING, OR MAINTAINING MICROORGANISMS; MUTATION OR GENETIC ENGINEERING; CULTURE MEDIA" (red solid line) and in the 4-digit IPC F02B “INTERNAL-COMBUSTION PISTON ENGINES; COMBUSTION ENGINES IN GENERAL" (green dashed line). Field C12N's policy-induced change in effective patent term is -56 days. Field F02B's policy-induced change in effective patent term is +558 days. The first vertical line marks the news date in 1992Q3 and the second vertical line marks implementation in 1995Q2. Panel (b) of the figure plots the difference between patenting in field F02B—gaining protection—and in field C12N—losing protection.

Figure 1.B.7: Correlation between bunching and policy treatment

(a) Change in patent term (b) Prob. pending period > 3 years




Panel (a) of the figure shows the correlation between the TRIPs-induced change in average effective patent term across technical fields and the excess mass of granted patents applied for in 1995Q2. The latter is computed as the level difference between the number of granted patents applied for in 1995Q2 and a baseline level implied by a field-specific linear trend fitted on the series of quarterly patents by application date in the period 1985Q1-1992Q3. Panel (b) of the figure shows the correlation between the fields-specific share of patents with a pending period longer than 3 years–computed using patents whose application date falls between 1985Q1 and 1992Q3–and the excess mass of granted patents applied for in 1995Q2. For graphical readability, both panels restrict the sample to fields with more than 15 granted applications per quarter. Evidence is analogous on the full sample.

protection from the policy change. The correlation is positively correlated, and consistent with the finding of panel (a). Fields with a relatively smaller change in patent term in panel (a) are also those where, on average, the probability of facing a pending period longer than three years is higher. This, in turn, increases the incentives to file applications before implementation.

#### 1.B.2.2 Citations-weighted patents

Figure 1.B.8 presents DiD estimates of specifications (1.2) and (1.3), where citations-weighted patents by application quarter and field are used as the outcome variable. Forward citations are a widely used measure of patent quality and indicate the scientific value of a patent, as they capture how many other technologies the patent is relevant to. The outcome of interest is computed by counting the number of forward citations received by each patent within five years from the grant date.

The DiD estimates shown in Figure 1.B.8 exhibit similar dynamics to those seen for patents in the paper. However, the magnitude of the effects is stronger. Specifically, news of a 1-month increase in patent term leads to a decline of 10.5 citations-weighted patents (approximately 6.6% of the 1992Q3 baseline) one year before implementation. After implementation, the average quarterly effect is -75 citations-weighted patents, which represents 47% of the baseline.

#### 1.B.2.3 Private economic value of patents

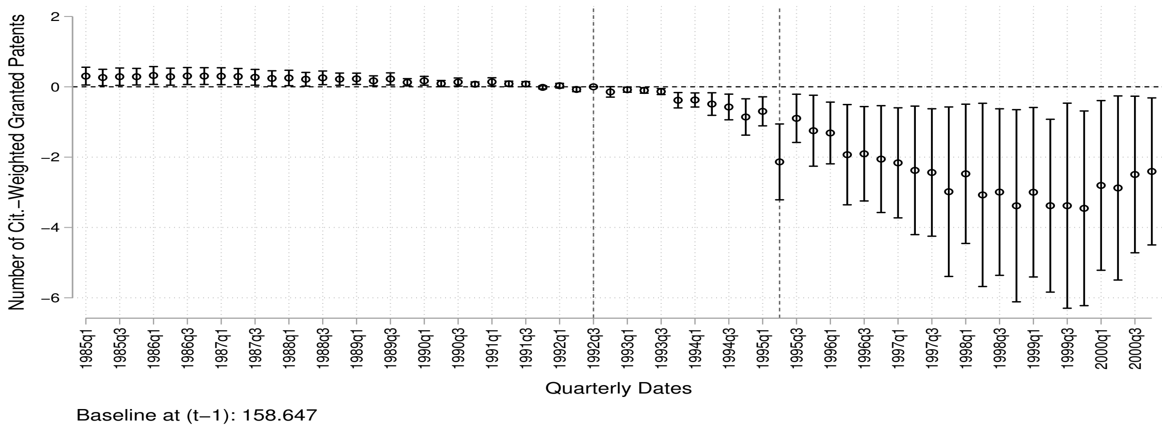
Results of specification (1.2) with patent value as dependent variable are in Figure 1.B.9.

#### 1.B.2.4 Claims-weighted patents

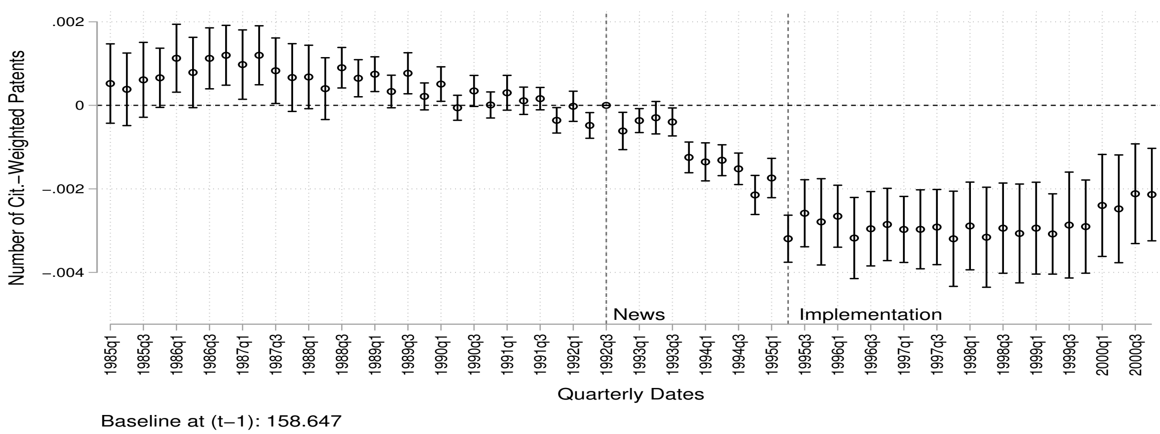
Results of regression (1.2) with claims-weighted patents as outcome are in Figure 1.B.10.

Figure 1.B.8: Marginal effect of effective patent term on citations-weighted patents

(a) Linear model

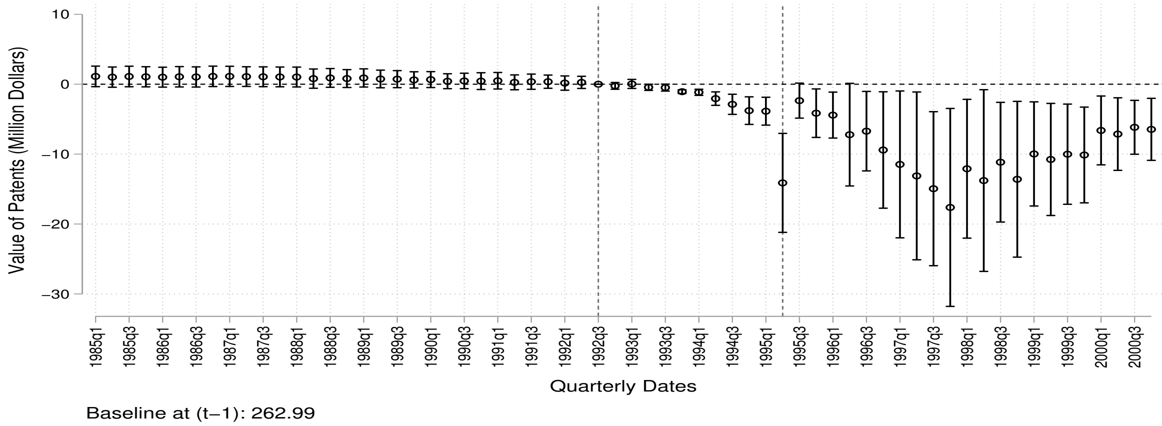



(b) Poisson model



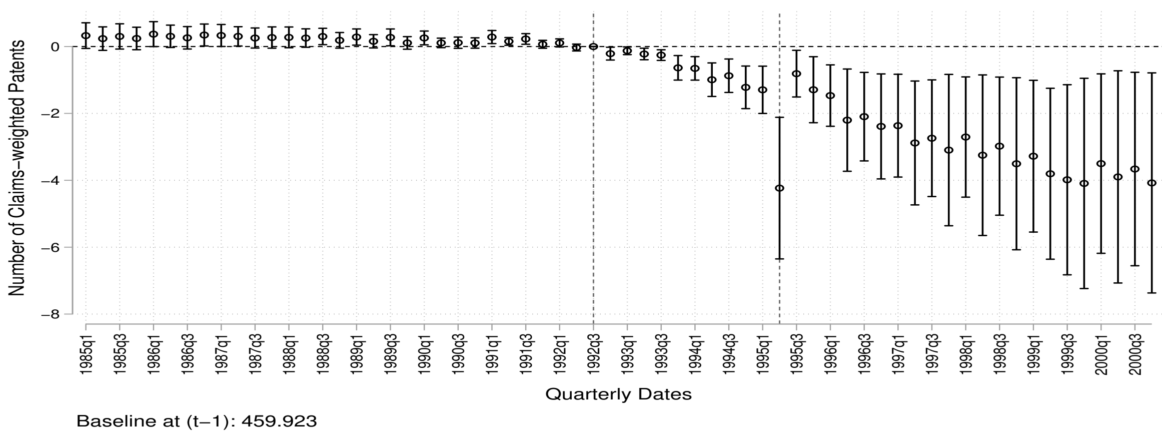

Panel (a) and panel (b) show the $\beta_k$ coefficients of specification (1.2) and (1.3), respectively, having as dependent variable quarter-$t$ and field-$j$ number of citations-weighted patents. Point estimates in panel (a) refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Point estimates in panel (b) refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.9: Effect of 1 more day of protection on patents value



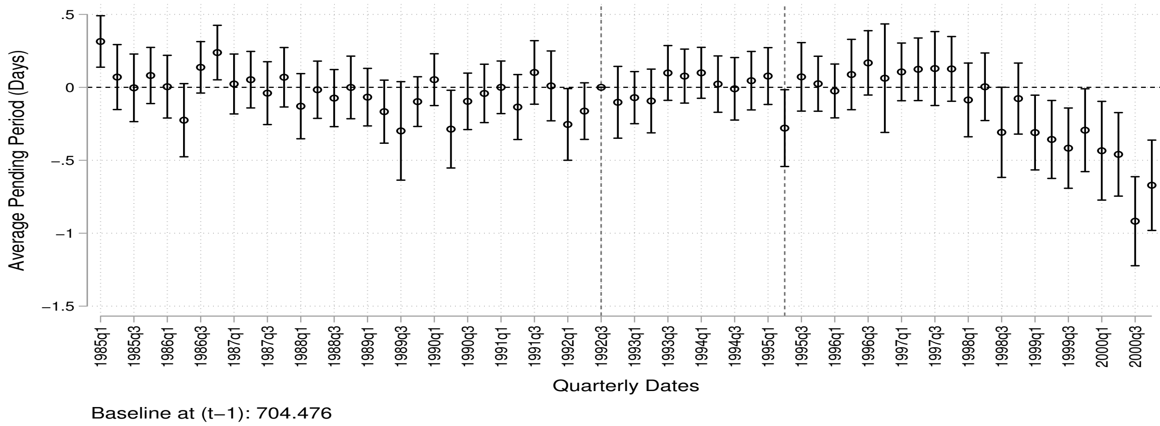

The plot shows the $\beta_k$ coefficients of specification (1.2). Dependent variable is quarter-$t$ and field-$j$ dollar value of granted patents built from Kogan et al. (2017). Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field. 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.10: Effect of 1 more day of protection on claims-weighted patents




The plot shows the $\beta_k$ coefficients of specification (1.2). Dependent variable is quarter-$t$ and field-$j$ claims-weighted granted patents. Standard errors are clustered by technical field. 95% confidence bands are plotted. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.11: Average pending time around the treatment date




The plot shows the $\beta_k$ coefficients of specification (1.2) having as dependent variable quarter-$t$ and field-$j$ average pending period. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

#### 1.B.2.5 Reaction of the average pending period to the policy

The $\beta_k$ coefficients of the difference-in-difference specification (1.2), with the average pending period of patents filed in a given quarter $t$ and classified in field $j$ as the dependent variable, are plotted in Figure 1.B.11. The results indicate that changes in the average pending period after policy shocks are not associated with ex-ante differences in the average pending period across fields before the news.

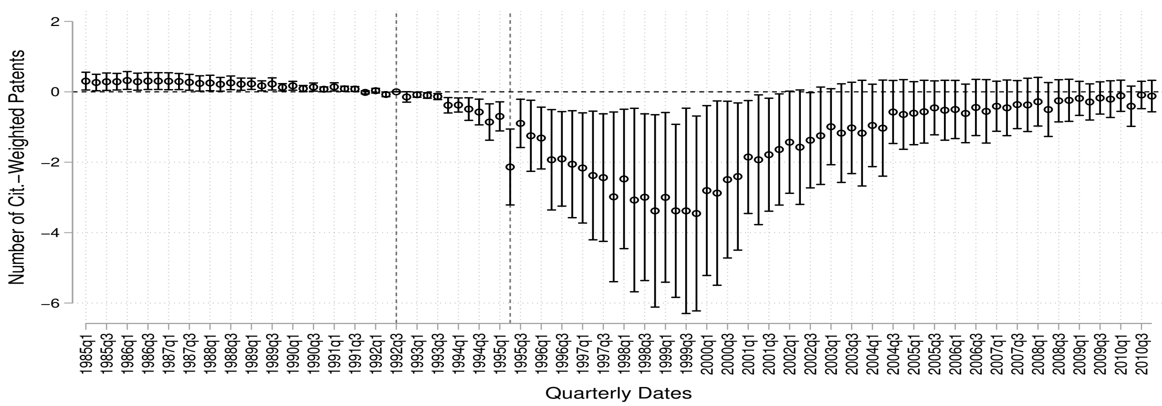
#### 1.B.2.6 Extension of the analysis to 2010Q4

Figure 1.B.12 presents the results of the specification (1.2) with citations-weighted patents as the dependent variable. The sample has been extended up to 2010Q4, and the results indicate a recovery trend of the DiD coefficients towards zero towards the end of the sample period.

#### 1.B.2.7 Market access to developing countries

This subsection examines the impact of stronger patent rights induced by TRIPs in Low and Middle-Income Countries (LMICs) on the DiD estimates in Section 1.4 of the

Figure 1.B.12: Effect of 1 more day of protection on cit.s-weighted patents

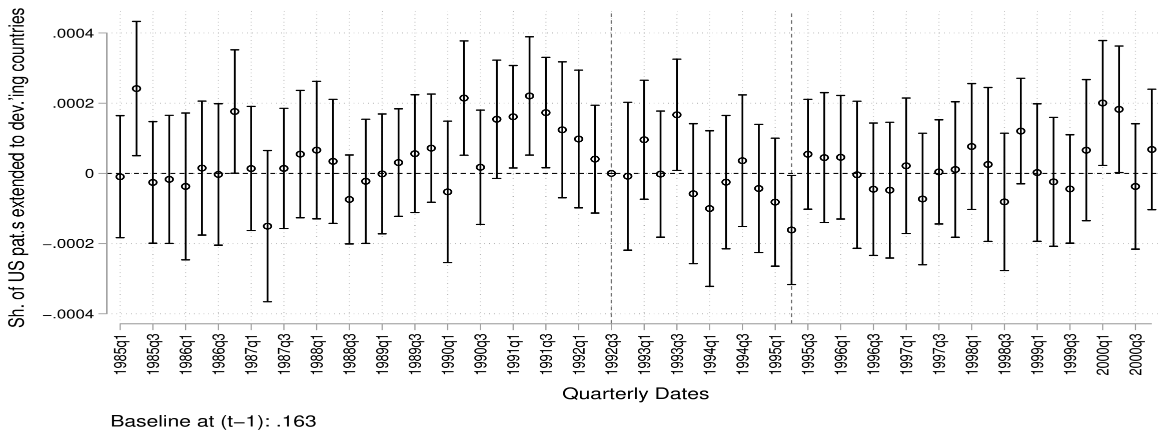



The plot shows the $\beta_k$ coefficients of specification (1.2) having as dependent variable quarter-$t$ and field-$j$ 5-years citations-weighted patents. The sample is extended to 2010Q4. Standard errors are clustered by technical field. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered at the field-level and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

paper. As discussed earlier, TRIPs strengthened intellectual property protection in many developing countries, facilitating the access of US innovators to foreign markets. If the pre-news average pending period correlates with field-specific benefits of accessing new markets, then the DiD estimates in Subsection 1.4.1.2 would be impacted by the patent term change as well as the access to new markets. In this subsection, evidence is presented to demonstrate that this is not the case.

The access of US innovators to new markets is measured by the field- and quarter-specific share of US patents for which applicants file additional applications in LMICs where TRIPs compliance necessitated strengthened patent rights. A list of such countries is obtained from Kyle and McGahan (2012), with the main ones being China, India, Brazil, and South Korea. For each US patent application, the additional patent applications to national offices of LMICs countries in the same patent family are checked, and the outcome of interest is the share of field-$j$ and quarter-$t$ US patents with at least one additional foreign filing in LMICs adopting the TRIPs, denoted by $S_{j,t}^{LMICs}$.

Figure 1.B.13: Marginal effect of patent term on the share of patents to LMICs




The plot shows the $\beta_k$ coefficients of specification (1.2). Dependent variable is quarter-$t$ and field-$j$ share of US fist filings seeking an extension of patent protection to low- and middle-income countries where the TRIPs strengthened patent rights. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field. 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.13 displays the $\beta_k$ coefficients of specification (1.2) with $S_{j,t}^{LMICs}$ as the dependent variable. The estimated coefficients are close to zero before the policy news, indicating the absence of pre-trends, and remain null after the implementation of TRIPs. This indicates that the TRIPs-related change in effective patent term is not related to TRIPs-induced access to new LMICs across technical fields. Similar results are obtained when focusing on individual countries such as China, India, South Korea, and Brazil, and when using a Poisson model instead of a linear specification or using the share of citations-weighted patents rather than the share of patents.

#### 1.B.2.8 Ex-post effective treatment instrumented by ex-ante treatment

This subsection employs an IV regression to address concerns about the representativeness of the ex-ante pending period in computing the policy-induced change in patent term. Specifically, the change in patent term is now based on the ex-post realized average pending period for patents filed in quarter-$t$ and field-$j$, which is instrumented by the field-specific change in patent term, as computed using the ex-ante pending period, interacted with quarterly dummy variables. This approach ensures that the analysis utilizes the ex-post effective change in patent term in the second stage regression, while leveraging the ex-ante pending period to induce plausibly exogenous variation in the ex-post patent term change.

The specification of the second stage regression is

$$Y_{j,t} = \alpha_j + \sum_{k=1985Q1}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta\tilde{T}_{j,t} + \varepsilon_{j,t} \tag{1.25}$$

where all the variables have the same meaning as in specification (1.2), and $\tilde{\Delta T}_{j,t}$ is the change in patent term based on the ex-post, realized effective average pending period computed for patents filed in quarter-$t$ and classified in field-$j$. In turn, the first stage regressions are

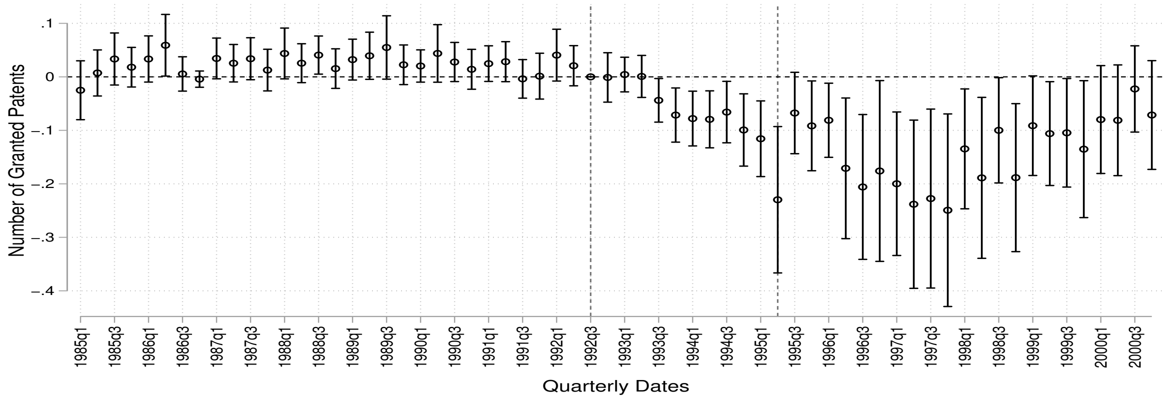
$$\mathbf{1}_{(t=k)} \tilde{T}_{j,t} = \eta_j + \sum_{k=1985Q1}^{2000Q4} \psi_k \mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \delta_k \mathbf{1}_{(t=k)} \Delta T_j + u_{j,t} \quad \forall k \tag{1.26}$$

Figure 1.B.14 displays the $\beta_k$ coefficients of (1.25) where the number of granted patents serves as the dependent variable. The findings are fully consistent with the primary evidence presented in Section 1.4, which applies to citations-weighted patents as well. However, due to space constraints, results for citations-weighted patents are not reported here.

#### 1.B.2.9 Triple difference analysis with the standard deviation of the pending period

In this subsection, I propose that the impact of TRIPs-induced patent term changes on R&D and innovation is more pronounced when firms can more accurately anticipate the change in patent term. To support this argument, I utilize a triple difference specification that interacts the expected change in protection time ($\Delta T_j$) for field $j$

Figure 1.B.14: Marginal effect of 1 more day of effective ex-post protection change on granted patents




The plot shows the $\beta_k$ coefficients of specification (1.25) having as dependent variable quarter-$t$ and field-$j$ number of granted patents. I omit the dummy for 1992Q3, which is the pre-treatment quarter. Point estimates in panel (a) refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

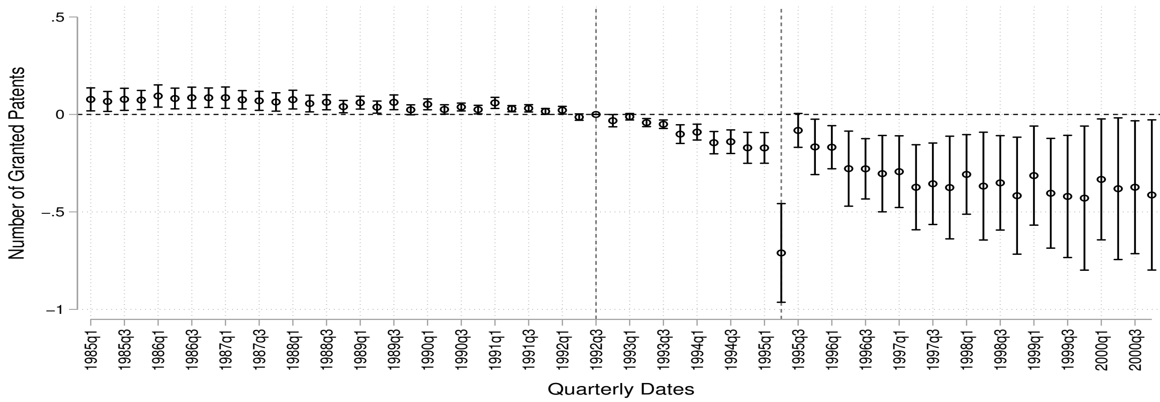
with a dummy variable that takes on a value of 1 if the standard deviation of the average pending period, as computed using patents granted before the policy news, exceeds the median value across technical fields. The specification of the regression is

$$\begin{aligned} Y_{j,t} = \alpha_j + \sum_{k=1985Q1}^{2000Q4} \gamma_{1,k} \mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \gamma_{2,k} \mathbf{1}_{(t=k)} d_{\sigma_j \leq \sigma^m} + \\ + \sum_{k=1985Q1}^{2000Q4} \psi_k \mathbf{1}_{(t=k)} \Delta T_j + \sum_{k=1985Q1}^{2000Q4} \theta_k \mathbf{1}_{(t=k)} \Delta T_j d_{\sigma_j \leq \sigma^m} + \varepsilon_{j,t} \end{aligned} \tag{1.27}$$

where all the variables follow the usual notation, $\sigma_j$ is the field-specific standard deviation of the pre-policy-news pending period, and $\sigma^m$ is the median value of such standard deviation across technical fields.

Figure 1.B.15 displays the $\widehat{\theta}_k$ coefficients obtained from the previous regression where the number of granted applications is the dependent variable. The negative triple-difference coefficients indicate that the negative effect of the policy change is greater when $d_{\sigma_j \leq \sigma^m} = 1$, which implies that the standard deviation of the average

Figure 1.B.15: Marginal effect of 1 more day of protection on granted patents - Triple difference specification




The plot shows the $\theta_k$ coefficients of regression (1.27) having as dependent variable $P_{j,t}$, i.e. quarter-$t$ and field-$j$ number of granted patents. I omit the dummy for 1992Q3, which is the pre-treatment quarter. Point estimates in panel (a) refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

pending period is below the median. This suggests that the impact of the policy-induced change in patent term is more accurately estimated in this case.

#### 1.B.2.10 IV strategy

This subsection presents the IV DiD specification discussed in Subsection 1.4.2 of the paper. To isolate variation in the average pre-TRIPs pending period that is unrelated to field-specific conditions of the US innovative environment after the TRIPs, the IV strategy employs two external instruments: $Z_{1,j}$ and $Z_{2,j}$. The first instrument exploits heterogeneity in the congestion of different technical units due to the numerosity of secondary patent applications from foreign applicants relative to domestic US inventors. This approach is motivated by the focus of the analysis on novel US patents, i.e., US domestic invention. The second instrument relates to the technical examination complexity that varies across fields and is proxied by the technical field-specific average pending period at the European Patent Office. Both instruments are computed using patents granted between January 1, 1990, and May 31, 1992, before the policy news in 1992Q4, in order to minimize potential endogeneity concerns.

The first stage regressions are

$$
\begin{aligned}
\Delta T_j \mathbf{1}_{(t=h)} = \phi_{h,j} + \sum_{k=1985Q1}^{2000Q4} \omega_{h,k} \mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \eta_{h,k,1} \mathbf{1}_{(t=k)} Z_{1,j} \\
+ \sum_{k=1985Q1}^{2000Q4} \eta_{h,k,2} \mathbf{1}_{(t=k)} Z_{2,j} + u_{h,j,t} \quad \forall h = \text{1985Q1,...,2000Q4}
\end{aligned}
\tag{1.28}
$$

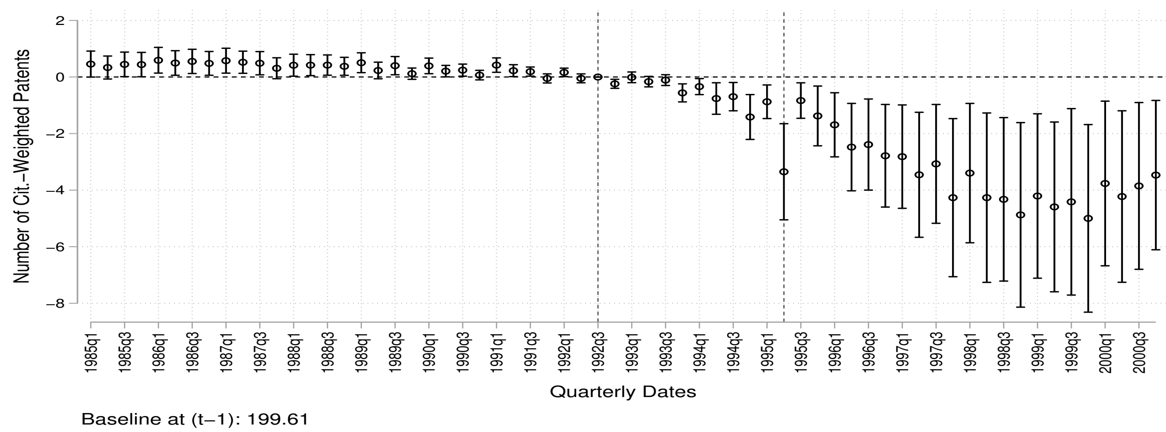
The left-hand-side variable of the regression is the product of the policy-driven patent term change $\Delta T_j$ in field $j$ and a dummy variable for quarter $h$. As such, $h$ indexes all first-stage equations ranging from 1985Q1 to 2000Q4, and subscripts on the coefficients indicate their associated variables. Specifically, $\phi_{h,j}$ represents the field fixed effects for equation $h$, $\omega_{h,k}$ denotes the quarterly effects for equation $h$, and $\eta_{h,k,1}$ and $\eta_{h,k,2}$ correspond to the quarter-specific impact of instruments $Z_{1,j}$ and $Z_{2,j}$ on the treatment variable in quarter $h$. The error term $u_{h,j,t}$ captures the residual variation.

The second stage regression follows the same form as regression (1.2), but the $\Delta T_j \mathbf{1}_{(t=h)}$ terms on the right-hand side of the equation are replaced with fitted values from (1.28). Results of the second stage regression are presented in Figure 1.B.16 for citations-weighted patents and in Figure 1.B.17 for R&D effort, proxied by the number of inventors listed on patents.

#### 1.B.2.11 IV Poisson model

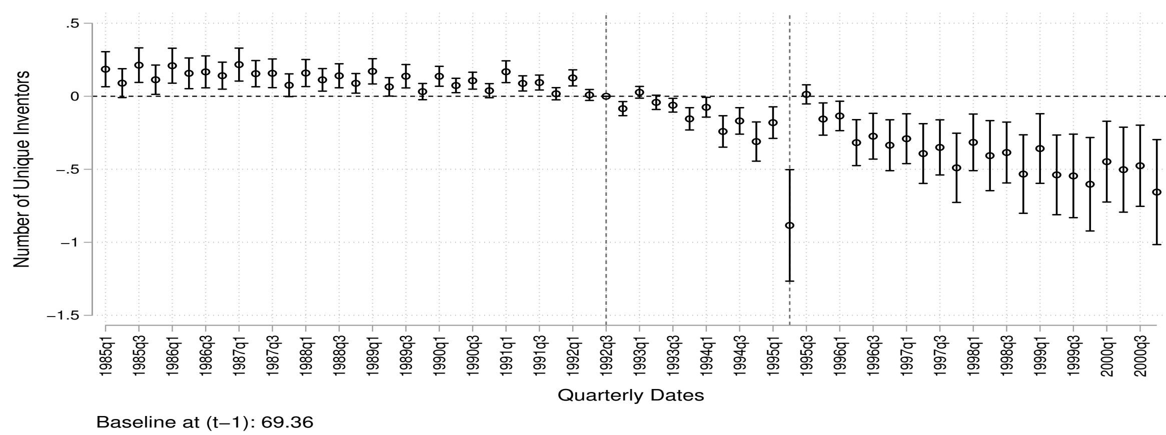
In this subsection, I present the results of an IV Poisson model estimated using the control function approach suggested by Wooldridge (1997). The aim of this empirical exercise is to isolate variation in $\Delta T_j$ that is plausibly unrelated to US-specific factors that may affect field-specific post-implementation innovation patterns beyond $\Delta T_j$.

Figure 1.B.16: Marginal effect of patent term on citations-weighted patents - IV




The plot shows the $\beta_k$ coefficients of 2SLS estimation of (1.2) following the IV strategy detailed in appendix 1.B.2.10. External instruments are proxies of (i) congestion by foreign secondary patent applications and (ii) technical examination complexity. The dependent variable is 5-years citations-weighted patents filed in field $j$ and quarter $t$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.17: Marginal effect of patent term on R&D effort - IV




The plot shows the $\beta_k$ coefficients of 2SLS estimation of (1.2) following the IV strategy detailed in appendix 1.B.2.10. External instruments are proxies of (i) congestion by foreign secondary patent applications and (ii) technical examination complexity. The dependent variable is the unique number of inventors operating on patents filed in field $j$ and quarter $t$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

To achieve this, the first external instrument $Z_{1,j}$ exploits heterogeneity in the congestion of different technical units due to the numerosity of secondary patent applications from foreign applicants relative to domestic US inventors[56]. The second external instrument $Z_{2,j}$ relates to heterogeneous technical examination complexity across fields, which I proxy by the technical field-specific average pending period at the European Patent Office. Both instruments are computed using patents granted between January 1, 1990 and May 31, 1992, i.e., before the policy news in 1992Q4, to minimize potential endogeneity concerns.

The first stage equation is

$$\Delta T_j = \gamma_1 Z_{1,j} + \gamma_2 Z_{2,j} + u_j$$

which I estimate by OLS to get residuals $\hat{u}_j$. The control function approach consists in pseudo-maximum likelihood estimation of the second stage Poisson model

$$Y_{j,t} = \exp\left\{\alpha_j + \sum_{k=1985Q1}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta T_j + \sum_{k=1985Q1}^{2000Q4} \theta_k \mathbf{1}_{(t=k)} \hat{u}_j + \varepsilon_{j,t}\right\} \tag{1.29}$$

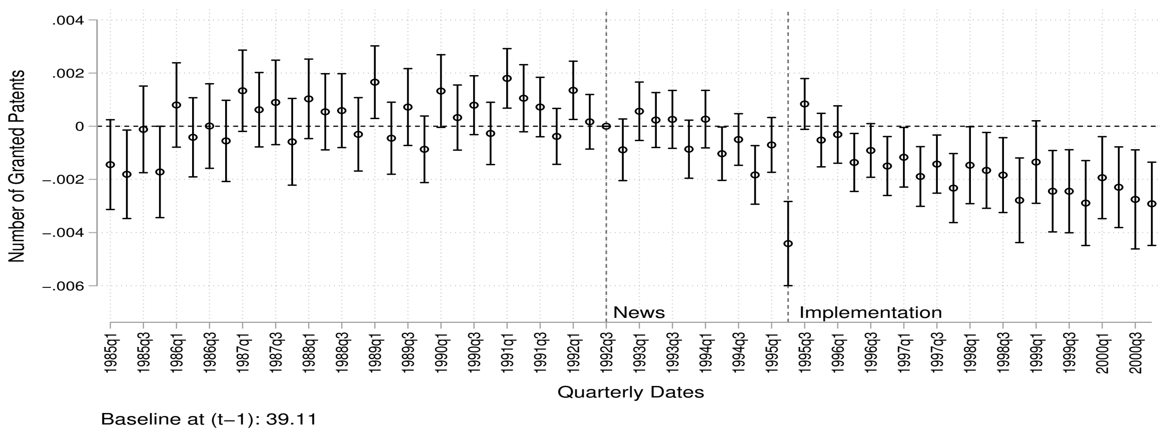
which augments specification (1.3) to control for residuals $\hat{u}_j$.

Figure 1.B.18 displays the $\widehat{\beta}_k$ estimates of (1.29) for raw patent count (panel a) and number of unique inventors (panel b) as outcome variables. These results are consistent with the DiD estimates of Subsection 1.4.1.2. Additionally, the $\widehat{\theta}_k$ coefficient estimates for $\hat{u}_j$ terms are largely insignificant (p-values above 0.4), indicating the exogeneity of $\Delta T_j$.

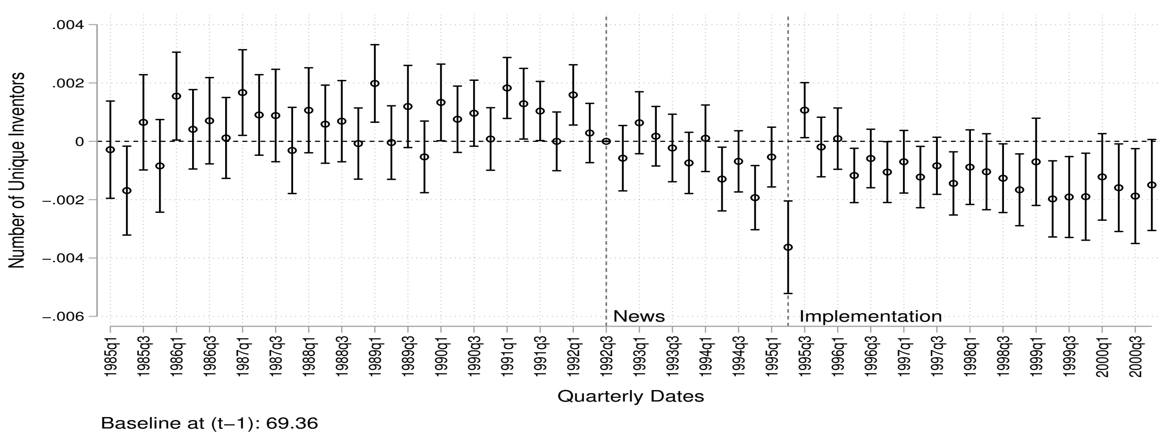
[56]A patent application is defined as a second filing if its application date at the USPTO is subsequent to its priority date, i.e., its earliest filing date is determined at some foreign patent office.

Figure 1.B.18: Marginal effect of effective patent term on granted patents

(a) Number of patents




(b) R&D effort




Panel (a) and panel (b) show the $\beta_k$ coefficients of the IV Poisson model (1.29) having as dependent variable quarter-$t$ and field-$j$ number of granted patents or number of unique inventors, respectively. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1992Q3, reported at the bottom of the figures. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

#### 1.B.2.12 Inclusion of a flexible trend by 3-digit IPC class

To account for the potential impact of unobserved macroeconomic shocks that may differentially affect innovation across sectors, I augment the DiD specifications (1.2) and (1.3) with 3-digit IPC $\times$ quarterly fixed effects. Although a broader classification of technological patents compared to the 4-digit IPC defining fields, the three-digit IPC is sufficiently detailed to control for macroeconomic confounders such as the rise of Information Technologies during the 1990s, the recovery from the 1991 recession, Clinton's tax increases, reductions in defense spending after the end of the Cold War, and changes to nominal interest rates.[57] Therefore, the richer specification is

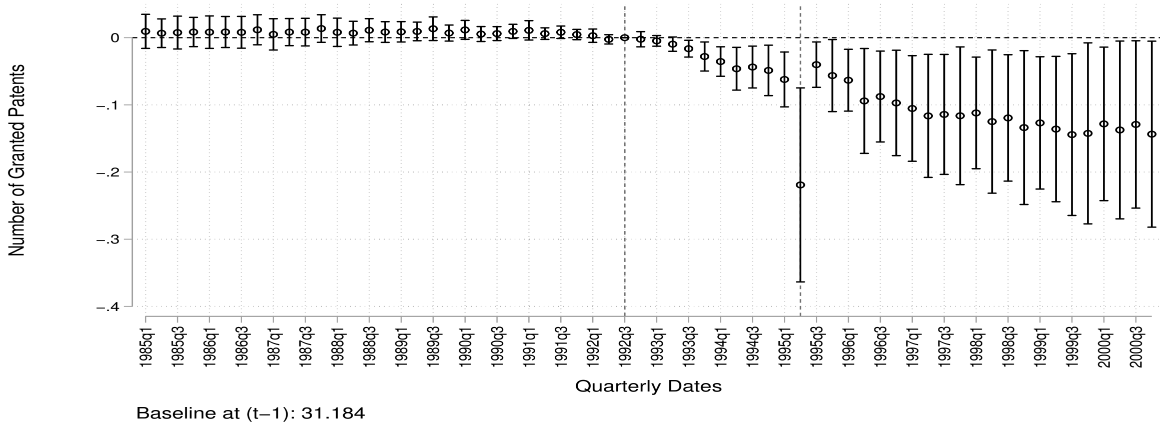
$$Y_{j,t} = \alpha_j + \sum_{k=1985Q1}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} T_j + \sum_f \sum_{k=1985Q1}^{2000Q4} d_{j\in f} \mathbf{1}_{(t=k)} + \varepsilon_{j,t} \tag{1.30}$$

where all the terms have the same meaning as in (1.2). The new term $\sum_f \sum_{k=1985Q1}^{2000Q4} d_{j\in f} \mathbf{1}_{(t=k)}$ collects all the interactions between 3-digit IPC dummy variables $d_{j\in f}$ and quarterly dummies. 3-digit IPCs are indexed by $f$ and $d_{j\in f}$ takes value one if 4-digit field $j$ belongs to the 3-digit field $f$. The coefficients of interest remain the $\beta_k$'s. Figures 1.B.19 and 1.B.20 plot them for granted patents and citations-weighted patents as outcome variables, respectively. Results are fully consistent with Section 1.4.

Moreover, the same holds when the batter of 3-digit times quarter fixed effects is included in Poisson model (1.3). The specification is

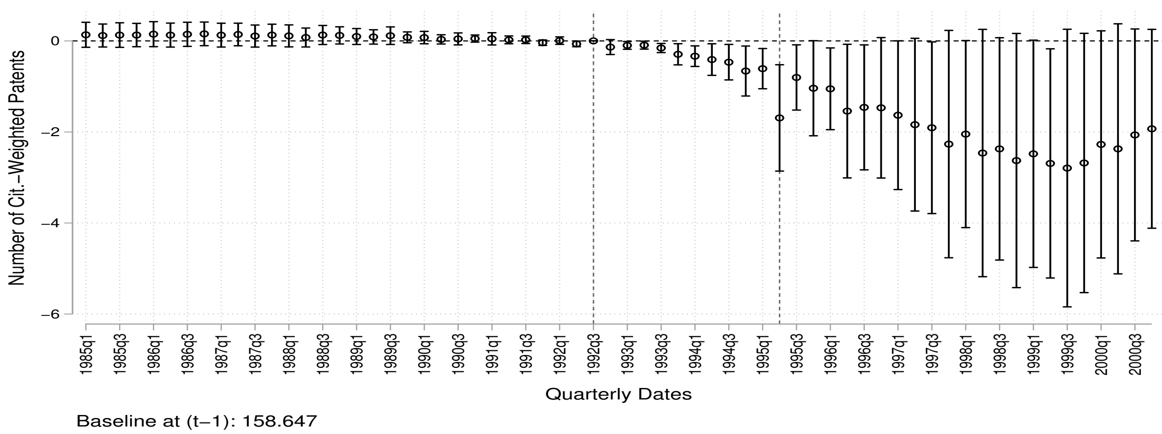
[57] For example, the 4-digit IPC "A23D" is "Edible Oils or Fats, e.g. Margarines Shortenings, Cooking Oils". It is included in the 3-digit IPC "A23", "Food or Foodstuffs; Their Treatment, not covered by other classes" and in the 1-digit IPC "A", "Human Necessities". It further includes two 8-digit IPCs: "A23D 7/00", "Edible oil or fat compositions containing an aqueous phase, e.g. margarines", and "A23D 9/00", "Other edible oils or fats, e.g. shortenings, cooking oils".

Figure 1.B.19: Effect of 1 more day of protection on granted patents



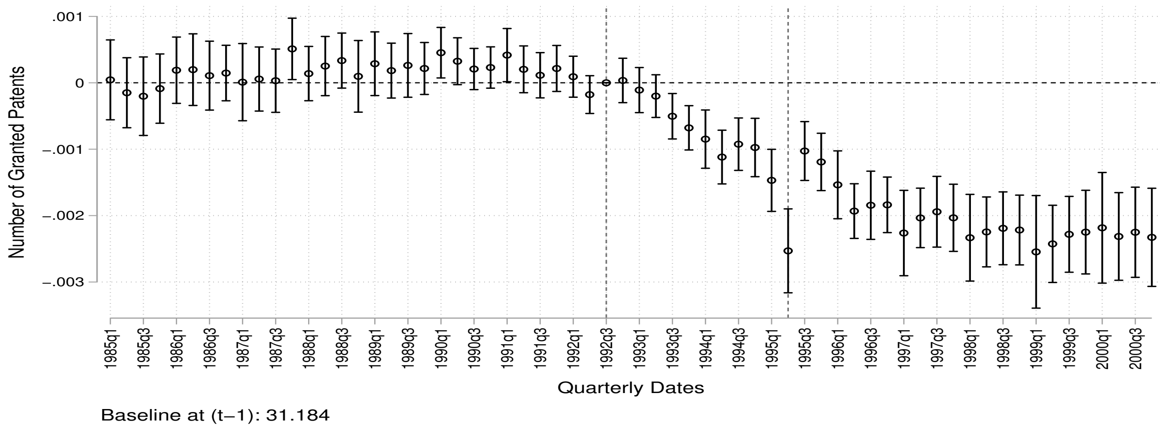

The plot shows the $\beta_k$ coefficients of specification (1.30) having as dependent variable quarterly number of patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.20: Effect of 1 more day of protection on citations-weighted patents




The plot shows the $\beta_k$ coefficients of specification (1.30) having as dependent variable quarterly citations-weighted patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.21: Effect of 1 more day of protection on granted patents




The plot shows the $\beta_k$ coefficients of specification (1.31) having as dependent variable the quarterly number of patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

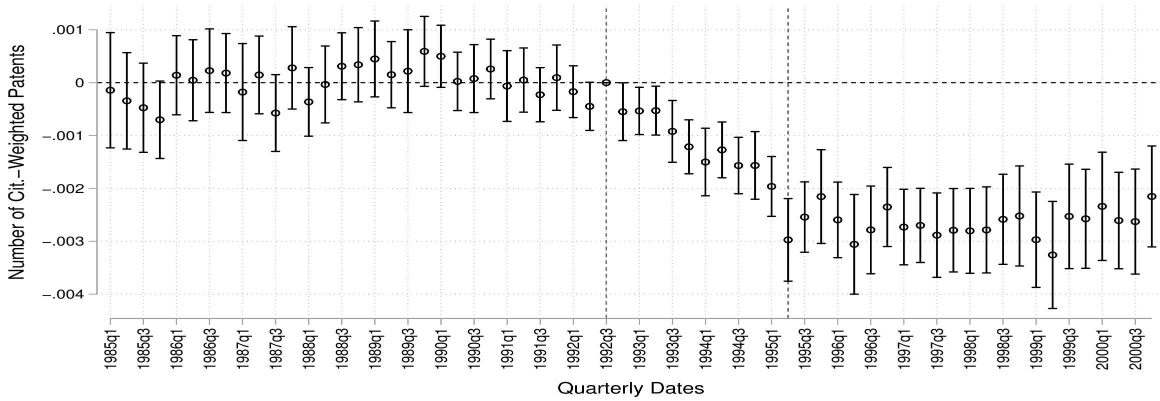
$$Y_{j,t} = \exp\left\{\alpha_j + \sum_{k=1985Q1}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_f \sum_{k=1985Q1}^{2000Q4} d_{j\in f}\mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta T_j + \varepsilon_{j,t}\right\} \tag{1.31}$$

Figures 1.B.21 and 1.B.22 show that results remain fully analogous.

#### 1.B.2.13 Triple difference with maintenance fees

In this subsection, I demonstrate that fields with a greater proportion of patents maintained until the maximum patent term display a stronger response to changes in patent term. To accomplish this, I employ a triple difference specification where I interact the alteration in patent term $\Delta T_j$ with a binary variable that indicates whether the field-specific proportion of patents for which maintenance fees are paid at 11.5 years from grant is above 0.25. The specification of the regression is

Figure 1.B.22: Effect of 1 more day of protection on citations-weighted patents




Baseline at (t–1): 158.647

The plot shows the $\beta_k$ coefficients of specification (1.31) having as dependent variable the quarterly number of citations-weighted patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

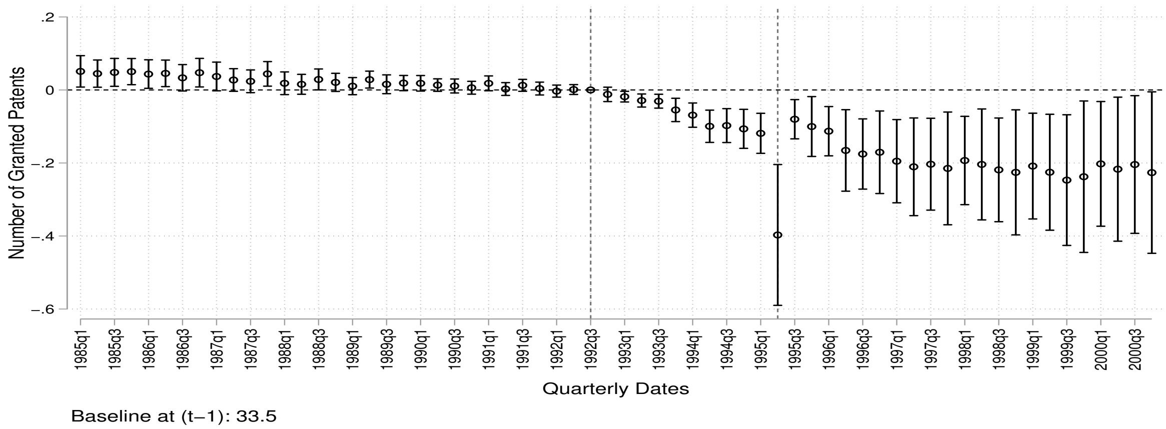
$$\begin{aligned} P_{j,t} = \alpha_j + \sum_{k=1985Q1}^{2000Q4} \gamma_{1,k} \mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \gamma_{2,k} \mathbf{1}_{(t=k)} d_{R_j>25\%} + \\ + \sum_{k=1985Q1}^{2000Q4} \psi_k \mathbf{1}_{(t=k)} \Delta T_j + \sum_{k=1985Q1}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta T_j d_{R_j>25\%} + \varepsilon_{j,t} \end{aligned} \tag{1.32}$$

where $P_{j,t}$ is quarter-$t$ and field-$j$ number of granted applications, $\Delta T_j$ is the field-specific change in patent term, and $d_{R_j>25\%}$ is the renewal dummy variable. I omit the dummy for 1992Q3, which is the pre-treatment quarter. Standard errors are clustered by technical field and 95% confidence bands are plotted. Figure 1.B.23 plots the triple-difference coefficients and shows that indeed fields where renewal rate is higher, the negative magnitude of DiD estimates is larger.

#### 1.B.2.14 Placebo date

In this subsection, I present the results of a placebo test conducted at the technical field-level to further examine the robustness of the findings. Specifically, I apply the same specification (1.2) as in Subsection 1.4.1.1, but I shift the analysis back in time

Figure 1.B.23: Effect of 1 more day of protection on granted patents - Triple difference specification




The plot shows the $\beta_k$ coefficients of specification (1.32) having as dependent variable quarter-$t$ and field-$j$ number of granted patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field. 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

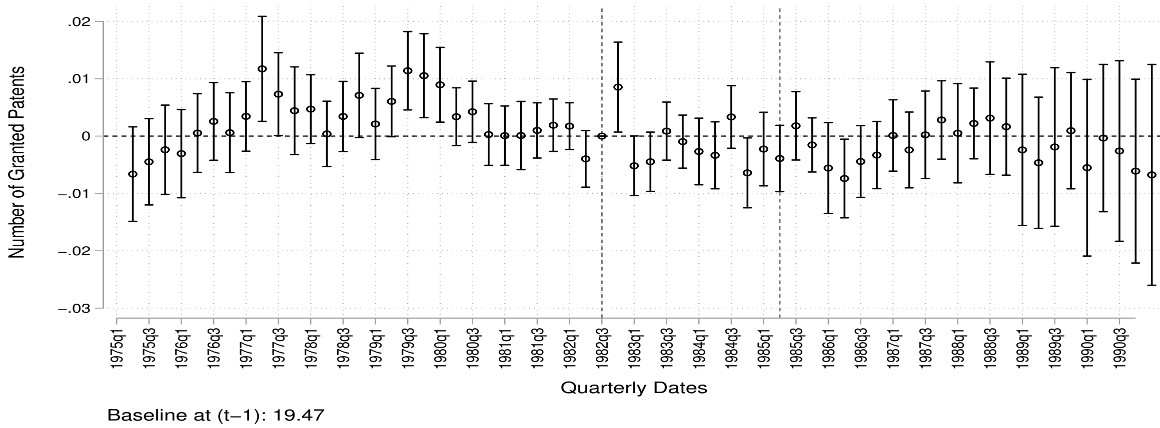
by 10 years, to a period where no treatment effect is expected to be observed. The results, depicted in Figure 1.B.24, confirm the validity of the estimated treatment effects by showing no significant changes in the outcome variables during the placebo period.

#### 1.B.2.15 TRIPs-related changes in tariffs

In this subsection, I demonstrate that the Uruguay Round of agreements-induced changes in tariffs do not affect the DiD estimates of Section 1.4.

Firstly, I illustrate in Figures 1.B.25, 1.B.26, and 1.B.27 that there is no correlation between the TRIPs-induced change in patent term $\Delta T_j$ and tariff intensity across technical fields for the US, Europe, and China, both in terms of pre-TRIPs 1996 level (left panels) and post-TRIPs 1996-2001 change (right panels). Tariff intensity by 4-digit IPC technical fields is computed as a weighted average of the share of HS-2002 product codes with a reported tariff on imports from WTO members above 5%, and

Figure 1.B.24: Marginal effect of 1 more day of protection on granted patents




The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable quarter-$t$ and field-$j$ number of granted patents. The sample covers 1975Q1-1990Q4. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1982Q3, reported at the bottom of the figure. Standard errors are clustered by technical field. 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1982Q3) and the second vertical line refers to the quarter before the policy implementation (1985Q2).

the data source for tariff profiles is the WTO.[58].

This confirms that the paper's quasi-experimental cross-sectional variation in patent term, which is based on the heterogeneous pending period across technical fields, is exogenous with respect to levels of and changes in import protection in the US and other countries.

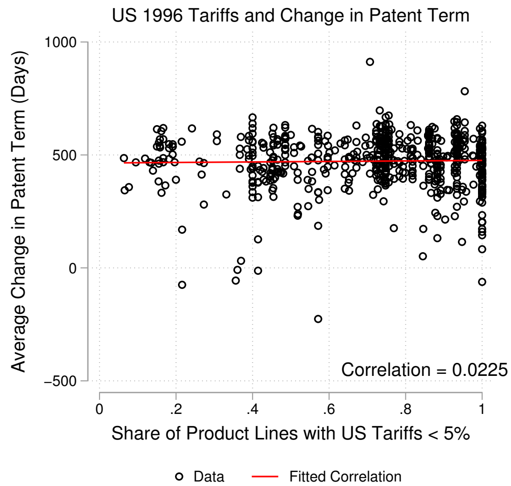
Furthermore, I confirm that tariff changes do not bias DiD estimated by modifying the DiD specification (1.2) as follows

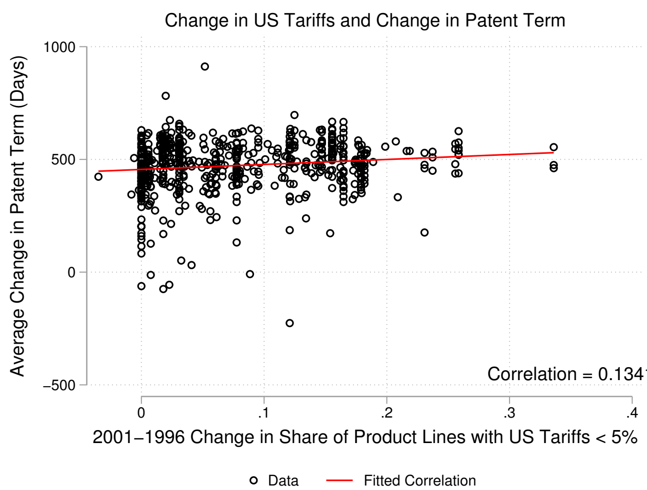
$$\begin{aligned} Y_{j,t} = \alpha_j + \sum_{\substack{k=1985Q1 \\ k\neq 1992Q3}}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_{\substack{k=1985Q1 \\ k\neq 1992Q3}}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta T_j + \\ + \sum_{c=\{\text{US,CH,EU}\}} \sum_{\substack{k=1985Q1 \\ k\neq 1992Q3}}^{2000Q4} \zeta_{k,c} \mathbf{1}_{(t=k)} \Delta Tariff_{c,j} + \varepsilon_{j,t} \end{aligned} \tag{1.33}$$

to control for the quarter-specific effect of the 2001-1996 change in tariff intensity in region $c$ (USA, China, Europe) and field $j$ on innovation outcome $Y_{j,t}$. Figures 1.B.28 and 1.B.29 plot the DiD estimates $\widehat{\beta}_k$ for patents and citations-weighted patents as

[58] Data were downloaded at the link http://tao.wto.org/ExportReport.aspx on 21/01/2022

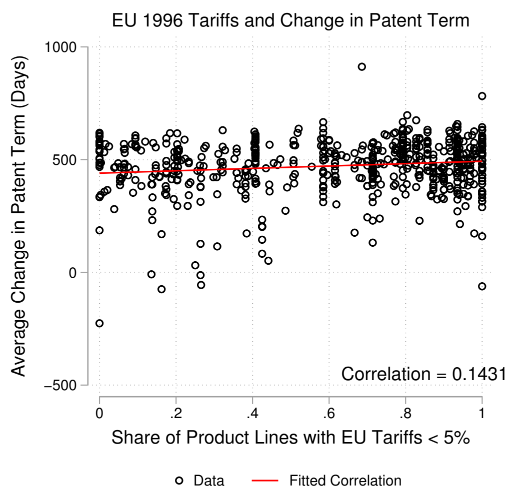
Figure 1.B.25: Correlation between US tariff intensity and change in patent term

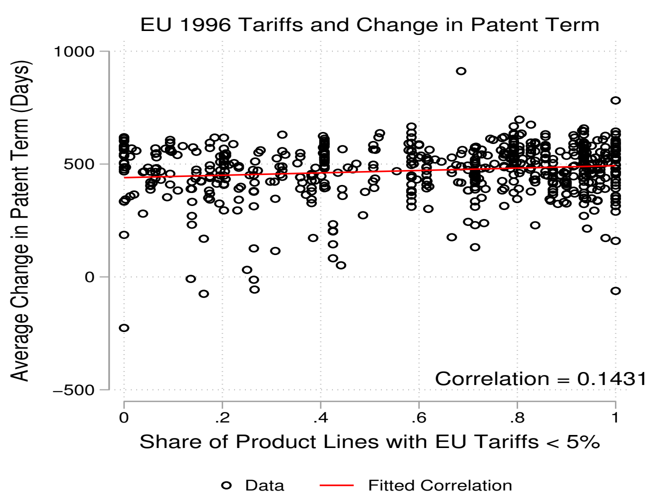



The left panel shows a scatter plot of a proxy of US tariff intensity by technological field on the x-axis, and of the TRIPs-induced change in US patent term by technological field on the y-axis. US tariff intensity by technological field is computed as a weighted average by field of the the share of HS-2002 product codes that had a US tariff on imports from WTO members above 5% in 1996. The data source for tariff profiles is the WTO website at the link http://tao.wto.org/ExportReport.aspx. Weights are the Algorithmic Probability Links by Goldschlag, Lybbert and Zolas (2019). The right panel shows a scatter plot of the change in the tariff intensity proxy over 1996-2001 on the x-axis, and of the TRIPs-induced change in US patent term by technological field on the y-axis.

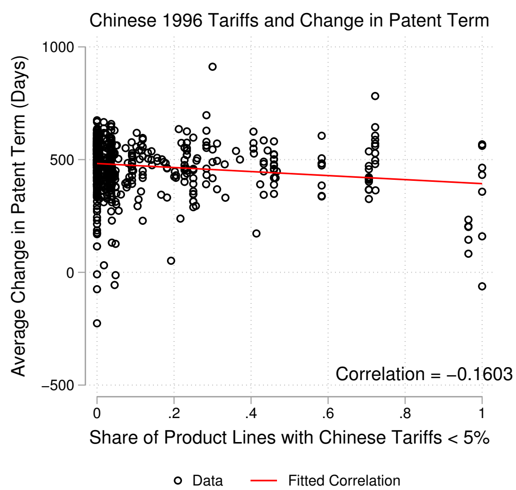
Figure 1.B.26: Correlation between EU tariff intensity and change in patent term

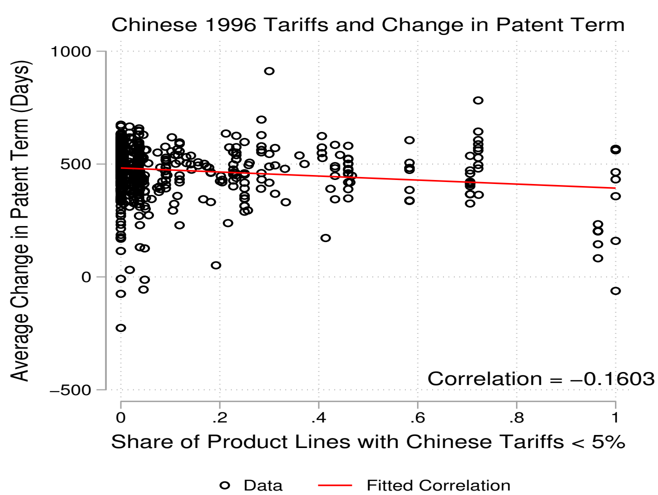



The left panel shows a scatter plot of a proxy of European tariff intensity by technological field on the x-axis, and of the TRIPs-induced change in US patent term by technological field on the y-axis. European tariff intensity by technological field is computed as a weighted average by field of the the share of HS-2002 product codes that had a EU tariff on imports from WTO members above 5% in 1996. The data source for tariff profiles is the WTO website at the link http://tao.wto.org/ExportReport.aspx. Weights are the Algorithmic Probability Links by Goldschlag, Lybbert and Zolas (2019). The right panel shows a scatter plot of the change in the tariff intensity proxy over 1996-2001 on the x-axis, and of the TRIPs-induced change in US patent term by technological field on the y-axis.

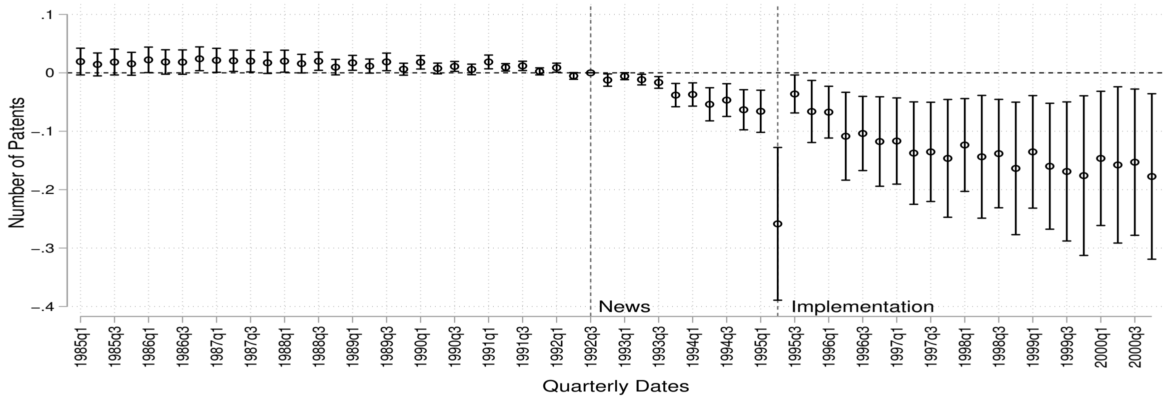
Figure 1.B.27: Correlation between Chinese tariff intensity and change in patent term




The left panel shows a scatter plot of a proxy of Chinese tariff intensity by technological field on the x-axis, and of the TRIPs-induced change in US patent term by technological field on the y-axis. European tariff intensity by technological field is computed as a weighted average by field of the the share of HS-2002 product codes that had a Chinese tariff on imports from WTO members above 5% in 1996. The data source for tariff profiles is the WTO website at the link `http://tao.wto.org/ExportReport.aspx`. Weights are the Algorithmic Probability Links by Goldschlag, Lybbert and Zolas (2019). The right panel shows a scatter plot of the change in the tariff intensity proxy over 1996-2001 on the x-axis, and of the TRIPs-induced change in US patent term by technological field on the y-axis.

Figure 1.B.28: Marginal effect of 1 more day of protection on granted patents



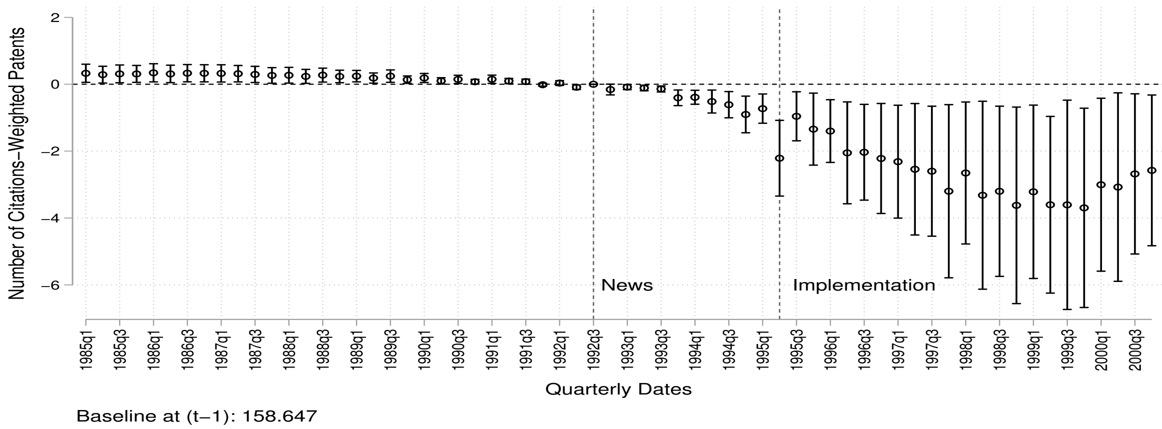

The plot shows the $\beta_k$ coefficients of the specification (1.33) having as dependent variable quarter-$t$ and field-$j$ number of granted patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

outcome variables. Results are fully consistent with those in the main text.

### 1.B.2.16 Dropping technical fields related to the pharmaceutical sector

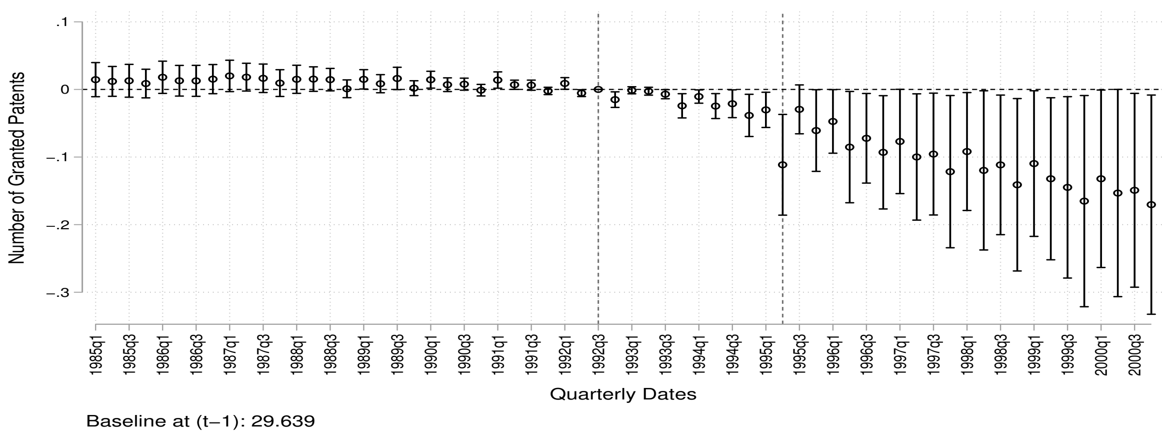
According to Kyle and McGahan (2012), US pharmaceutical firms increased their R&D investments after the implementation of TRIPs, which mandated that developing countries allow patenting of several pharmaceutical products. To address concerns about the potential influence of a specific sector on the findings presented in Section 1.4 of this paper, I have re-estimated the specification 1.2 on a restricted sample. This sample excludes all technical fields, such as A01H, A61K, A61P, C07D, C02F, C07G, C07H, C07J, C07K, C12M, C12N, C12P, C12Q, C12S, and G01N, that may be related to the pharmaceutical and biotech industries. The results, as shown in Figure 1.B.30, indicate that DiD estimates for granted patents as a dependent variable are nearly identical to those presented in Section 1.4.

Figure 1.B.29: Marginal effect of 1 more day of protection on granted patents




The plot shows the $\beta_k$ coefficients of the specification (1.33) having as dependent variable quarter-$t$ and field-$j$ number of citations-weighted patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.30: Effects of patent term on granted patent excluding pharmaceutical




The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable quarter-$t$ and field-$j$ number of granted patents. Pharma-related technical fields A01H, A61K, A61P, C07D, C02F, C07G, C07H, C07J, C07K, C12M, C12N, C12P, C12Q, C12S, and G01N are dropped from the sample. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

### 1.B.2.17 Isolating direct implementation effect – Linear model IV

In this subsection, an extension of the empirical strategy discussed in Subsection 1.4.4 is analyzed in an instrumental variable (IV) setting.

The second stage equation of the IV strategy is identical to specification (1.7). However, 2SLS estimation employs as excluded instruments for the $\overline{Y}_{j,k-\mathcal{A}-1:k-1}$ terms the fitted values of the two regressions

$$\overline{P}_{j,t-\mathcal{A}-1:t-1} = \omega_j^P + \sum_k \theta_k^P \mathbf{1}_{(t=k)} + \sum_k \eta_k^P \mathbf{1}_{(t=k)} \Delta T_j + u_{j,t}^P \tag{1.34}$$

and

$$\overline{C}_{j,t-\mathcal{A}-1:t-1} = \omega_j^C + \sum_k \theta_k^C \mathbf{1}_{(t=k)} + \sum_k \eta_k^C \mathbf{1}_{(t=k)} \Delta T_j + u_{j,t}^C \tag{1.35}$$

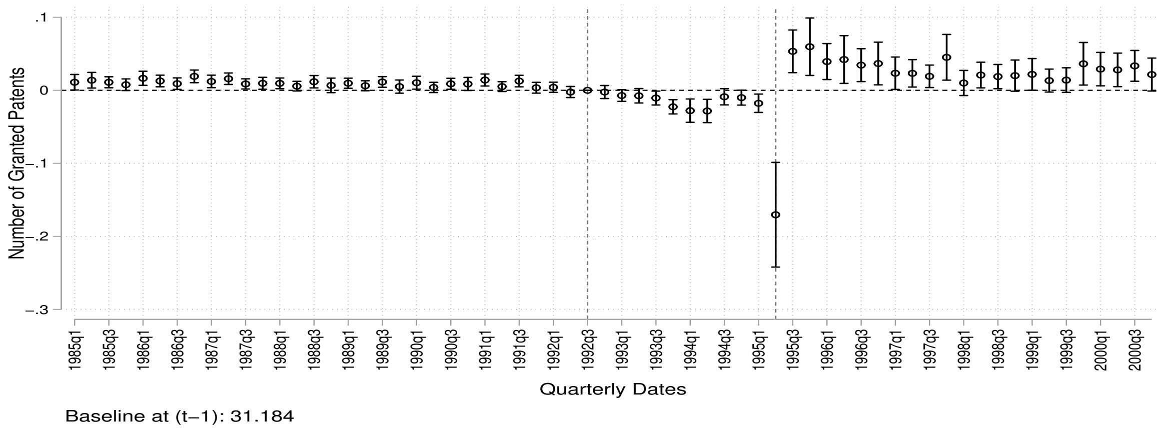
where $\overline{P}_{j,t-\mathcal{A}-1:t-1}$ and $\overline{C}_{j,t-\mathcal{A}-1:t-1}$ are the average of quarterly field-$j$ patents and citations-weighted patents over the $\mathcal{A}$ quarters preceding $t$. The use of fitted values of (1.34) and (1.35) as instruments for $\overline{Y}_{j,k-\mathcal{A}-1:k-1}$ controls for the effect that changes in the evolution of the outcome variable due to the impact of news shock on the innovative environment of field $j$.

Figures 1.B.31 and 1.B.32 display the 2SLS DiD estimates of regression (1.7) for patent count and R&D effort (inventors), respectively. The results demonstrate that they are equivalent to those presented in Subsection 1.4.4 using OLS estimation of (1.7).

### 1.B.2.18 Isolating direct implementation effect – Influence of other fields

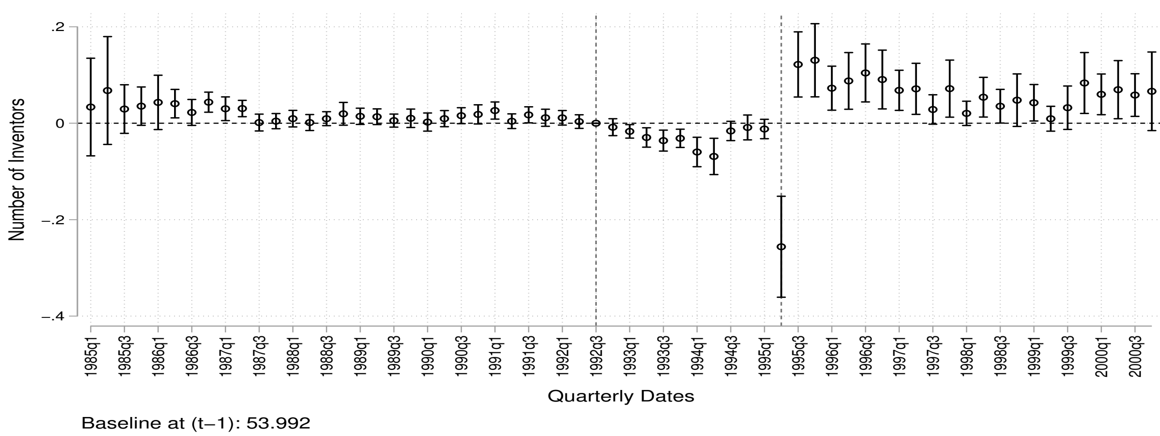
In this subsection, I extend the analysis from Subsection 1.4.4 to consider the potential impact of news-driven innovation patterns across fields, rather than within them. Although prior analyses have concentrated on the within-field aspect of potential dynamic news effects, innovative outcomes within a field may also be influenced by

Figure 1.B.31: Marginal effect of patent term on patents controlling for anticipation




The figure shows the $\widehat{\beta}_k$ coefficients of 2SLS estimation of specification (1.7) with $Y$ being the number of patents in field $j$ and applied for in quarter $t$. Each point-estimates represents the marginal effect of a one-day change in patent term $\Delta T_j = +1$ on the number of patents in absolute deviation from the 1992Q3 baseline level. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.32: Marginal effect of patent term on inventors controlling for anticipation




The figure shows the $\widehat{\beta}_k$ coefficients of 2SLS estimation of specification (1.7) with $Y$ being the number of inventors listed on field $j$ patents applied for in quarter $t$. Each point-estimates represents the marginal effect of a one-day change in patent term $\Delta T_j = +1$ on the number of inventors in absolute deviation from the 1992Q3 baseline level. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

developments in other technologically-related fields.ù Therefore, I enrich specification (1.7) with new controls that represent the quarter-specific impact of innovation in other fields as follows

$$
\begin{aligned}
Y_{j,t} = & \sum_{k \neq' 92Q3} \mathbf{Z}_{pre,j} \mathbf{1}_{(t=k)} \eta_k + \sum_{k \neq' 92Q3} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k \neq' 92Q3} \phi_k \mathbf{1}_{(t=k)} \Delta T_j + \\
& + \sum_{k \neq' 92Q3} \psi_k \mathbf{1}_{(t=k)} \overline{Y}_{j,k-\mathcal{A}-1:k-1} + \psi_0 \overline{Y}_{j,t-\mathcal{A}-1:t-1} \\
& + \sum_{k \neq' 92Q3} \lambda_k \mathbf{1}_{(t=k)} \overline{Y}_{-j,k-\mathcal{A}-1:k-1} + \lambda_0 \overline{Y}_{-j,t-\mathcal{A}-1:t-1} + + \upsilon_{j,t}
\end{aligned} \tag{1.36}
$$

where: $Y_{j,t}$ is the outcome of variable in field $j$ and quarter $t$; $\mathbf{1}_{(t=k)}$ are quarterly fixed effects estimated by $\gamma_k$; $\Delta T_j$ is field-$j$ change in effective patent term whose quarterly marginal effect on $Y_{j,t}$ is estimated by $\beta_k$'s; $\mathbf{Z}_{pre,j}$ is a vector of pre-determined field characteristics, i.e., (i) field size, (ii) average number of forward citations per patent and (iii) average number of inventors per patent, in 1980-1985; $\overline{Y}_{j,k-\mathcal{A}-1:k-1}$ is the average value of the outcome over the previous $\mathcal{A}$ quarters, whose quarter-specific effect on the outcome is captured by $\psi_k$'s; $\overline{Y}_{-j,k-\mathcal{A}-1:k-1}$'s are the new terms defined below, whose quarter-specific effect on the outcome is captured by $\lambda_k$'s; and $\upsilon_{j,t}$ is an error term. $\overline{Y}_{-j,k-\mathcal{A}-1:k-1}$ is defined as

$$
\overline{Y}_{-j,k-\mathcal{A}-1:k-1} = \sum_{h \neq j} \rho_{h,j} \overline{Y}_{h,k-\mathcal{A}-1:k-1} \tag{1.37}
$$

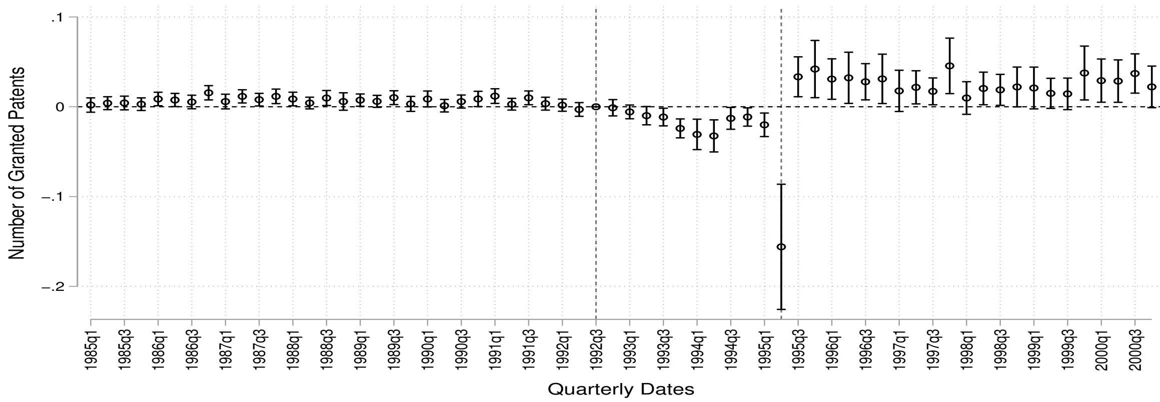
where $\rho_{h,j}$ is Jaffe (1986)'s measure of technological proximity between field $h$ and field $j$ and $\overline{Y}_{h,k-\mathcal{A}-1:k-1}$ is the average value of the outcome over $\mathcal{A}$ quarters before $k$ in field $h$. In turn, Jaffe (1986)'s technological proximity is

$$
\rho_{h,j} = \frac{\mathbf{f}_h \mathbf{f}_j'}{\sqrt{(\mathbf{f}_h \mathbf{f}_h')(\mathbf{f}_j \mathbf{f}_j')}} \tag{1.38}
$$

where $\mathbf{f}_h$ $(\mathbf{f}_j)$ is the vector that collects the field-specific number of backward citations from field $h$ $(j)$ patents. The greater the overlap between the distribution of citations from fields $h$ and $j$, the closer $\rho_{i,j}$ is to unity. Hence, the new $\overline{Y}_{-j,k-\mathcal{A}-1:k-1}$ terms capture the effect of other fields' innovation, weighted by their technological proximity to field $j$.

The regression results indicate that the impact of other fields on field $j$ is statistically significant, but economically insignificant. Figure 1.B.33 shows that the direct effect of $\Delta T_j$ on granted patents is similar to that shown in Figure 1.6a in Subsection 1.4.4. Thus, the richer specification (1.36), which includes cross-field effects, produces comparable results to the original (1.7) specification that focuses only on within-field effects. A formal test on the joint statistical significance of $\lambda_0$ and $\lambda_k$ for $k \in [1995Q3; 2000Q4]$ rejects the null hypothesis that they are jointly null with a p-value of 0.007. However, their magnitude is much smaller compared to the within-field channel. For example, a one-standard deviation increase in $\overline{Y}_{j,k-\mathcal{A}-1:k-1}$ for $k = 1995Q3$ leads to a $+77.4$ increase in field $j$ granted applications filed in quarter $k$, while a one-standard deviation increase in $\overline{Y}_{-j,k-\mathcal{A}-1:k-1}$ for $k = 1995Q3$ leads to a -3.3 change in the same outcome, which is of opposite sign to the within-field effect and 23 times smaller in absolute value. Similar results are obtained when focusing on $k = 2000Q3$, which is five years after policy implementation. A one-standard deviation increase in $\overline{Y}_{j,2000Q3-\mathcal{A}-1:2000Q3-1}$ leads to a $+154.9$ increase in field $j$ granted applications filed in 2000Q3, while a one-standard deviation increase in $\overline{Y}_{-j,2000Q3-\mathcal{A}-1:2000Q3-1}$ leads to a change in the same outcome that is more than 80 times smaller ($+1.9$). These findings suggest that Section 1.5's analysis on the structural transmission channels of news effects should focus on within-field forces.

Figure 1.B.33: Marginal effect of patent term on patent count for anticipation effects within- and across-fields




The figure shows the $\widehat{\beta}_k$ coefficients of OLS estimation of specification (1.36) with $Y_{j,t}$ being the number of patents in field $j$ and applied for in quarter $t$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

#### 1.B.2.19 Isolating direct implementation effect – Poisson model

This subsection describes the extension of the empirical strategy of Subsection 1.4.4 to a Poisson model for count variables. The model is

$$\begin{aligned} Y_{j,t} = \exp\Big\{ \sum_{k \neq' 92Q3} \mathbf{Z}_{pre,j} \mathbf{1}_{(t=k)} \eta_k + \sum_{k \neq' 92Q3} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k \neq' 92Q3} \beta_k \mathbf{1}_{(t=k)} \Delta T_j + \\ + \sum_{k \neq' 92Q3} \psi_k \mathbf{1}_{(t=k)} \ln \overline{Y}_{j,k-\mathcal{A}-1:k-1} + \psi_0 \ln \overline{Y}_{j,t-\mathcal{A}-1:t-1} + v_{j,t} \Big\} \end{aligned} \tag{1.39}$$

where: $Y_{j,t}$ is field-$j$ and quarter-$t$ outcome of interest; $\mathbf{1}_{(t=k)}$ are quarterly dummies whose effects is captured by $\gamma_k$'s; $\Delta T_j$ is field-$j$ change in average patent term, whose quarter-specific effect is estimated by $\beta_k$'s; ; $\mathbf{Z}_{pre,j}$ is a vector of pre-determined field characteristics, i.e., (i) field size, (ii) average number of forward citations per patent and (iii) average number of inventors per patent, in 1980-1985; and $v_{j,t}$ is the error term.

The Poisson model results for raw patent count and R&D effort are displayed in Figure 1.B.34. As with the linear model, the evidence supports the findings of Subsection 1.4.4. After controlling for the impact of the news shock on field-specific innovation patterns, it is evident that the implementation of a patent term extension leads to an increase in R&D and innovation, as demonstrated by the positive post-implementation $\widehat{\beta}_k$ estimates. Additionally, the news of a future patent term extension is still observed to have a negative effect on R&D and innovation prior to implementation, as indicated by the negative pre-implementation, post-news $\widehat{\beta}_k$ estimates.

### 1.B.3 Heterogeneity in elasticity of innovation to patent term

Table 1.B.3 presents heterogeneity in the elasticity estimates of Subsection 1.4.5 by broad technological area, identified by one-digit IPC sections. The first column lists the technical sections, while the second and third columns report the elasticity estimates of patenting and R&D effort to a news shock of +1% patent term change one year before implementation, respectively (standard errors in parentheses). The fourth and fifth columns show the elasticity estimates of patenting and R&D effort to the unanticipated implementation of a +1% change in patent term five years after implementation, respectively (standard errors in parentheses).

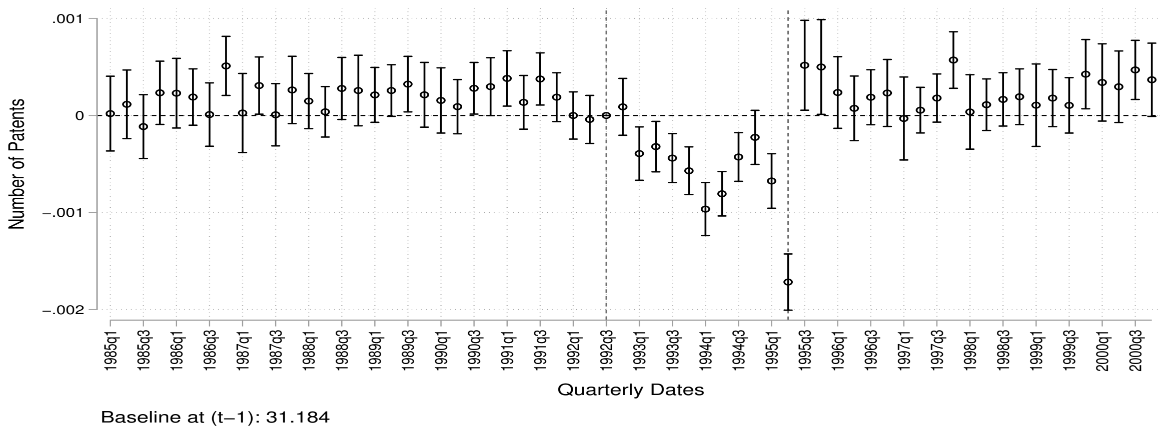
### 1.B.4 Firm-level analyses

#### 1.B.4.1 Number of patents

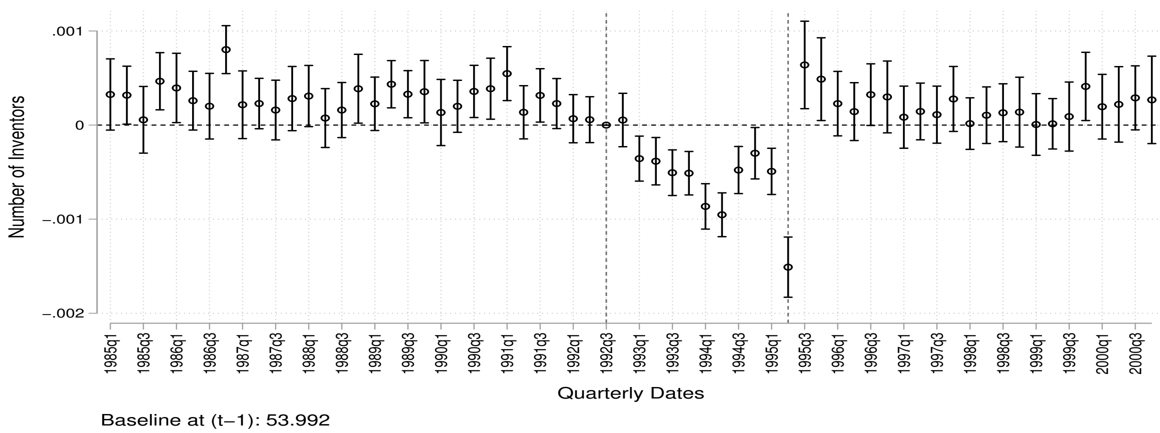
In Figure 1.B.35, I present the results of firm-level DiD specification (1.4) having as dependent variable the number of patents. The figure depicts the $\beta_k$ coefficients capturing the effect of a one-day increase of patent term on yearly firm-level patenting in percent deviation from the 1991 baseline average. The findings are consistent with

Figure 1.B.34: Marginal effect of patent term controlling for anticipation

(a) Number of patents




(b) Number of inventors (R&D effort)



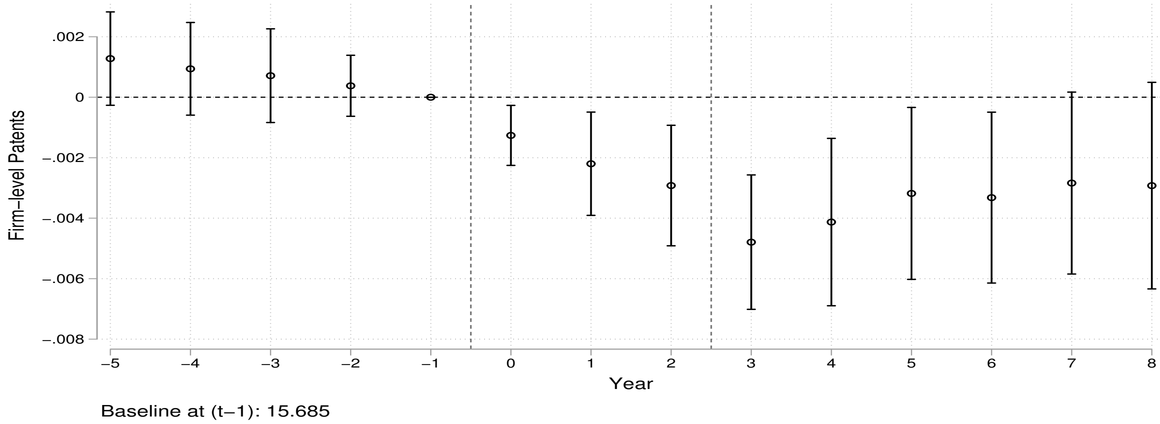

Panel (a) and panel (b) show the $\widehat{\beta}_k$ coefficients of the Poisson model (1.39) with outcome variables being raw count of patents or the number of inventors, respectively. Inventors count avoids multiple counting of the same individual appearing on more than one patent in the same field and quarter. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Table 1.B.3: Elasticity of R&D and innovation to patent term

| Technical Section | $e^{news}_{y-1,T}$ | | $e^{post}_{y+5,T}$ | |
|---|---|---|---|---|
| | Patents | R&D (Inventors) | Patents | R&D (Inventors) |
| All fields | -8.56 | -12.09 | 4.20 | 4.19 |
| | ( 2.31 ) | ( 3.13 ) | ( 1.34 ) | ( 1.54 ) |
| A Human Necessities | -9.32 | -9.90 | 5.97 | 2.15 |
| | ( 7.57 ) | ( 2.57 ) | ( 2.03 ) | ( 1.87 ) |
| B Performing Operations, Transporting | -1.15 | -18.37 | -0.37 | 1.51 |
| | ( 1.84 ) | ( 4.76 ) | ( 1.89 ) | ( 1.83 ) |
| C Chemistry, Metallurgy | -12.00 | -9.14 | 8.07 | 5.26 |
| | ( 4.68 ) | ( 2.37 ) | ( 2.56 ) | ( 2.20 ) |
| D Textiles, Paper | -1.76 | -45.94 | 2.54 | -0.07 |
| | ( 5.16 ) | ( 11.91 ) | ( 4.74 ) | ( 7.95 ) |
| E Fixed Constructions | 0.58 | -18.73 | -3.67 | -5.93 |
| | ( 5.72 ) | ( 4.85 ) | ( 7.20 ) | ( 9.82 ) |
| F Mechanical Engineering, etc | 2.97 | -23.72 | -0.60 | -6.15 |
| | ( 1.95 ) | ( 6.15 ) | ( 1.84 ) | ( 2.82 ) |
| G Physics | -8.62 | -7.65 | 0.00 | 0.93 |
| | ( 5.69 ) | ( 1.98 ) | ( 2.64 ) | ( 2.11 ) |
| H Electricity | -8.83 | -5.96 | 0.14 | 1.82 |
| | ( 4.89 ) | ( 1.54 ) | ( 1.67 ) | ( 1.55 ) |

The table reports the elasticity of R&D and innovation to (i) news of +1% future patent term change implemented in one year and (ii) an unanticipated +1% patent term extension 5 years after implementation. Subsection 1.4.5 describes computation details. Standard errors clustered by technical field in parentheses. Rows refer to 1-digit technical sections of the International Patent Classification (IPC) scheme.

Figure 1.B.35: Effect of one-day longer patent term on firm-level patenting




The plot shows the $\beta_k$ coefficients of regression (1.4) having as dependent variable $P_{i,t}$, i.e., year-$t$ and firm-$i$ number of granted patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1991, reported at the bottom of the figure. Standard errors are clustered by firm and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

the observed behavior of patenting at the technical field level. Prior to implementation, a 30-day future increase of patent term decreases yearly patenting by 2.6% at the firm level on average. This estimate is consistent with the field-level effect. Post-implementation, the impact of the same policy change leads to a decrease of yearly firm-level patenting of 2.1%.

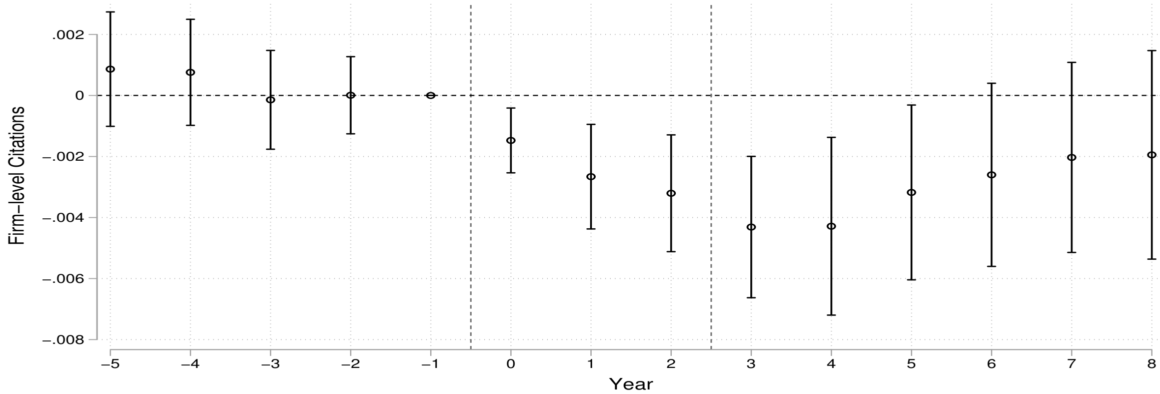
### 1.B.4.2 Citations-weighted patents

Figure 1.B.36 confirms the robustness of firm-level results by using citation-weighted patents as a measure of innovation. The citation-weighted patent count is obtained from the NBER Patent database, and calculated following the method of Hall, Jaffe and Trajtenberg (2001).

### 1.B.4.3 Private economic value of patents

I merge the dataset provided by Kogan et al. (2017) with the NBER patent database using USPTO patent numbers and then aggregate the patent values at the firm-level and by year. The $\beta_k$ coefficients of specification (1.4) are then plotted in Figure

Figure 1.B.36: Effect of one-day longer patent term on firm-level forward citations




Baseline at (t−1): 287.524

The plot shows the $\beta_k$ coefficients of regression (1.4) having as dependent variable year-$t$ and firm-$i$ citations-weighted granted patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1991, reported at the bottom of the figure. Standard errors are clustered by firm and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

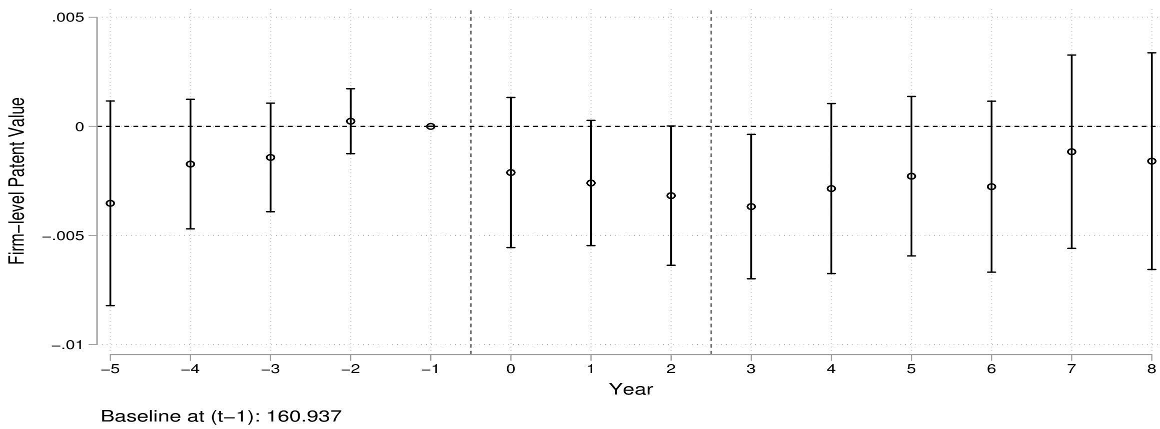
1.B.37, where the dependent variable is firm-level yearly patent value. The estimated effects are in line with the evidence obtained for patents, providing further support for the robustness of the findings.

#### 1.B.4.4 Placebo analyses: Costs, Capital Expenditures, and Sales

In this subsection, I present a placebo analysis of the effect of TRIPs patent term change on firm-level variables costs (`cogs` in COMPUSTAT), capital expenditures (`capx` in COMPUSTAT), and sales (`sale` in COMPUSTAT). In principle, the patent term change should have no (immediate) effect on previous variable, while affecting R&D and patenting activity, as shown before.

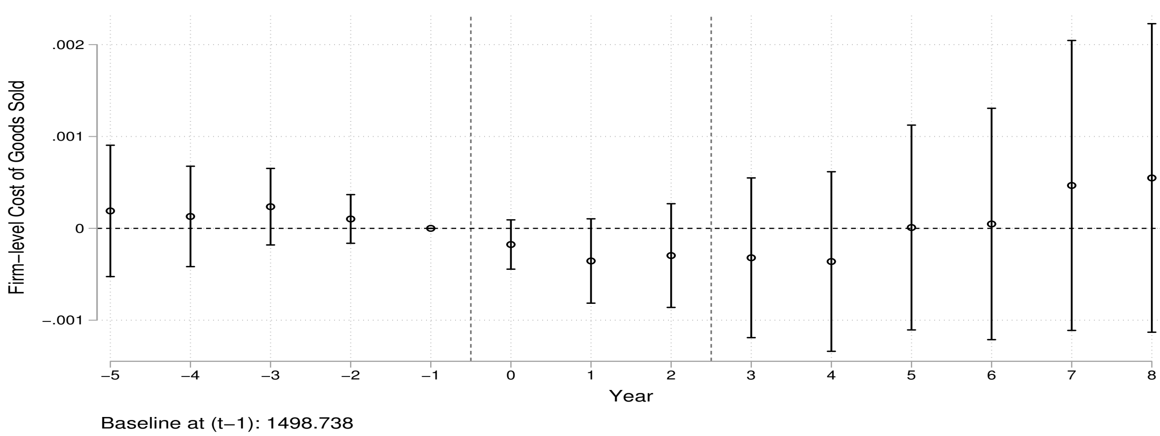
Figures 1.B.38, 1.B.39, and 1.B.40 show the DiD estimates for costs, capital expenditures, and sales, respectively, confirming that the patent term change does not immediately affect those firm-level variables.

Figure 1.B.37: Effect of one-day longer patent term on firm-level patent value



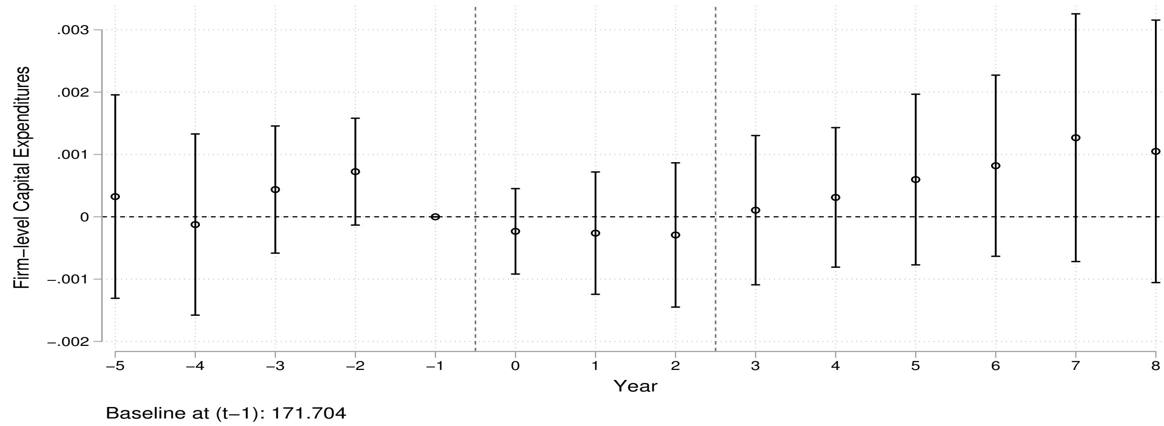

The plot shows the $\beta_k$ coefficients of regression (1.4) having as dependent variable year-$t$ and firm-$i$ total patent value. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1991, reported at the bottom of the figure. Standard errors are clustered by firm and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

Figure 1.B.38: Effect of one-day longer patent term on firm-level variable costs



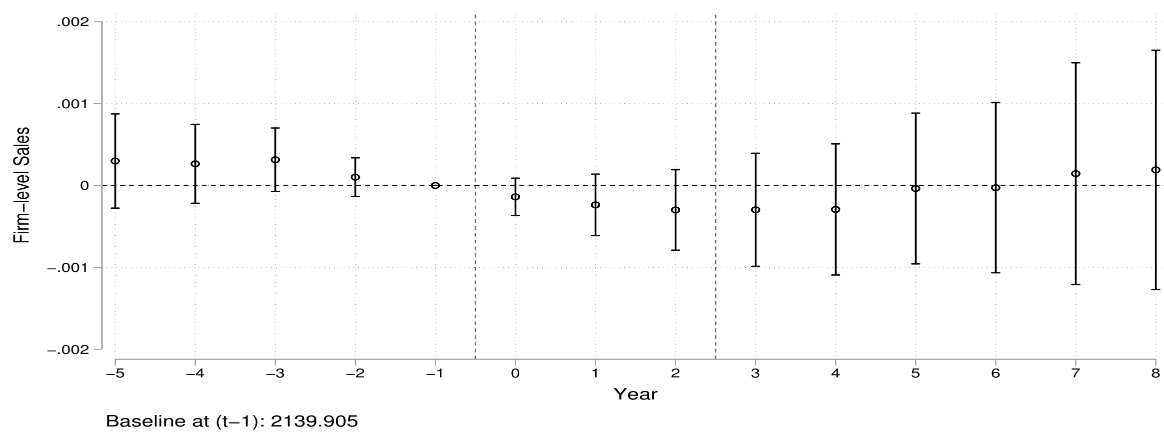

The plot shows the $\beta_k$ coefficients of regression (1.4) having as dependent variable year-$t$ and firm-$i$ variable costs (`cogs` in COMPUSTAT). Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1991, reported at the bottom of the figure. Standard errors are clustered by firm and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

Figure 1.B.39: Effect of one-day longer patent term on firm-level capital expenditures




The plot shows the $\beta_k$ coefficients of regression (1.4) having as dependent variable year-$t$ and firm-$i$ capital expenditures (`capx` in COMPUSTAT). Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1991, reported at the bottom of the figure. Standard errors are clustered by firm and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

Figure 1.B.40: Effect of one-day longer patent term on firm-level sales




The plot shows the $\beta_k$ coefficients of regression (1.4) having as dependent variable year-$t$ and firm-$i$ sales (`sale` in COMPUSTAT). Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviation* of the outcome variable from its baseline value in 1991, reported at the bottom of the figure. Standard errors are clustered by firm and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

#### 1.B.4.5 Within-firm analysis of innovation outcomes

To study the effect of the patent term change on the reallocation of innovation across technical fields within firms, I construct a panel dataset with the cross-sectional unit being a firm $\times$ technical field. To reduce computational burden, I aggregate the sample over five periods: (0) 1983-1985, (1) 1986-1988, (2) 1989-1991, (3) 1992-1995, and (4) 1996-1999. Periods 0 and 1 are used to check for pre-trends, period 2 is the pre-treatment period, period 3 is the period between the policy news and the policy implementation of 1995, and period 4 is the post-implementation period. I begin with the NBER Patent Database, matching patents to COMPUSTAT identifiers of applicant firms, and then aggregate granted patents, citations-weighted patents, and patent value by firm, technical field, and time period, using the 4-digit IPC class reported in the NBER Patent Database for each patent. The specification of the Poisson DiD regression is

$$Y_{i,j,p} = \exp\left\{\alpha_i + \chi_j + \omega_{i,j} + \sum_{age \in A} \delta_{age} + \sum_{p=1}^{4} \gamma_k \mathbf{1}_{(p=k)} + \sum_{p=1}^{4} \beta_k \mathbf{1}_{(p=k)}(\Delta T_j/100) + \varepsilon_{i,j,p}\right\} \tag{1.40}$$

where $i$ indexes firms, $j$ technical fields, and $p$ the time period. $\alpha_i$ are firm fixed effects, $\chi_j$ are technical field fixed effects, $\omega_{i,j}$ are firm $\times$ field fixed effects, $\delta_{age}$ are fixed effects by median age of the firm during the period, $\mathbf{1}_{(p=k)}$ is an indicator taking value 1 when period $p = k$, $\Delta T_j$ is technical field $j$'s change in patent term, and $\varepsilon_{i,j,p}$ is an idiosyncratic error term. Through firm$\times$field fixed effects the model controls for any pre-existing firm- and field-specific differences, such as firm's technological expertise. The dependent variables $Y_{i,j,p}$ used in the regression include the number of patents granted to firm $i$ in field $j$ with application filed in period $p$ ($P_{i,j,p}$), the citations-weighted patents granted to firm $i$ in field $j$ with application filed in period $p$ ($C_{i,j,p}$), and the economic value of patents granted to firm $i$ in field $j$ with application filed in period $p$ ($V_{i,j,p}$).

Table 1.B.4: **Within-firm cross-technical fields effect of a patent term change**

| | (1) Patents | (2) Citations | (3) Value |
|---|---|---|---|
| $\mathbf{1}_{(p=0)} \times (\Delta T_j/100)$ | 0.01171 | -0.00114 | 0.05283 |
| | (0.01302) | (0.03500) | (0.05426) |
| $\mathbf{1}_{(p=1)} \times (\Delta T_j/100)$ | 0.00969 | -0.00862 | 0.06708 |
| | (0.00831) | (0.03115) | (0.04152) |
| $\mathbf{1}_{(p=3)} \times (\Delta T_j/100)$ | -0.02329*** | -0.08448*** | -0.17461*** |
| | (0.00898) | (0.02012) | (0.03437) |
| $\mathbf{1}_{(p=4)} \times (\Delta T_j/100)$ | 0.00264 | -0.11445*** | -0.14546*** |
| | (0.01115) | (0.02979) | (0.03992) |
| Observations | 238,939 | 229,450 | 208,767 |

The Table reports the pseudo maximum likelihood estimates of specification (1.40). See subsection 1.B.4.5 for details. Statistical significance levels: $^*(p < 0.05),^{**}(p < 0.01),^{***}(p < 0.001)$

Pre-trends coefficients in Table 1.B.4 confirm that the change in patent term is unrelated to differential trends in innovation across technical fields. The post-news and post-implementation DiD coefficients capture the baseline effect of the policy and provide evidence that, at news of $\Delta T_j > 0$, firms tend to reallocate innovation effort towards technical fields expected to lose protection after implementation and that this negative effect continues post-implementation. This is consistent with the patterns documented in Section 1.5.

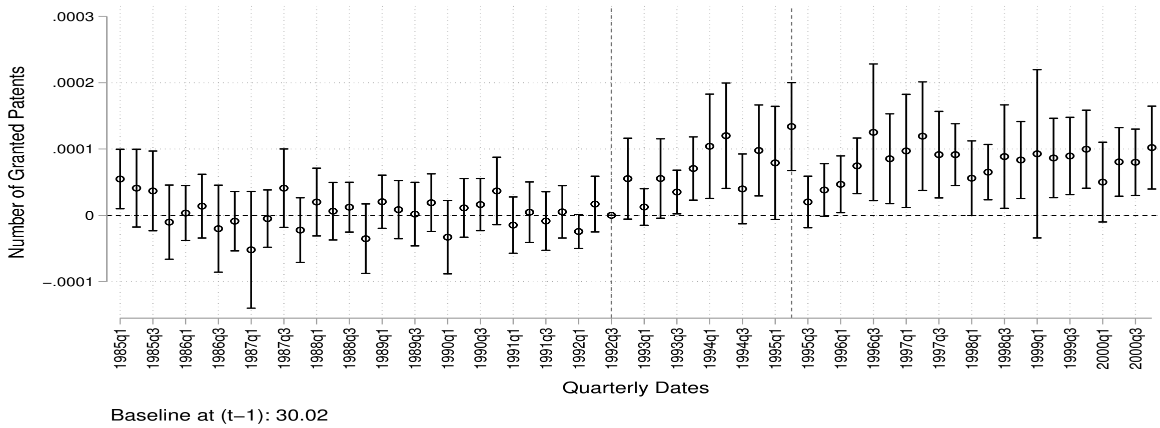
## 1.B.5 Evidence on transmission channels

### 1.B.5.1 Evidence on concentration as interactor

To test whether the patent term change has stronger effects on innovation in more competitve fields, I run the following triple difference specification

$$\begin{aligned} Y_{j,t} = \alpha_j &+ \sum_{k=1985Q1}^{2000Q4} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985Q1}^{2000Q4} \eta_k \mathbf{1}_{(t=k)} HHI_j \\ &+ \sum_{k=1985Q1}^{2000Q4} \theta_k \mathbf{1}_{(t=k)} \Delta T_j + \sum_{k=1985Q1}^{2000Q4} \beta_k \mathbf{1}_{(t=k)} \Delta T_j HHI_j + \varepsilon_{j,t} \end{aligned} \tag{1.41}$$

Figure 1.B.41: Triple difference analysis of patents with HHI as interactor

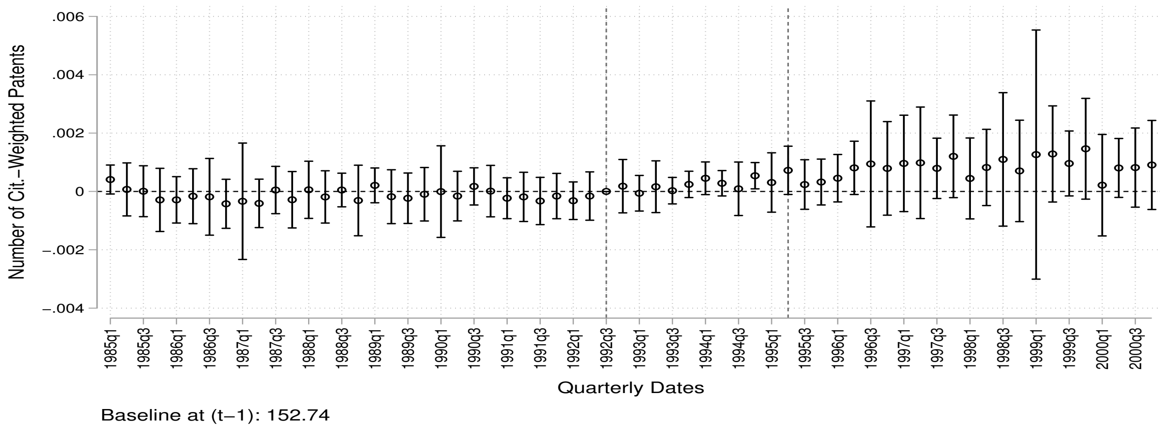



The plot shows the $\beta_k$ coefficients of regression (1.41) having as dependent variable quarter-$t$ and field-$j$ number of granted patents. Point estimates refer to the marginal effect of a one-day anticipated change in patent term $\times$ a unit-increase in HHI on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

where $Y_{j,t}$ is either the number of patents or citations-weighted patents, $\alpha_j$ are technical field fixed effects, $\mathbf{1}_{(t=k)}$ are quarterly dummy variables, $HHI_j$ is the Herfindahl-Hirschman Index of concentration based on the share of patents granted to different applicants in a given field before the policy news, and $\Delta T_j$ is the policy-induced, field-specific change in effective patent term.To confirm whether innovators respond more strongly to patent protection time in less concentrated technical fields, it is important to check if the $\beta_k$ coefficients in the previous regression are positive. This is because the HHI is smaller in less concentrated technical fields.

Figure 1.B.41 plots the estimated $\widehat{\beta}_k$ coefficients of the previous specification for the number of granted patents as the outcome. The results show that the $\widehat{\beta}_k$ coefficients are positive, indicating that the treatment has a stronger effect on innovation in more competitive fields. Similar evidence is observed for citations-weighted patents, as shown in Figure 1.B.42.

Figure 1.B.42: Triple difference analysis of citations with HHI as interactor



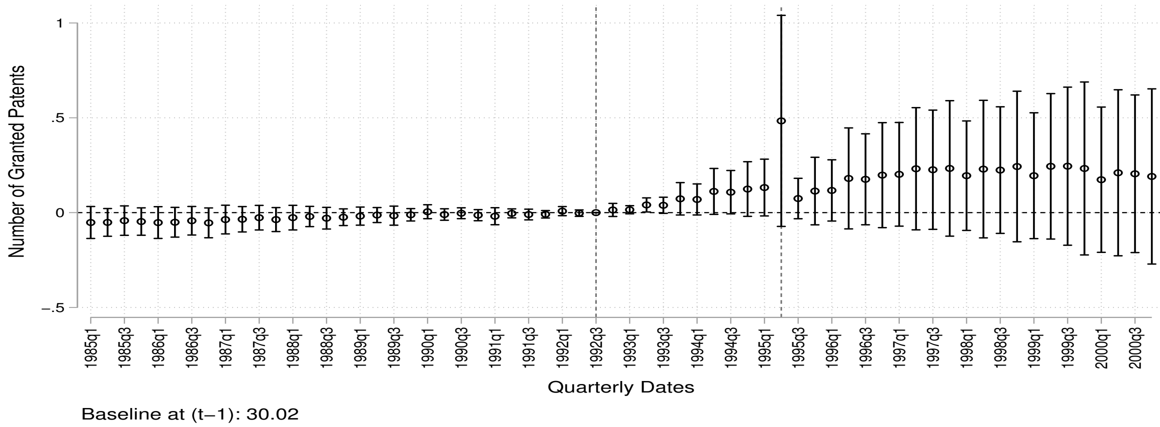

The plot shows the $\beta_k$ coefficients of regression (1.41) having as dependent variable quarter-$t$ and field-$j$ 5-years citations-weighted patents. See Appendix 1.B.5.1 for all the details about the empirical strategy and the specification. Point estimates refer to the marginal effect of a one-day anticipated change in patent term $\times$ a unit-increase in HHI on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

#### 1.B.5.2 Evidence on entry rates as interactor

To test whether the change in patent term affects innovation more strongly in more competitive fields, I conducted a further analysis using the triple difference specification (1.41). In this analysis, I replaced $HHI_j$ with the share $s_j^E$ of patents granted to applicants who have never patented in a given field, calculated before the policy news. Higher values of $s_j^E$ indicate a higher entry intensity in a technical field. Negative $\widehat{\beta}_k$ coefficients would suggest that innovators are more responsive to patent term in more competitive fields.

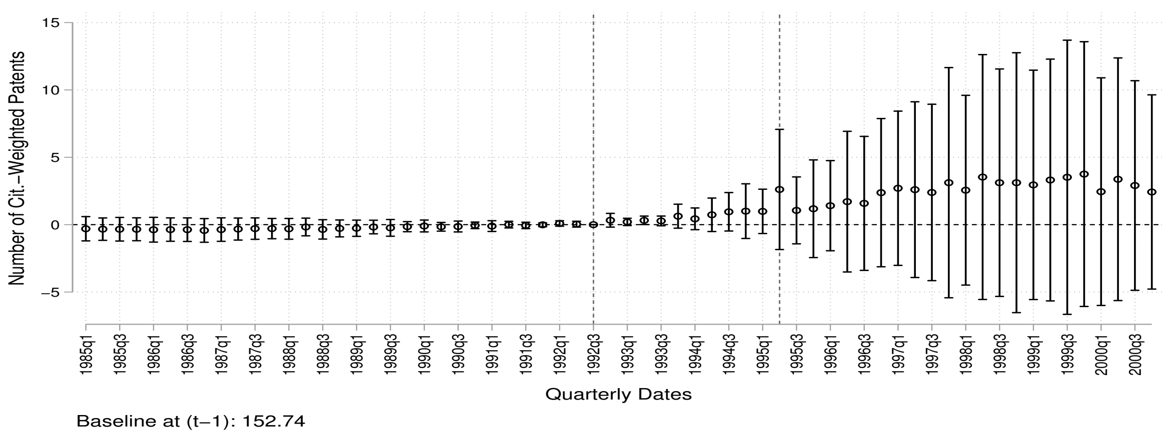
The estimated $\widehat{\beta}_k$ coefficients are plotted in Figure 1.B.43, and the results indicate that the effects are not stronger in more competitive fields. Similar results were obtained when citations-weighted patents were used as the outcome variable (see Figure 1.B.44).

Figure 1.B.43: Triple difference analysis of patents with entry rate as interactor



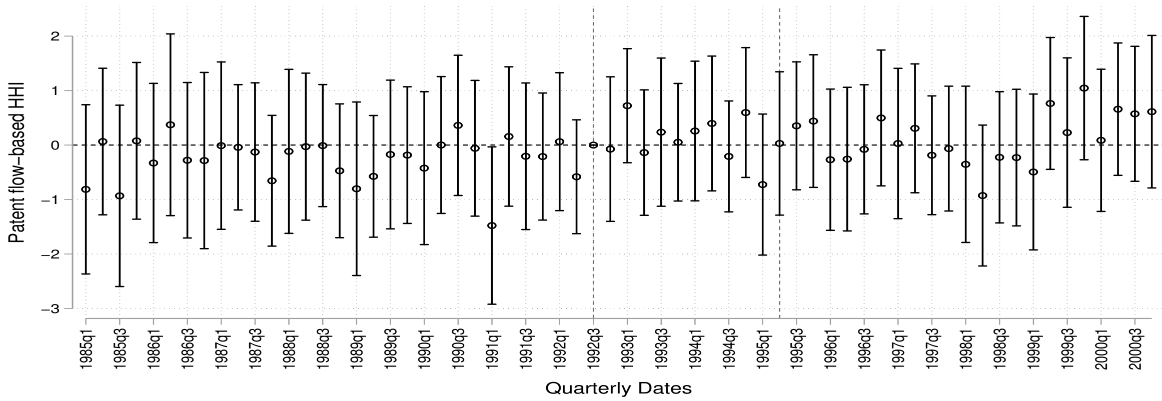

The plot shows the $\beta_k$ coefficients of regression (1.41) having as dependent variable quarter-$t$ and field-$j$ number of granted patents and $s_j^E$ as interactor of $\Delta T_j$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term $\times$ a $+100\%$ increase in entry rate on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.44: Triple difference analysis of citations with entry rate as interactor




The plot shows the $\beta_k$ coefficients of regression (1.41) having as dependent variable quarter-$t$ and field-$j$ 5-years citations-weighted patents and $s_j^E$ as interactor of $\Delta T_j$. See Appendix 1.B.5.2 for all the details about the empirical strategy and the specification. Point estimates refer to the marginal effect of a one-day anticipated change in patent term $\times$ a $+100\%$ increase in entry rate on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.45: Effect of 1 more day of protection on concentration




The plot shows the $\beta_k$ coefficients of regression (1.2) having as dependent variable quarter-$t$ and field-$j$ Herfindahl–Hirschman index. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

#### 1.B.5.3 Evidence on concentration as outcome

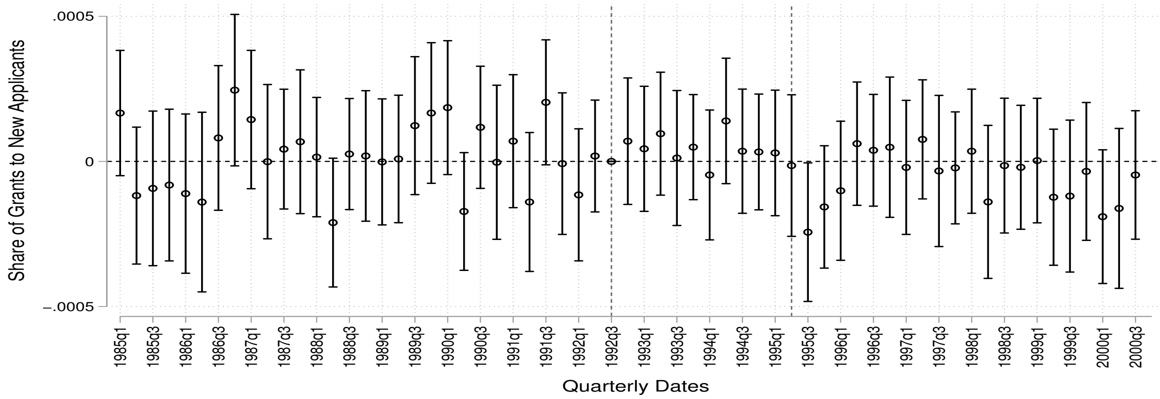
To examine whether a change in patent term affects competition, I estimate specification (1.2) with $HHI_{j,t}$, the Herfindahl–Hirschman Index based on the flow of patents filed by different applicants in quarter $t$ and classified in field $j$, as the dependent variable. If a longer patent term results in reduced competition, DiD post-implementation estimates of $\widehat{\beta}_k$ in specification (1.2) should be positive. However, Figure 1.B.45 illustrates that concentration is not affected by the change in patent term.

#### 1.B.5.4 Evidence on entry as outcome

To examine the impact of patent term on competition, an alternative test is conducted using entry rate as the outcome. To construct the entry intensity measure, new applicants in quarter-$t$ and field-$j$ are identified as entrants.[59] The entry intensity is defined as the *share* of granted patents filed by new applicants. The regression in specification

[59]New applicants at the quarterly level are determined using STAN harmonized applicant's identifiers from the EPO Worldwide Bibliographic Database available in PATSTAT and selecting, among the applicants observed in a given field-quarter, those that are never observed before.

Figure 1.B.46: Effect of 1 more day of protection on entry rates



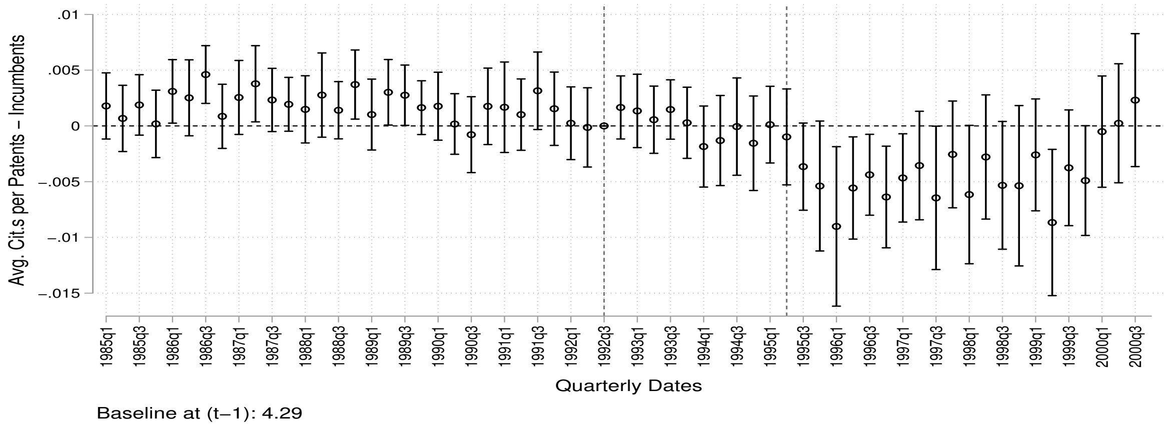

The plot shows the $\beta_k$ coefficients of regression (1.2) having as dependent variable quarter-$t$ and field-$j$ *share* of granted patents filed by new applicants (entrants). Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field. 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

(1.2) is run using entry as the outcome variable. The results in Figure 1.B.46 suggest that entry does not respond to the policy change, providing an alternative perspective on the impact of patent term on competition.

#### 1.B.5.5 Evidence on the average quality of incumbents' patents

An extension of patent term may lead to incumbents using their patent rights to exclude other innovators from the market. However, this should be reflected in a decline in the average quality of patents granted to incumbents, both in absolute terms and relative to those granted to new entrants. To examine this, I estimate specification (1.2) using the average quality of patents granted to incumbent firms as the dependent variable. Figure 1.B.47 shows that, in absolute terms, the average quality of incumbents' patents decreases slightly in response to an increase in patent term. However, this effect is quantitatively weak and not statistically significant. To assess the relative quality of incumbents' patents, I estimate the same regression using the average quality of patents granted to incumbent firms **divided** by the average

Figure 1.B.47: Effect of 1-day longer patent term on the average citations per patent received by incumbents



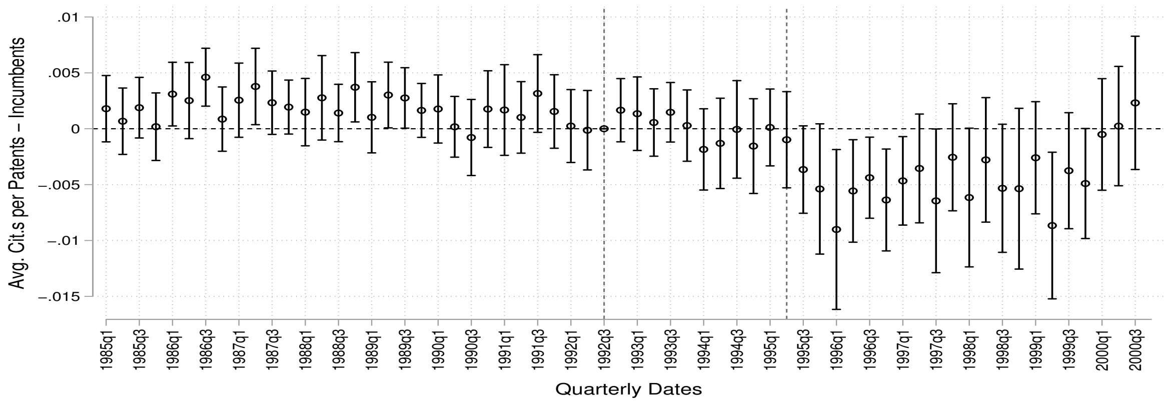

The plot shows the $\beta_k$ coefficients of regression (1.2) having as dependent variable the average number of forward citations received by quarter-$t$ and field-$j$ patents granted to incumbent innovators. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

quality of patents granted to new applicants. Figure 1.B.48 shows that, in relative terms, the average quality of incumbents' patents does not respond to the policy change. Overall, these results suggest that there is no evidence of anti-competitive behavior by incumbent innovators in response to longer patent terms.

#### 1.B.5.6 Within-field backward citation intensity as interactor

In this subsection, I replicate the triple-difference specification (1.8) having as dependent variables the number of inventors, as a proxy of R&D effort at the field level, and the number of citations-weighted patents, as a quality-adjusted patent-based innovation measure. Figure 1.B.49 and 1.B.50 show the triple-difference $\widehat{\theta}_k$ and the difference-in-difference $\widehat{\beta}_k$ estimates for inventors and citations, respectively. Results are widely consistent with those shown for granted patents in Subsection 1.5.1.

Figure 1.B.48: Effect of 1-day longer patent term on the average citations per patent received by incumbents relative to entrants



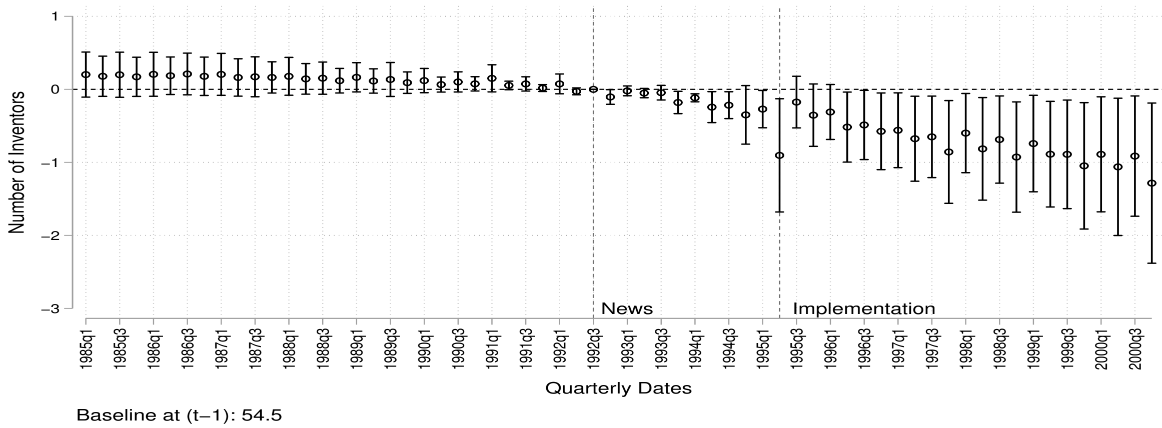

The plot shows the $\beta_k$ coefficients of regression (1.2) having as dependent variable the average number of forward citations received by quarter-$t$ and field-$j$ patents granted to incumbent innovators divided by the average number of forward citations received by quarter-$t$ and field-$j$ patents granted to new entrants. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

### 1.B.5.7 Within-field backward citations as an outcome

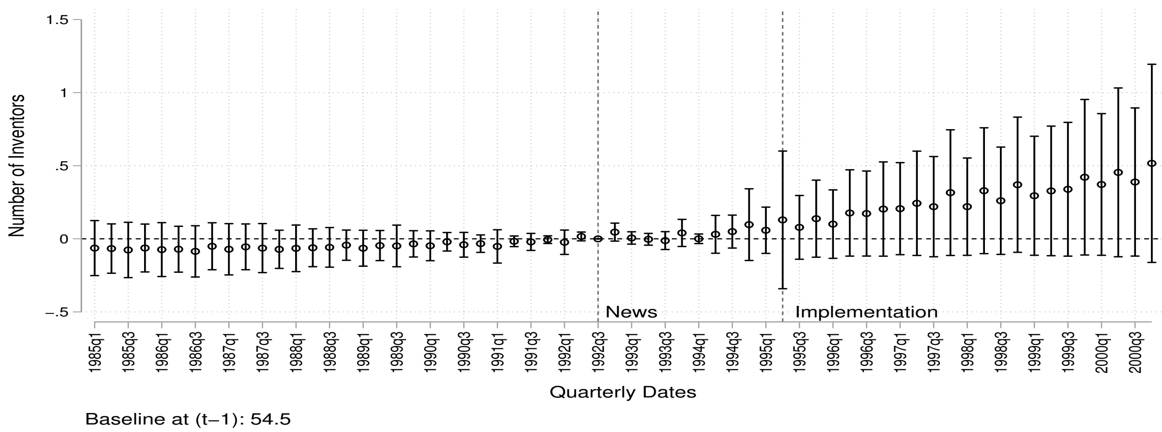
This subsection presents evidence that within-field technological dependence measures decline in fields with a positive patent term change after implementation. Two measures of within-field dependence are considered: the average number of backward citations made by applicants to previous patents from the same field of the citing patent, denoted by $\overline{B}_{jj,t}$, and the share of patents filed in quarter-$t$ and classified in technical field-$j$ that report at least one applicant-made backward citation to previous patents also classified in field $j$, denoted by $S_{jj,t}$. Using either of these variables as outcomes of interest, the benchmark DiD regression (1.2) is run. Figures 1.B.51 and 1.B.52 report the DiD estimates for $\overline{B}_{jj,t}$ and $S_{jj,t}$, respectively. Both figures provide consistent evidence with the narrative proposed in Section 1.5 of the paper, showing that time-varying measures of technological dependence decline in fields that experience an increase in average patent term. This suggests that patents that would have

Figure 1.B.49: Marginal effect on inventors and within-field dependence

(a) Triple difference coefficients $\widehat{\theta}_k$



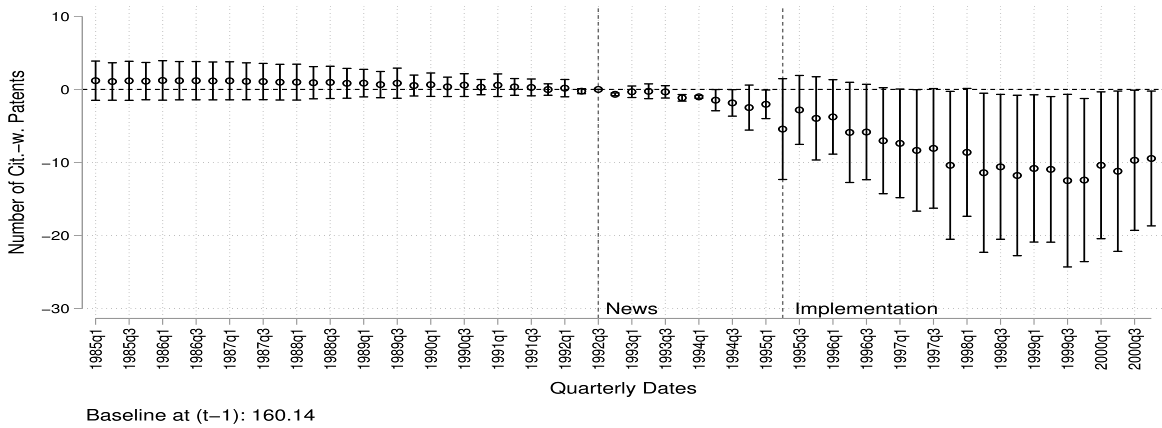

(b) Difference-in-Difference coefficients $\widehat{\beta}_k$



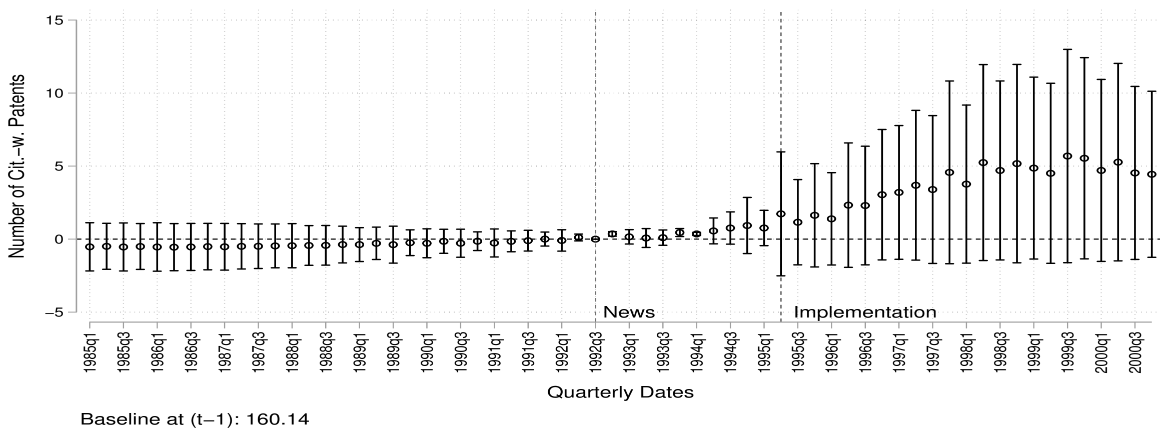

Panel (a) and panel (b) show the $\widehat{\theta}_k$ and $\widehat{\beta}_k$ coefficient OLS estimates of specification (1.8) with outcome of interest being the count of unique inventors listed on field-$j$ patents whose application is filed in quarter $t$. The former coefficients represent the change in the marginal effect of a one-day increase in patent term $\Delta T_j = +1$ on the number of inventors corresponding to an increment of one in the average number of within-field backward citations per patent $\Delta \overline{B}_{jj} = +1$. The DiD estimates $\widehat{\beta}_k$ represent the marginal effect of a one-day increase in patent term $\Delta T_j = +1$ on the number of inventors conditional on the average number of within-field backward citations per patent being zero $\overline{B}_{jj} = 0$. Standard errors are two-way clustered by technical field and treatment period (pre-news: 1985Q1-1992Q2; news: 199Q4-1995Q2; post-implementation: 1995Q3-2000Q4) and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.50: Marginal effect on citations and within-field dependence

(a) Triple difference coefficients $\widehat{\theta}_k$

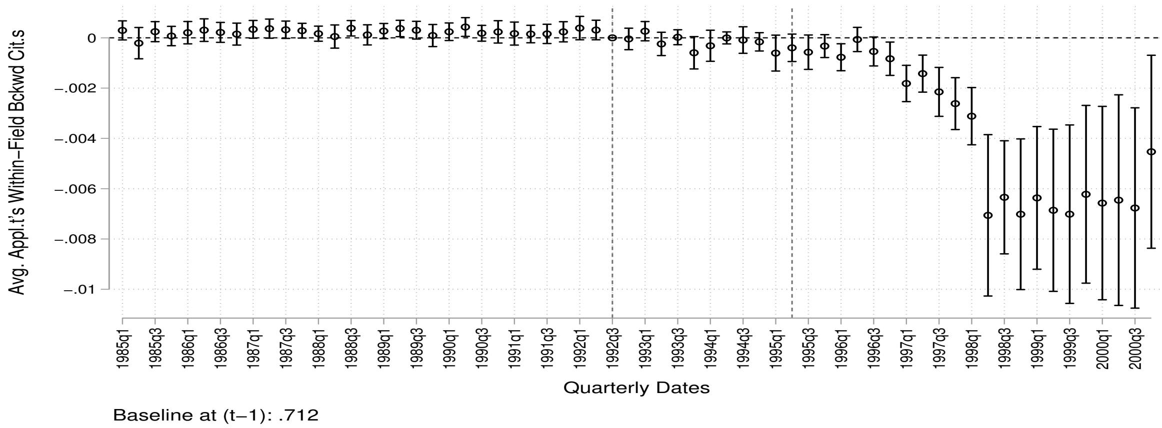



(b) Difference-in-Difference coefficients $\widehat{\beta}_k$




Panel (a) and panel (b) show the $\widehat{\theta}_k$ and $\widehat{\beta}_k$ coefficient OLS estimates of specification (1.8) with outcome of interest being the citations-weighted count of field- and quarter-specific patents. The former coefficients represent the change in the marginal effect of a one-day increase in patent term $\Delta T_j = +1$ on the number of 5-year forward citations-weighted patents corresponding to an increment of one in the average number of within-field backward citations per patent $\Delta\overline{B}_{jj} = +1$. The DiD estimates $\widehat{\beta}_k$ represent the marginal effect of a one-day increase in patent term $\Delta T_j = +1$ on the number of 5-year forward citations-weighted patents conditional on the average number of within-field backward citations per patent being zero $\overline{B}_{jj} = 0$.Standard errors are two-way clustered by technical field and treatment period (pre-news: 1985Q1-1992Q2; news: 199Q4-1995Q2; post-implementation: 1995Q3-2000Q4) and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.B.51: Effect of patent term on average within-field applicants' citations



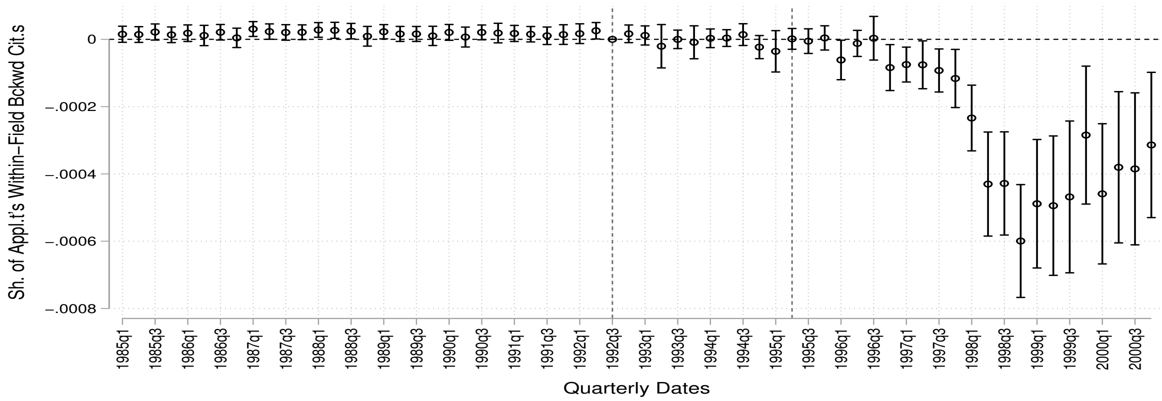

The plot shows the $\widehat{\beta}_k$ coefficients of specification (1.2) having as dependent variable the average number of applicant-made backward citations per patent classified in field $j$ and filed in quarter $t$. The reported coefficients represent the marginal effect of a one-day anticipated increase in patent term on the *level* of the outcome variable relative to its pre-news average baseline, reported at the bottom of the figure. Clustered 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

built on previous inventions from the same field disproportionally contribute to the post-implementation innovation decline, potentially due to the unavailability of the material to build on caused by the effects of the news shock.

#### 1.B.5.8 Direct within-field links among pre- and post-implementation innovations

In this subsection, I demonstrate a direct link between innovations created in the pre- and post-implementation periods within the same technology field. To establish this connection, I count the number of applicant's backward citations from patents filed between 1995Q3 and 1999Q4 to patents filed between 1992Q4 and 1995Q2, which are classified in the same technological field as the citing patent. I then relate the change in protection by technical field to three outcomes: (i) the average number of such citations per patent filed in the post-implementation period; (ii) the proportion of patents filed in the post-implementation phase that have at least one applicant-made, within-field, backward citation to a patent filed in the pre-implementation

Figure 1.B.52: Effect of patent term on within-field technological dependence




The plot shows the $\widehat{\beta}_k$ coefficients of specification (1.2) having as dependent variable the share of patents classified in field $j$ and filed in quarter $t$ that have at least one applicant-made backward citation to patents also classified in field $j$. The reported coefficients represent the marginal effect of a one-day anticipated increase in patent term on the *level* of the outcome variable relative to its pre-news average baseline, reported at the bottom of the figure. Clustered 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

period; (iii) the proportion of applicant-made citations from patents filed in the post-implementation phase to a patent filed in the pre-implementation period and classified in the same field. To establish a control group, I use the same technical fields ten years before, i.e. between 1985Q3 and 1989Q4 and 1982Q4 and 1985Q2. The difference-in-difference regression equation is presented in equation (1.42),

$$Y_{j,p} = d_p + \delta\Delta T_j + \beta d_p \Delta T_j + \varepsilon_{j,p} \tag{1.42}$$

where $d_p$ is a dummy variable indicating whether the outcome refers to the 1992Q4-1999Q4 period or the 1982Q4-1989Q4 period. $\Delta T_j$ is the policy-driven change in patent term for technical field $j$, and $\beta$ is the difference-in-difference coefficient of interest. Table 1.B.5 reports the estimated coefficients of the regression for the share of patents, the number of backward citations, and the number of patents satisfying the criteria outlined above. Standard errors are clustered by technological field. The negative difference-in-difference estimates suggest that fields with an expected patent term extension, i.e. those with a decrease in innovation during the pre-implementation

Table 1.B.5: **Direct evidence on within-field intertemporal technology link**

| | (1) Avg. Bckwd. Cit. | (2) Avg. Bckwd. Cit. | (3) Pat. Share | (4) Pat. Share | (5) Cit. Share | (6) Cit. Share |
|---|---|---|---|---|---|---|
| $d_{post}$ | 1.42091*** | 1.45996*** | 0.24389*** | 0.25251*** | 0.05182*** | 0.05404*** |
| | (0.00413) | (0.17865) | (0.02435) | (0.03523) | (0.00612) | (0.00862) |
| $\Delta T_j$ | -0.00007 | | -0.00005 | | -0.00000 | |
| | (0.00018) | | (0.00003) | | (0.00001) | |
| $d_{post} \times T_j$ | -0.19126*** | -0.19912*** | -0.02676*** | -0.02867*** | -0.00250** | -0.00298* |
| | (0.00078) | (0.03430) | (0.00473) | (0.00681) | (0.00123) | (0.00170) |
| Constant | 0.00044 | 0.00011 | 0.00026 | 0.00024 | 0.00003 | 0.00005 |
| | (0.00091) | (0.01210) | (0.00018) | (0.00257) | (0.00003) | (0.00097) |
| Tech. field F.E. | | Y | | Y | | Y |
| Obs. | 1206 | 1206 | 1206 | 1206 | 1206 | 1206 |

The Table reports the OLS estimates of specification (1.42). See 1.B.5.8 for all the details. Standard errors are clustered by technical field. Statistical significance levels: $^{*}(p < 0.10)$,$^{**}(p < 0.05)$,$^{***}(p < 0.01)$

phase, exhibit a lower backward citation intensity to patents produced in the same technological field during the pre-implementation period. This indicates the existence of a technology disclosure externality.

#### 1.B.5.9 Does the technology link act within-firm or between-firms?

In this subsection, I detail the steps of the decomposition of the technology disclosure externality effect in within vs between firms. Firstly, I define the theoretical objects of the decomposition.

$$\Delta \hat{P}^{A}_{j,p} \equiv \mathbf{E}[P_{j,p}|\Delta T = \Delta T_j] - \mathbf{E}[P_{j,p}|\Delta T = 0] \tag{1.43}$$

is the difference between expected patents–filed in period $p$ and field $j$ (conditional on the policy-induced change in protection time $\Delta T_j$) and expected patents absent any treatment. This represents the aggregate impact of the policy change on innovation in period $p$. $\Delta \hat{P}^{A}_{j,p}$ can be decomposed in two parts. The first is policy-driven innovation by incumbent firms ($\Delta \hat{P}^{A,I}_{j,p}$), and the second is the contribution of entrant firms

$(\Delta\hat{P}^{A,E}_{j,p})$, i.e.

$$\Delta\hat{P}^{A}_{j,p} = \Delta\hat{P}^{A,I}_{j,p} + \Delta\hat{P}^{A,E}_{j,p} \tag{1.44}$$

Further, I assume that $\Delta\hat{P}^{A,I}_{j,p}$ can be broken down into: 1) the direct impact of the patent term change on innovation $\Delta\hat{P}^{A,I,\Delta T}_{j,p}$, 2) the between-firms component generated by the aggregate policy-driven innovation from the previous period $\Delta\hat{P}^{A}_{j,p-1}$, and 3) the within-firm component driven by within-firm technological linkages between past and present innovation $\Delta\hat{P}^{A,I,W}_{j,p}$. So,

$$\Delta\hat{P}^{A,I}_{j,p} = \Delta\hat{P}^{A,I,\Delta T}_{j,p} + \Delta\hat{P}^{A,I,B}_{j,p} + \Delta\hat{P}^{A,I,W}_{j,p} \tag{1.45}$$

I assume that for entrant firms the within-firm component of their contribution to the aggregate effect is 0. This leads to the following decomposition

$$\Delta\hat{P}^{A,E}_{j,p} = \Delta\hat{P}^{A,E,\Delta T}_{j,p} + \Delta\hat{P}^{A,E,B}_{j,p} \tag{1.46}$$

Finally, define the relative contribution of incumbents to the total effect of the policy in period $p$ as

$$s^{I}_{p} = \frac{\Delta\hat{P}^{A,I}_{j,p}}{\Delta\hat{P}^{A}_{j,p}} \tag{1.47}$$

The second step concerns the estimation of these objects. The main dataset for this is the firm $\times$ technical field panel dataset described in Appendix 1.B.4.5. The cross-sectional unit is a firm in a given technical field (firm $\times$ technical field) and there are 5 time-periods: (0) 1983-1985, (1) 1986-1988, (2) 1989-1991, (3) 1992-1995, (4) 1996-1999. To estimate $\Delta\hat{P}^{A}_{j,3}$, i.e. the aggregate policy impact in period (3), I consolidate the data by technical field and period and estimate by OLS the specification

$$P_{j,p} = \sum_{k=0}^{3} \gamma_k \mathbf{1}_{(p=k)} + \sum_{k=0}^{3} \beta_k \mathbf{1}_{(p=k)} \Delta T_j + \sum_{k=0}^{3} \mathbf{1}_{(p=k)} \mathbf{X}_{pre,j} \theta'_k + \varepsilon_{j,p} \tag{1.48}$$

All the variables have the same meaning as in specification (1.2) of Section 1.4, and $P_{j,p}$ is the number of granted patents filed in period $p$ and classified in technical field $j$. Moreover, $\mathbf{X}_{pre,j}$ includes field-specific controls comprising field size (number of patents), average citations, and average patent value in years 1980-1982, and replaces field fixed effects, as the empirical strategy will requires the inclusion of lagged patents among regressors in specification (1.48). The post-implementation period is excluded from estimation and the sample aggregates patents from *all* firms regardless of when they enter. $\Delta\hat{P}^{A}_{j,3}$ is estimated according to definition (1.43) using the linear specification (1.48).

Then, I estimate $\hat{P}^{A,I}_{j,3}$, i.e. the contribution of incumbent firms to the total effect in period (3), by aggregating the data by technical field as above, but *excluding* patents by firms that start innovating in period (3) itself, i.e. the entrants in period (3). I run specification (1.48) on such sample, and I estimate $\Delta\hat{P}^{A,I}_{j,3}$ using expression (1.43), given the new parameter estimates. Finally, the contribution of entrants to the aggregate policy effect in period (3) can be determined residually using (1.44).

Under the assumption that the between-firms policy-driven spillover is at work in the post-implementation period only, for period (3) expressions (1.45) and (1.46) can be rewritten as $\Delta\hat{P}^{A,I}_{j,3} = \Delta\hat{P}^{A,I,\Delta T}_{j,3}$ and $\Delta\hat{P}^{A,E}_{j,3} = \Delta\hat{P}^{A,E,\Delta T}_{j,3}$. Once we have the estimated $\Delta\hat{P}^{A,I}_{j,3}$ and $\Delta\hat{P}^{A,E}_{j,3}$ from the previous steps, these coincide with the direct policy effect.

To estimate $\Delta\hat{P}^{A}_{j,4}$, i.e. the aggregate policy impact in period (4), I consolidate the data by technical field and period and I estimate by OLS the specification

$$P_{j,p} = \sum_{k=0}^{3} \gamma_k \mathbf{1}_{(p=k)} + \sum_{k=0}^{3} \beta_k \mathbf{1}_{(p=k)} \Delta T_j + \sum_{k=0}^{3} \mathbf{1}_{(p=k)} \mathbf{X}_{pre,j} \theta'_k + \sum_{k=0}^{3} \psi_k \mathbf{1}_{(p=k)} P_{j,p-1} + \varepsilon_{j,p} \tag{1.49}$$

All the variables have the same meaning as in specification (1.48) of Section 1.4, but the new regression also includes period (4). Again, *all* firms are included, regardless of when they start innovating. $\Delta\hat{P}^{A}_{j,4}$ is estimated according to definition (1.43) using the linear specification (1.49).

Then, I estimate $\hat{P}^{A,I}_{j,4}$, i.e., the contribution of incumbent firms to the total effect in period (4), by aggregating the data by technical field as above, but *excluding* patents by firms that start innovating in period (4) itself, i.e., the entrants in period (4). I run specification (1.49) on such sample, and I estimate $\Delta\hat{P}^{A,I}_{j,4}$ using expression (1.43), given the new parameter estimates. Finally, the contribution of entrants to the aggregate policy effect in period (4) can be determined residually using (1.44). The relative contribution of incumbents to the total post-implementation policy effect is $\hat{s}^{I}_{4} = \frac{\Delta\hat{P}^{A,I}_{j,4}}{\Delta\hat{P}^{A}_{j,4}}$.

To isolate the direct effect of the policy on innovation in the post-implementation period for the case of incumbents, I follow the strategy described in subsection 1.4.4 and I augment the baseline difference-in-difference specification by lagged patenting in the field in the previous period, interacted with period-specific dummy variables. The latter terms are instrumented by policy-induced variation in patenting and citations estimated using (1.49). These terms capture the impact of the lagged spillover on innovation. So, the specification is

$$P_{j,p} = \alpha_j + \sum_{k=0}^{4} \gamma_k \mathbf{1}_{(p=k)} + \sum_{k=0}^{4} \beta_k \mathbf{1}_{(p=k)} \Delta T_j + \sum_{k=0}^{4} \eta_k \mathbf{1}_{(p=k)} P_{j,p-1} + \chi P_{j,p-1} + \varepsilon_{j,p} \tag{1.50}$$

The regression is run excluding from the sample patents from new entrants. Using definition (1.43) once more, I isolate the direct effect of the policy on incumbents, net of the intertemporal effects generated by the within and between components, i.e., $\Delta\hat{P}^{A,I,\Delta T}_{j,4}$. I assume that the direct effect of the policy affects entrants proportionally to their contribution to the total post-implementation effect. Therefore, I compute $\Delta\hat{P}^{A,E,\Delta T}_{j,4} = \frac{1-\hat{s}^{I}_{4}}{\hat{s}^{I}_{4}} \Delta\hat{P}^{A,I,\Delta T}_{j,4}$.

Equation (1.46) can be used to infer $\Delta\hat{P}_{j,4}^{A,E,B} = \Delta\hat{P}_{j,4}^{A,E} - \Delta\hat{P}_{j,4}^{A,E,\Delta T}$, i.e., the contribution of the between-firms technological spillover to aggregate entrants' post-implementation innovation. Assuming that such effect is proportional to the aggregate policy-induced innovation from the previous period, I can retrieve such coefficient of proportionality as $\hat{\kappa}^B = \frac{\Delta\hat{P}_{j,4}^{A,E,B}}{\Delta\hat{P}_{j,3}^{A}}$, and use it to infer $\Delta\hat{P}_{j,4}^{A,I,B}$, i.e., the between-firms component of the aggregate policy impact for incumbent firms in period (4), as $\Delta\hat{P}_{j,4}^{A,I,B} = \hat{\kappa}^B \frac{\hat{s}_4^I}{1-\hat{s}_4^I}\Delta\hat{P}_{j,3}^{A}$. The final step is to residually infer from expression (1.45) the contribution of the within-firm internality in period (4) as $\Delta\hat{P}_{j,4}^{A,I,W} = \Delta\hat{P}_{j,4}^{A,I} - \Delta\hat{P}_{j,4}^{A,I,\Delta T} - \Delta\hat{P}_{j,4}^{A,I,B}$, where all the terms on the right hand side are known from previous calculations.

Therefore, the aggregate policy impact in period (4) can be decomposed as

$$\Delta\hat{P}_{j,4}^{A} = \underbrace{\Delta\hat{P}_{j,4}^{A,I,\Delta T} + \Delta\hat{P}_{j,4}^{A,E,\Delta T}}_{\text{Direct policy effect}} + \underbrace{\Delta\hat{P}_{j,4}^{A,I,B} + \Delta\hat{P}_{j,4}^{A,E,B}}_{\text{Between-firms spillover}} + \underbrace{\Delta\hat{P}_{j,4}^{A,I,W}}_{\text{Within-firm internality}}$$

Estimation of the differrent terms of previous expression implies that the direct policy effect is equivalent to -15% of the total change $\Delta\hat{P}_{j,4}^{A}$. The negative effect is entirely driven by the between-firm component, which is equivalent to 115% of the (negative) left hand side term. The within component is quantitatively negligible, suggesting that the observed dynamic effect of the news shock on post-implementation innovation acts as an externality.

#### 1.B.5.10 Technology disclosure externality: Firm-level analysis of post - implementation R&D investment

In this subsection, I present further evidence of the proposed technology disclosure externality by demonstrating that firms with greater exposure to technological fields that experience a decrease in R&D due to news of a future patent term extension have lower firm-level R&D expenditures in the post-implementation period.

To conduct the empirical exercise, I assume that the proposed externality does not affect the response of R&D to the news shock, which is solely driven by the firm-level treatment $\Delta T_i$. Furthermore, I investigate whether policy-driven changes to R&D investment in the news period impact post-implementation firm-level R&D. If such changes, conditioned on the direct effect of $\Delta T_i$, exist, I consider it as empirical evidence in support of the proposed transmission channel.

The analysis proceeds in steps. I aggregate the firm-level sample over the 4 time windows: 1986-1988, 1989-1991, 1992-1995, and 1995-1999, that correspond to control (-2), pre-news (-1), news (0), and post-implementation (1) periods, respectively. Under the first assumption, it is possible to use the specification adapt the Poisson DiD specification (1.4) to estimate the effect of $\Delta T_i$ on firm-level R&D in the pre-implementation periods (-2),(-1), and (0) only, disregarding the lagged spillover effect. The post-implementation period ($p = 1$), when the spillover should be in action, is excluded from estimation. The fitted values of the treatment-induced R&D for firm $i$ in period $p$ are computed and denoted by $\hat{R}_{i,p}$. To develop a firm-specific measure of spillover, I compute Jaffe (1986)'s measure of technological proximity, denoted by $\rho_{i,j}$, for every pair of firms $(i, j)$. The formula for the technological proximity measure is $\rho_{i,j} = \frac{f_i f_j'}{\sqrt{(f_i f_i')(f_j f_j')}}$, where $f_i$ is a vector that reports the number of patents obtained by firm $i$ in a given class over the period 1971-1991. The externality measure for firm $i$ in period $p$ is then computed as $E_{i,p} = \sum_{j \neq i} \rho_{i,j} R\&D_{j,p}$, which can also be calculated using the fitted R&D measure $\hat{R}_{i,p}$ as $\hat{E}_{i,p}$. Finally, the regression of interest estimates the period-specific effect of the *lagged* spillover measure and of the firm-specific treatment on firm-level R&D spending. The specification is

$$\begin{aligned} \ln(1 + R\&D_{i,p}) =& \alpha_i + \sum_{k=0}^{1} \gamma_k \mathbf{1}_{(p=k)} + \sum_{k=0}^{1} \beta_k \mathbf{1}_{(p=k)} \Delta T_i + \theta' \mathbf{X}_{i,p} + \\ & \sum_{k=0}^{1} \delta_k \mathbf{1}_{(p=k)} \ln(E_{i,p-1}) + \zeta \ln(E_{i,p-1}) + \varepsilon_{i,t} \end{aligned} \tag{1.51}$$

and it includes firm fixed effects $\alpha_i$, period fixed effects, a vector of controls $\mathbf{X}_{i,t}$

comprising firm-age fixed effects, 3-digit SIC industry $\times$ period fixed effects, and a 3-digit-SIC-specific quadratic trend in age. The idiosyncratic error term is $\varepsilon_{i,t}$. The results are presented in Table 1.B.6, which includes the OLS estimates in the first column and the IV specification estimates in the second column. The implementation of the IV strategy motivates the use of a log-one-plus transformation of the outcome variable in a linear model rather than the use of a Poisson model. The IV uses the externality measure based on the fitted values of the effect of $\Delta T_i$ on firm-level R&D an en external instrument for $ln(1+E_{i,p-1})$ and its interactions. Columns 3 to 5 report the first-stage regression estimates of $\ln(1+E_{i,p-1})$ alone and its interaction with the 1989-1991 and 1992-1995 dummies. In all first-stage regressions, the F-statistic of the excluded instruments exceeds 30.

The firm-specific treatment remains negative in the pre-implementation phase but becomes positive (though not statistically significant) in the post-implementation period. These findings support the proposed narrative.

#### 1.B.5.11 Elasticity of current innovation to past innovation

To analyze the magnitude of the technology disclosure externality discussed in Section 1.5, this subsection derives a synthetic elasticity measure. The sample is aggregated into four periods: (1) 1985Q1-1988Q4 (control period); (2) 1989Q1-1992Q3 (pre-news period); (3) 1992Q4-1995Q2 (post-news, pre-implementation period); and (4) 1995Q3-2000Q4 (post-implementation period). This aggregation is done to precisely capture innovation during the news and post-implementation periods. The first step is to estimate the DiD specification (1.2) with the number of patents $P_{j,p}$ and citations-weighted patents $C_{j,p}$ as dependent variables for each field $j$ and applied for in period $p = 1, 2, 3, 4$. The estimated coefficients of the original DiD (1.2) for granted patents as the outcome variable are reported in Column (1) of Table 1.B.7. In the second step, the specification (1.7) is replicated on the aggregate sample, and the specification

Table 1.B.6: **Firm-level evidence on R&D externality**

| | (1) OLS | (2) IV | (3) FS1 | (4) FS2 | (5) FS3 |
|---|---|---|---|---|---|
| $d_{92-95} \times \Delta T_i$ | -0.00019 | -0.00011 | -0.00003** | 0.00002** | -0.00005* |
| | (0.00028) | (0.00028) | (0.00001) | (0.00001) | (0.00003) |
| $d_{96-99} \times \Delta T_i$ | 0.00034 | 0.00050 | 0.00000 | 0.00004 | 0.00002 |
| | (0.00040) | (0.00042) | (0.00001) | (0.00002) | (0.00005) |
| $d_{92-95} \times$ R&D Ext.$_{(t-1)}$ | 0.00859 | 0.00150 | | | |
| | (0.01595) | (0.01658) | | | |
| $d_{96-99} \times$ R&D Ext.$_{(t-1)}$ | 0.03549 | 0.02921 | | | |
| | (0.02336) | (0.02365) | | | |
| R&D Ext.$_{(t-1)}$. | -0.01505 | 0.31755 | | | |
| | (0.19155) | (0.28432) | | | |
| $d_{92-95} \times \widehat{\text{R\&D Ext}}.{}_{(t-1)}$ | | | 1.00569*** | 0.00010 | 0.01529*** |
| | | | (0.00180) | (0.00039) | (0.00304) |
| $d_{96-99} \times \widehat{\text{R\&D Ext}}.{}_{(t-1)}$ | | | 0.00014 | 1.00067*** | 0.01063** |
| | | | (0.00062) | (0.00154) | (0.00468) |
| $\widehat{\text{R\&D Ext}}.{}_{(t-1)}$ | | | 0.01586 | 0.06208** | 1.13118*** |
| | | | (0.01055) | (0.02465) | (0.05231) |
| Firm F.E. | Y | Y | Y | Y | Y |
| Period F.E. | Y | Y | Y | Y | Y |
| Age F.E. | Y | Y | Y | Y | Y |
| Industry×Period F.E. | Y | Y | Y | Y | Y |
| Observations | 4921 | 4921 | 4921 | 4921 | 4921 |

Column (1) reports the OLS estimates of the specification (1.51). Column (2) reports the results of IV estimation of the same specification where the externality variable and its interaction terms are instrumented with the externality measure computed using the fitted value from a regression of firm-level R&D on the firm-specific change in protection based on the 1986-1988, 1989-1991, and 1992-1995 periods. Columns (3), (4), and (5) report the first stage regressions coefficients. Statistical significance levels: $^{*}(p < 0.10)$,$^{**}$ $(p < 0.05)$,$^{***}$ $(p < 0.01)$

(1.52) is estimated using OLS. Column (2) reports the estimated coefficients.

$$P_{j,p} = \gamma_p + \sum_{k=2}^{4} \mathbf{1}_{p=k}\mathbf{Z}_j\eta_k + \beta_0\Delta T_j + \sum_{k=2}^{4} \beta_k \mathbf{1}_{p=k}\Delta T_j + \sum_{k=2}^{4} \theta_k \mathbf{1}_{p=k} P_{j,p-1} + \theta_0 P_{j,p-1} + \varepsilon_{j,t} \tag{1.52}$$

The vector $\mathbf{Z}_j$ comprises field-specific characteristics observed prior to the beginning of the sample period (1980Q1-1984Q4), such as (i) the average number of citations per patent, (ii) the average number of inventors per patent, and (iii) the size of the fields, measured by the total number of patents. Since the outcome variable includes lags among regressors, field fixed effects must be excluded, and these variables serve as substitutes.

In the final step, specification (1.52) is estimated by 2SLS using the lagged fitted values of the estimation of (1.2) as external instruments for $P_{j,p-1}$. The estimated coefficients are reported in column (3). As in the analysis of subsection 1.4.4, the direct impact of $\Delta T_j$ on innovation in the post-implementation period is positive and statistically significant.

Furthermore, the IV estimates of $\theta_0$ and $\theta_{k=96-00}$ in column (3) provide information on the elasticity of current innovation to past innovation. Specifically, $\widehat{\theta}_0 + \widehat{\theta}_{k=96-00}$ captures the impact of a shift in past innovation on current innovation outcomes in the post-implementation period. Because the proposed IV strategy exploits only variation that originates from the impact of the news shock, the shift in past innovation is plausibly exogenous. The point estimate of $\widehat{\theta}_0 + \widehat{\theta}_{k=96-00}$ implies that an increase of past innovation by 1 patent leads to a current innovation increase of approximately 5.1 patents. Given the average number of patents in the news period (408), +1 patent is equivalent to a +0.0245 percent increase, while given the average number of patents in the post-implementation period (1000), +5.1 patents is equivalent to a +0.51 percent increase. Therefore, the implied elasticity is 2.1.

Table 1.B.7: **Decomposition of the post-implementation effect**

| | (1)<br>(DiD) | (2)<br>(Augmented DiD OLS) | (3)<br>(Augmented DiD IV) |
|---|---|---|---|
| $\mathbf{1}_{85-89} \times \Delta T_j$ | 0.10328<br>(0.07427) | | |
| $\mathbf{1}_{93-95} \times \Delta T_j$ | -0.58255$^{***}$<br>(0.13934) | -0.59537$^{***}$<br>(0.13718) | -0.59694$^{***}$<br>(0.13505) |
| $\mathbf{1}_{96-00} \times \Delta T_j$ | -3.13164$^{***}$<br>(1.13146) | 0.54082<br>(0.40044) | 0.87689$^{*}$<br>(0.50444) |
| $P_{j,t-1}$ | | 1.42867$^{***}$<br>(0.10966) | 1.77714$^{***}$<br>(0.18164) |
| $\mathbf{1}_{93-95} \times P_{j,t-1}$ | | -0.04022<br>(0.18083) | -0.00115<br>(0.26824) |
| $\mathbf{1}_{96-00} \times P_{j,t-1}$ | | 3.05545$^{***}$<br>(0.89086) | 3.35558$^{***}$<br>(0.78411) |
| Period F.E. | Y | Y | Y |
| Field F.E. | Y | | |
| Observations | 2484 | 1856 | 1856 |

Column (1) reports the OLS estimates of the DiD specification (1.2) estimated on an aggregated sample over periods: 1985Q1-1988Q4; 1989Q1-1992Q3; 1992Q4-1995Q2; 1995Q3-2000Q4. Column (2) reports the OLS estimates of specification (1.52) over the same aggregate sample. Column (3) reports the IV 2SLS estimates of specification (1.52) over the same aggregate sample. In all columns, standard errors are clustered by technical field. Statistical significance levels: $^{*}(p < 0.10)$,$^{**}(p < 0.05)$,$^{***}(p < 0.01)$

### 1.B.6 Evidence by industry

#### 1.B.6.1 The effect of innovation on welfare and TFP

In this subsection, I present empirical findings regarding the impact of innovation (as measured by patents, citations-weighted patents, and patent value) on productivity and welfare. To this end, I conduct a sectoral-level analysis employing the NBER CES manufacturing database and utilizing the most finely-grained sectoral classification available, namely the 6-digit NAICS.[60]

To isolate the impact of innovation on welfare and productivity, I exploit in an IV setting the variation in innovation induced by the news and the subsequent implementation of the TRIPs-related patent term change. I measure productivity by the 5-factors Total Factor Productivity (TFP) and (inverse) measure of welfare is the value of shipments deflator. To focus on the policy-related window, the time dimension of the panel is restricted to 1985-2000. The second stage regression is

$$y_{s,t} = \alpha_s + \sum_{k=1985}^{2000} \gamma_k \mathbf{1}_{(t=k)} + \beta I_{s,t} + \Xi X_{s,t} + \varepsilon_{s,t} \tag{1.53}$$

where $y_{s,t}$ denotes the natural logarithm of either the value of shipments deflator or TFP for industry $s$ in year $t$, $\alpha_s$ are industry fixed effects, $\mathbf{1}_{(t=k)}$ are yearly dummy variables, $X_{s,t}$ is a matrix of controls that include: 4-digit NAICS industry $\times$ yearly effects, the log of the energy price deflator and, and the log of energy consumption. $\varepsilon_{s,t}$ is an idiosyncratic error term. (1.5) is estimated by weighted least squares with weights representing the number of patents produced in the sector in 1985, to take into account heterogeneous innovation-related industry sizes. $I_{s,t}$ is the innovation measure for industry $s$ and year $t$. To aggregate measures of innovation by 6-digit

[60] An example of the depth of the sectoral classification I use in the analysis is the following. *31-33* is the aggregate 2-digit classification for *Manufacturing*; *324* is the 3-digit *Petroleum and Coal Products Manufacturing*, *3241* is the 4-digit *Petroleum and Coal Products Manufacturing*; which includes the 5-digit *32412 Asphalt Paving, Roofing, and Saturated Materials Manufacturing*, which includes the 6-digit sectors 324121 *Asphalt Paving Mixture and Block Manufacturing* and 324122 *Asphalt Shingle and Coating Materials Manufacturing*.

NAICS and year, I start from measures of innovation by technical field at the yearly level, and I map them into 6-digit NAICS through the formula $I_{s,t} = \sum_j I_{j,t}\pi_{s|j}$. $I_{j,t}$ is innovation in 4-digit IPC field $j$ and year $t$, and $\pi_{s|j}$ is the probability that a patent classified in technical field $j$ is linked to sector $s$. $\pi_{s|j}$ is taken from the 'Algorithmic Links with Probabilities' crosswalk by Goldschlag, Lybbert and Zolas (2019).

The first stage regression is

$$I_{s,t} = \kappa_s + \sum_{k=1985}^{2000} \iota_k \mathbf{1}_{(t=k)} + \sum_{k=1985}^{2000} \psi_k \mathbf{1}_{(t=k)} \Delta T_s + \Lambda X_{s,t} + u_{s,t} \tag{1.54}$$

where the LHS innovation variables used are patents, citations-weighted patents, or patent value. $\Delta T_s$ is the policy-induced change in protection time in sector $s$. The technical field level treatment $\Delta T_j$ is converted into a sectoral treatment $T_s$ by the formula $\Delta T_s = \sum_j \Delta T_j \pi_{j|s}$, where $\pi_{j|s}$ is the probability that, given that a patent is assigned to NAICS $s$, it comes from technical field $j$. These probabilities are again taken from Goldschlag, Lybbert and Zolas (2019).

Table 1.B.8 presents the estimated impact of innovation on the natural logarithm of the value of shipments price deflator. Specifically, the results indicate that an industry×year increase of 100 patents leads to a 2.7% reduction of the value of shipment deflator, while an industry×year increase of 1,000 citations-weighted patents implies a 1.5% lower value of shipment deflator. It is worth noting that the sectoral averages of industry×year patents and citations-weighted patents in the pre-treatment year 1991 are 280 and approximately 1,450, respectively. Additionally, the F-statistics for the first stage regressions are always above 10.

Table 1.B.9 presents the estimated impact of innovation on the natural logarithm of 5-factors TFP estimated by the NBER. An increase of 100 industry×year patents implies a 3.3% increase in TFP.[61] Similarly, an increase of 1,000 industry×year citations-

[61] The sectoral average of industry×year patents in the pre-treatment year 1991 is 280.

Table 1.B.8: **Sectoral evidence on prices**

| | (1) OLS | (2) IV | (3) OLS | (4) IV | (5) OLS | (6) IV |
|---|---|---|---|---|---|---|
| Patents/100 | -0.024*** | -0.027*** | | | | |
| | (0.003) | (0.008) | | | | |
| Citations/1000 | | | -0.012*** | -0.015*** | | |
| | | | (0.001) | (0.003) | | |
| Patent value ($M$)/1000 | | | | | -0.002*** | -0.007** |
| | | | | | (0.001) | (0.003) |
| 6-d NAICS f.e. | Y | Y | Y | Y | Y | Y |
| Year f.e. | Y | Y | Y | Y | Y | Y |
| 4-d NAICS × Year f.e. | Y | Y | Y | Y | Y | Y |
| Observations | 6684 | 6684 | 6684 | 6684 | 6684 | 6684 |

Columns (1), (3), and (5) report the OLS estimates of the $\beta$ coefficient of specification (1.5) having as dependent variable the natural logarithm of the price of shipment deflator, normalized to 100 in 1997. Columns (2), (4), and (6) report the 2-stage estimates of the IV regression. Standard errors are clustered by 3-digit NAICS × year. Statistical significance levels: $^{*}(p < 0.05),^{**}(p < 0.01),^{***}(p < 0.001)$

weighted patents implies a 1.8% increase in productivity.[62] The first stage regressions have F-statistics that are always above 10.

**1.B.6.1.1 Pass-through of productivity gains** The ratio of the estimated impact of innovation on TFP to the estimated impact of innovation on the value of shipments deflator (with sign flipped) can provide insight into the pass-through of productivity gains to higher consumer welfare. Based on the estimates presented in Tables 1.B.8 and 1.B.9, the pass-through of TFP gains from an increase of 100 patents is around 83% and 84% for citations-weighted patents. When using the private economic value of patents, the pass-through drops to 76%. These results suggest a high and consistent pass-through of TFP gains into lower prices across the different measures of innovation.

[62]The sectoral average of industry×year citations-weighted patents in the pre-treatment year 1991 is approximately 1,450.

Table 1.B.9: **Sectoral evidence on TFP**

| | (1) OLS | (2) IV | (3) OLS | (4) IV | (5) OLS | (6) IV |
|---|---|---|---|---|---|---|
| Patents/100 | 0.027*** | 0.033*** | | | | |
| | (0.003) | (0.008) | | | | |
| Citations/1000 | | | 0.013*** | 0.018*** | | |
| | | | (0.001) | (0.003) | | |
| Patent value ($M$)/1000 | | | | | 0.003*** | 0.009** |
| | | | | | (0.001) | (0.004) |
| 6-d NAICS f.e. | Y | Y | Y | Y | Y | Y |
| Year f.e. | Y | Y | Y | Y | Y | Y |
| 4-d NAICS × Year f.e. | Y | Y | Y | Y | Y | Y |
| Observations | 6684 | 6684 | 6684 | 6684 | 6684 | 6684 |

Columns (1), (3), and (5) report the OLS estimates of the $\beta$ coefficient of specification (1.5) having as dependent variable the natural logarithm of the 5-factors TFP, normalized to 100 in 1997. Columns (2), (4), and (6) report the 2-stage estimates of the IV regression. Standard errors are clustered by 3-digit NAICS × year. Statistical significance levels: $^{*}(p < 0.05)$,$^{**}$ $(p < 0.01)$,$^{***}$ $(p < 0.001)$

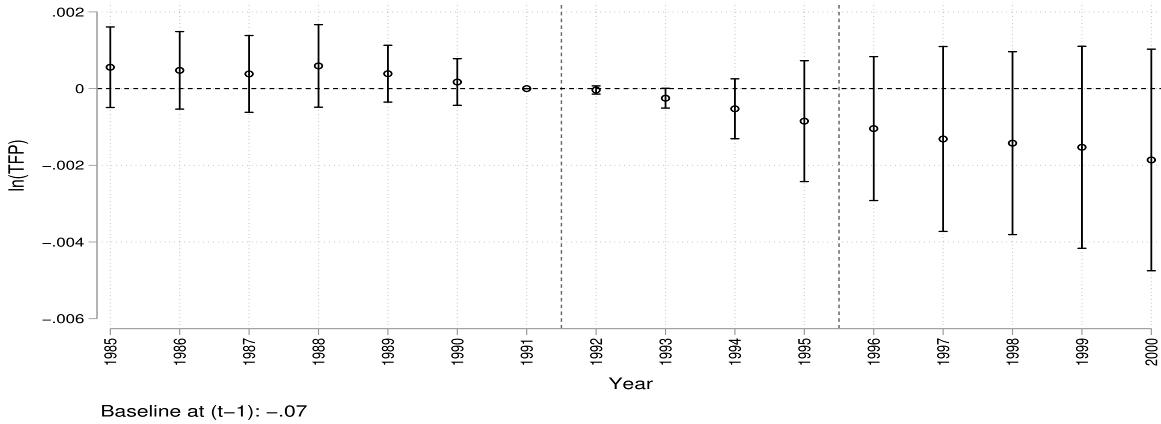
#### 1.B.6.2 The dynamic effect of the policy on welfare and TFP

This subsection investigates the dynamic effects of the policy on welfare and TFP at the industry level using a difference-in-difference analysis. The measures of welfare and productivity and the sectoral treatment are the same as in the previous subsection. The policy-relevant time-window is 1985-2000 and the specification of the regression is

$$y_{s,t} = \alpha_s + \sum_{k=1985}^{2000} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985}^{2000} \beta_k \mathbf{1}_{(t=k)} \Delta T_s + \Xi X_{s,t} \varepsilon_{s,t} \tag{1.55}$$

where the dependent variable $y_{s,t}$ for sector $s$ and year $t$ is the natural logarithm of either of the two outcomes described above, $\alpha_s$ are industry fixed effects, $\mathbf{1}_{(t=k)}$ denotes yearly dummies, $X_{s,t}$ is matrix of controls that including 4-digit NAICS industry × year effects, the natural logs of the energy price deflator, and the natural logs of material costs deflator. $\Delta T_s$ is the sectoral treatment and $\varepsilon_{s,t}$ is the error term. Specification (1.55) is estimated by weighted least squares with weights being the number of patents produced in the sector in 1985 to take into account heterogeneous

Figure 1.B.53: Marginal effect of 1 more day of protection on sectoral TFP



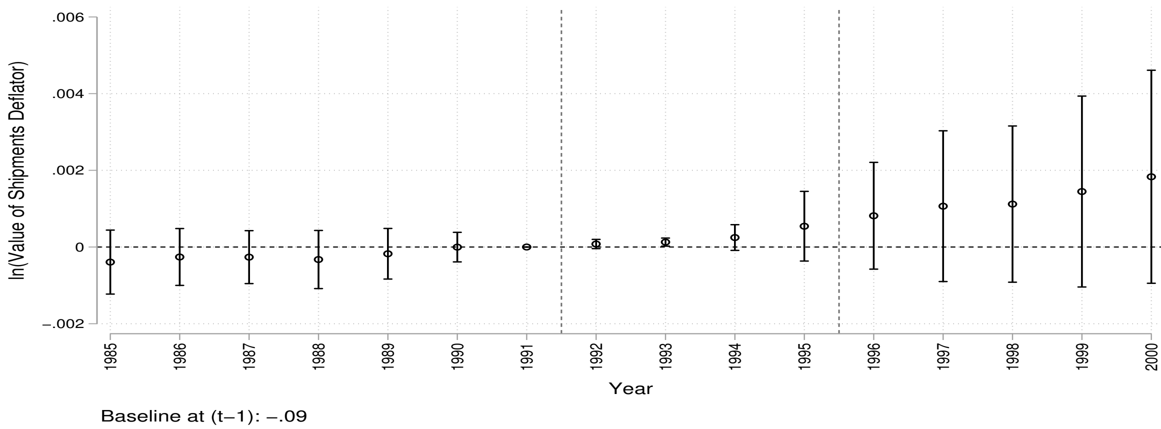

The plot shows the $\beta_k$ coefficients of regression (1.55) having as dependent variable the natural logarithm of TFP in sector $s$ and year $t$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviations* of the outcome variable. Clustered 95% confidence bands by 3-digit NAICS industry and year are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

innovation-related industry sizes.

Figure 1.B.53 illustrates the results of a difference-in-difference analysis, which examines the dynamic effect of a change in patent protection term on the logarithm of sectoral TFP. The plot displays the difference-in-difference coefficients for various industries. When $\Delta T_s < 0$, the point-estimates are initially very close to zero and gradually increase over time, indicating a slow but positive impact of higher policy-induced innovation on the level of productivity.

Figure 1.B.54 illustrates the difference-in-difference coefficients depicting the dynamic impact of a change in patent protection term on the logarithm of the value of shipments deflator, which serves as the inverse measure of welfare. The figure reveals that the gains in welfare resulting from innovation take time to materialize, as TFP gains are gradual in nature.

Figure 1.B.54: Marginal effect of 1 more day of protection on sectoral value of shipments deflator




The plot shows the $\beta_k$ coefficients of regression (1.55) having as dependent variable the natural logarithm of the values of shipments deflator in sector $s$ and year $t$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *percent deviations* of the outcome variable. Clustered 95% confidence bands by 3-digit NAICS industry and year are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

# Appendix 1.C Additional theoretical results

## 1.C.1 Model derivations

This section presents the details and the derivations of the model of Section 1.6.

### 1.C.1.1 Consumers

The consumer has linear utility $u(c(t)) = c(t)$ in per-capita consumption $c(t)$, invests in real-assets $a(t)$, and inelastically supplies labor. The maximization problem of the representative agent is

$$\max_{c(t),a(t)} \int_0^\infty e^{-\rho} c(t)dt \tag{1.56}$$

$$\text{subject to} \quad \dot{a}(t) = r(t)a(t) - c(t) + w(t) \tag{1.57}$$

where $c(t)$ is defined as aggregate consumption divided by population, i.e. $c(t) \equiv C(t)/L(t)$, and $a(t) \equiv A(t)/L(t)$ are total assets per capita. Aggregate real assets are and $A(t) \equiv K(t) + \int_0^\infty v(t-s,t)S(t-s,t)ds$. The first term is the total stock of physical capital. The second term represent the total value of firms owning patents on profit-generating intermediate capital varieties.

In particular, the last term is defined by the following expressions

$$v(t-s,t) = \int_t^{t-s+T} \pi(t')e^{-\int_{t'}^{t-s+T}(\rho+\lambda(z))dz}dt' \text{ if } s \leq T$$

$$v(t-s,t) = 0 \text{ if } s \geq T$$

and it represents the residual value at time $t$ of a patent generated at time $t-s$.The term $S(t-s,t)$ represents the mass of patents generates at time $t-s$ that have not been creatively destroyed up to time $t$ and it is defined by the expression

$$S(t-s,t) = (1+\psi)\dot{V}(t-s)e^{-\int_{t-s}^{t}\lambda(t')dt'}$$

No arbitrage conditions ensure that all the real assets give a net real return equal to $r(t)$. The solution of problem (1.56) gives the Euler equation $r(t) = \rho$.

#### 1.C.1.2 Final good production

The final good is produced by a competitive firm that optimally chooses labor and each of the intermediates to maximize profits. The problem is

$$\max_{\{X(i,t)\}_{i\in[0,V(t)]},L(t)\}} \Big[h(t)L(t)\Big]^{1-\alpha}\Big[\int_0^{V(t)} X^\alpha(i,t)di\Big] - \int_0^{V(t)} z(i,t)X(i,t)di - w(t)L(t)$$

Equation (1.58) is the production function.

$$Y(t) = \Big[h(t)L(t)\Big]^{1-\alpha}\Big[\int_0^{V(t)} X^\alpha(i,t)di\Big] \tag{1.58}$$

The first order conditions of the problem are

$$w(t) = (1-\alpha)h(t)^{1-\alpha}L(t)^{-\alpha}\Big[\int_0^{V(t)} X^{\alpha}(i,t)di\Big] \tag{1.59}$$

$$z(i,t) = \alpha h(t)^{1-\alpha}L(t)^{1-\alpha}X^{\alpha-1}(i,t) \ \ \forall\ i \in [0, V(t)] \tag{1.60}$$

Equation (1.59) is the inverse labor demand and determines the equilibrium wage rate. (1.60) is the inverse demand for intermediate $i$.

#### 1.C.1.3 Monopolistic intermediate goods production

The existing $V(t)$ intermediate good varieties are protected by a valid patent, with a share $\zeta(t)$ being granted a monopoly. The monopolistic producer of each variety $i$ maximizes profits subject to the inverse demand given by (1.60) and a linear production function that uses one unit of raw capital $K(t)$. Raw capital is rented from households at a rate of $r_K(t) = r(t) + \delta$, where $\delta$ represents the depreciation rate of physical capital. The maximization problem is

$$\begin{aligned} &\max_{X(i,t),z(i,t)} \Big\{z(i,t)X(i,t) - (r(t)+\delta)X(i,t)\Big\} \\ &\text{s.t.} \qquad z(i,t) = \alpha h(t)^{1-\alpha}L(t)^{1-\alpha}X^{\alpha-1}(i,t) \end{aligned}$$

and the first order condition implies

$$z(i,t) = \alpha(h(t)L(t))^{1-\alpha}X(i,t)^{\alpha-1} = \frac{1}{\alpha}(r(t)+\delta) \tag{1.61}$$

i.e. the price is a constant markup $1/\alpha$ over the marginal cost $(r(t)+\delta)$. The produced quantity and the profits are symmetric across monopolistic $i$'s and satisfy

$$X(i,t) = X_p(t) = \alpha^{\frac{2}{1-\alpha}}(r(t)+\delta)^{-\frac{1}{1-\alpha}}h(t)L(t) \quad \forall\ i \in [0, \zeta(t)V(t)] \tag{1.62}$$

$$\pi(i,t) = \pi(t) = \Big(\frac{1}{\alpha}-1\Big)(r(t)+\delta)X_p(t) \tag{1.63}$$

### 1.C.1.4 Non-monopolistic intermediate goods production

A fraction $1-\zeta(t)$ of intermediates are competitively produced because legal patent protection on them has expired after the maximum patent term $T$. These non-monopolistic varieties are produced in a regime of Bertrand competition and therefore the price $z(i,t)$ is driven to the marginal cost of production $(r(t)+\delta)$. It follows from the inverse demand function (1.60) that the production of these competitively-produced intermediate varieties is symmetric and given by

$$X_{np}(t) = \alpha^{\frac{1}{1-\alpha}}(r(t)+\delta)^{-\frac{1}{1-\alpha}}h(t)L(t) \quad \forall\ i \in (\zeta(t)V(t), V(t)] \tag{1.64}$$

which implies that $X_p(t) = \alpha X_{np}(t)$. Since $\alpha \in (0,1)$ by assumption, this implies that the quantity produced of monopolistic varieties is lower than the one of competitive varieties, which is the main distortion from monopoly in the model.

### 1.C.1.5 Physical capital market clearing condition

Physical capital market clearing requires that the quantity of capital supplied by households $K(t)$ is equal to the quantity of capital demanded by firms to produce the intermediate capital goods, i.e.

$$\begin{aligned} K(t) =& \zeta(t)V(t)X_p(t) + (1-\zeta(t))V(t)X_{np}(t) \\ =& [\alpha\zeta(t) + (1-\zeta(t))]V(t)X_{np}(t) \end{aligned} \tag{1.65}$$

### 1.C.1.6 Research investment to discover new projects

The model features an unit mass of identical firms that invest in research. The output of research investment is new ideas that need subsequent development by successful firms. The research investment problem of the representative research firm is

$$\max_{I_R(t)} \quad \left\{ P(t)E(t)^{\chi}V(t)^{\phi_1}I_R(t)^{\phi_2} - I_R(t) \right\}$$

$P(t)$ is the economic value of a new idea, or, alternatively, it can be thought as the exclusivity value of a development project. The optimal research investment is given by

$$I_R(t) = \Big[\phi_2 P(t) E(t)^{\chi} V(t)^{\phi_1}\Big]^{\frac{1}{1-\phi_2}}$$

#### 1.C.1.7 Investment in development of projects

Development occurs independently on each existing project, even in the case of a single firm running multiple projects. The project-specific maximization problem can be written in recursive form as

$$r(t)P(t) - \dot{P}(t) = \max_{\iota_D(t)} \Big\{\iota_D(t)\Big[\upsilon(t) - P(t)\Big] - \mu\iota_D(t)^{\theta}\upsilon(t)\Big\} \tag{1.66}$$

where the equation captures the fact that if the project is successful with instantaneous probability $\iota_D(t)$, the firm receives a value $\upsilon(t)$ for the intermediate variety obtained but it loses the value of the project $P(t)$, which expires after completion. $\upsilon(t)$ is the value of a patent on a variety, and it is defined by (1.12) in the paper. The optimal development project completion rate is

$$\iota_D(t) = \left[\frac{1}{\theta\mu}\left(1 - \frac{P(t)}{\upsilon(t)}\right)\right]^{\frac{1}{\theta-1}} \tag{1.67}$$

The process of creative destruction captured by the $\lambda(t)$ term is endogenous, and it is driven by the rate of growth of the number of varieties $V(t)$. It is defined as $\lambda(t) \equiv \psi\frac{\dot{V}(t)}{V(t)}$, i.e. in times when the rate of growth of varieties is higher, the rate of creative destruction is higher.

#### 1.C.1.8 Evolution of aggregate quantities

Previous optimal policies determine the evolution of aggregate quantities. First, the number of varieties $V(t)$ evolves according to

$$(1+\psi)\dot{V}(t) = \iota_D(t)N(t) \tag{1.68}$$

where $\psi\dot{V}(t)$ is by how much creative destruction reduces the mass of intermediate goods available, and $\iota_D(t)N(t)$ is the number of development projects successfully turned into a variety. $\iota_D(t)$ is the instantaneous probability that each of the existing projects $N(t)$ is successfully completed. Since it is identical and independent across projects, a suitable law of large numbers applies and the aggregate representation provided holds. Second, the evolution of projects is given by

$$\dot{N}(t) = E(t)^{\chi}V(t)^{\phi_1}I_R(t)^{\phi_2} - \iota_D(t)N(t) \tag{1.69}$$

where the first term captures the mass of new projects generated by research investment, and the second term captures the destruction of projects due to successful completion.

The evolution of the share of existing varieties that are covered by monopoly, i.e. $\zeta(t)$, is given by

$$\dot{\zeta}(t) = (1-\zeta(t))\frac{\dot{V}(t)}{V(t)} - (1+\psi)\frac{\dot{V}(t-T)}{V(t)}e^{-\int_{t-T}^{t}\lambda(t')\mathrm{d}t'} \tag{1.70}$$

where the first term captures the additions to monopolistic varieties due to new patented innovations, and the second term captures the fact that all those varieties that have not already been creatively destroyed become competitive when the maximum patent term $T$ expires.

The derivation of equation (1.70) is the following. Let $V_p(t)$ be the mass of existing varieties covered by monopoly. Then, $\zeta(t) \equiv \frac{V_p(t)}{V(t)}$. Re-organizing the definition of $\zeta(t)$ and taking time derivatives, we get

$$\dot{\zeta}(t)V(t) + \zeta(t)\dot{V}(t) = \dot{V}_p(t)$$

$\dot{V}_p(t)$ is given by the inflow of new varieties in the stock of monopolistic ones, minus the outflow from this stock, due to the expiration of the maximum patent term $T$. This is what needs to be derived. At every instant $t$, the gross production of new varieties (which are monopolistic upon creation) is given by $(1+\psi)\dot{V}(t) = \iota_D(t)N(t)$. I assume for simplicity that all creatively destroyed varieties $\psi\dot{V}(t)$ come from the pool of monopolistic ones. This simplifies things because it implies that the net addition to the stock of existing varieties. $\dot{V}(t)$ also coincides with the net addition to the stock of monopolistic varieties $V_p(t)$. Therefore, the net inflow component of $\dot{V}_p(t)$ is simply $\dot{V}(t)$. As to the outflow, we need to consider that the mass of varieties of vintage $t-T$, i.e. $(1+\psi)\dot{V}(t-T)$, which go out of monopoly at instant $t$, has been eroded by creative destruction over time. Let $S(t_0)$ be the stock of such patents issued at time $t_0$. In practice, take $S(t_0) = (1+\psi)\dot{V}(t_0)$. Due to creative destruction, the evolution of this stock responds to the following law of motion: $S(t+dt) = S(t) - (\lambda(t)dt)S(t)$, which can be re-written as a first order differential equation $\dot{S}(t) = \lambda(t)S(t)$. Its solution, for two generic points in time $t_0$ and $t_1$, is $S(t_1) = S(t_0)e^{-\int_{t_0}^{t_1}\lambda(t')dt'}$. Now, the outflow from the mass of monopolistic varieties is given by the residual mass of gross varieties produced at $t-T$ and survived from $t-T$ up to $t$. Therefore, replacing $S(t_0) = (1+\psi)\dot{V}(t_0)$, $t_0 = t-T$, and $t_1 = t$, we get that the outflow from the mass of monopolistic varieties is the right hand side of the last equation. i.e. $(1+\psi)\dot{V}(t-T)e^{-\int_{t-T}^{t}\lambda(t')dt'}$. Therefore,

$$\dot{\zeta}(t)V(t) + \zeta(t)\dot{V}(t) = \dot{V}(t) - (1+\psi)\dot{V}(t-T)e^{-\int_{t-T}^{t}\lambda(t')dt'}$$

Moving the second LHS addend to the right, and dividing everything by $V(t)$, we get exactly (1.70).

The evolution of aggregate capital satisfies $\dot{K}(t) = I_K(t) - \delta K(t)$, where $I_K(t)$ is the investment in physical capital done by the households out of the final good, and $\delta K(t)$ is the depreciation of the existing stock.

#### 1.C.1.9 Final good market clearing

Given the production decisions of intermediate producers and final good producers, GDP for this economy can be rewritten as

$$Y(t) = [\alpha^{\alpha}\zeta(t) + (1 - \zeta(t))]V(t)h(t)^{1-\alpha}L(t)^{1-\alpha}X_{np}^{\alpha}(t) \tag{1.71}$$

where $[\alpha^{\alpha}\zeta(t) + (1 - \zeta(t))]V(t)h(t)^{1-\alpha}$ is the measured TFP. The productivity of the economy grows with the number of varieties available, and decreases with the share of monopolistic varieties, as $\alpha^{\alpha} < 1$. On the other hand, the total production of the final good must also satisfy the resource constraint

$$Y(t) = C(t) + I_K(t) + I_R(t) + \mu\iota_D(t)^{\theta}\upsilon(t)N(t) \tag{1.72}$$

#### 1.C.1.10 Balanced growth path

Population $L(t)$ and the productivity term $h(t)$ exogenously grow at constant rate $n$ and $g_h$, respectively. Since $r(t) = \rho$, the real interest rate is constant. From equations (1.62), (1.64), and (1.63) the growth rate of $X_p(t)$, $X_{np}(t)$, and profits is identical in the b.g.p and equal to $g_h + n$. From the definition of $\upsilon(t)$, the patent value must grow at the same rate of profits. In addition, the rate of creative destruction $\lambda(t)$ is constant along the balanced growth path. From the value function of the development investment problem, $P(t)$ must grow at the same rate of $\upsilon(t)$, i.e. $g_P = n + g_h$, and the development speed $\iota_D(t)$ must be constant. A constant $\iota_D(t)$ also implies that the externality term $E(t)$ is constant in the b.g.p. The evolution of $V(t)$ in (1.68) implies that $g_V = g_N$, and the evolution of $N(t)$ in (1.69) requires that $g_N = \phi_1 g_V + \phi_2 g_{I_R}$. From (1.72), the rate of growth of $C(t)$, $I_K(t)$, and $I_R(t)$ must be the same as output, i.e. $g_Y = g_C = g_{I_K} = g_{I_R}$. In addition, from (1.70), $\zeta(t)$ is constant in the b.g.p., and therefore the equilibrium production function (1.71) requires $g_Y = (1 - \alpha)(g_h + n) + g_V + \alpha g_X$. Since $g_X = n + g_h$, we then obtain

$g_Y = g_V + n + g_h$. Using $g_{I_R} = g_Y$ and $g_V = g_N$, and plugging the last expression into $g_N = \phi_1 g_V + \phi_2 g_{I_R}$, $g_V$ can be solved as $g_V = \frac{\phi_2}{1-\phi_1-\phi_2}(n + g_h)$. The latter can be used to solve explicitly for all the other growth rates.

### 1.C.2 Transitional dynamics computational algorithm

I solve the stationary version of the system, which can be obtained by re-scaling each variable by its growth rate along the balanced growth path, as computed in Subsection 1.C.1.10. The stationary version of the variables of the model is denoted with a tilde, as in the main text. In any solution of the model $r(t) = \rho$, which gives an explicit solution for the full dynamic path of $\tilde{X}_p(t)$, $\tilde{X}_{np}(t)$, and $\tilde{\pi}(t)$. For the other variables, I setup a mesh that goes from $t_0 = 0$ to $t_{max} = 2000$, and I assume that (i) just before $t_0$, the stationary version of the system is in the pre-policy news steady state, and (ii) by $t_{max}$ it has reached the post-policy change steady state.

I start from a guess of $\tilde{\lambda}(t)$ from $t_0 = 0$ to $t_{max} = 2000$, which I initially fix to be equal to $\psi g_V = \psi \frac{g_h+n}{1-\phi_1-\phi_2}$ at any time. Given $\tilde{\lambda}(t)$, I can solve for the full dynamic path of $\tilde{v}(t)$ using equation (1.12). I impose the terminal condition on $\tilde{P}(t)$, i.e., that it must be at the post-policy steady state at $t_{max}$. Then, for each $\tilde{P}(t+dt)$, I solve the development investment problem given $\tilde{v}(t)$, obtaining $\iota_D(t)$ and $\tilde{P}(t)$. I use the full sequence of $\iota_D(t)$ to build the delayed externality term and, given the computed $\tilde{P}(t)$, I solve for the optimal $\tilde{I}_R(t)$ at every instant using the fact that both $\tilde{N}(t)$ and $\tilde{V}(t)$ are assumed to be at the old steady state at $t_0$, as they are state variables. With all previous objects, I solve forward (1.15) and (1.14) obtaining $\tilde{N}(t + dt)$ and $\tilde{V}(t + dt)$ $\forall t$. Also, given the full series of $\tilde{\lambda}(t)$, I solve forward for $\zeta(t)$, again assuming that this state variable is at the pre-policy steady state at $t_0$. With $\tilde{V}(t)$, $\zeta(t)$, and $X_{np}(t)$, I use the capital market clearing condition to compute the aggregate series for $\tilde{K}(t)$ and, subsequently, the series $\tilde{I}_K(t)$ that is required to sustain $\tilde{K}(t)$, assuming that at $t_0$ the level of physical capital is at the old steady state. Using the exogenous $\tilde{L}(t)$

and $\tilde{h}(t)$ with $\tilde{X}_{np}(t)$, $\tilde{V}(t)$ and $\zeta(t)$, I solve for $\tilde{Y}(t)$ and $\tilde{C}(t)$ using the resource constraint. As a final step, I use the series $\tilde{V}(t)$ to update the guess for $\tilde{\lambda}(t)$ according to $\tilde{\lambda}(t) = \psi\Big(g_V + \frac{\dot{\tilde{V}}(t)}{\tilde{V}(t)}\Big)$, and I iterate the previous steps until convergence of the $\tilde{\lambda}(t)$ series.

### 1.C.3 Computation of standard errors

The quadratic loss function used for simulated method of moments estimation is $F = \mathbf{g}'(\mathbf{\Gamma})W\mathbf{g}(\mathbf{\Gamma})$, where $\mathbf{\Gamma}$ is the vector of estimated parameters and $\mathbf{g}(\mathbf{\Gamma})$ is the vector of the deviation of model-based moments computed at $\mathbf{\Gamma}$ from the empirically estimated moments. Overall, there are 69 moment restrictions. 33 are the post-announcement reduced-form estimates of the effect of the reform on patenting activity, 33 are the post-announcement reduced-form estimates of the effect of the reform on patent-read R&D effort, and 3 are the long-run moment restrictions on the capital-output ratio, the consumption-output ratio, and the R&D spending-output ratio. In estimation, $W$ is a diagonal matrix giving unit weight to the first 66 moments, and weights 0.01, 0.1, and 10,000, to the $K/Y$, $C/Y$, and $R\&D/Y$ long-run restrictions, to correct for their respective scale. The variance-covariance matrix of the estimated parameters for the resulting GMM estimator is

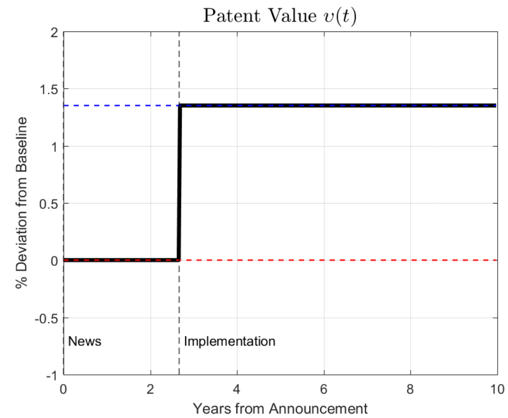
$$\hat{\mathbf{V}} = (D(\hat{\mathbf{\Gamma}})WD'(\hat{\mathbf{\Gamma}}))^{-1}D(\hat{\mathbf{\Gamma}})W\mathbf{g}(\mathbf{\Gamma})\mathbf{g}'(\mathbf{\Gamma})W'D'(\hat{\mathbf{\Gamma}})(D(\hat{\mathbf{\Gamma}})WD'(\hat{\mathbf{\Gamma}}))^{-1}/69$$

where $W$ was defined above and $D'(\hat{\mathbf{\Gamma}})$ is defined as $D'(\hat{\mathbf{\Gamma}}) = \frac{\partial \mathbf{g}(\mathbf{\Gamma})}{\partial \mathbf{\Gamma}'}\Big|_{\mathbf{\Gamma}=\hat{\mathbf{\Gamma}}}$. The latter is computed numerically around the optimal $\hat{\mathbf{\Gamma}}$. The standard errors of the parameters are computed as the square root of the main diagonal elements of $\hat{\mathbf{V}}$.

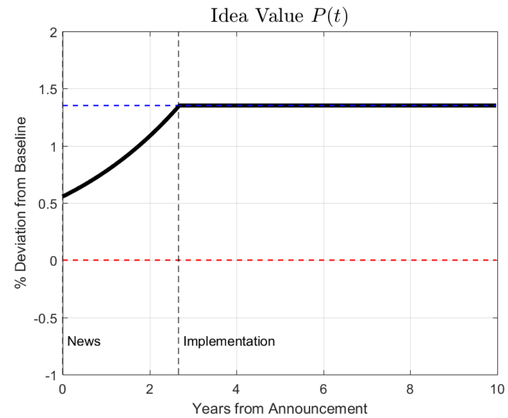
### 1.C.4 The mechanism at work in the model

The plots illustrate how various theoretical objects respond to an anticipated increase in patent term of 100 days, starting from a 17-year patent term. The anticipation

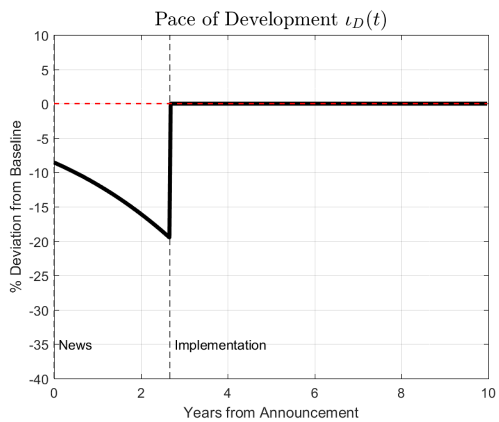
Figure 1.C.1: Evolution of aggregates



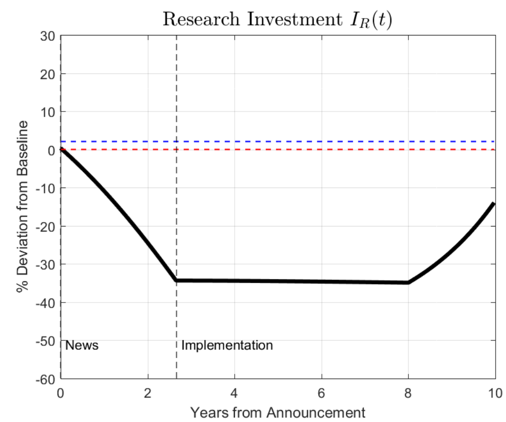

(a) Patent value: $\upsilon(t)$




(b) Ideas value: $P(t)$




(c) Development pace: $\iota_D(t)$




(d) Research investment: $I_R(t)$

period is assumed to be 2 years and 8 months, consistent with the TRIPs anticipation. The news is assumed to break at time $t = 0$, with the vertical line indicating the policy implementation. The red horizontal line represents the steady state in the old regime, while the blue horizontal line represents the steady state in the new regime. The black solid lines depict the response of the variables of interest. Specifically, the top-left panel of Figure 1.C.1 shows the evolution of patent value $\upsilon(t)$, the top-right panel shows project value $P(t)$, the bottom-left panel shows development pace $\iota_D(t)$, and the bottom-right panel shows research investment $I_R(t)$.

### 1.C.5 New ingredients and comparison with existing models

In this Appendix subsection, I examine the role of the two novel ingredients introduced by the semi-endogenous growth model of Section 1.4: the distinction of Research and Development activity into two different steps and the technology disclosure externality. The objective of the subsection is twofold. Firstly, I argue that the joint action of both ingredients is crucial to empirically replicate the effects of an anticipated patent term change documented by Section 1.4. Secondly, I show how the proposed framework nests workhorse models in the endogenous growth literature and illustrate that, in those models, an anticipated patent term change generates effects inconsistent with the data. I proceed in two steps. In subsection 1.C.5.1, I examine a model with neither ingredient and show that it reduces to the semi-endogenous growth framework first proposed by Jones (1995). I discuss that it cannot replicate the new effects of the policy (Fact 1) because it misses the intertemporal trade-off on the development of existing projects. Next, in Subsection 1.C.5.2, I examine a model that distinguishes research and development but mutes the technology disclosure externality. The mathematical structure of the two-stage R&D model is close to Comin and Gertler (2006*a*), but the setups differ in the interpretation of two stages and in the technology disclosure externality. Absence of the latter from Comin and Gertler (2006*a*) implies that R&D and innovation would immediately increase after the implementation of a longer patent term, even in the presence of anticipation. This is in contrast with empirical Fact 2.

#### 1.C.5.1 Research and Development as a single activity

I begin by presenting a simplified version of the model where Research and Development are combined into a single step, and there is no technology disclosure externality. To achieve this, I set the development cost parameter $\mu = 0$, which implies that the value of an undeveloped idea $P(t)$ is equal to the value of a patented technology $v(t)$

at any point in time. In other words, the whole R&D process collapses to a single stage when the cost of development is zero. Therefore, the R&D activity can be described by the maximization problem

$$\max_{I_R(t)} \upsilon(t)V(t)^{\phi_1} I_R(t)^{\phi_2} - I_R(t) \tag{1.73}$$

which is equivalent to the formulation of the R&D problem in the standard semi-endogenous growth model by Jones (1995). Moreover, the coincidence of ideas and varieties implies that the measures thereof are equal at any instant, i.e., $N(t) = V(t)$, and varieties evolve according to the law of motion

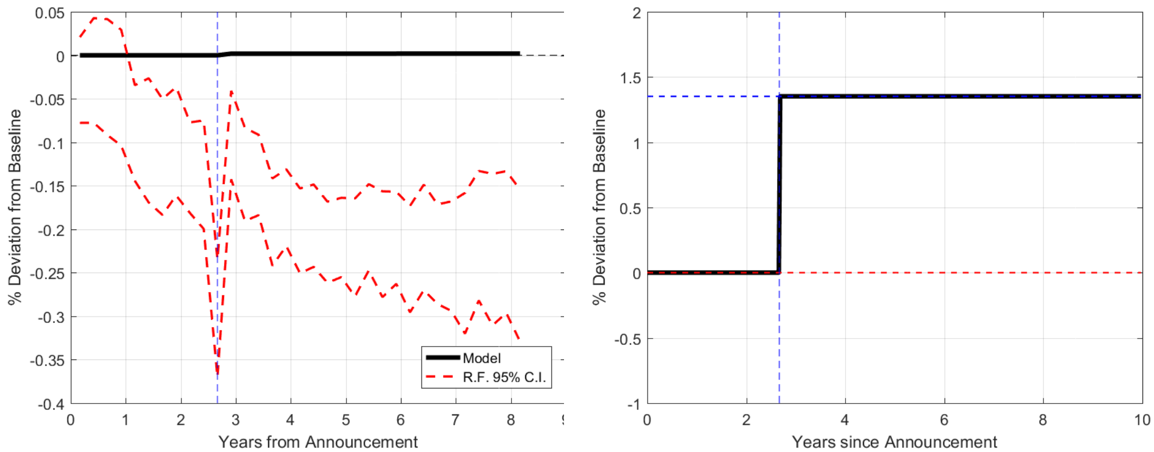
$$(1+\psi)\dot{V}(t) = V(t)^{\phi_1} I_R^*(t)^{\phi_2} \tag{1.74}$$

where $I_R^*(t)$ is optimal R&D investment solving problem (1.73).

In this model, I simulate a policy episode involving a one-off patent term increase of 100 days with an anticipation of 2 years and 8 months, identical to that used for structural estimation. Figure 1.C.2 presents the evolution of innovation $V(t)^{\phi_1} I_R^*(t)^{\phi_2}$ (panel a) and the value of innovations $\upsilon(t)$ (panel b) in this model. Unlike empirical estimates, innovation does not decrease between the news and policy implementation but rises immediately afterward. The evolution of patent value $\upsilon(t)$ and problem (1.73) explain this outcome. Assuming that innovators file a patent application immediately after obtaining a new technology, $\upsilon(t)$ does not vary upon news because the old patent term still applies until the new policy's implementation. If innovators delay the filing of applications, $\upsilon(t)$ could even increase upon news of a longer patent term in the future. Therefore, the optimal R&D investment remains constant or even increases after the news shock, contrary to the empirical DiD estimates.

The model proposed in Section 1.6 successfully predicts the decline in R&D and innovation following news of a future patent term extension by accurately capturing

Figure 1.C.2: TRIPs effect without distinction of Research and Development




(a) Patenting

(b) Patent value $v(t)$

In panel (a), the black solid line represents the response of innovation (patents) to a 100-days patent term increase anticipated by 2 years and 8 months in Jones (1995)'s model with finite patent term. The news shock occurs at time $t = 0$. The red dashed lines represent the 95% confidence intervals implied by the reduced-form DiD estimates of Section 1.4. In panel (b), the black solid line shows the response of patent value in the same model. The red (blue) dashed line represents the pre-TRIPs (post-TRIPs) steady-state value.

the intertemporal trade-off involved. This is achieved by introducing a distinction between ideas and technologies, made possible by the separation of R&D activity into two steps. While the research problem reflects the standard trade-off between investment and the resulting idea's value, development activity represents a new economic force.

Innovators who successfully generate a new idea in research want to develop it into a patented technology as quickly as possible, as this allows them to begin earning profits sooner. At any given moment, the relative value of new patented technologies and ideas provides information about how profitable it is to complete the project in that moment, as opposed to keeping the idea and attempting to develop it at a later time. However, faster development is subject to convex costs due to factors such as declining productivity as developers work more intensely, laboratory equipment depreciation, or the increasing cost of reducing the time required for activities.

Upon the news of a future patent term increase, the optimal speed of development declines due to the decreasing relative value of newly patented technologies and ideas. As explained earlier, the news shock does not affect the value of new patents obtained before implementation, but it increases the value of future patents obtained thereafter. Consequently, the value of new ideas, which represents the expected value of obtaining a patented technology at some future date net of development costs, increases. However, being fast becomes less attractive but remains equally costly, leading to a decline in the optimal development pace.

Therefore, the model's two-stage representation of R&D, which generates an intermediate output with a distinct value from final technologies, is crucial to correctly capture this intertemporal trade-off.

#### 1.C.5.2 Technology disclosure externality

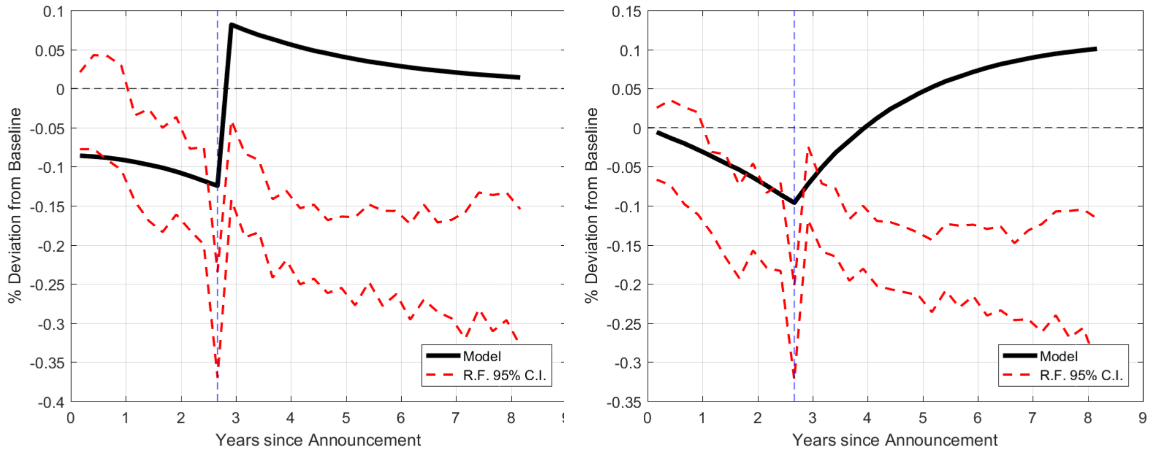
In their study, Comin and Gertler (2006*a*) present an endogenous growth model with a two-stage R&D structure that bears similarities to the model proposed in Section 1.6. However, there are two key differences between the two setups. Firstly, Comin and Gertler (2006*a*) interpret the first stage as encompassing the entire R&D process from idea generation to patenting of developed technologies, as discussed in the previous Subsection 1.C.5.1. The second stage pertains to adoption, which refers to the incorporation of patented technologies into a consumption good. Since the adoption decision is assumed to be independent of the TRIPs patent term change, the model's response to the policy is analogous to that depicted in Figure 1.C.2, which contradicts the empirical evidence. Specifically, the patent term change affects the value of both technology and adoption symmetrically. Therefore, optimal second-stage decisions remain unchanged following the shock, and first-stage investment only increases with policy implementation. This finding is consistent with the discussion in Subsection 1.C.5.1.

The model in Section 1.4 and Comin and Gertler (2006*a*) differ in a second key way: the technology disclosure externality documented in Section 1.5. To clarify the role of this externality, I simulated a version of the model with $\chi = 0$, muting the new externality. The black solid lines in Figure 1.C.3 show the responses of innovation (panel a) and R&D effort (panel b) in this version of the model to a 100-day patent term increase anticipated 2 years and 8 months in advance, while the red dashed lines represent the empirical 95% confidence bands of specification 1.3 in response to an equivalent shock.

Before the policy implementation, both R&D and innovation decline due to the intertemporal trade-off described in the previous subsection, which is consistent with the empirical evidence. However, absent the externality, R&D and innovation increase shortly after the implementation of the new, longer, patent term, which is in stark contrast with the empirical estimates. This increase occurs because of the joint action of three forces: (i) the incentive to slow down development ends, which was the main reason for the decline in R&D and innovation during the anticipation period; (ii) a higher value of ideas stimulates research investment and innovation as a direct effect; and (iii) since the stock of knowledge $V(t)$ is temporarily lower due to the news shock, productivity of research is also lower than normal due to the standard "standing on the shoulders of giants" externality. However, because the decline in innovation due to news is small relative to the overall stock of knowledge, the direct effect (ii) dominates (iii) and total R&D investment increases.

In contrast, while the decline in innovation due to news may not have a significant impact on overall R&D investment, it has a significant effect on the diffusion of new knowledge, which is the main focus of the new externality. As a result, when $\chi > 0$, the decline in knowledge diffusion caused by the news shock leads to a decrease in research productivity that is strong enough to offset the direct positive effect of higher idea value. This explains the observed decline in total R&D investment and lower innovation in the data.

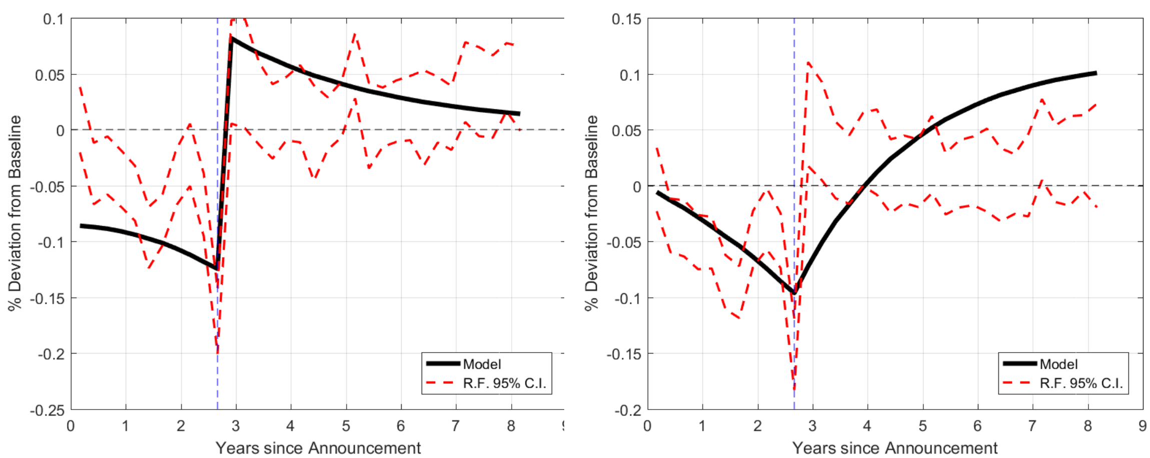
Figure 1.C.3: TRIPs effect without technology disclosure externality




(a) Patenting (b) R&D

The black solid lines represent the response of patenting and R&D effort to a 100-days patent term increase anticipated by 2 years and 8 months in the model of Section 1.6 with $\chi = 0$ and other parameters fixed to the values of Table 1.1. The red dashed lines represent the 95% confidence intervals implied by the reduced-form DiD estimates of Section 1.4. The economy is assumed to be at the steady state before the news shock.

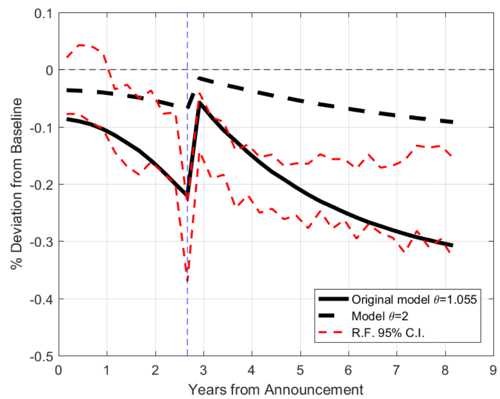
Figure 1.C.4: TRIPs effect without technology disclosure externality



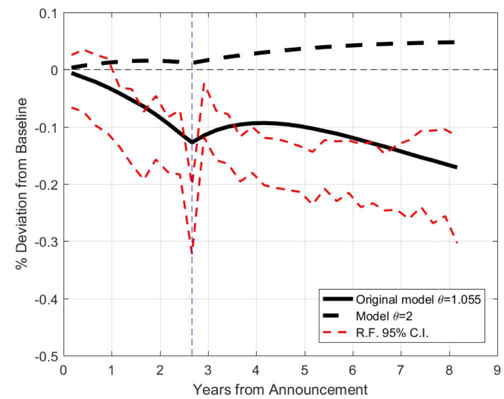

(a) Patenting (b) R&D

The black solid lines represent the response of patenting and R&D effort to a 100-days patent term increase anticipated by 2 years and 8 months in the model of Section 1.6 with $\chi = 0$ and other parameters fixed to the values of Table 1.1. The red dashed lines represent the 95% confidence intervals implied by the DiD estimates of the augmented Poisson model (1.39) controlling for lagged news effects. The economy is assumed to be at the steady state before the news shock.

Figure 1.C.5: Policy simulation in a model with $\theta = 1.055$ or $\theta = 2$ *vs.* empirical estimates




(a) Innovation (Patents)




(b) Patent-read R&D effort

The black solid line is the model-based responses of the model with parameter values reported in Table 1.1. The dashed line refers to $\theta = 2$. The red dashed lines are 95% confidence bands of the reduced form estimates of Section 1.4. The system is assumed to be at the pre-policy change steady state at $t = 0$, when the news of 100-days increase in protection time implemented after 2 years and 8 months (blue vertical line) happens.

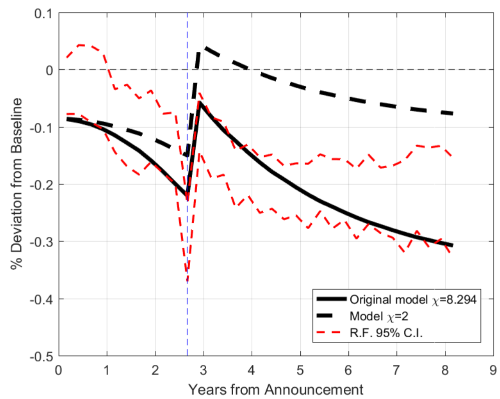
### 1.C.6 Identification of key structural parameters

In this subsection, I will discuss how variations in key model parameters affect the model-based responses of patenting and R&D to TRIPs, supporting the identification of key structural parameters.

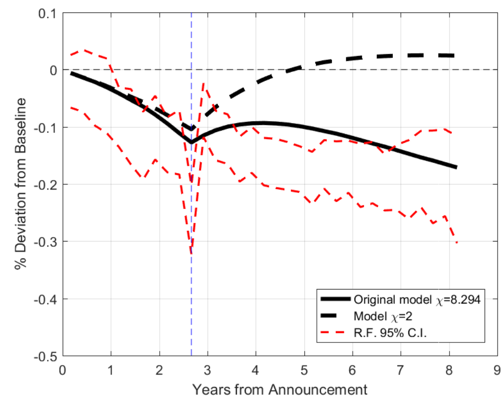
Figure 1.C.5 illustrates the response of innovation and patent-read R&D effort, in the model and in the data, while fixing $\theta$ at two different values: $\theta = 2$ or $\theta = 1.055$, which is the point estimate from Section 1.7. Increasing $\theta$ from 1.055 to 2 means moving from a mild to a severe cost convexity of the pace of development. As a result, the adjustment of the pace of development becomes much more costly for innovators. This leads to a much more subdued response of innovation and R&D to the news shock in the model. Therefore, the strong response of both variables observed in the data is informative about the mild cost convexity estimated in the model.

Figure 1.C.6 illustrates the response of innovation and patent-read R&D effort in the model and in the data, holding $\chi$ constant at two different values: $\chi = 8.2937$ and

Figure 1.C.6: Policy simulation in a model with $\chi = 8.2937$ or $\chi = 2$ *vs.* empirical estimates




(a) Innovation (Patents)




(b) Patent-read R&D effort

The black solid line is the model-based responses of the model with parameter values reported in Table 1.1. The dashed line refers to $\chi = 2$. The red dashed lines are 95% confidence bands of the reduced form estimates of Section 1.4. The system is assumed to be at the pre-policy change steady state at $t = 0$, when the news of 100-days increase in protection time implemented after 2 years and 8 months (blue vertical line) happens.

$\chi = 2$. By reducing $\chi$ from the estimated value in Table 1.1, we move from a strong technology disclosure externality to a milder one. This results in a weaker maximum decline in innovation and R&D in the model during the post-implementation period. Thus, the substantial response of both variables observed in the data provides valuable information about the strength of the spillover, which supports the estimation of a high $\chi$.

### 1.C.7 Multi-field model

In this subsection, I extend the model of Section 1.6 to a setting with $F = 621$ fields that differ in terms of (i) size and (ii) average pending period. The extended model allows me to exactly replicate the TRIPs policy change and infer model's structural parameters by replicating the DiD Poisson regression (1.3) on model-based simulated data. I start by presenting the model in Subsection 1.C.7.1. Next, Subsections 1.C.7.2 and 1.C.7.3 illustrate the policy experiment and the estimation results, which are remarkably close to those obtained using the simple one-field model of the paper.

#### 1.C.7.1 Model environment

Let $f$ index different fields. I assume that competitive production of the final good employs varieties $V_f(t)$ from each of the $f$ fields and labor $L(t)$ according to the production function

$$Y(t) = \Big(h(t)L(t)\Big)^{1-\alpha}\left[\sum_{f}^{F=621}\omega_f\int_0^{V_f(t)} X_f(i,t)^{\alpha}di\right] \tag{1.75}$$

where $h(t)$ is an exogenous productivity term, $i$ indexes capital varieties and $X_f(i,t)$ is the quantity of field-$f$'s variety $i$ used in production, and $\omega_f$ is the weight of field-$f$ technologies in the production of the final good. $\omega_f$'s directly map to the size of the field and will be calibrates to replicate the pre-TRIPs field size distribution.

Therefore, the final good profit maximization problem becomes

$$\max_{L(t),\{X(i,t)\}_i}\left\{\Big(h(t)L(t)\Big)^{1-\alpha}\left[\sum_{f}^{F=621}\omega_f\int_0^{V_f(t)} X_f(i,t)^{\alpha}di\right] - w(t)L(t) - \sum_{f}^{F=621}\int_0^{V_f(t)} z_f(i,t)X_f(i,t)di\right\}$$

where $z_f(i,t)$ is the price of field-$f$ variety $i$ at time $t$ and $w(t)$ is the wage rate. The optimal input choice of competitive final good producers generates an inverse demand for intermediate monopolistic varieties which patent owners take into account when maximizing profits as follows

$$\max_{X_f(i,t),z_f(i,t)}\Big\{z_f(i,t)X_f(i,t) - (r(t)+\delta)X_f(i,t)\Big\}$$
$$\text{s.t.}\qquad z_f(i,t) = \omega_f \alpha h(t)^{1-\alpha}L(t)^{1-\alpha}X_f^{\alpha-1}(i,t)$$

As in the one-field model, this problem determines non-negative per-variety profits $\pi_f(t) > 0$, which are in this setting field-specific due to the heterogeneous weights $\omega_f$. In contrast, competition drives the price of varieties not protected by patents to the marginal cost of production, i.e., $z_f(i,t) = r(t) + \delta$, and profits to zero.

Equilibrium $\pi_f(t)$ determine the value of patented technologies in field $f$. In the extended model, I assume that (i) profits cannot be collected during the pending period, consistently with the discussion of Section 1.2.1, and (ii) the pending period differs across fields. Therefore, the pre-TRIPs value of a field-$f$ patent whose application is filed at time $t$ is

$$\upsilon_f^{pre}(t) = \int_{t+W_f^h}^{t+W_f^h+17} \pi_f(t) e^{-\int_t^s (r(t')+\lambda_f(t'))dt'} ds \tag{1.76}$$

and the post-TRIPs patent value is

$$\upsilon_f^{post}(t) = \int_{t+W_f^h}^{t+20} \pi_f(t) e^{-\int_t^s (r(t')+\lambda_f(t'))dt'} ds \tag{1.77}$$

Field-specific values of undeveloped ideas $P_f(t)$ and R&D activity are a simple specialization of their one-field counterparts. Therefore, in field $f$ the research problem is

$$\max_{I_{R,f}(t)} \quad \left\{ P_f(t) \Big[ E_f(t)^{\chi} V_f(t)^{\phi_1} I_{R,f}(t)^{\phi_2} \Big] - I_{R,f}(t) \right\}$$

and the development problem is

$$r(t)P_f(t) - \dot{P}_f(t) = \max_{\iota_{D,f}(t)} \left\{ \iota_{D,f}(t) \Big[ \upsilon_f(t) - P_f(t) \Big] - \mu \iota_{D,f}(t)^{\theta} \upsilon_f(t) \right\}$$

The evolution of field-specific state variables $N_f(t)$, $V_f(t)$, $\zeta_f(t)$, and others is analogous to the main model.

#### 1.C.7.2 Calibration of additional parameters and policy simulation

I calibrate weights $\omega_f$ to match the relative size of the flow of patents $\iota_f(t)N_f(t)$ in different fields. In particular, $\iota_f(t)$ is symmetric across fields in the balanced growth path and the ratio of patent flows is equivalent to the ratio of projects stocks $N_f(t)$, which is proportional to the ratio of $\omega_f$ weights. Therefore, I fix $\omega_{f=1} = 1$ and I calibrate $\omega_f = \frac{Pat_{f,1992Q3}}{Pat_{1,1992Q3}}$, where the terms of the ratio are the number of patents in field $f$ and field 1 in 1992Q3.

Moreover, I calibrate the field-specific pending period $W_f$ as the average pre-TRIPs pending period used in the empirical part of the paper to construct the change in patent term $\Delta T_j$.

I simulate in the model the TRIPs-induced patent term change by assuming an anticipated change of field-specific patent term $T_f$ from 17 years for all fields to 20 years minus the field-specific pending period $W_f$. I solve the transition of the model to the new balanced growth path equilibrium following the shock and I aggregate the series for field-specific patenting $\iota_{D,f}(t)N_f(t)$ and patent-based R&D is

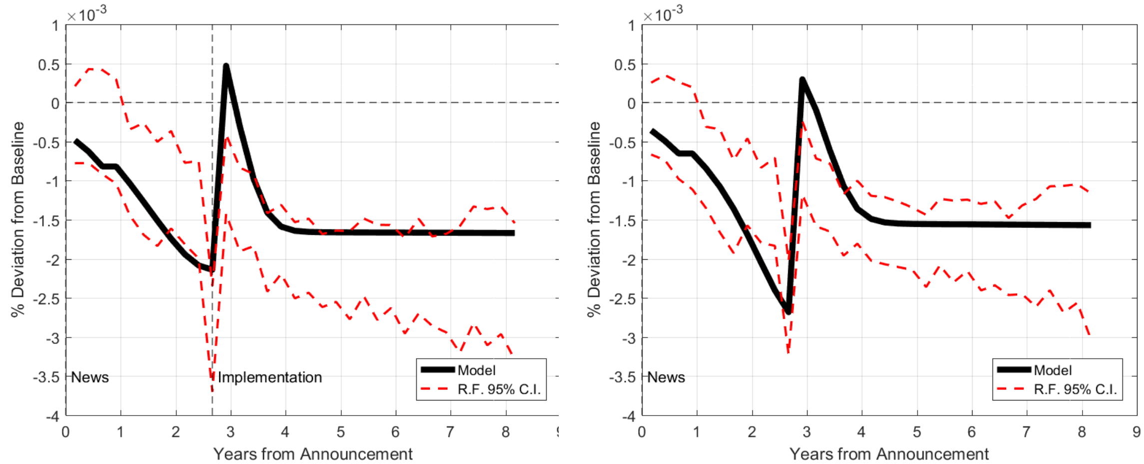
$$R\&D_f(t) = \int_{-\infty}^{t} \left( I_{R,f}(\tau)/n_f(\tau,\tau) + \int_{\tau}^{t} \mu \iota_{D,f}(s)^{\theta} \upsilon_f(s) ds \right) \Big[ \iota_{D,f}(t) n_f(t,\tau) \Big] d\tau \quad (1.78)$$

at quarterly frequency. In expression (1.78), $n_f(\tau,\tau)$ defines the measure of new field-$f$ ideas discovered at time $\tau$ and $n_f(t,\tau)$ the measure of these field-$f$ ideas created at time $\tau$ that have survived undeveloped until time $t$.

#### 1.C.7.3 Estimation and results

In this section, I replicate the calibration strategy from Section 1.7 of the paper. Specifically, I set $\rho = 0.04$, $n = 0.011$, and calibrate the growth rate of exogenous productivity $h(t)$ to match a 2% per capital output growth in the balanced growth path. Moreover, I set the delay $d$ of the externality term to 8 years to match the 4-year half-life observed in the data. The remaining parameters $(\alpha, \delta, \phi_1, \phi_2, \chi, \theta, \mu, \psi)$ are estimated using GMM to match the Poisson DiD estimates of specification (1.3) and restrictions on R&D-output, consumption-output, and capital-output ratios along the balanced growth path. To estimate (1.3), I use the quarterly aggregations of the model-implied responses of patenting and patent-based R&D to the TRIPs shock as dependent variables, and I search for the vector of parameters that yields DiD

Figure 1.C.7: Model-based vs empirical DiD estimates




(a) New patents (b) R&D Investment

The black solid lines represent the model-based DiD estimates of the effect of the TRIPs on patenting (left panel) and R&D effort (right panel). The red dashed lines represent 95% confidence bands of the reduced form DiD estimates of specification (1.3). Model parameters are reported in Table 1.1. I assume that the system is on the pre-policy change balanced growth path at $t = 0$ and that the anticipation period is 2 years and 8 months (blue vertical line).

coefficients based on the model that are as close as possible to those of Figure 1.2b.

Figure 1.C.7 presents the multi-sector model's performance relative to the data. The solid line in the left (right) panel of the figure shows the DiD point-estimates for patenting (R&D) based on the model's simulated response to the TRIPs shock. The red dashed lines in both panels report the 95% confidence bands of the original DiD empirical estimates from Figure 1.2b. The model replicates the empirical evidence very closely.

In the multi-field model, the point estimates of the structural parameters are presented in Table 1.C.1, and are found to be very similar to those obtained for the one-field model framework. The main difference is that the cost of a faster speed of development is almost linear in $\iota_{D,f}$, and the marginal cost $\mu$ is larger. Despite this, the insights from the estimated one-field model remain unchanged.

Table 1.C.1: Estimated and Calibrated Structural Parameters

| Symbol | Value | Parameter | Target/Source |
|---|---|---|---|
| *A: Calibration* | | | |
| $\rho$ | 0.04 | Discount rate | |
| $g_h$ | 0.0083 | Exog. Prod, Growth | 2% p.c. Output Growth |
| $n$ | 0.011 | Population Growth | World Bank |
| *B: Estimation* | | | |
| $\alpha$ | 0.5089 | Capital share | |
| $\delta$ | 0.0745 | Capital Depreciation | |
| $\phi_1$ | 0.6755 | Research $V$-Curvature | |
| $\phi_2$ | 0.1227 | Research $I_R$-Curvature | |
| $\chi$ | 8.2937 | Spillover Exponent | |
| $\theta$ | 1.0001 | Dev.'t Curvature | |
| $\mu$ | 0.9828 | Dev.'t M. Cost | |
| $\psi$ | 0.0001 | Endog. Creative Destruction | |

The table reports the calibrated parameters ($\rho$, $n$, and $g_h$) and the structural estimates for the other parameters, obtained by GMM targeting (i) the reduced form DiD estimates of granted patents and R&D effort of specification (1.3) and (ii) three restrictions on balanced growth path rations: a capital-output ratio of 3, a consumption-output ratio of 0.65, and a private R&D investment-output ratio of 0.017. Appendix subsection 1.C.7.3 reports additional details on estimation.

### 1.C.8 Patenting vs trade secrecy in the model

In Section 1.4, it was discussed that the TRIPs-induced change in patent term may have affected both innovation incentives and patenting incentives, given any level of innovative effort. While a significant proportion of innovations are kept as trade secrets and not patented, it is challenging to measure their relevance in the data and estimate their response to the TRIPs. However, in the empirical analysis, it was argued that some of the observed impact of the TRIPs on patenting is associated with actual changes in innovation, as firm-level R&D expenditures and sectoral productivity measures respond consistently with variations in patenting. In this Appendix, a simple extension of the model is proposed that considers trade secrecy and an explicit patenting decision. The aim of this exercise is to illustrate the potential mechanisms at play.[63]

Consider the trade-off faced by innovators when deciding whether or not to patent their technology. On one hand, patenting provides protection against any form of imitation for the duration of the patent term, which lasts for a specified number of

[63] While estimation of the extended version of the model would allow a quantification of the innovation vs. patenting responses to the TRIPs, this is beyond the scope the present application.

years, denoted as $T$. However, the technical details of the invention are disclosed in the patent documents, allowing competitors to perfectly imitate the technology as soon as the patent expires. On the other hand, choosing trade secrecy entails a non-zero probability of being imitated, but allows the innovator to potentially extend their monopoly indefinitely, as they do not have to disclose the details of the invention through patent documents. The two choices can be represented by the values

$$\upsilon(t) = \int_t^{t+T} e^{-\int_t^s (r(t')+\lambda(t'))dt'} \pi(s)ds \tag{1.79}$$

and

$$secret(t) = \int_t^{\infty} e^{-\int_t^s (r(t')+\lambda(t')+\xi)dt'} \pi(s)ds \tag{1.80}$$

Equation (1.79) derived in Subsection 1.6.2 of the paper gives the value of a patent, while equation (1.80) provides the value of a trade secret at time-$t$. Notably, there are two key differences between these equations. First, the upper limit of the integral in (1.79) is $t+T$, where $T$ is the finite patent term, while in (1.80), the upper limit is unbounded, but future profits are discounted by a factor of $\xi > 0$. This discount accounts for the positive probability of imitation faced by innovators who choose trade secrecy, whereas with patenting, the imitation probability is zero.

Considering for simplicity (1.79) and (1.80) along the balanced growth path, we can rewrite the two values as

$$\tilde{\upsilon} = \left[1 - e^{-(\rho+\psi g_V+g_\pi)T}\right] \frac{e^{-g_\pi t}\tilde{\pi}}{\rho + \psi g_V + g_\pi}$$

and

$$\tilde{secret} = \frac{e^{-g_\pi t}\tilde{\pi}}{\rho + \psi g_V + g_\pi + \xi}$$

where $\tilde{\pi}$ is the flow of profits in the balanced growth path detrended by is growth rate $g_\pi$, $g_V$ is the growth rate of varieties, and $\rho$ is the discount rate. Therefore, patenting is preferable to trade secrecy if the the patent term is long enough, i.e.,

$$T > -\frac{\ln\left(1 - \frac{\psi g_V + \rho + g_\pi}{\psi g_V + \rho + g_\pi + \xi}\right)}{\psi g_V + \rho + g\pi} \tag{1.81}$$

In the case of homogeneous innovations, patenting decisions are symmetric. However, if the imitation rate $\xi$ varies across inventions while the patent term $T$ remains constant, only innovations with a sufficiently high imitation risk would be patented. Thus, absent any changes to the imitation probability, a patent term extension would increase the share of patented inventions.

To understand the extent to which observed changes in patenting are due to genuine changes in innovation as opposed to patenting decisions, we can examine the relative magnitudes of the responses of patenting and R&D effort to a change in patent term. In this simple setup, we can calculate that approximately two-thirds of the estimated effect of patenting corresponds to genuine changes in innovation, based on the estimated effect of policy news on firm-level R&D expenditures and patenting. Pre-implementation DiD coefficients suggest that news of a 1-day increase in future patent term generates a 0.05% decline in R&D and a 0.075% decline in the number of patents, which are in a ratio of 2/3.

# Appendix 1.D Variables construction

## 1.D.1 Number of granted patents by field

Using PATSTAT table `tls201`, which contains information on patent applications, I select "patent of invention" applications for which the reported application authority is the USPTO, and for which the application filing date is the same as the priority date, i.e. the earliest filing date in PATSTAT. This is because, in the main analysis, I want to focus on innovations that primarily refer to the US, excluding technologies that are developed and protected elsewhere at first, and subsequently try to obtain protection in the US too. In addition, I just keep applications tha are subsequently granted. Then, using PATSTAT table `tls209`, I attach to each patent application information on the IPC classes associated to the invention, and I truncate the IPC codes to the 4-digit level. A patent to which multiple 4-digit IPC codes are associated is counted once for each of them in my dataset. Finally, in order to compute the quarterly measure, I build synthetic quarterly dates that better fit the timing of the TRIPs implementation. In particular, since the TRIPs was formally adopted in the US system on December 8, 1994, and the new patent law entered into force on June 8, 1995, I define quarters starting from the eighth day of the month. Hence, for example, 1995Q1 starts on January 8, 1995 and ends on March 7, 1995. A patent is counted in quarter $t$ if its priority date falls in that quarter. Finally, the variable $Pat_{j,t}$ is the total count of granted patent applications satisfying the conditions outlined above, i.e. patents classified in IPC class $j$, and whose priority date falls in quarter $t$.

## 1.D.2 Number of citations-weighted granted patents by field

Citations-weighted patent counts are usually employed to weigh patents by their scientific quality, as measured by their relevance for subsequent technological developments. In order to build this measure, I follow the same steps described in subsection

1.D.1, and I stop before the IPC-quarterly aggregation step. I assign to the selected patent applications the associated patent publications using PATSTAT table `tls211`, which contains publication information. PATSTAT table `tls212`, instead, reports for each publication the list of applications and publications that cite it. I use information in `tls212` to assign to each patent application the publications or applications that cite publications associated with it. I select as a citation date the publishing date of the citing publication, and I just keep citations that occur within 5 years from the application date. This is done to avoid truncation bias in the citation-weighted patent measure. In a robustness check, not reported, I keep citations that occur within 3 years from the application date, and results are fully robust. Finally, I count for each patent application the number of forward citations received, and I build the citation-weighted patent measure by summing this citations count by IPC and quarter of priority date of the focal patent application.

### 1.D.3 Pending period and treatment by field

In order to build this measure, I follow the same steps described in subsection 1.D.1, and I stop before the IPC-quarterly aggregation step. When I build the treatment variable, I restrict the sample to patents whose priority date is between January 1, 1990 and May 31, 1992, in order to focus on a time-window close enough to the news of the policy change, but also unaffected by it. For this sample of patents, I compute the pending period by counting the number of days between the grant date, i.e. the publication date of the official document granting the patent, and the priority date reported in PATSTAT, which, given my sample restriction, coincides with the application date. I compute an average of such patent-level pending time at the IPC level, and I subtract it to 1095, which is 3 years in number of days. Therefore, the treatment variable is negative if the average pending period computed for applications filed between 1/1/1990 and 5/31/1992 is longer than 3 years, and positive otherwise.

When I build the quarterly version of the pending period underlying Figure 1.B.11, I still compute the patent-specific pending time in the same way described above, and I compute its average at the IPC×quarter level, with quarters defined as in subsection 1.D.1. Finally, as a measure of treatment precision that I use to conduct a triple difference analysis, I compute the standard deviation of the average pending period by technical field.

### 1.D.4 Patent renewal rate by field

To build the patent renewal rate, I use information on legal events related to patents reported in the PATSTAT LEGAL section of PATSTAT and, specifically, in table `tls803`. This dataset reports, for each US granted patent application, whether maintenance fees at 3.5 years, 7.5 years, and 11.5 years since patent grant have been paid in order to maintain the patent active. Therefore, for each patent selected according to the criteria explained in subsection 1.D.1, I can compute whether or not the maintenance fees at 11.5 years since grant have been paid. This indicates whether, for the specific patent, the maximum patent term was binding or not. In order to compute the IPC-specific pre-policy change measure of incidence of the maximum patent term, I focus again only on patents whose priority date is between January 1, 1990 and May 31, 1992, and I average out at the 4-digit IPC level the indicator variable that takes value 1 if the 11.5 years maintenance fees have been paid for a patent and 0 otherwise. The resulting IPC-specific measure is the ratio of patents classified in the IPC for which the maximum patent term was binding.

### 1.D.5 Unique number of inventors by field

PATSTAT table `tls207` associates to each application a list of personal id's that correspond to the inventors and to the applicants listed on the patent. Table `tls206`, instead, reports, for each of these personal id's, details such as the full name listed on the patent, the address of the inventor or the applicant, and other information. Since these personal id's assigned by PATSTAT do not uniquely identify a person or a firm, a substantial harmonization effort has been done by the EPO, the OECD, and other researchers. Among the harmonized id's available in table `tls206`, I chose the STAN harmonized applicant's identifiers developed starting from the EPO Worldwide Bibliographic Database. Hence, combining `tls207` and `tls206` with patent application information as selected in subsection 1.D.1, I can assign to each patent the unique (up to harmonization errors) identifiers of the inventors listed on the patent. In order to build the quarterly measure of unique inventors working in a given IPC, I simply count the number of id's that are associated to a patent classified in the IPC and with priority date in the quarter, dropping from this count multiple records of the same inventor in multiple patents in the same IPC-quarter.

### 1.D.6 Entry rate by field

In order to compute the number of new applicants and measures associated to this concept, I follow a similar approach as the one just described in subsection 1.D.5, and I attach to each patent application selected according to the rules of subsection 1.D.1 the harmonized identifiers of the applicants associated to the patent according to table `tls207`. To determine whether an applicant is a new or an incumbent one, for each quarter and IPC I build a list of applicant's ids that have already appeared at least once in the specific IPC and, for each applicant, I check whether the id belongs to this list or not. If the id does not belong to the list, the applicant is assigned a flag of 1 as a new entrant for that IPC-quarter pair. The unique number of new applicants is computed by counting the unique number of ids for which the flag is 1 by IPC and quarterly priority date of the application. Similarly, the number of granted patents attributable to new applicants is computed by assigning a value of 1 to a dummy variable in case at least one of the applicants is an entrant, and 0 otherwise. Then, the number of patents with such dummy equal to 1 is counter by IPC and quarter. Finally, the share of patents attributable to new applicants is simply computed by dividing the absolute figure just described by the total number of patents filed in the corresponding IPC-quarter.

### 1.D.7 Herfindahl-Hirschman Index of concentration by field

In order to compute the HHI by technological field, I follow a similar approach as in subsection 1.D.5, and I attach to each patent application, selected according to the rules of subsection 1.D.1, the harmonized identifiers of the applicants associated to the patent, taken from table `tls207`. Then, I compute the total number of patents (or citations-weighted patents) made by a specific applicant in a given technical field and quarter, and the total number of patents (or citations-weighted patents) generated in the same technical field and quarter by any applicant. Let $s_{i,j,t}$ be the share of patents made by applicant $i$ over the total number of patents in field $j$ and quarter $t$. Then, the concentration index is

$$HHI_{j,t} = \sum_i s_{i,j,t}^2 100^2$$

### 1.D.8 Within-field backward citations by field

To compute the number of backward citations by field and quarter, I start from the pool of patents selected according to the criteria of Subsection 1.D.1, and I follow Subsection 1.D.2 to relate, to each patent application, the associated publications and the citations information of table `tls212`. However, in this case, rather than keeping the list of citing publications, I keep the list of documents that each application (or publications associated to each application) cite. Also, I separately keep track of citations directly made by the applicant (`citn_origin`='APP') rather than added by examiners or during search. This distinction may be important because previous literature has pointed out that only backward citations made by applicants are representative of genuine knowledge flows. Therefore, for each patent, I compute the overall number of patent documents backward cited (overall and by applicants only), *and* the number of backward-cited patents (overall and by applicants only) that are classified in the same field of the patent considered. I aggregate both variables by field and quarterly priority date of the citing patent application. The aggregation of the latter variable is called in the main text within-field backward citations. The intensity measures are computed either as the average number of citations per patent or as the fraction of patents where the applicant makes at least one backward citation directed to another patent in the same field over the number of patents having at least one backward citation.

To compute the number and the intensity of within-field backward citations made by patents filed during the post-implementation period July 1995 - July 2000 and directed to patents filed during the pre-implementation period November 1992 - June 1995, I repeat the same steps described above, but I restrict my attention to patents satisfying previous timing criteria. Obviously, the steps are the same for the control group of patents filed during July 1985 - July 1990 and backward citing other patents classified in the same technical field and filed during the period November 1982 - June 1985.

### 1.D.9 Private economic value of innovation by field

To compute a measure of economic value of patents by technical field and quarter, I start from the data provided in the replication package of Kogan et al. (2017). The variables relevant for the present analysis are: *i*) the 7-digit US patent number, *ii*) the private economic value of a patent $\xi$, and *iii*) the application date of the patent. Using the 7-digit US patent number, I merge the dataset with the NBER patent database and, specifically, with the dataset which contains information on International Patent

Classification classes assigned to the patent. Then, using the original application filing date and the IPC classes from the NBER database, I add up the economic value of patents by quarterly application date and technical field.

### 1.D.10 Firm-level number of patents and citations

For the firm-level dataset, I rely on the NBER Patent Database merged with COMPUSTAT using the applicant-`gvey` cross-walk provided in the NBER Database itself. In particular, the NBER Database provides a list of `gvey` identifiers associated to each patent over its life. Multiple `gvey`'s over time indicate that the ownership of the patent has changed. However, here I am just interested in the firm which has originated the invention through its R&D effort, and this is why I just keep the `gvey` associated to the patent in the year of application. Then, I download from COMPUSTAT firm-level information, and I match this dataset with the `gvey`'s retrieved from the NBER Database. I build the patent count and the citations-weighted patent variable by summing for each `gvey` and year the number of patents applied for by the firm and the truncation-adjusted citations variable available in the database, respectively. Truncation adjustment is performed in the original dataset by applying to citations the weights proposed by Hall, Jaffe and Trajtenberg (2001).

### 1.D.11 Firm-level R&D expenditure

Data on firm-level R&D expenditure is downloaded from COMPUSTAT and merged with information on patents using the `gvey` link. The name of the original R&D expenditure variable in COMPUSTAT is `xrd`.

### 1.D.12 Firm-level change in patent term

In order to build the treatment at the firm level, I start from the patent-level dataset of the NBER Database, which reports also information on the 4-digit IPC classes associated to the patents. Then, for each `gvey` identifier, I just keep those patents with application year between 1971 and 1991, in order to have enough patenting-related information for each firm and to exclude possible effects of the policy news. Then, for each firm, I compute the share of the total number of patents, filed during this period, that is classified in each of the 4-digit IPC. Let's call it $s_{i,j}$, where $i$ indexes firms and $j$ IPCs. I interpret this fraction as the exposure of firm $i$ to the technical field $j$ before the policy news. The firm-level treatment is then built as a weighted average of the field-specific treatment described in subsection 1.D.3, i.e.

$$\Delta T_i = \sum_j s_{i,j} \Delta T_j$$

I take this approach because the main source of ex-ante heterogeneity in pending period is linked to the different technical fields and, relatedly, to the different technical offices and examination difficulties. Therefore, I still want to use field-level heterogeneity, interacting it with heterogeneity in the technological location of firms. An alternative would be to compute the firm-level treatment by computing the average pending period of patents filed by firm $i$, i.e. a pending period based on the specific experience of the firm. I do not follow this route because I think this treatment variable would be more prone to endogeneity concerns that the one I propose: In this case, the treatment might be correlated with the quality of innovation performed by the firm, or with the responsiveness of the firm to the inquiries of the patent office.

### 1.D.13 Other COMPUSTAT variables

I compute firm age using the `begyr` NBER patent database variable, and I use 2-digit SIC industry code assigned to each firm in the database. Firm's yearly sales are taken from COMPUSTAT using the variable `sales`.

### 1.D.14 Firm-level aggregate investment externality

To compute the firm-level externality measure used in Section 1.5 of the paper, I try to follow what has been done in the literature on the topic. Therefore I compute, for the period 1971-1991, the total number of patents obtained by each of the firms in my sample in any 4-digit IPC. This information is included in firm-specific vector $f_i$, which stacks, in each entry, the number of patents obtained by firm $i$ in IPC $j$ in the above-mentioned period. Then, based on these vectors, I compute for every pair of firms $(i, k)$ a technological distance measure proposed by Jaffe (1986)

$$d_{i,k} = \frac{f_i f_k'}{\sqrt{(f_i f_i')(f_k f_k')}}$$

The externality measure for firm $i$ at time $t$ is then

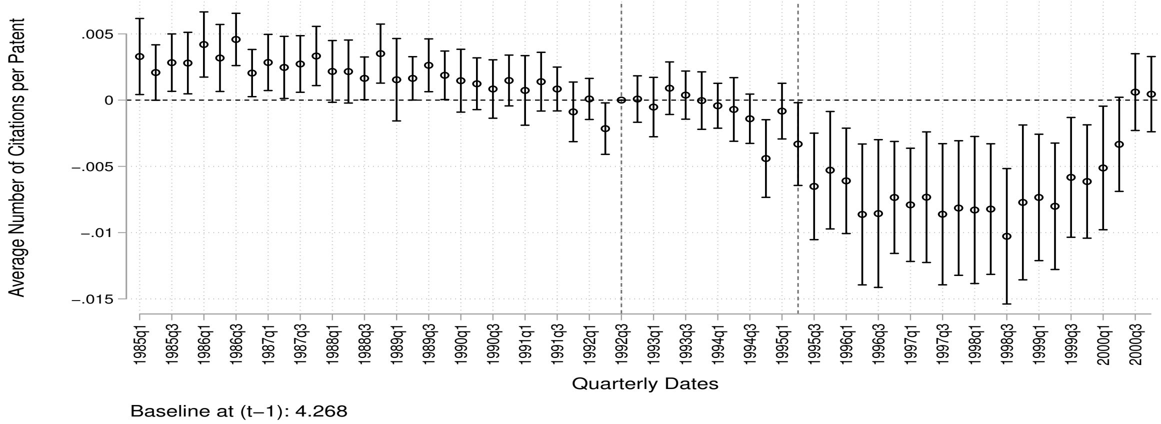
$$E_{i,t} = \sum_{k \neq i} d_{i,k} R\&D_{k,t}$$

i.e. it is an aggregation of the firm-level R&D expenditure of other firms that uses as aggregation weights the Jaffe (1986) measure of technological distance across firms. The idea underlying such externality variable is that the influence of other firms' R&D is stronger if such firms are technologically closer to the firm of interest.

### 1.D.15 Sectoral productivity and welfare

The productivity and price variables used in the sectoral welfare analysis are directly taken from the NBER CES manufacturing database. Productivity is measured as 5-factors TFP, whose constructions is detailed in the technical paper Bartelsman and Gray (1996). Welfare is (inversely) measured by the value of shipments price deflator, which is built aggregating product-specific deflators computed by the Bureau of Economic Analysis.

Figure 1.E.1: Marginal effect of 1 more day of protection on average citations




The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable the average number of forward citations obtained by patents filed in quarter-$t$ and field-$j$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

# Appendix 1.E Additional empirical results

## 1.E.1 Results at the technical field level

### 1.E.1.1 Average number of citations per patent

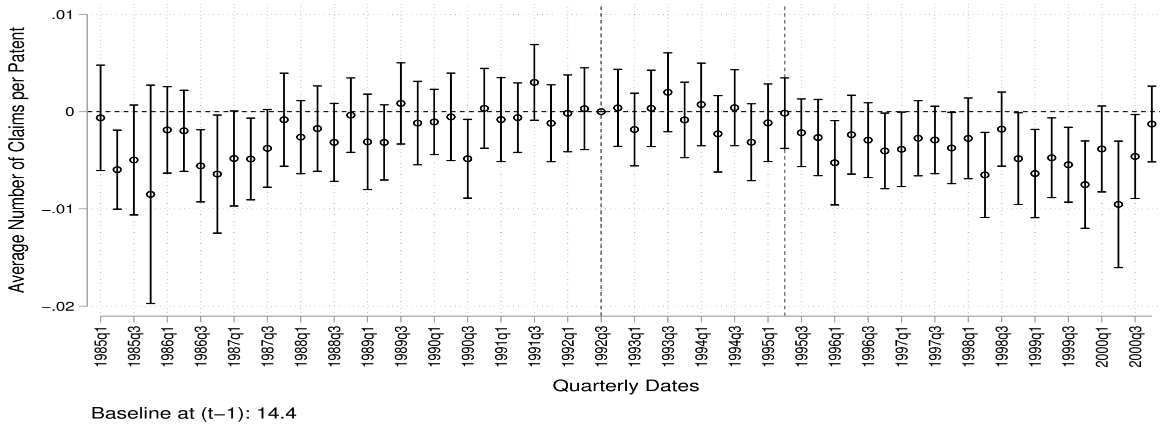
Figure 1.E.1 plots the $\beta_k$ coefficients of regression (1.2) having as dependent variable the *average* number of forward citations per patent, for patents filed in quarter-$t$ and classified in field-$j$.[64] Fields with zero patents in at least one quarter are excluded from the estimation sample because the average number of citations is not well-defined in such cases. Results are analogous, however, when just excluding the field-quarter observation which is not well-defined.

### 1.E.1.2 Average number of claims per patent

Figure 1.E.2 plots the $\beta_k$ coefficients of regression (1.2) having as dependent variable the *average* number of claims per patent, for patents filed in quarter-$t$ and classified

[64] I count citations obtained within 5 years from application, to avoid truncation bias.

Figure 1.E.2: Marginal effect of 1 more day of protection on average number of claims




The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable the average number of claims made by patents filed in quarter-$t$ and field-$j$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

in field-$j$. Fields with zero patents in at least one quarter are excluded from the estimation sample because the average number of claims is not well-defined in such cases. Results are analogous, however, when just excluding the field-quarter observation which is not well-defined.

### 1.E.1.3 Average originality and average generality

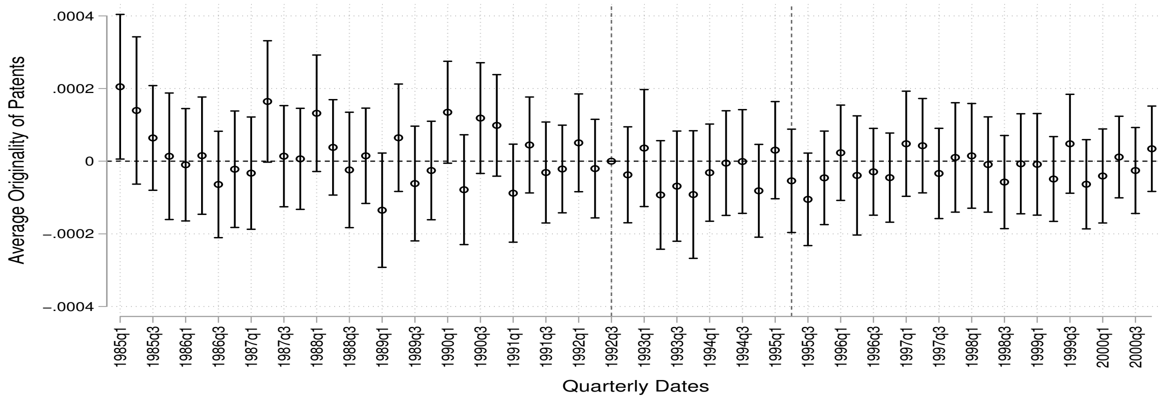
Figure 1.E.3 plots the $\beta_k$ coefficients of regression (1.2) having as dependent variable the *average* originality of patents filed in quarter-$t$ and classified in field-$j$. The originality index of each patent $i$ is taken from the NBER patent database and it is computed as

$$O_i = 1 - \sum_{j=1}^{n} s_{i,j}^2$$

where $s_{i,j}$ denotes the percentage of citations made by patent $i$ that belong to patent class $j$, out of $n$ patent classes. The results show that the policy does not affect the average originality of patents, which is often taken as a proxy of patent quality.

Figure 1.E.4 plots the $\beta_k$ coefficients of regression (1.2) having as dependent vari-

Figure 1.E.3: Marginal effect of 1 more day of protection on average originality




The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable the average originality of patents filed in quarter-$t$ and field-$j$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

able the *average* generality of patents filed in quarter-$t$ and classified in field-$j$. The generality index of each patent $i$ is taken from the NBER patent database and it is computed as

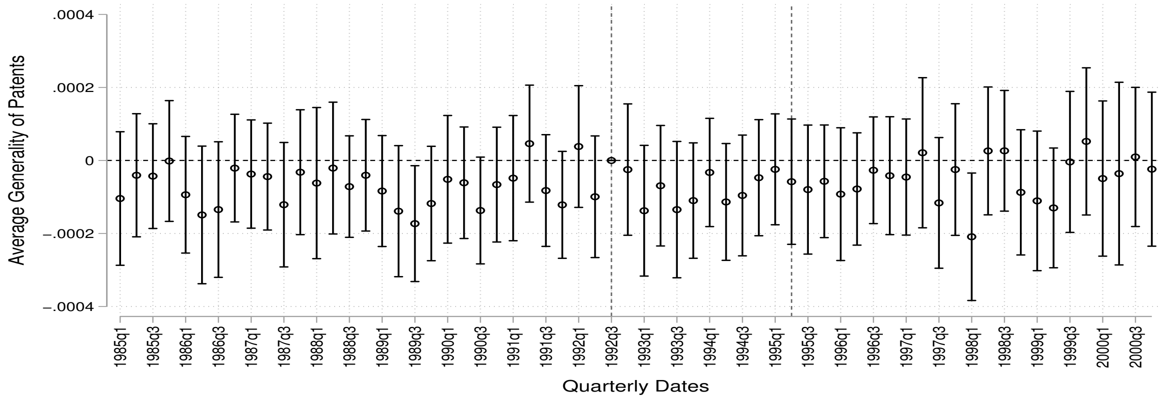
$$G_i = 1 - \sum_{j=1}^{n} s_{i,j}^2$$

where $s_{i,j}$ denotes the percentage of citations received by patent $i$ that belong to patent class $j$, out of $n$ patent classes. The results show that the policy does not affect the average generality of patents, which is often taken as a proxy of patent quality.

#### 1.E.1.4 Maintenance fee payment probability

In order to keep patent protection active, patent owners must pay fees after 3.5 years, 7.5 years, and 11.5 years from the grant. The payment of renewal fees is commonly linked to the quality of patents–i.e., higher quality patents are renewed for longer– and to the rate of creative destruction. If a technology is competed away by a new invention, it is pointless to pay fees to keep alive the patent on an old technology

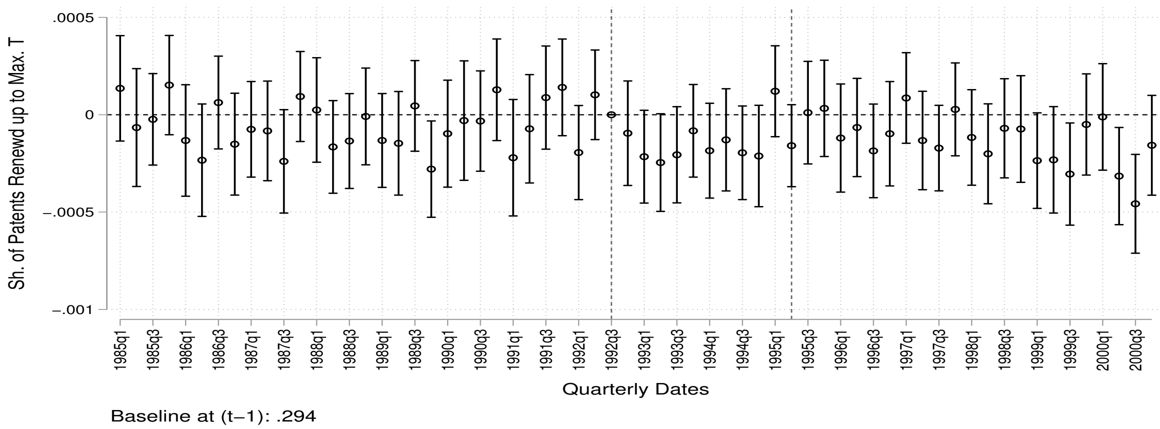
Figure 1.E.4: Marginal effect of 1 more day of protection on average generality




The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable the average generality of patents filed in quarter-$t$ and field-$j$. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

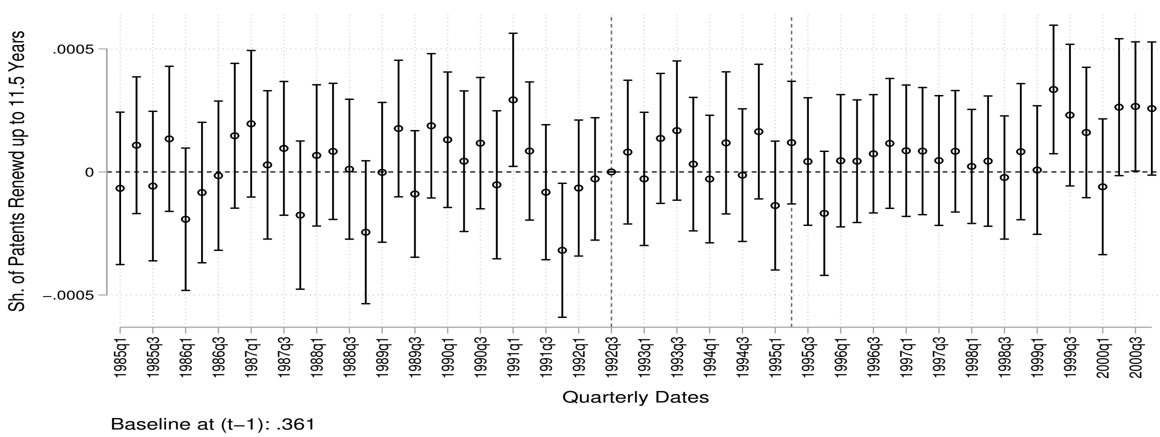
that will not generate profits. In this subsection I examine whether a patent term extension has any effects on the average renewal rate of patents at later stages of their maintenance. Figure 1.E.5 plots the $\beta_k$ coefficients of regression (1.2) having as dependent variable the share of patents filed in quarter-$t$ and classified in field-$j$ that are renewed up to the maximum patent term. The results show that a patent term extension does not induce innovators to renew their patents for longer. Since other analyses showed that the average quality of patents was not changing due to the policy, I interpret this finding as suggestive of the fact that the pressure of creative destruction does not fall in fields getting a patent term extension. Figure 1.E.6 shows that results are analogous when using as the outcome variable the share of patents filed in quarter-$t$ and classified in field-$j$ that are renewed until 11.5 years since the grant.

Figure 1.E.5: Effect of 1-day longer patent term on average patent renewal rate



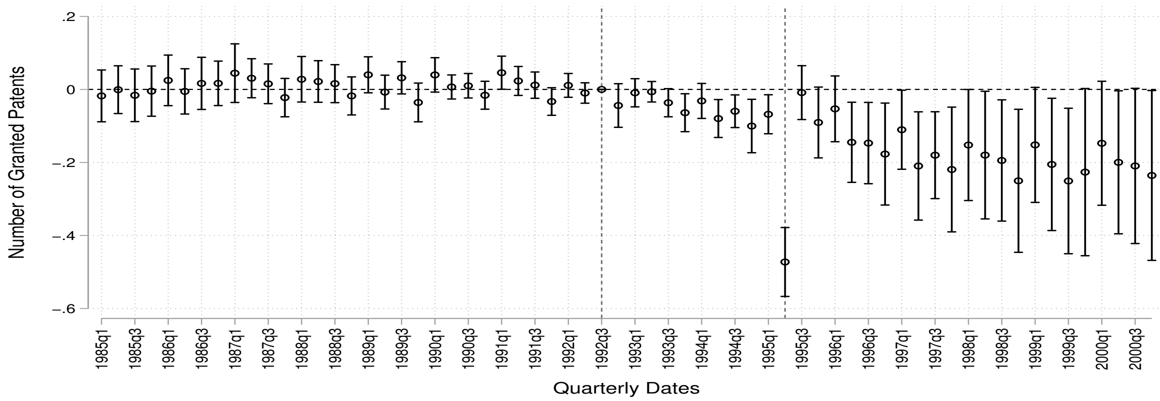

The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable the share of patents filed in quarter-$t$ and classified in field-$j$ that are renewed up to the maximum patent term. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.E.6: Effect of 1-day longer patent term on average patent renewal rate




The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable the share of patents filed in quarter-$t$ and classified in field-$j$ that are renewed up to 11.5 years since the grant. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

Figure 1.E.7: Effect of 1-day longer patent term on granted patents



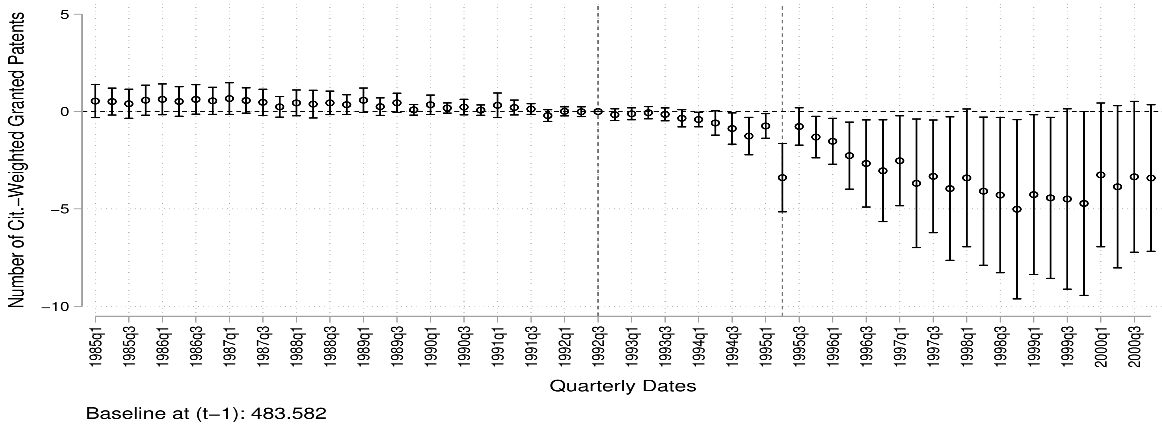

The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable granted patents in quarter-$t$ and field-$j$. The sample is restricted to technical fields that, in all quarters, have not less than 25 patents and not more than 500. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

### 1.E.1.5 Alternative sample restrictions

A potential concern with the empirical results of Section 1.4 is the strong skewness of the distribution of patenting outcomes across fields. In this subsection, I verify that very large or very small fields do not influence the empirical evidence by showing how the DiD $\beta_k$ coefficients of specification (1.2) vary when the sample is restricted to technical fields that, in all quarters, have not less than 25 patents and not more than 500.[65] Figures 1.E.7 and 1.E.8 show for granted patents and citations-weighted patents, respectively, that the results are identical to those obtained on the full sample.

[65] For sake of clarity, these figures refer to the number of applications that are subsequently granted. As in the other parts of the paper, the count of patents is done based on the quarter when the applications is filed, irrespective of the subsequent grant quarter.

Figure 1.E.8: Effect of 1-day longer patent term on citations-weighted patents




The plot shows the $\beta_k$ coefficients of the specification (1.2) having as dependent variable citations-weighted granted patents in quarter-$t$ and field-$j$. The sample is restricted to technical fields that, in all quarters, have not less than 25 patents and not more than 500. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by technical field and 95% confidence bands are plotted. The first vertical line refers to the quarter before the policy news (1992Q3) and the second vertical line refers to the quarter before the policy implementation (1995Q2).

## 1.E.2 Results at the sector-level

### 1.E.2.1 Evidence on innovation outcomes

In this subsection I provide evidence on the effect of the policy on innovation outcomes, as measured by patents, citations-weighted patents, and patent value, at the NAICS 6-digit industry level.[66] This layer of analysis requires aggregation of innovation measures by industry, and the adaptation of the technical-field level treatment variable, i.e. the policy-induced change in patent protection time, at the industry-level.

To build measures of innovation by 6-digit NAICS and year, I start from measures of innovation, i.e. number of granted patents, number of citations-weighted patents, and private economic value of patents, by technical field and quarter. The first step is to aggregate previous innovation measures at the yearly level. The second step involves

[66] An example of the depth of the sectoral classification I use in the analysis is the following. *31-33* is the aggregate 2-digit classification for *Manufacturing*; *324* is the 3-digit *Petroleum and Coal Products Manufacturing*, *3241* is the 4-digit *Petroleum and Coal Products Manufacturing*; which includes the 5-digit *32412 Asphalt Paving, Roofing, and Saturated Materials Manufacturing*, which includes the 6-digit sectors 324121 *Asphalt Paving Mixture and Block Manufacturing* and 324122 *Asphalt Shingle and Coating Materials Manufacturing*.

mapping them into 6-digit NAICS. This is done through the following formula

$$I_{s,t} = \sum_j I_{j,t} \pi_{s|j}$$

$I_{s,t}$ is innovation in 6-digit NAICS sector $s$ and year $t$, $I_{j,t}$ is innovation in 4-digit IPC field $j$ and year $t$, and $\pi_{s|j}$ is the probability that a patent classified in technical field $j$ is linked to sector $s$ or, alternatively, contributes to innovation in sector $s$. $\pi_{s|j}$ is directly taken from the 'Algorithmic Links with Probabilities' crosswalk by Goldschlag, Lybbert and Zolas (2019), which exactly compute these conditional probabilistic links between sectors and technical field based on text analysis.

To convert the technical field-level treatment into a 6-digit NAICS sectoral treatment, I rely again on probabilistic links between 4-digit IPC classes and 6-digit NAICS industries computed by Goldschlag, Lybbert and Zolas (2019). Specifically,

$$\Delta T_s = \sum_j \Delta T_j \pi_{j|s}$$

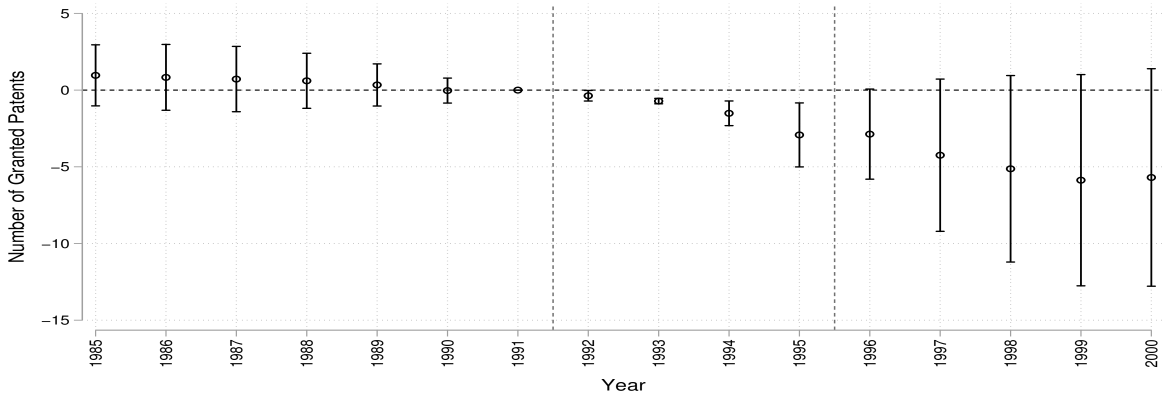
The treatment $\Delta T_s$ for sector $s$ is the sum of technical field-level treatments $\Delta T_j$'s, weighted by the probability that, given that a patent is assigned NAICS $s$, it comes from technical field $j$.

The specification of the difference-in-difference regression at the industry-level is analogous to the one by technical field

$$Y_{s,t} = \alpha_s + \sum_{k=1985}^{2000} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985}^{2000} \beta_k \mathbf{1}_{(t=k)} \Delta T_s + \Xi X_{s,t} + \varepsilon_{s,t} \tag{1.82}$$

where $\alpha_s$ are industry fixed effects, $\mathbf{1}_{(t=k)}$ are yearly dummy variables, $\Delta T_s$ is the sectoral treatment, $X_{s,t}$ is matrix of controls that includes 4-digit NAICS industry $\times$ year effects, the natural logarithm of the energy price deflator, and the natural logarithm of the material costs deflator, $\varepsilon_{s,t}$ is an idiosyncratic error term. Standard errors are clustered by 3-digit NAICS industry$\times$ year in this case and the regressions.

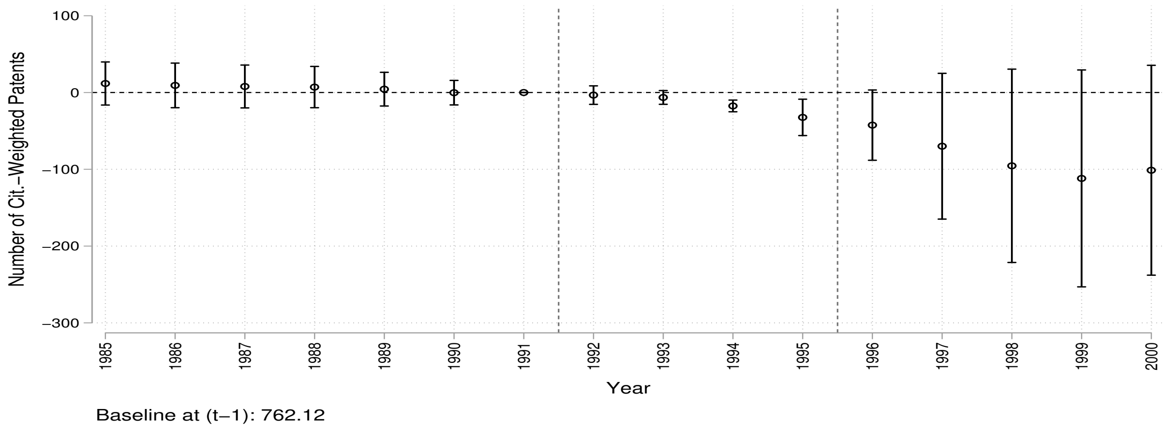
Figure 1.E.9: Effect of one-day longer patent term on sectoral patents




The plot shows the $\beta_k$ coefficients of regression (1.82) $P_{s,t} = \alpha_s + \sum_{k=1985}^{2000} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985}^{2000} \beta_k \mathbf{1}_{(t=k)} \Delta T_s + \varepsilon_{s,t}$. $P_{s,t}$ is the number of patents attributable to sector $s$ and filed for in year $t$, and $T_s$ is the industry-specific treatment. I omit the dummy for 1991, which is the pre-treatment year. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by 3-digit NAICS industry and year and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

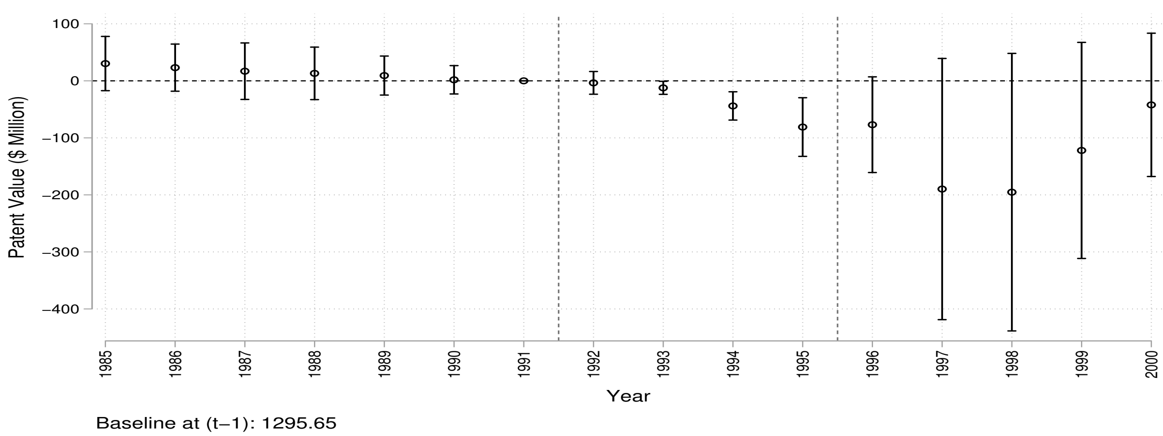
Figure 1.E.9 plots the difference-in-difference $\beta_k$ coefficients of interest, together with their 95% confidence bands, for specification (1.82) run having the number of granted patents by industry and year as dependent variable. The pre-treatment coefficients are remarkably close to 0, confirming the absence of pre-trends, and the pattern of post-treatment estimated marginal effects is similar to the evidence by technical field presented in Section 1.4 of the paper. Figures 1.E.10 and 1.E.11 plot the same coefficients for citations-weighted patents and patent value as dependent variables , respectively. Again, the evidence is very consistent with previous one, even though confidence bands are larger in this case.

Figure 1.E.10: Effect of one-day longer patent term on sectoral citations-weighted patents




The plot shows the $\beta_k$ coefficients of regression (1.82) $C_{s,t} = \alpha_s + \sum_{k=1985}^{2000} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985}^{2000} \beta_k \mathbf{1}_{(t=k)} T_s + \varepsilon_{s,t}$. $C_{s,t}$ is the number of citations-weighted patents attributable to sector $s$ and filed for in year $t$, and $T_s$ is the industry-specific treatment. I omit the dummy for 1991, which is the pre-treatment year. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by 3-digit NAICS industry and year and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

Figure 1.E.11: Effect of one-day longer patent term on sectoral patent value




The plot shows the $\beta_k$ coefficients of regression (1.82) $V_{s,t} = \alpha_s + \sum_{k=1985}^{2000} \gamma_k \mathbf{1}_{(t=k)} + \sum_{k=1985}^{2000} \beta_k \mathbf{1}_{(t=k)} T_s + \varepsilon_{s,t}$. $V_{s,t}$ is the private economic value of patents attributable to sector $s$ and filed for in year $t$, and $T_s$ is the industry-specific treatment. I omit the dummy for 1991, which is the pre-treatment year. Point estimates refer to the marginal effect of a one-day anticipated change in patent term on the *level* of the outcome variable, relative to its baseline value in 1992Q3, reported at the bottom of the figure. Standard errors are clustered by 3-digit NAICS industry and year and 95% confidence bands are plotted. The first vertical line lies just before the news year (1992) and the second vertical line lies just before the implementation year (1995).

# Appendix 1.F Additional model extensions

## 1.F.1 Model with labor as R&D input

In this section, I will introduce an alternative model specification to the one presented in Section 1.6. Instead of using units of the final good, research and development activities are carried out by hiring labor at the competitive wage $w(t)$. Following the approach in subsection 1.C.1, I will begin with the agents' maximization problem, derive the aggregate laws of motion, and establish the balanced growth path. The consumer behavior remains the same as in the main model, with a risk-neutral representative agent maximizing utility by choosing consumption and savings and supplying $L(t)$ units of labor. The labor is allocated to production of the final good in quantity $L_P(t)$, research in quantity $L_R(t)$, and development in quantity $L_D(t)$. Equilibrium wage rates for all three types of labor are equal. The agent can save in either physical capital or shares of intermediate good firms, with both assets delivering the same net rate of return under the no-arbitrage condition. Therefore, the equilibrium condition $r(t) = \rho$ is derived from the dynamic consumer's problem, indicating that the net return of savings must equal the consumer's discount rate.

### 1.F.1.1 Final good production

The final good is produced by a competitive firm that chooses labor and the optimal quantity of each of the intermediate goods in the economy to maximize profits. The problem is

$$\max_{\{X(i,t)\}_{i\in[0,V(t)]},L_P(t)\}} \Big[h(t)L_P(t)\Big]^{1-\alpha}\Big[\int_0^{V(t)} X^{\alpha}(i,t)di\Big] - \int_0^{V(t)} z(i,t)X(i,t)di - w(t)L_P(t)$$

where output is

$$Y(t) = \Big[h(t)L_P(t)\Big]^{1-\alpha}\Big[\int_0^{V(t)} X^{\alpha}(i,t)di\Big] \tag{1.83}$$

and it is determined by $h(t)$, which is an exogenous labor-augmenting technology term that grows exponentially at a given constant rate $g_h$, $L_P(t)$, which is the hours devoted to production, exponentially growing at constant rate $n$, and a mass of $V(t)$ intermediate capital goods varieties. $w(t)$ is the wage rate and $z(i,t)$ is the instant-$t$ price of intermediate variety $i$. The first order conditions of the problem are

$$w(t) = (1-\alpha)h(t)^{1-\alpha}L_P(t)^{-\alpha}\Big[\int_0^{V(t)} X^{\alpha}(i,t)di\Big] \tag{1.84}$$

and

$$z(i,t) = \alpha h(t)^{1-\alpha}L_P(t)^{1-\alpha}X^{\alpha-1}(i,t) \;\; \forall\; i \in [0, V(t)] \tag{1.85}$$

The former equation determines the equilibrium wage rate and it is the inverse demand for production labor, while the latter equation is the inverse demand for intermediate $i$.

#### 1.F.1.2 Monopolistic intermediate goods production

A share $\zeta(t)$ of the existing $V(t)$ intermediate goods varieties are protected by a monopoly, granted by a valid patent. The monopolistic producer of variety $i$ chooses the quantity to produce in order to maximize profits subject to the inverse demand given by (1.85), and subject to the production function. In particular, one unit of each of the intermediate goods can be produced by using one unit of raw capital $K(t)$, which can be rented from households at a rate $r_K(t) = r(t) + \delta$, where $\delta$ is the depreciation rate of physical capital. Therefore, the maximization problem is

$$\max_{X(i,t),z(i,t)} \Big\{ z(i,t)X(i,t) - (r(t)+\delta)X(i,t) \Big\}$$

$$\text{s.t.} \qquad z(i,t) = \alpha h(t)^{1-\alpha} L_P(t)^{1-\alpha} X^{\alpha-1}(i,t)$$

and the first order condition implies

$$z(i,t) = \alpha (h(t)L_P(t))^{1-\alpha} X(i,t)^{\alpha-1} = \frac{1}{\alpha}(r(t)+\delta) \tag{1.86}$$

i.e. the price is a constant markup $1/\alpha$ over the marginal cost $(r(t)+\delta)$. This implies that the price of each of the monopolistically-produced intermediate capital varieties is the same and, therefore, also the produced quantity and the profits will be symmetric. In particular, these will satisfy

$$X(i,t) = X_p(t) = \alpha^{\frac{2}{1-\alpha}} (r(t)+\delta)^{-\frac{1}{1-\alpha}} h(t) L_P(t) \quad \forall\ i \in [0, \zeta(t)V(t)] \tag{1.87}$$

$$\pi(i,t) = \pi(t) = \Big(\frac{1}{\alpha} - 1\Big)(r(t)+\delta)X_p(t) \tag{1.88}$$

#### 1.F.1.3 Non-monopolistic intermediate goods production

A fraction $1-\zeta(t)$ of intermediates are not monopolistically produced because legal patent protection on it has expired. These non-monopolistic varieties are produced in a regime of Bertrand competition, and therefore the price $z(i,t)$ is equal to the marginal cost of production $(r(t)+\delta)$. It follows from the inverse demand function (1.85) that the production of these competitively-produced intermediate varieties is symmetric and given by

$$X_{np}(t) = \alpha^{\frac{1}{1-\alpha}} (r(t)+\delta)^{-\frac{1}{1-\alpha}} h(t) L_P(t) \quad \forall\ i \in (\zeta(t)V(t), V(t)] \tag{1.89}$$

which implies that $X_p(t) = \alpha X_{np}(t)$. Since $\alpha \in (0,1)$ by assumption, this implies that the quantity produced of monopolistic varieties is lower than the one of competitive varieties, which is what the distortion of monopoly consists in.

#### 1.F.1.4 Physical capital market clearing condition

The equilibrium in the physical capital market requires that the quantity of capital supplied by households $K(t)$ is equal to the quantity of capital demanded by firms to produce the intermediate capital goods, i.e.

$$\begin{aligned} K(t) =& \zeta(t)V(t)X_p(t) + (1-\zeta(t))V(t)X_{np}(t) \\ =& [\alpha\zeta(t) + (1-\zeta(t))]V(t)X_{np}(t) \end{aligned} \tag{1.90}$$

#### 1.F.1.5 Research investment to discover new projects

The model features an unit mass of identical firms that invest in research. The output of research investment is new ideas, on which the successful firm can exclusively invest in order to develop the idea into a new intermediate variety. The research investment problem of the representative research firm is

$$\max_{L_R(t)} \left\{ P(t)E(t)^{\chi}V(t)^{\phi_1}L_R(t)^{\phi_2} - w(t)L_R(t) \right\}$$

Research requires $L_R(t)$ units of labor for the production of $E(t)^{\chi}V(t)^{\phi_1}L_R(t)^{\phi_2}$ new ideas, where $E(t)^{\chi}$ is the delayed externality term already discussed in Sections 1.5 and 1.6, and $V(t)^{\phi_1}$ is an externality from existing varieties that is common in endogenous growth models. Parameters are constrained so that $\phi_1 + \phi_2 < 1$. $\phi_1 < 1$ captures the fact that ideas become harder to find as the knowledge frontier expands, and $\phi_2 < 1$ captures the degree of decreasing returns to scale in research investment. Finally, $P(t)$ is the economic value of a new idea, or, alternatively, it can be thought as the exclusivity value of a development project. The optimal research investment is given by

$$L_R(t) = \left[\frac{\phi_2}{w(t)} P(t) E(t-d)^{\chi} V(t)^{\phi_1}\right]^{\frac{1}{1-\phi_2}}$$

#### 1.F.1.6 Development of projects

Development occurs independently on each existing project, even in the case when a single firm is running multiple projects. Therefore, for each project firms hire labor to obtain a patentable intermediate variety, and firms are successful with a Poisson arrival rate of

$$\left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}}$$

where $\theta > 1$ still captures the cost-convexity of the intensity with which development is carried out. $l_D(t)$ can be interpreted as development labor intensity. The innovation arrival rate is re-scaled by the total labor force, so that $l_D(t)/L(t)$ can be interpreted as the share of the labor force on each development project, and it is increasing in the number of existing varieties $V(t)$, to make sure that a balanced growth path is admissible for this economy. Then, the development problem can be written in recursive form as

$$r(t)P(t) - \dot{P}(t) = \max_{l_D(t)} \left\{ \left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}} \Big[\upsilon(t) - P(t)\Big] - w(t)l_D(t) \right\} \tag{1.91}$$

where the equation captures the fact that if, with instantaneous probability $\left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}}$ the project is successful, the investing firm receives a value $\upsilon(t)$ for the intermediate variety obtained, but it loses the value of the project $P(t)$, which expires after completion. The expected value of a newly patented variety, which is what the developing firm cares about when working on the project, is

$$\upsilon(t) = \int_t^{t+T} e^{-\int_t^s (r(t')+\lambda(t'))dt'} \pi(s) ds \tag{1.92}$$

where $\pi(t)$ is the flow of profits at instant $t$, $r(t)$ is the real interest rate, and $\lambda(t)$ is an endogenous Poisson rate at which, depending on aggregate innovation intensity, a monopoly can be creatively destroyed. Therefore, $\upsilon(t)$ is the expected net present discounted value of profits on a variety. The optimal labor hiring decision on each development project is

$$l_D(t) = \left[ \frac{1}{\theta} \Big( \frac{V(t)}{L(t)} \Big)^{\frac{1}{\theta}} \Big( \upsilon(t) - P(t) \Big) \frac{1}{w(t)} \right]^{\frac{1}{1-\frac{1}{\theta}}} \tag{1.93}$$

The dynamic spillover term must be re-defined here as

$$E(t) \equiv d^{-1} \int_{t-d}^{t} \Big( \frac{l_D(s)V(s)}{L(s)} \Big)^{\frac{1}{\theta}} ds$$

which is identical in spirit the the expression of the benchmark model of Section 1.6, because the externality is simply a function of the development completion probability.

The process of creative destruction captured by the $\lambda(t)$ term is endogenous and it is driven by the rate of growth of the number of varieties $V(t)$. Specifically, it is defined as

$$\lambda(t) \equiv \psi \frac{\dot{V}(t)}{V(t)}$$

i.e. in times when the rate of growth of varieties is higher, the rate of creative destruction is higher. This strategy to model entry and creative destruction is motivated by the fact that, in the data, I observe that innovation by new applicants increases when overall innovation rate increases, but their relative weight does not change.

#### 1.F.1.7 Evolution of aggregate quantities

The decisions resulting from the previous optimization problems shape the evolution of aggregate quantities as follows. First, the number of varieties $V(t)$ evolves according to

$$(1+\psi)\frac{\dot{V}(t)}{V(t)} = \left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}} N(t) \tag{1.94}$$

where $\psi\frac{\dot{V}(t)}{V(t)}$ is by how much creative destruction reduces the mass of intermediate goods available, while $\left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}} N(t)$ is the number of development projects successfully turned into a variety. This is the case because $\left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}}$ is the instantaneous probability that each of the existing projects $N(t)$ is successfully completed, generating varieties. Since this instantaneous probability is identical and independent across projects, a suitable law of large numbers applies, and the aggregate representation provided holds.

The evolution of projects is instead given by

$$\dot{N}(t) = E(t-d)^{\chi} V(t)^{\phi_1} L_R(t)^{\phi_2} - \left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}} N(t) \tag{1.95}$$

where the first term captures the mass of new projects generated by research investment and the second term captures the destruction of projects due to successful completion.

The evolution of the share of existing varieties that are covered by monopoly, i.e. $\zeta(t)$, is given by

$$\dot{\zeta}(t) = (1-\zeta(t))\frac{\dot{V}(t)}{V(t)} - (1+\psi)\frac{\dot{V}(t-T)}{V(t)} e^{-\int_{t-T}^{t} \lambda(t')\mathrm{d}t'} \tag{1.96}$$

where the first term captures the additions to the monopolistic varieties due to current innovation, and the second term captures the fact that all those varieties that have not already been creatively destroyed become competitive when the maximum patent term $T$ expires.

The evolution of aggregate capital satisfies

$$\dot{K}(t) = I_K(t) - \delta K(t) \tag{1.97}$$

where $I_K(t)$ is the investment in physical capital done by the households out of the final good, and $\delta K(t)$ is the depreciation of the existing stock.

#### 1.F.1.8 Market clearing in the goods market

Given the production decisions of the intermediate varieties producers and of the final good producer, GDP for this economy can be rewritten as

$$Y(t) = [\alpha^{\alpha}\zeta(t) + (1-\zeta(t))]V(t)h(t)^{1-\alpha}L_P(t)^{1-\alpha}X_{np}^{\alpha}(t) \tag{1.98}$$

where $[\alpha^{\alpha}\zeta(t) + (1-\zeta(t))]V(t)h(t)^{1-\alpha}$ is the measured TFP. Notice that the productivity of the economy grows with the number of varieties available, and decreases with the share of monopolistic varieties, as $\alpha^{\alpha} < 1$.

On the other hand, the total production of the final good must also satisfy

$$Y(t) = C(t) + I_K(t) \tag{1.99}$$

as consumption and capital investment are funded out of the final good.

#### 1.F.1.9 Market clearing in the labor market

Market clearing of labor market requires that the exogenous amount of labor available $L(t)$ equals the sum of labor used in production, research, and development in equilibrium.

$$L(t) = L_P(t) + L_R(t) + L_D(t) \tag{1.100}$$

where $L_D(t) = l_D(t)N(t)$ is the total labor used in development, given by the labor $l_D(t)$ optimally hired on each project times the number of projects.

#### 1.F.1.10 Balanced growth path

Population $L(t)$ and the productivity term $h(t)$ exogenously grow at constant rate $n$ and $g_h$, respectively. Also, since $r(t) = \rho$, the real interest rate is constant. From the labor market clearing condition, it follows that production labor $L_P(t)$ and research labor $L_R(t)$ must also grow at rate $n$, while labor employed in each single project $l_D(t)$ must grow at less than $n$, namely at $n$ minus the growth rate of projects. From equations (1.87), (1.89), and (1.88), it follows that the growth rate of $X_p(t)$, $X_{np}(t)$, and profits along the balanced growth path is identical and equal to $g_h + n$. Also, from the definition of $\upsilon(t)$, it follows that the patent value must grow at the same rate of profits, i.e. $g_h + n$, and that, as a consequence, the rate of creative destruction $\lambda(t)$ is constant along the balanced growth path. In addition, from the value function of the development problem, it follows that, for a b.g.p. to be possible, $P(t)$ must grow at the same rate of $\upsilon(t)$, i.e. $g_P = n + g_h$, and that the arrival rate of innovations $\left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}}$ must be constant. This implies that the rate of growth of $l_D(t)$ must be equal to population growth $n$ minus the rate of growth of varieties. Notice that a constant $\left(\frac{l_D(t)V(t)}{L(t)}\right)^{\frac{1}{\theta}}$ is consistent with the optimality condition (1.93), and it implies that also the externality term $E(t)$ is constant in the b.g.p.. The evolution of the stock varieties in equation (1.94) implies that $g_V = g_N$, and the evolution of the stock of projects in equation (1.95) requires that

$$g_N = \phi_1 g_V + \phi_2 n \tag{1.101}$$

Since $g_V = g_N$, it follows that the rate of growth of endogenous productivity is $g_V = g_N = \frac{\phi_2}{1-\phi_1}n$, and the rate of growth of labor devoted to each development project is

$$g_{l_D} = n - g_V = \Big(1 - \frac{\phi_2}{1-\phi_1}\Big)n = \Big(\frac{1-\phi_1-\phi_2}{1-\phi_1}\Big)n$$

which is smaller than population growth as long as $\phi_2 > 0$. From (1.99), the rate of growth of consumption and capital investment must be the same as output. Hence, $g_Y = g_C = g_{I_K} =$. In addition, from (1.96), it follows that $\zeta(t)$ is constant along the b.g.p. and, as a consequence, the equilibrium production function (1.98) requires

$$g_Y = (1-\alpha)(g_h + n) + g_V + \alpha g_X$$

But $g_X = n + g_h$, and therefore the last implies $g_Y = \frac{\phi_2}{1-\phi_2}n + n + g_h$, i.e.

$$g_Y = \frac{1-\phi_1+\phi_2}{1-\phi_2}n + g_h$$

which fully solves for balanced growth path growth rates, and shows that the previous model admits a balanced growth path.

# Chapter 2

# Dynamics of Expenditures on Durable Goods: the Role of New-Product Quality

**Abstract**

We study the role of new-product quality for the dynamics of durable-goods expenditures around the Great Recession. We assemble a rich dataset on US new-car markets during 2004-2012, combining data on transaction prices with detailed information about vehicles' technical characteristics. During the recession, a reallocation of expenditures away from high-quality new models accounts for a significant decline in the dispersion of expenditures. In turn, car manufacturers introduced new models of lower quality. The drop in new-model quality persistently depressed the technology embodied in vehicles, and likely contributed to the slow recovery of expenditures.

## 2.1 Introduction

Households adopt new technologies by purchasing new durable goods, such as vehicles. During the Great Recession of 2008-2009, consumer expenditures on durable goods dropped by approximately 17%. Expenditures on motor vehicles—which constitute approximately 35% of durable-goods expenditures—accounted for more than half of this decrease and remained low during the recovery.

The goal of this paper is to empirically investigate the role of new-product quality for these dynamics. Our descriptive analysis suggests that complementary demand and supply factors contributed to a downward quality adjustment in durable-goods purchases during the recession. Specifically, households reallocated their purchases of new cars toward cheaper models—which tend to be continuing models, of lower quality than new models—or delayed their purchases. Amid this decline in demand, manufacturers introduced new models of low quality, persistently depressing the path of technology.

Cars represent an ideal object for our analysis for two reasons. First, they are a large and procyclical component of durable-goods expenditures. Second, detailed information on car markets allows us to measure quality dynamics, providing evidence on the importance of new products. To this end, we assemble a rich dataset on US new-car markets, combining two data sources. The first dataset contains the universe of new-car transactions in several US states between 2004 and 2012 and reports transaction prices as well as car features, such as make and model. The second dataset contains detailed information on the technical characteristics of each vehicle model sold in the US during the same period.

We exploit these data to provide new evidence about the distribution of vehicle expenditures and quality around the Great Recession. Our analysis proceeds in four steps, each yielding a main finding.

First, we document a drop in the dispersion of new-car expenditures during the

Great Recession—and a smaller decline in the average price—due to a decline in the volume of high-price transactions.

Second, we show that the drop in dispersion is due to expenditure reallocation across models—specifically, a decline in expenditures on expensive newly introduced models. Furthermore, exploiting geographical variation, we relate this drop in demand for high-quality models with the severity of the recession. Because the supply of vehicles does not vary across locations, this finding shows that shocks to household demand play a primary role in the downward quality adjustment.

Third, we connect car prices and characteristics. We use hedonic regressions to construct a measure of vertical quality that summarizes vehicle technical characteristics (Griliches, 1961). We show that compositional changes in the characteristics of cars sold account for the drop in expenditures. Furthermore, vehicle quality, based on pre-recession hedonic prices, displays no growth during the recovery.

Fourth, we estimate the level of technology embodied in vehicles using only data on car characteristics. We document that new models introduced during the Great Recession featured a significantly worse trade-off between their main attributes than models introduced in other years. This finding is consistent with an endogenous response of manufacturers that contributed to the drop in durable-goods quality. Moreover, this technological slowdown had persistent effects throughout the recovery, reducing the quality of the stock of registered vehicles.

Overall, our analysis highlights the complementary role of demand and supply forces for quality dynamics. The narrative that emerges from our findings is that a drop in household demand for quality led to an endogenous response on the supply side, with a decrease in both volume and quality of new products, which further reduced technology adoption.

Our findings have several implications. Most directly, the motor vehicle industry experienced a deep crisis in 2008-2009, which led to a drop in employment and government bailouts. Moreover, because of the centrality of this industry in the US production structure, the effects of this crisis spread across different sectors.[1] Thus, understanding the micro dynamics of expenditures on vehicles is an important step toward understanding the Great Recession and the subsequent slow recovery.

Furthermore, our findings have broader implications, contributing to several strands of the literature. First, we provide evidence for the complementary roles of demand and supply factors for innovation and technology adoption. Several papers show that downward adjustment in consumer demand for quality is an important margin in the Great Recession (Jaimovich, Rebelo and Wong, 2019; Argente and Lee, 2021).[2] A related literature emphasizes the entry and exit of retail products as an important margin for the evolution of technology around the same period (Argente, Lee and Moreira, 2018; Jaravel, 2019; Granja and Moreira, 2020).[3] Whereas these studies mainly focus on services and nondurable goods, we analyze one of the most important household durable goods, building on the insights of Bils and Klenow (2001) and Bils (2009). The evidence on complementarity between demand and supply is also consistent with the mechanism in Shleifer (1986).[4]

Second, a large literature studies the role of durable goods for business cycles (for seminal contributions, see Mankiw, 1982; Bernanke, 1985; Caballero, 1993). An important force in models of durables demand (Barsky, House and Kimball, 2007; Berger and Vavra, 2015; Dupor et al., 2018; Attanasio et al., 2020; Gavazza and Lanteri, 2021; McKay and Wieland, 2021; Beraja and Wolf, 2022) is intertemporal substitution, which implies that pent-up demand may induce strong recoveries after

[1] Atalay (2017) and vom Lehn and Winberry (2022) document that the auto industry plays a central role in the US production network.

[2] Fisher, Johnson and Smeeding (2013) and Meyer and Sullivan (2013) find that consumption inequality declined during the Great Recession.

[3] Broda and Weinstein (2010) documents that product creation is procyclical during the period 1999-2003.

[4] Acemoglu and Linn (2004) provides related evidence from the pharmaceutical industry and Einav (2007) from the motion picture industry.

drops in expenditures on durables.[5] However, expenditures on durables recovered sluggishly after the Great Recession. Our finding that new-car quality was persistently depressed during the recovery may partially account for the slow recovery in expenditures.

Relatedly, our findings on the persistent implications of the downward quality adjustment during the Great Recession are consistent with the literature on medium-run business cycles (e.g., Comin and Gertler, 2006*b*; Benigno and Fornaro, 2018; Anzoategui et al., 2019; Bianchi, Kung and Morales, 2019; Vinci and Licandro, 2020). Our contribution is to measure the medium-run effects of new-product introduction around the Great Recession.

## 2.2 Data

Our empirical analysis exploits two datasets on new-car transactions and model characteristics, respectively. We introduce them in this section.

**2.2.0.0.1 New-car Prices, Dominion Dealer Solutions (2019).** This dataset (henceforth Dominion dataset) reports the universe of new-car sales in five states—Colorado, Idaho, North Dakota, Ohio, and Texas—for the period 2004-2012. For each sale, the dataset reports the transaction price, the month of the transaction, and the make, model, body type, and trim of the vehicle. The dataset contains more than 16.5 million vehicle transactions.[6]

**2.2.0.0.2 New-car Model Characteristics, IHS Markit (2020).** This dataset (henceforth IHS dataset) reports detailed characteristics of all new passenger-car mod-

[5]Several papers build on Eberly (1994) and Attanasio (2000), which abstract from business cycles. Adda and Cooper (2000, 2006) and Gavazza, Lizzeri and Roketskiy (2014) develop quantitative models of car replacement.

[6]For North Dakota, prices are reported for 2008-2012 only. Transaction prices in Colorado exhibit some unusually low values than those in the other states; all our empirical findings are robust to excluding transactions in Colorado.

els sold during 2003-2012, including make, model, trim, body type, generation year, dimensions, as well as engine attributes, such as size and horsepower, fuel type, fuel consumption, transmission, and turbo injection.[7]

The dataset also reports the aggregate number of US sales for each model at annual frequency during 2003-2012. We exclude pick-up trucks from our analysis because the dataset does not have comprehensive information about them.

The product life cycle of cars typically features the replacement of a "generation" of a car model with a new generation on average every 5.8 years. For example, all 2007–2011 Toyota Camry models belong to the 2007 generation. Whereas small changes in characteristics happen at annual frequency within a generation, a new generation features a larger redesign. Hence, we define a vehicle model in the IHS data as a triplet of make, model, and generation. We further define a new model in year $t$ as a model for which we observe the first transaction in year $t$ or $t-1$, to account for the fact that the first transaction on a new model tends to appear in the second half of the year. This definition of a new model encompasses entirely new model names.

Based on this definition, we merge the Dominion and IHS datasets by matching vehicle models across the two datasets and allocating each transaction in the Dominion dataset to a model generation in the IHS dataset. Appendix 2.A provides more details on our model definition and procedure to merge the datasets.

We thus obtain a rich dataset on car sales that combines information on prices and technical characteristics. Throughout the paper, we refer to a car model as a make-model-generation triplet. According to this industry-wide definition, our dataset contains over 500 models.

[7]Information about weight is missing in approximately 40% of models. Thus, we use all models for which we observe their weight to estimate a log-linear relationship between weight and other physical dimensions: wheelbase, width, height, and number of seats. This regression has an $R^2$ of 0.93. We use its predicted values to impute the weight whenever we do not observe it.

## 2.3 Empirical Patterns

In this section, we describe several empirical patterns: (i) we document the dynamics of the distribution of expenditures on new cars around the Great Recession; (ii) we decompose the dispersion in expenditures highlighting the role of new models; (iii) we relate expenditures to car characteristics; and (iv) we analyze the level of technology embodied in cars. Appendix 2.B reports additional details and robustness checks.

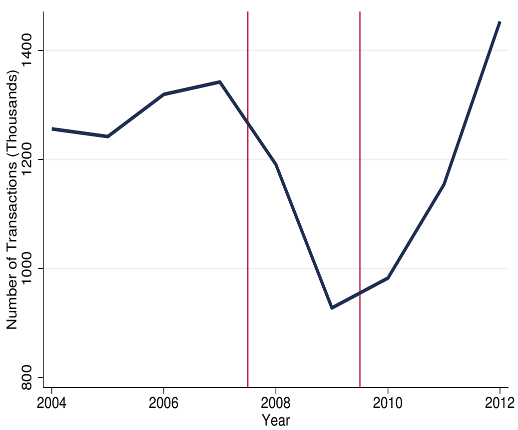
### 2.3.1 Dynamics of the Distribution of Expenditures on New Vehicles

We begin by describing the distribution of expenditures on new cars in the Dominion dataset. Figure 2.1 displays the main features of this distribution during 2004-2012. The transactions in this dataset provide a representative account of the dramatic effects of the Great Recession on US car markets: The top-left panel shows that the total number of new-car sales drops by approximately 30% during the recession and only returns to pre-recession levels in 2012, similar to the US aggregate dynamics.

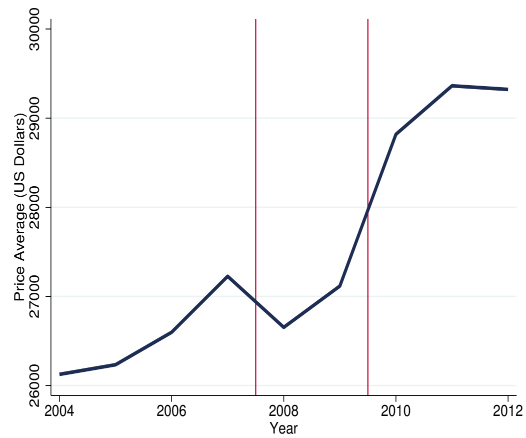
We thus exploit the dataset to analyze the micro dynamics of the expenditure distribution. The top-right panel plots the average transaction price; the bottom-left panel the standard deviation; and the bottom-right panel the 10th, 50th, and 90th percentiles of the distribution, all normalized to zero in 2007.

Both first and second moments of the expenditure distribution display an increasing trend. On average, transaction prices increase by 1.6% annually between 2004 and 2012. However, during the Great Recession, we observe a decline in the average price and a larger decline in the dispersion of prices. Notably, the average price, which equals \$27,226 in 2007, displays a peak-to-trough decline of approximately 2%. The standard deviation, which equals \$13,614 in 2007, declines by approximately 5%. Relative to their respective trends, the average price drops by approximately 3% and

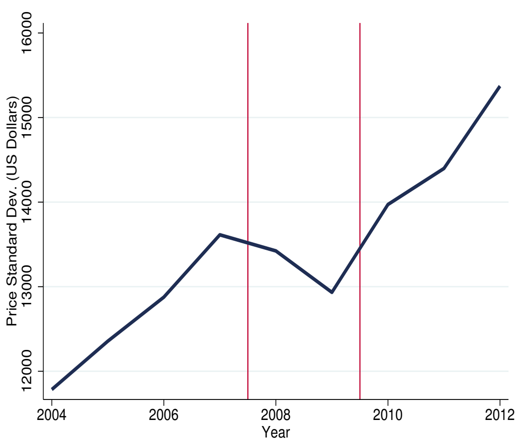
Figure 2.1: Dynamics of New-Vehicle Expenditures



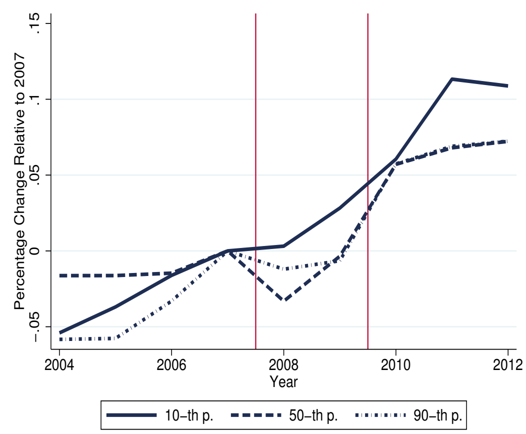

(a) Number of Transactions




(b) Average Transaction Price




(c) Standard Deviation of Prices




(d) Percentiles of Prices

*Notes:* The figure displays the number of new-car sales (top-left panel), the average (top-right panel), the standard deviation (bottom-left panel), and three percentiles—10th, 50th, and 90th—(bottom-right panel) of the distribution of transaction prices from the Dominion dataset. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

the standard deviation by approximately 6% during the recession. In summary, our first main finding is that the decrease in dispersion during the recession is about twice as large as the decrease in average expenditures.

The evidence on the first two moments of the distribution suggests that households reallocated their expenditures away from expensive vehicles during the recession. Different percentiles of the distribution confirm this pattern. Consistent with the low-frequency dynamics of average prices, all percentiles increase over time between 2004 and 2012. However, the median and the 90th percentile decline significantly during the recession, both in absolute terms and relative to their trends. In contrast, the 10th percentile remains on its trend. This analysis suggests that a drop in expenditures on intermediate- and high-quality cars accounts for the declines in the average and the dispersion of expenditures.

These findings are consistent with the evidence on household expenditures based on the Consumer Expenditure Survey. Meyer and Sullivan (2013) documents a low-frequency increase in consumption inequality and a decrease in dispersion during the Great Recession, with lower percentiles of expenditures displaying smaller declines than higher percentiles. However, our dataset allows us to take further steps to connect the distribution of expenditures with features of the goods purchased.

### 2.3.2 Decomposing the Dispersion of Expenditures

We perform several decompositions of the variance of prices to investigate the drivers of the cyclical dynamics of the distribution of expenditures. Our second main finding is that reallocation of expenditures *between* car models—specifically a drop in expenditures on newly introduced models with high price—accounts for the compression in the distribution in the recession. In contrast, average prices conditional on vehicle model do not display significant changes relative to their trend.

#### 2.3.2.1 Between versus Within Models

We decompose the total variance of expenditures on new vehicles in year $t$, $V_t$, as follows:

$$V_t = V_t^B + V_t^W,$$

where $V_t^B$ denotes the between-models component of the total variance and $V_t^W$ denotes the within-model component.[8] Formally, we have

$$\begin{aligned} V_t &\equiv \frac{1}{N_t}\sum_{i\in M_t}\sum_{j\in X_{it}}\left(p_{ijt}-\overline{p}_t\right)^2, \\ V_t^B &\equiv \sum_{i\in M_t} s_{it}\left(\overline{p}_{it}-\overline{p}_t\right)^2, \\ V_t^W &\equiv \frac{1}{N_t}\sum_{i\in M_t}\sum_{j\in X_{it}}\left(p_{ijt}-\overline{p}_{it}\right)^2, \end{aligned}$$

where $i \in M_t$ denotes a model sold in year $t$, $j \in X_{it}$ denotes a transaction on model $i$ in year $t$, with market share $s_{it}$; $N_t$ is the total number of transactions in year $t$; $p_{ijt}$ are individual prices; $\overline{p}_{it}$ is the average price of model $i$ in year $t$; and $\overline{p}_t$ is the average price in year $t$.

The top-left panel of Figure 2.2 displays the total variance $V_t$ (solid line) and its components: between models $V_t^B$ (dashed line) and within models $V_t^W$ (dashed-dotted line). The between-models component accounts for almost 80% of total variation in prices before the recession, whereas within-model dispersion in transaction prices accounts for approximately 20% of total variation.[9] Notably, the between-models component accounts for the entire reduction in total dispersion during the recession. In contrast, during the same period there are no significant changes in the dispersion of prices within models. This evidence establishes that households reallocated their expenditures toward models with a price close to the average.

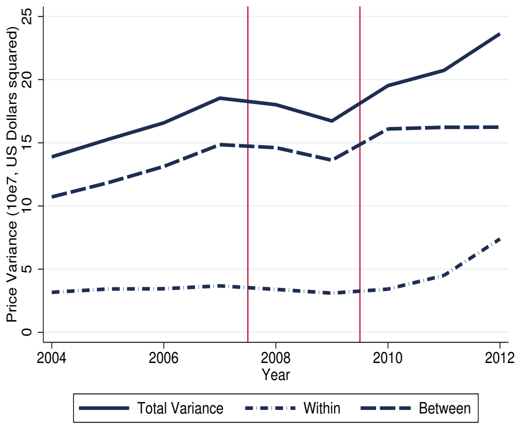
#### 2.3.2.2 New versus Old Models

The reallocation of expenditures away from expensive models prompts us to analyze the role of newly introduced models. New models tend to be more expensive than

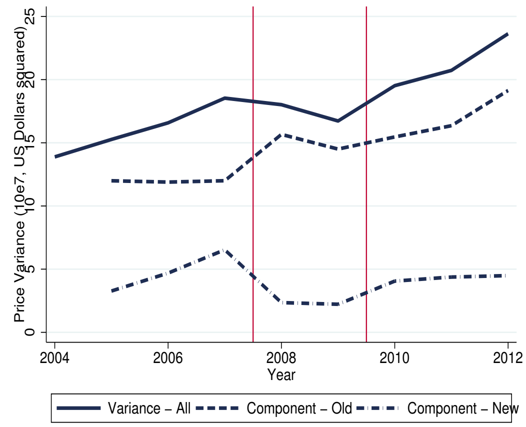
[8] The covariance term equals zero.

[9] Variation in prices within models is mostly due to different trims within each model. This variation does not appear to be relevant for the cyclical dynamics, which confirms that our approach of merging the Dominion and IHS datasets at the model level is sound.

Figure 2.2: Variance Decomposition

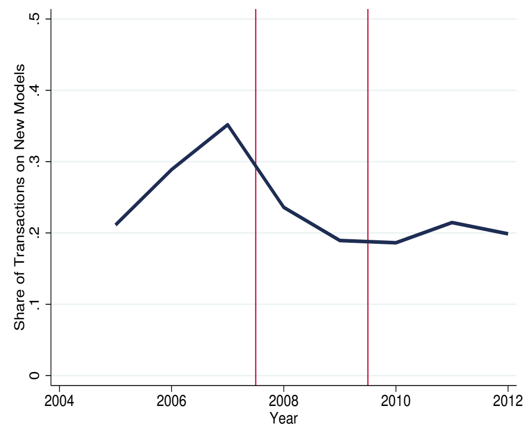



(a) Variance of New-Car Prices, Between and Within




(b) Variance of New-Car Prices, New and Continuing


(c) Variance of Newly Introduced Models




(d) Share of Newly Introduced Models

*Notes:* The figure displays several decompositions of the variance of transaction prices in the Dominion dataset. The top-left panel displays the decomposition of the variance of new-vehicle transaction prices $V_t$ (solid line) into the following components: between models $V_t^B$ (dashed line) and within models $V_t^W$ (dashed-dotted line). The top-right panel displays the decomposition of the variance $V_t$ (solid line) into two components: new models $s_t^N V_t^N$ (dashed-dotted line) and old models $(1 - s_t^N)V_t^O$ (dashed line). The bottom-left panel displays the variance of expenditures on new models $V_t^N$ (solid line) and its decomposition into between-models component $V_t^{N,B}$ (dashed line) and within-models component $V_t^{N,W}$ (dashed-dotted line). The bottom-right panel displays the share of transactions on new models $s_t^N$. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

continuing models, fueling the long-run growth in the average price.

Based on our definition of a new model (Section 3.4.1), we find that new models play a prominent role in the dynamics of the expenditure distribution. Strikingly, between 2005 and 2007, the average transaction price for new models is \$28,080, which is higher than the average for old models, \$26,144. However, in 2008, the average price of new models drops to \$25,764, which is lower than the average for old models, \$26,927.

We analyze the contribution of new models to the variance of expenditures, using the following variance decomposition:

$$V_t = s_t^N V_t^N + (1 - s_t^N) V_t^O,$$

where $s_t^N$ is the share of transactions on new models in year $t$ and $V_t^N$ ($V_t^O$) is the variance of expenditures on new (old) models. In turn, these variances equal:

$$\begin{aligned} V_t^N &\equiv \tfrac{1}{N_t^N} \textstyle\sum_{i \in M_t^N} \sum_{j \in X_{it}} \left(p_{ijt} - \overline{p}_t\right)^2, \\ V_t^O &\equiv \tfrac{1}{N_t^O} \textstyle\sum_{i \in M_t^O} \sum_{j \in X_{it}} \left(p_{ijt} - \overline{p}_t\right)^2, \end{aligned}$$

where $M_t^N$ and $M_t^O$ are the sets of new and continuing models in year $t$, and $N_t^N$ and $N_t^O = N_t - N_t^N$ are the respective number of transactions.

The top-right panel of Figure 2.2 displays the decomposition of the total variance of expenditures $V_t$ into expenditures on new models, $s_t^N V_t^N$, and on old models, $(1 - s_t^N) V_t^O$. The component due to new models displays a sharp drop during the recession, fully accounting for the drop in total variance. This pattern arises for two concurring reasons. First, the dispersion of prices of new models drops by nearly one-half during the recession. The bottom-left panel of Figure 2.2 portrays the dynamics of the variance of expenditures on new models $V_t^N$, showing that its between-model component accounts for its drop, consistent with the same decomposition for all models.

Second, the share of transactions on new models $s_t^N$ decreases sharply, from a peak in 2007 of approximately 35% to less than 20% in 2009, as the bottom-right panel of Figure 2.2 shows, despite the fact that new models were cheaper during the recession.[10] This pattern suggests a drop in the quality of new models during the recession, which is thus the focus of the following subsections. Nonetheless, we do not observe large changes in the variance of expenditures on old models, $V_t^O$, relative to its trend, suggesting that households did not substitute the "missing" new models of high quality with old models of high quality—most likely delaying their purchases.

In the aftermath of the recession, the dispersion of expenditures on new models $V_t^N$ returns to its trend. However, Figure 2.2, as well as Figure 2.B.9 in Appendix 2.B, show that neither the share of transactions on new models $s_t^N$ nor the fraction of new models on sale overshoots during the recovery. This evidence suggests that car manufacturers did not simply respond to the recession by delaying the introduction of high-quality new models; rather, there was a missing generation of new products, likely contributing to the slow recovery of expenditures.

In Appendix 2.B, we analyze cross-sectional heterogeneity in new-model introduction across carmakers. We divide carmakers in three groups, depending on their geographical origin (Europe, Asia, and US). This analysis reveals two patterns. First, all groups of carmakers decreased the volume of new-model introduction during the recession. Second, European carmakers specialize in the introduction of high-quality models. As a result, they largely account for the drop in high-quality new models during the recession.

We also decompose the margin of new-model introduction between new model names, which may expand the set of models available to consumers (*horizontal* innovation), and new generations of existing model names, which improve on past generations of existing products (*vertical* innovation). Before the recession, both margins

[10] The 2007 peak in the market share of new models is due to the simultaneous introduction of new generations of three popular models: Toyota Camry, Nissan Altima, and Chevrolet Tahoe. Figure 2.B.9 in Appendix 2.B displays the time series of the number of transactions on new models $N_t^N$, as well as the share of models we classify as new.

account for approximately half of new-model introduction. During the recession, both margins decline, but the bulk of the overall drop in new models is due to missing new generations of existing models. This evidence (tentatively) suggests that the vertical margin of product introduction is more responsive to the drop in demand. However, we acknowledge that it is challenging to tightly associate these categories of new products to different types of innovation because carmakers may launch a new model name to refresh the image of a new generation of an existing model.

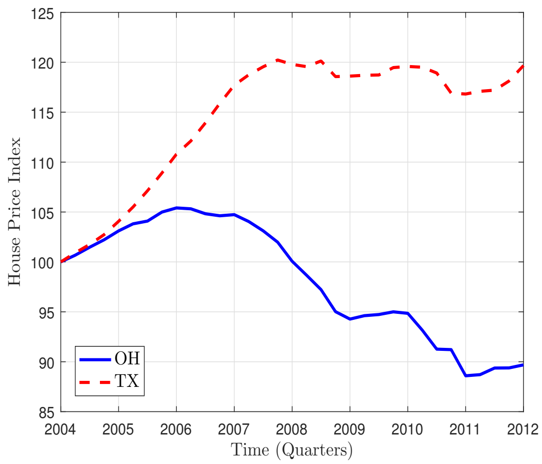
#### 2.3.2.3 Geographical Variation: Ohio versus Texas

We now exploit geographical variation across states to connect the dynamics of the dispersion of expenditures with the depth of the recession. This decomposition isolates the role of household demand for quality, because the set of products is constant across states. In particular, we observe variation in the magnitude of the drop in the dispersion of expenditures and a larger quality adjustment in states where households were hit more strongly by the recession.

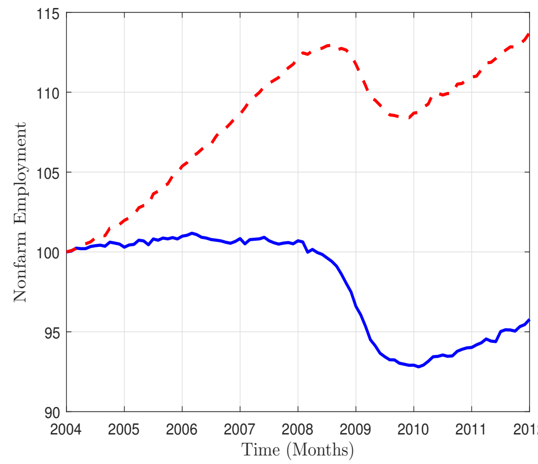
To document this pattern, we compare Ohio and Texas, for two main reasons. First, they are the two largest states in our data and account for the bulk of transactions (approximately 80%). Second, Ohio and Texas experienced starkly different macroeconomic dynamics during the Great Recession, making the comparison of these two states insightful.

To highlight the macroeconomic differences between Ohio and Texas, we follow the approach of Gertler and Gilchrist (2018*a*), which analyzes state-level variation in the intensity of the Great Recession, focusing on house-price and employment dynamics (see also the related approach of Mian, Rao and Sufi, 2013). The top panels of Figure 2.3 portray the Federal Housing Authority house-price index (top-left) and total non-farm employment (top-right) in Ohio (solid lines) and Texas (dashed lines). Ohio experienced a deep recession, with a 10% home price decline and an 8% employment

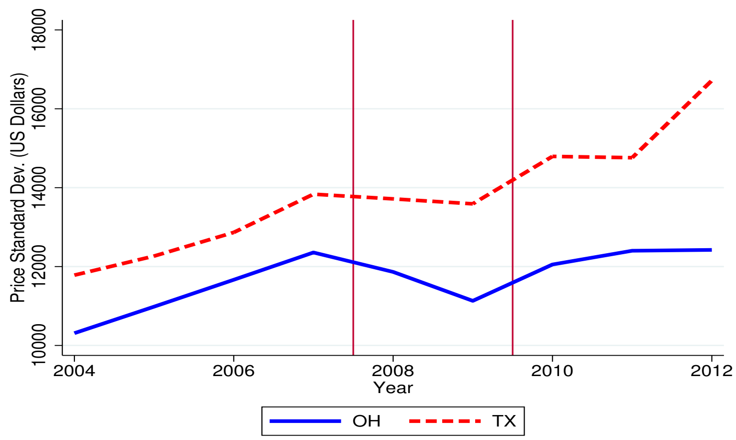
Figure 2.3: Ohio versus Texas




(a) House Price Index




(b) Total Nonfarm Employment




(c) Standard Deviation of Prices

*Notes:* The figure displays the dynamics of house prices, employment, and dispersion of expenditures on new cars in Ohio and Texas around the Great Recession. The top-left panel displays the quarterly Purchase Only Index of house prices from the Federal Housing Authority and the top-right panel displays monthly Total Nonfarm Employment from the Bureau of Labor Statistics (Gertler and Gilchrist, 2018*b*). Both series are normalized to equal 100 in both states at the beginning of 2004. The bottom panel displays the standard deviation of the distribution of transaction prices from the Dominion dataset. Horizontal axes report years. Solid lines refer to Ohio, dashed lines to Texas.

decline. In contrast, Texas did not experience any housing bust and its decline in employment was less significant.

Geographical heterogeneity in the depth of the recession is likely associated with variation in household *demand* for durable-goods quality. Accordingly, Ohio experienced a downward adjustment in the demand for quality more sizable than Texas: The bottom panel of Figure 2.3 displays the standard deviation of the distribution of transaction prices in these two states and shows that the dispersion in Ohio (solid line) dropped more significantly than in Texas (dashed line) during the Great Recession. Consistent with a differential drop in demand for quality, we also find that the compression in the distribution of expenditures in Ohio is primarily due to a relative decline in the median and in higher percentiles, whereas these changes are less pronounced in Texas.

### 2.3.3 Dynamics of the Distribution of Quality

Our decompositions establish that the heterogeneity between models and, critically, new models are the main drivers of the dynamics of the distribution of new-car expenditures. Moreover, quality differences between new and continuing models were lowest during the recession. These patterns spur us to study vehicle characteristics.

To this end, we use hedonic regressions to estimate the function that maps vehicle characteristics to prices (for a seminal contribution, see Griliches, 1961). Formally, let the average price $p_{it}$ of car model $i$ in year $t$ equal:

$$p_{it} = h_t(X_{it}, W_{it}, \eta_{it}),$$

where $h_t(\cdot)$ is the hedonic function; $X_{it}$ are observed continuous vehicle attributes, such as fuel efficiency, horsepower, engine size, weight, and wheelbase; $W_{it}$ are observed discrete attributes, such as indicator variables for make, four-wheel drive, number of gears, manual transmission, turbo injection, number of cylinders, diesel, number of seats, and number of doors; and $\eta_{it}$ are unobserved determinants of prices. We transform all continuous variables in logarithms and assume that the log of the hedonic function $h_t(\cdot)$ is linear:

$$\log p_{it} = \beta_t \log X_{it} + \gamma_t W_{it} + \eta_{it}, \tag{2.1}$$

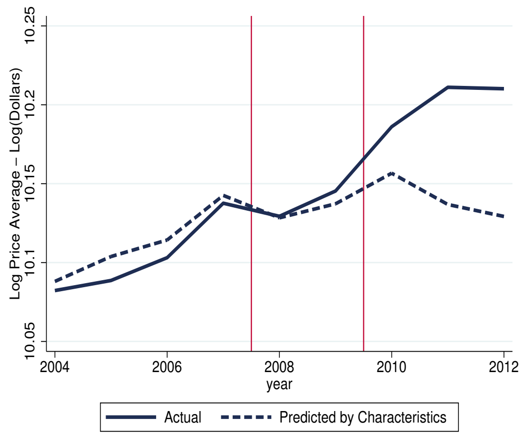
where $\beta_t$ and $\gamma_t$ are the vectors of coefficients, or "hedonic prices" of car characteristics.

We observe detailed characteristics of different trims of each model in the IHS dataset, whereas we observe transaction prices at a coarser level of aggregation—namely car models—in the merged dataset. Thus, we aggregate all continuous characteristics of different trims of each model, weighting different trims according to their transaction shares in the IHS dataset, whereas we consider different discrete characteristics as different observations, or, equivalently, different models.

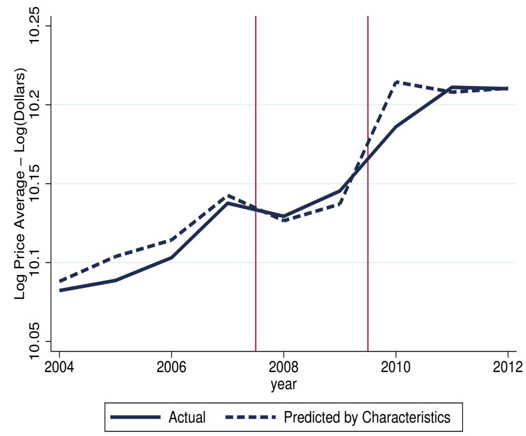
We consider three subsamples: pre-recession (2004-2007), recession (2008-2009), and post-recession (2010-2012), assuming the coefficients are constant within each subsample but are potentially different across subsamples. We use these hedonic regressions to implement decompositions between the differences in the mean characteristics of vehicles over time and the differences in the hedonic prices of these characteristics over time (Oaxaca, 1973; Blinder, 1973). We leverage these estimates to track the evolution of the distribution of quality, by assigning a predicted value based on characteristics to each model. Formally, given the estimated hedonic prices $\hat{\beta}_{2004-2007}$ and $\hat{\gamma}_{2004-2007}$, we measure the quality of vehicle $j$ in year $t = 2004, 2005, ..., 2012$ as $\hat{\beta}_{2004-2007} \log X_{jt} + \hat{\gamma}_{2004-2007} W_{jt}$. This prediction represents the value of the bundle of characteristics contained in model $j$ in year $t$, based on the dollar value of these characteristics implicit in pre-recession prices.

The left panel of Figure 2.4 displays our third main finding, which relates the dynamics of average price and average quality during and after the recession. The panel shows that they grow at a similar rate until the recession and, crucially, quality predicts the decline in the average price during the recession. In fact, the decline in average quality between 2007 and 2008 is slightly larger than the decline in the

Figure 2.4: Hedonics and Vehicle Quality




(a) Constant Hedonic Prices




(b) Time-varying Hedonic Prices

*Notes:* The figure displays the dynamics of average (log) transaction price in the merged Dominion-IHS dataset (solid lines) and the average (log) value predicted with a hedonic regression—equation (2.1)—(dashed lines). Each model is weighted according to its transaction share in the IHS dataset. The left panel refers to constant pre-recession hedonic prices (2004-2007); the right panel to time-varying hedonic prices, estimated in three subsamples: pre-recession (2004-2007), recession (2008-2009), and post-recession (2010-2012). Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

average price. We relate the dynamics of prices to the dynamics of selected characteristics during the recession analyzing the evolution of several variables associated with high quality based on our hedonic regressions, such as wheelbase, horsepower, and engine size. The averages of all these characteristics decline during the recession, which suggests a reallocation of expenditures toward smaller and less powerful cars, consistent with the dynamics of prices displayed in Figure 2.1.

However, the left panel of Figure 2.4 displays a striking pattern from 2009 onward. Specifically, the average price grows at a rate of approximately 2% per year, whereas the average value implied by car characteristics declines protractedly, diverging from the average price until the end of our sample. Notably, average quality shows no growth in 2007-2012, while the average price grows by 7%.

This apparent decoupling between prices and predicted quality, based on pre-recession prices, indicates that the post-recession hedonic prices of some characteristics are higher than their pre-recession values. Different car attributes or brands may have different costs or may be valued differently over time, implying that changes in the state of the economy likely affect hedonic prices (Pakes, 2003). Accordingly, we re-estimate equation (2.1) separately in the three subsamples, and use these different estimates to compute a second measure of average quality. The right panel of Figure 2.4 displays the dynamics of this second measure of average quality, based on time-varying hedonic prices. The panel shows that this measure of average quality tracks the average price closely in all sub-periods.

The difference between our first and our second measures of quality confirms that the hedonic prices of some characteristics increased over time. Specifically, the hedonic prices of two important characteristics—wheelbase and horsepower—increased by over 20% in the post-recession sample relative to the pre-recession sample. Changes in the hedonic prices of characteristics associated with high quality have different potential explanations, including a relative scarcity of models in the most expensive segments or time-varying markups. Nevertheless, this increase in the price of quality may partially account for the slow recovery in new-car sales after the Great Recession.

Critically, we find that pre-recession hedonic prices accurately predict the dynamics of expenditures on new models during the recession. The hedonic regression accounts for approximately 98% of the observed drop in between-model dispersion of new-model prices, though it slightly overpredicts the decrease in their average price. These results confirm that reallocation across different levels of quality accounts for the dynamics of the distributions of expenditures on all and new models.

In Appendix 2.B, we analyze geographical heterogeneity in the dynamics of car quality, estimating separate hedonic regressions in Ohio and Texas. Both states experience a decline in average prices relative to their respective trends. However, in Ohio—where the recession was deeper—we observe a larger substitution toward models with lower quality, as well as a larger and more persistent gap between price and quality, which buttresses the primary role of household demand for quality.

Finally, we investigate any differential effects between US and foreign carmakers. While the hedonic regressions show that the point estimates of US carmaker fixed effects are lower than those of Asian and European carmakers, respectively, the estimates do not show differential changes across periods.

Overall, our hedonic regression analysis highlights some striking dynamics in the quality of vehicles and confirms a reallocation in expenditures away from high-quality new models. In the next subsection we present a complementary analysis that focuses on technological trade-offs in the set of models available on the market, abstracting from information on prices. This analysis allows us to address some potential limitations of the hedonic methodology, such as the difficulty of disentangling changes in marginal costs from changes in markups and in preferences for different models that may occur around the recession.

### 2.3.4 New Models and Technological Progress

We now analyze the level of technology embodied in vehicles and document a sharp drop in the quality of new models introduced during the Great Recession. This analysis allows us to isolate the role of supply factors for the downward quality adjustment in durable goods.

We follow Knittel (2011) to measure the technological trade-off between fuel efficiency, weight, and engine power, and to estimate its evolution over time. This methodology posits a marginal-cost function that depends on vehicle attributes and estimates the level sets of this function, using time fixed effects to capture the evolution of the technological frontier. Specifically, the marginal cost function for vehicle $i$ in year $t$ equals:

$$c_{it} = c_t^1(mpg_{it}, hp_{it}, w_{it}, Z_{it}^1, \mathcal{I}_{it}^N) + c_t^2(Z_{it}^2),$$

where $c_t^1(\cdot)$ is the component of marginal cost related to fuel economy, which depends on fuel efficiency $mpg_{it}$, horsepower $hp_{it}$, weight $w_{it}$, a subset of characteristics $Z_{it}^1$ that are relevant for the trade-off of interest, and $\mathcal{I}_{it}^N$ is an indicator variable for new models; $c_t^2(\cdot)$ is the component of the marginal cost that depends on other characteristics that are less related to fuel economy, $Z_{it}^2$. We include a large set of indicator variables for vehicle characteristics $Z_{it}^1$, such as make, diesel engine, turbo injection, manual transmission (also interacted with a time trend).

We further assume that vehicle attributes enter the marginal-cost function $c_t^1(\cdot)$ in a log-linear form—i.e., the cost function is Cobb-Douglas—and that time $t$ affects this function in multiplicative form—i.e., technological progress is input neutral. Under these assumptions, we estimate the level sets of the marginal cost $c_t^1(\cdot)$ with the following specification:

$$\log mpg_{it} = \alpha_{hp} \log hp_{it} + \alpha_w \log w_{it} + \alpha_Z Z_{it}^1 + \alpha_N \mathcal{I}_{it}^N + T_t + T_t \times \mathcal{I}_{it}^N + \varepsilon_{it}, \qquad (2.2)$$

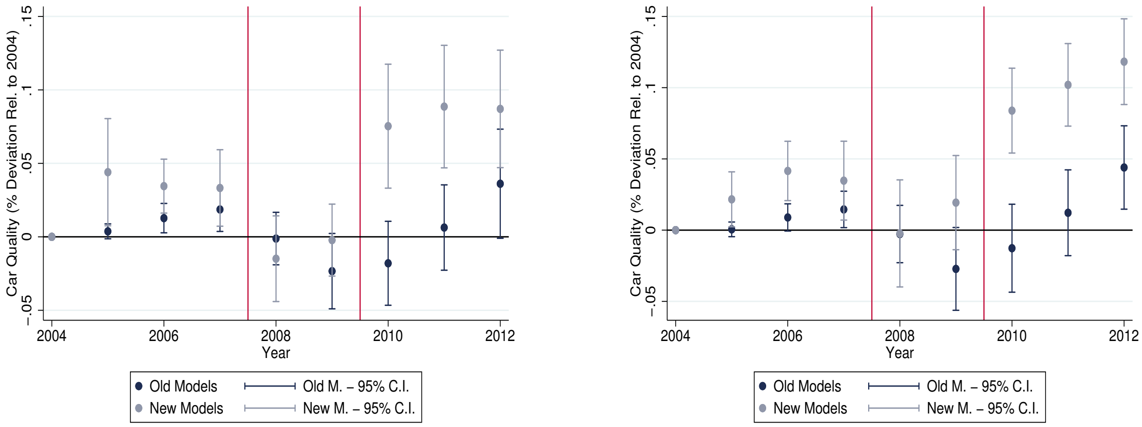
where $T_t$ is a year fixed effect; $T_t \times \mathcal{I}_{it}^N$ is the interaction between time fixed effects and the indicator variable for new models, which allows the regression (2.2) to flexibly capture a differential effect of the recession on new models; and $\varepsilon_{it}$ are unobservables.

Whereas the hedonic approach combines the reallocation of demand and changes in the supply of quality, the marginal-cost estimation likely highlights quality changes that originate on the supply side of the market. We estimate equation (2.2) in two ways, first weighting models by the number of transactions, and then without sales weights, which further isolates changes in the quality of products supplied.[11]

Figure 2.5 displays the estimated year fixed effects for new models (clear markers) and old models (dark markers), relative to their pooled baseline value in 2004, normalized to zero. The left panel portrays the estimates of the sales-weighted regression

[11] In both cases, for consistency with our analysis of Section 2.3.3, we aggregate all continuous characteristics of different trims of each model at the model level, weighting different trims according to their transaction shares, and we consider different discrete characteristics as different observations.

Figure 2.5: Technology of New and Old Models




(a) Weighted by Sales

(b) Not Weighted by Sales

*Notes:* The figure displays the estimated average level of technological efficiency for new models (clear markers) and old models (dark markers), measured as the estimated time fixed effects in regression equation (2.2). The left panel refers to a regression with weights based on the number of transactions in the IHS dataset, whereas the right panel refers to a regression without weights. The horizontal axis reports years (2004-2012); vertical lines highlight recession years (2008 and 2009).

and the right panel refers to the unweighted regression. In both cases, we find that, typically, the level of technology grows over time, with new models displaying superior technology than old models. However, our fourth main finding is that, during the Great Recession, the growth rate of quality of new models declines: In 2008, the estimated quality of new models is similar to the quality of old models, which implies a halt in the adoption of frontier technologies embodied in new vehicles. Consistent with this drop in technology adoption, we estimate that the quality of continuing models also declines in 2008 due to an inferior mix of characteristics.

Quantitatively, the coefficients displayed in Figure 2.5 mean that the average level of technology of new models declines by almost 5% between 2006 and 2008. The similarity of the left and right panels supports the notion that the main driver of this decline is that the quality of newly introduced vehicles drops in the recession.

We further estimate the technology levels separately for models introduced by European, Asian, and US carmakers. We find that the drop in new-product quality is largest for European carmakers, which on average specialize in high-quality models. This finding, along with our finding on the crucial role of European carmakers for high-quality models (Section 2.3.2.2), supports our interpretation that the downward quality adjustment on the supply side is likely an endogenous response to the drop in demand, and less likely due to other shocks hitting carmakers, such as financial shocks, which were more severe for US manufacturers.[12]

Although the technological level of new models recovers sharply from 2010, the low quality of new models introduced during the recession—which remain in the set of available models for several years—persistently drags the average level of technology for the continuing models, which remains on a lower path throughout the recovery. Overall, the technological level of old models breaks its pre-recession 2007 level only at the end of our sample, as models introduced during the recession are gradually replaced.

Accordingly, we perform a back-of-the-envelope calculation of the effects of these dynamics on the average quality of the overall stock of registered cars, combining our estimated level of technology for new cars with information on new-car registrations during the period of our analysis. Appendix 2.B.4 provides the details of this calculation. We estimate that by 2012, the quality of the car stock was 1.3% lower than if new-car technology and new-car registrations had remained on their pre-recession trends. The drop in new-car quality accounts for almost one percentage point of this decline.

## 2.4 Concluding Remarks

Our analysis shows that both demand and supply factors contributed to a downward quality adjustment in expenditures during the Great Recession. Amid a decline in

[12] Furthermore, we find that the technology level evolves similarly for new model names and new generations of existing model names.

demand and a reallocation of expenditures away from expensive models, automakers introduced models of low quality, leading to a persistent decline in technology.

We argue that alternative mechanisms that affect exclusively demand or supply cannot fully account for all patterns on quality dynamics that we uncover. Geographical variation in expenditures highlights the critical role of household demand for quality, thus inconsistent with supply shocks hitting only manufacturers—such as financial shocks—determining quality dynamics. Our finding that manufacturers modified the path of technology embodied in new models points to an important role for supply, inconsistent with an explanation based exclusively on household demand, through substitution toward lower quality within a fixed set of products.

We believe that this evidence will prove useful in informing quantitative models of innovation over the business cycle.

# Appendices

## Appendix 2.A Data and Measurement

In this appendix, we describe our procedure for merging the Dominion dataset and the IHS dataset and explain our definitions of vehicle models.

### 2.A.1 Merging Dominion and IHS Datasets

For each transaction in the Dominion dataset, we observe a string for make name—e.g., "TOYT" for Toyota—and a string for model name—e.g., "Camry"—as well as the corresponding model-year, which may or may not correspond with the calendar year in which the transaction takes place because new models marketed as model-year $t$ are often introduced in year $t-1$.

For each vehicle model in the IHS dataset, we observe a string for make name—e.g., "Toyota"—and a string for model name—e.g., "Toyota Camry"—as well as a variable named generation-year, which allows us to identify different generations of a same model—e.g., first generation, second generation, etc. Moreover, we also observe the total number of US transactions by calendar year.

1. In the Dominion dataset we identify all strings corresponding to make and model names.

2. We perform the same step, identifying make and model names in the IHS dataset.

3. For all make-model names in the Dominion dataset (point 1), we find a single corresponding make-model name in the IHS dataset (point 2). Whenever we do not find a match for the make-model name (approximately 19% of cases), we assign as model name the combination of make name and the first word of the model string from the Dominion dataset.

4. For each make-model name in the Dominion dataset, we identify the corresponding set of model-years for which we observe a positive number of transactions. For example, in the case of the Toyota Camry, these model-years are 2003, 2004, ..., 2013.

5. For each make-model-generation in the IHS dataset, we identify the first model-year with a positive number of transactions in the IHS dataset. If the first year with a positive number of transactions of a make-model-generation is year $t$, we infer that the first model-year for that make-model-generation is year $t + 1$, to account for the fact that vehicles marketed as model-year $t$ are typically first introduced in the market in year $t - 1$.

6. We merge the dataset of Dominion make-model-years (point 4) with the Dominion-IHS matched list of make-model names (point 3).

7. We assign each make-model-year from the Dominion dataset (point 6) to the corresponding make-model-generation (point 5) as follows: Toyota Camry model-years 2007-2011 are assigned to the generation-year 2007 and Toyota Camry model-years 2012 through 2013 are assigned to generation-year 2012.

### 2.A.2 Model Definitions

We define a vehicle model as a triplet of make, model, and generation obtained following the merging procedure described above—e.g., Toyota Camry generation-year 2007.

We define a new model in year $t$ as a model for which we observe the first transaction in year $t$ or in year $t-1$, to account for the fact that the first transaction on a new model tends to appear in the second half of the year. Specifically, this implies that we consider a model as new whenever its model year in the Dominion dataset corresponds with its generation year, and possibly also whenever we observe a transaction for this model that occurs in a calendar year preceding its model year. Thus, this definition includes new model names as the first generation of a model, as well as new generations of existing model names. We exclude 2004 from our analysis of new models because this is the first year in the Dominion dataset, and thus we cannot cleanly identify new models.

We should point out that because we observe transaction prices at the model level in the Dominion dataset and, thus, we merge information from the Dominion dataset and the IHS dataset at the model level, there remains some residual heterogeneity in vehicle characteristics across different trims of each model in the IHS dataset. To deal with this heterogeneity, in our analyses of car characteristics in Sections 2.3.3 and 2.3.4, we average all continuous car characteristics across different trims of each model using their respective transaction shares in the IHS dataset, whereas we treat vehicles with different values of discrete characteristics—such as diesel, or turbo injection—as different models. In Appendix 2.B we consider an alternative approach, aggregating both continuous and discrete characteristics at the model level using their transaction shares. As Figures 2.B.12 and 2.B.13 show, our main findings are robust to this alternative approach, suggesting that the level of aggregation of car characteristics, as well as the exact number of models, do not affect our results.

# Appendix 2.B Additional Empirical Evidence

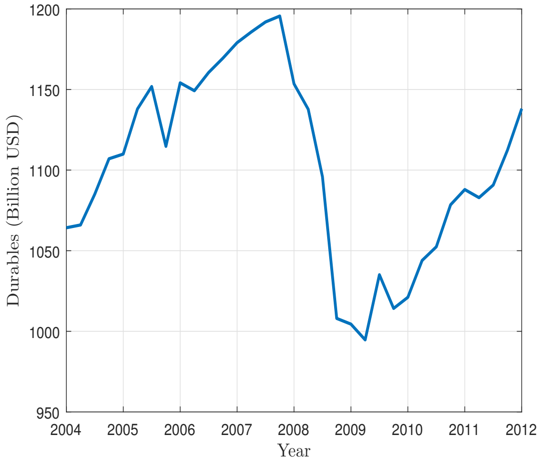
In this appendix, we provide additional empirical evidence and document several robustness checks.

## 2.B.1 Dynamics of the Distribution of Expenditures

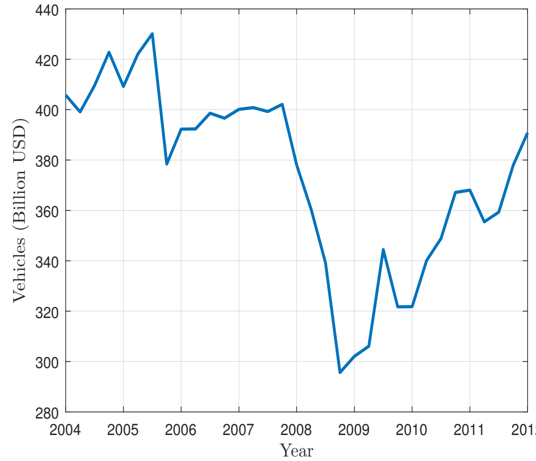
Figure 2.B.1 displays aggregate consumer expenditures on durable goods (left panel) and on vehicles (right panel) during 2004-2012 (US Bureau of Economic Analysis, 2022) and shows the large drop in these components of household expenditures during the Great Recession.

During July and August of 2009, the Car Allowance Rebate System, commonly known as "Cash for clunkers," subsidized the replacement of highly polluting cars with new ones, potentially affecting the pool of new-car buyers (Hoekstra, Puller and West, 2017). Figure 2.B.2 reproduces the findings displayed in Figure 2.1, but excluding the months of July and August in each year to show that the patterns of the distribution of expenditures on new vehicles are not significantly affected by the Cars Allowance Rebate System. Figure 2.B.3 displays the same variables, but excludes fleet sales—which account for approximately 4.4% of transactions—to show that our main findings are unchanged if we restrict attention to consumer sales only.

Figure 2.B.1: Consumer Expenditures on Durable Goods and on Motor Vehicles



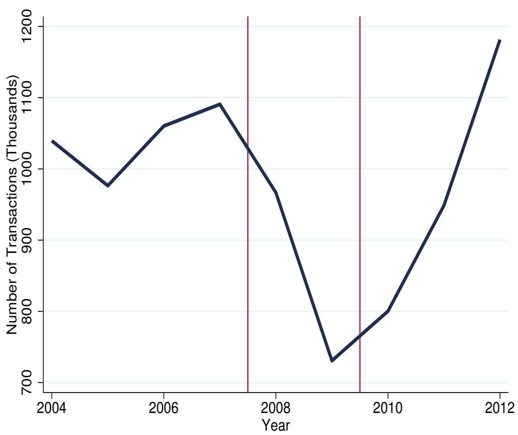

(a) Durables



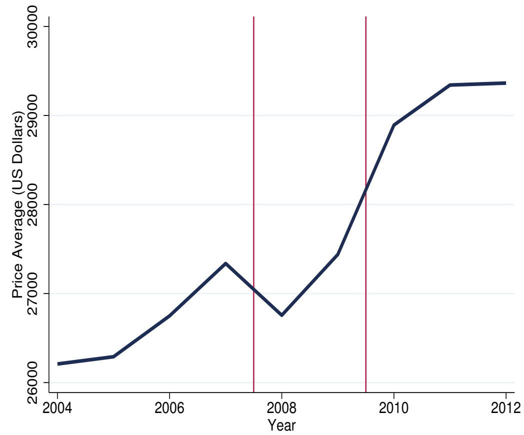

(b) Vehicles

*Notes:* The figure displays personal consumption expenditures on durable goods (left panel) and on motor vehicles and parts (right panel), at quarterly frequency, seasonally adjusted annual rate, from the Bureau of Economic Analysis during 2004-2012.

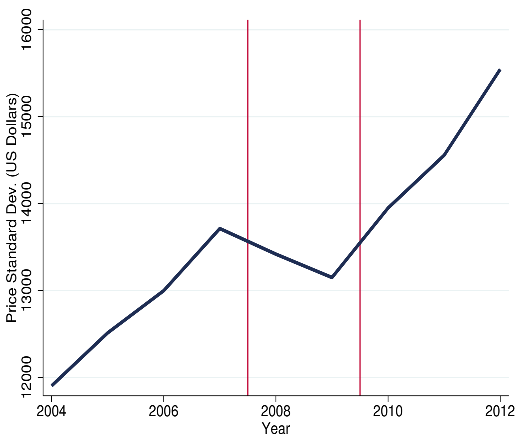
Figure 2.B.2: Dynamics of New-Vehicle Expenditures, Excluding July and August of Each Year



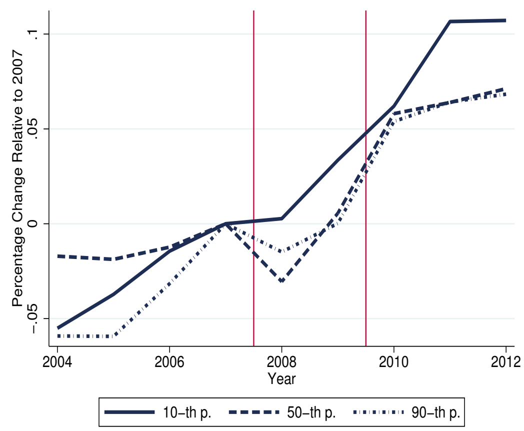

(a) Number of Transactions




(b) Average Transaction Price



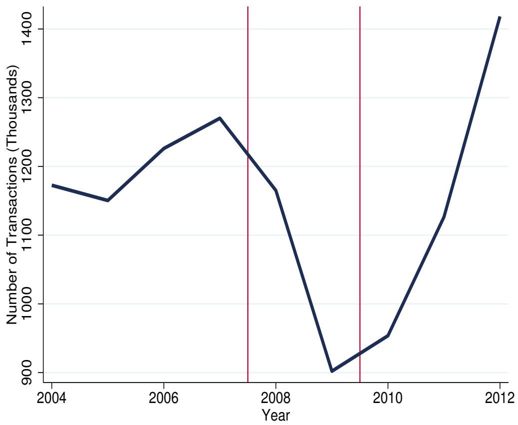

(c) Standard Deviation of Prices



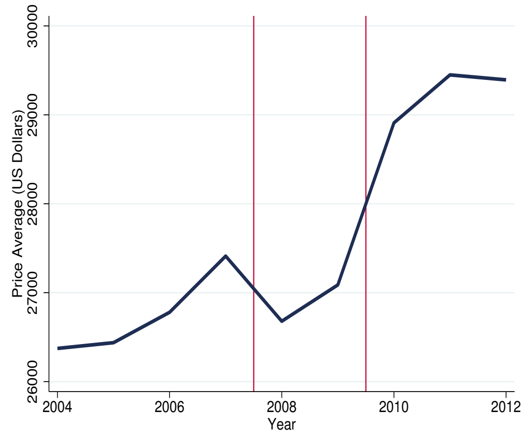

(d) Percentiles of Prices

*Notes:* The figure displays the number of new-car sales (top-left panel), the average (top-right panel), the standard deviation (bottom-left panel), and three percentiles—10th, 50th, and 90th—(bottom-right panel) of the distribution of transaction prices from the Dominion dataset, excluding the months of July and August of each year. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

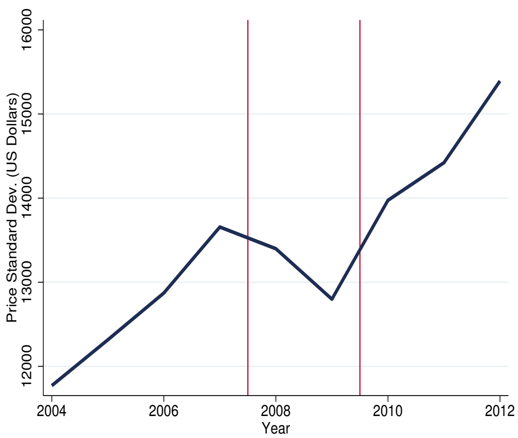
Figure 2.B.3: Dynamics of New-Vehicle Expenditures, Excluding Fleet Sales



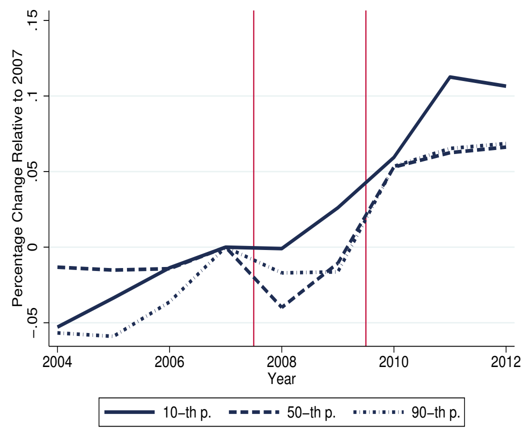

(a) Number of Transactions




(b) Average Transaction Price




(c) Standard Deviation of Prices




(d) Percentiles of Prices

*Notes:* The figure displays the number of new-car sales (top-left panel), the average (top-right panel), the standard deviation (bottom-left panel), and three percentiles—10th, 50th, and 90th—(bottom-right panel) of the distribution of transaction prices from the Dominion dataset, excluding fleet sales. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

### 2.B.2 Decomposing the Dispersion of Expenditures

Figures 2.B.4 and 2.B.5 reproduce the findings displayed in Figure 2.2 under the same two robustness checks described above: namely, removing July and August to exclude the effects of “Cash for clunkers” and removing fleet sales, respectively.

Figure 2.B.6 portrays the path of the average transaction price for ten popular models. Specifically, we select the five models with the highest sales volume with price below the overall sample median, and the five models with highest sales volume with price above the median. For all of these models, the figure shows that prices did not significantly deviate from trend during the Great Recession. This confirms that reallocation between models, instead of price changes at the model level, account for changes in the distribution of expenditures during the recession. Consistent with this evidence, Gavazza and Lanteri (2021) show that price changes during the Great Recession were concentrated in used-car markets.

We further verify that a reallocation of market shares across different models accounts entirely for our findings on the dynamics of between-model price variance—as well as average price—by performing the following analysis. We decompose the difference between the between-model variance in year $t$, $V_t^B$, and the between-model variance in the whole sample, $V^B$, as follows:

$$\begin{aligned} V_t^B - V^B &= \sum_{i \in M_t} s_{it} \left(\overline{p}_{it} - \overline{p}_t\right)^2 - \sum \overline{s}_i \left(\overline{p}_i - \overline{p}\right)^2 \\ &= \sum_{i \in M_t} \left(s_{it} - \overline{s}_i\right) \left(\overline{p}_i - \overline{p}\right)^2 + \sum_{i \in M_t} \overline{s}_i \left[\left(\overline{p}_{it} - \overline{p}_t\right)^2 - \left(\overline{p}_i - \overline{p}\right)^2\right] + \\ &\quad + \sum_{i \in M_t} \left(s_{it} - \overline{s}_i\right) \left[\left(\overline{p}_{it} - \overline{p}_t\right)^2 - \left(\overline{p}_i - \overline{p}\right)^2\right], \end{aligned} \tag{2.3}$$

where the index $i$ refers to models, $t$ denotes years, and we use bars to denote averages of prices $p_{it}$ and market shares $s_{it}$.

The first term on the second line of equation (2.3) measures the role of reallocation of expenditures across models; the second term on the second line measures the role of changes in model prices; and the final term denotes the covariance term between changes in market shares and prices.

Figure 2.B.7 shows that between 2007 and 2009, the component due to reallocation (dashed line) accounts for the entire decline in between-model variance. This

finding buttresses our interpretation of the variance decompositions in Section 2.3.2: A reallocation of expenditures toward models of lower quality accounts for the drop in dispersion of expenditures.

We also perform the same decomposition for the average price in year $t$ (equation (2.4)) and obtain again a tight match between the overall average-price dynamics around the recession and the component due to reallocation of market shares across models, as Figure 2.B.8 shows.

$$\begin{aligned}
\overline{p}_t - \overline{p} &= \sum_{i \in M_t} s_{it}\overline{p}_{it} - \sum \overline{s}_i \overline{p}_i \qquad (2.4)\\
&= \sum_{i \in M_t} \left(s_{it} - \overline{s}_i\right) \overline{p}_i + \sum_{i \in M_t} \overline{s}_i \left(\overline{p}_{it} - \overline{p}_i\right) + \sum_{i \in M_t} \left(s_{it} - \overline{s}_i\right) \left(\overline{p}_{it} - \overline{p}_i\right).
\end{aligned}$$

Furthermore, we obtain similar results when we restrict attention to the variance of prices of new models.

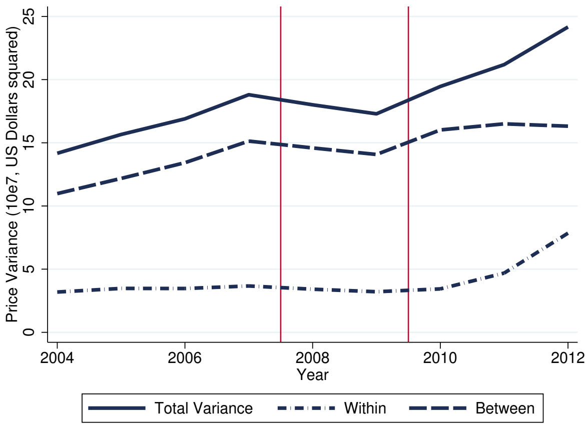
Figure 2.B.9 displays the time series of the total number of sales and the number of sales of new models (left panel) and the share of models we classify as new models (right panel). These two figures show that both the share of transactions on new models and the flow of new-product introduction are procyclical, peaking in 2007 and dropping during the Great Recession.

Figure 2.B.10 displays our findings on the patterns of new-model introduction across carmakers of different geographical origin (Europe, Asia, and US). The left panel shows that the number of new models dropped for all three groups during the recession. Between 2007 and 2009, the volume of new-model introduction dropped by for European carmakers, by for Asian carmakers, and by for US carmakers. As a result, there is a missing generation of new models across all makes. After the recession, we observe some heterogeneity in the speed of recovery, with European carmakers increasing new-model introduction faster than Asian and US carmakers.

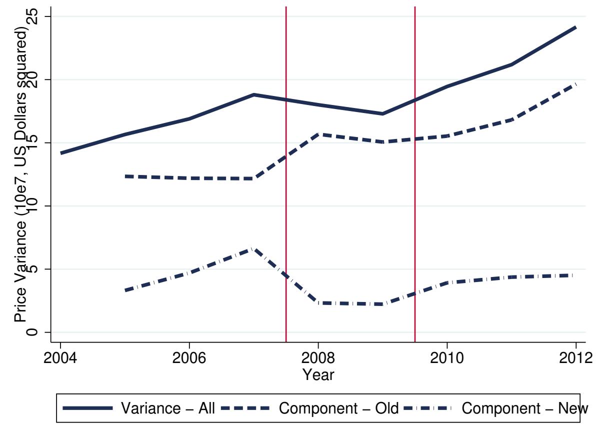
The right panel of Figure 2.B.10 focuses on new models with an average price above \$40,000, which approximately corresponds to the 90th percentile of the distribution in 2007. In this range, we observe that European carmakers account for the majority of new models. In 2007, out of 24 new models introduced by European carmakers, 17 are above the \$40,000 price threshold. In contrast, out of 26 new models introduced by US carmakers, only 5 are above the same threshold; the fraction of high-price new models introduced by Asian carmakers is even smaller. As the right panel of Figure 2.B.10 shows, high-price new-model introduction from European carmakers dropped almost by half during the recession, which largely accounts for the missing generation of high-quality new models in 2008 and 2009.

Figure 2.B.11 displays the decomposition of new-model introduction into new model names and new generations of existing model names.

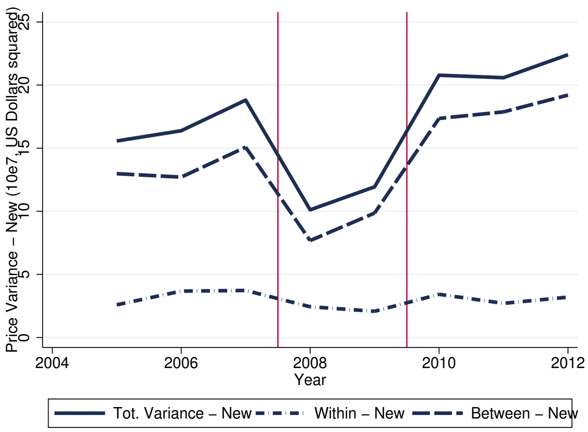
Figure 2.B.4: Variance Decomposition, Excluding July and August of Each Year




(a) Variance of New-Car Prices, Between and Within




(b) Variance of New-Car Prices, New and Continuing

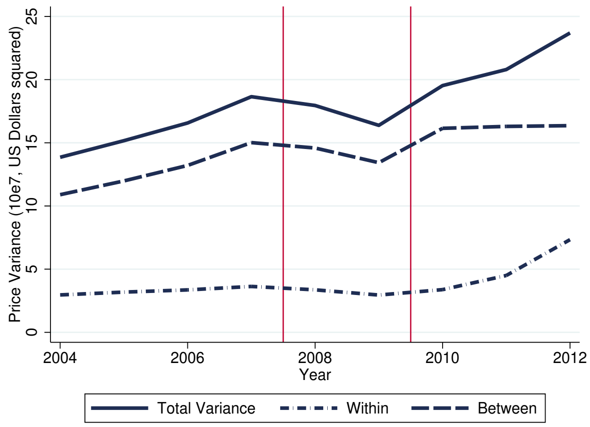



(c) Variance of Newly Introduced Models

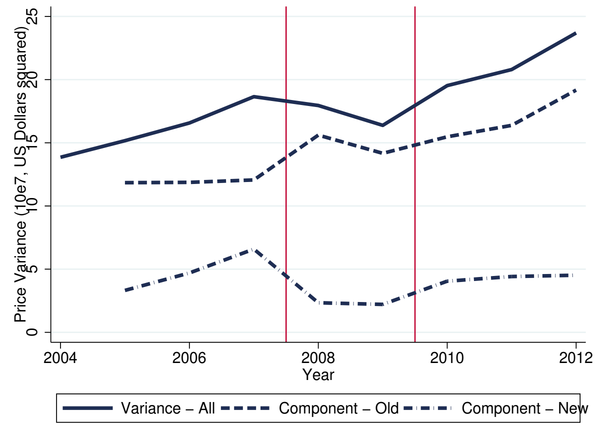

(d) Share of Newly Introduced Models

*Notes:* The figure displays several decompositions of the variance of transaction prices in the Dominion dataset, excluding the months of July and August of each year. The top-left panel displays the decomposition of the variance of new-vehicle transaction prices $V_t$ (solid line) into the following components: between models $V_t^B$ (dashed line) and within models $V_t^W$ (dashed-dotted line). The top-right panel displays the decomposition of the variance $V_t$ (solid line) into two components: new models $s_t^N V_t^N$ (dashed-dotted line) and old models $(1 - s_t^N)V_t^O$ (dashed line). The bottom-left panel displays the variance of expenditures on new models $V_t^N$ (solid line) and its decomposition into between-models component $V_t^{N,B}$ (dashed line) and within-models component $V_t^{N,W}$ (dashed-dotted line). The bottom-right panel displays the share of transactions on new models $s_t^N$. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

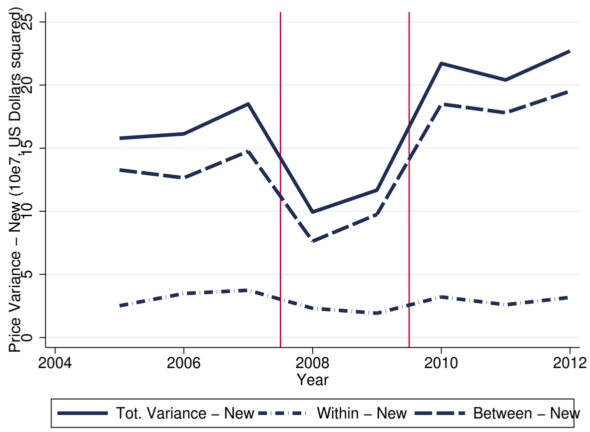
Figure 2.B.5: Variance Decomposition, Removing Fleet Sales




(a) Variance of New-Car Prices, Between and Within




(b) Variance of New-Car Prices, New and Continuing

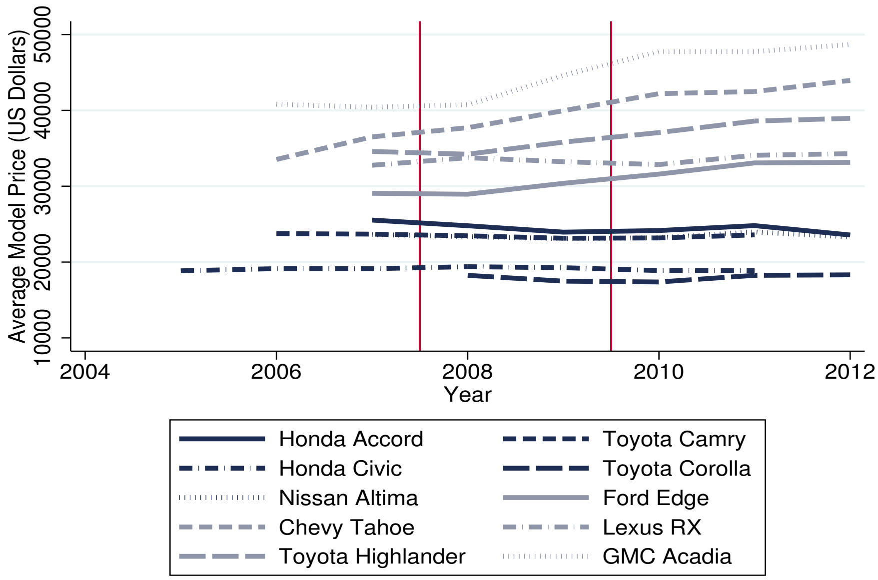



(c) Variance of Newly Introduced Models


(d) Share of Newly Introduced Models

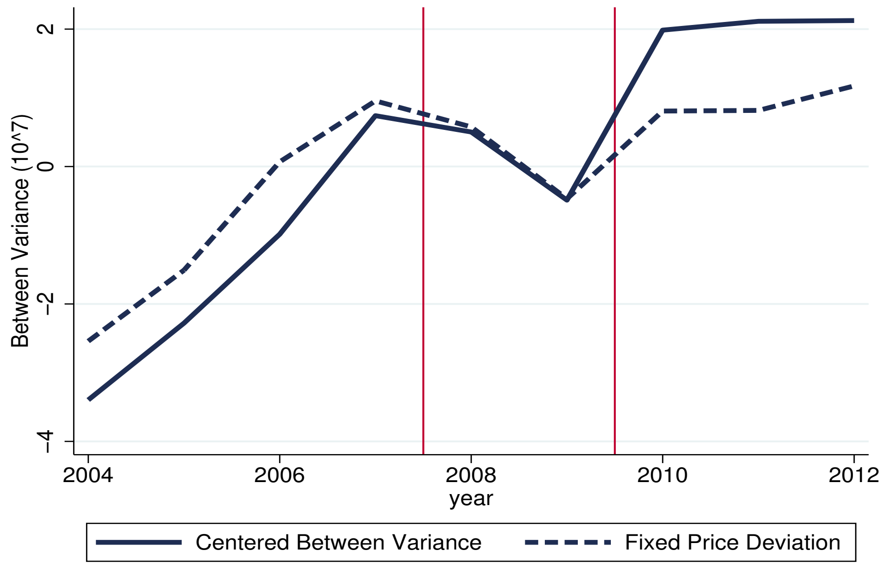
*Notes:* The figure displays several decompositions of the variance of transaction prices in the Dominion dataset, excluding fleet sales. The top-left panel displays the decomposition of the variance of new-vehicle transaction prices $V_t$ (solid line) into the following components: between models $V_t^B$ (dashed line) and within models $V_t^W$ (dashed-dotted line). The top-right panel displays the decomposition of the variance $V_t$ (solid line) into two components: new models $s_t^N V_t^N$ (dashed-dotted line) and old models $(1 - s_t^N)V_t^O$ (dashed line). The bottom-left panel displays the variance of expenditures on new models $V_t^N$ (solid line) and its decomposition into between-models component $V_t^{N,B}$ (dashed line) and within-models component $V_t^{N,W}$ (dashed-dotted line). The bottom-right panel displays the share of transactions on new models $s_t^N$. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

Figure 2.B.6: Average Price of Ten Popular Models



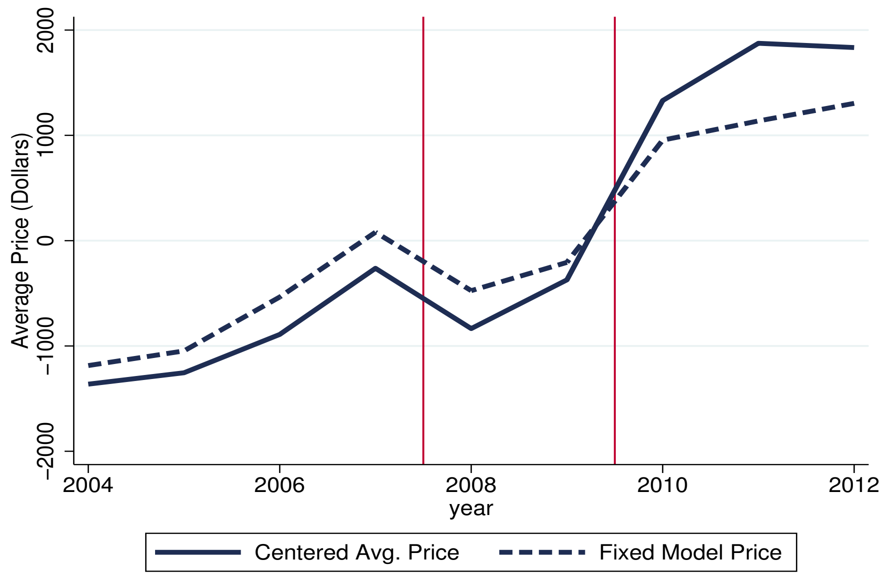

*Notes:* The figure displays the average transaction price of ten popular models in the Dominion dataset. Specifically, we select the five models with the highest levels of sales and price below the median, and the five models with the highest levels of sales and price above the median. Horizontal axes report years (2004-2012); vertical lines highlight the recession years (2008 and 2009).

Figure 2.B.7: Decomposition of Between-Model Variance: Role of Expenditure Reallocation



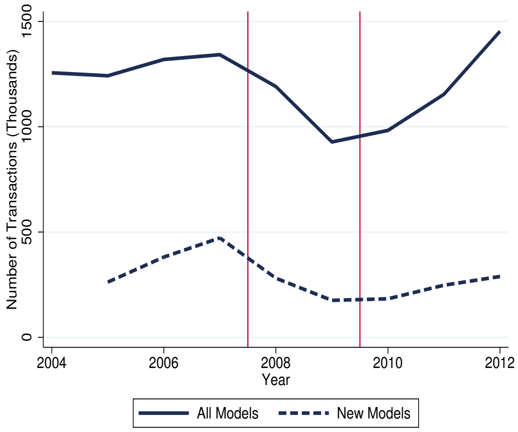

*Notes:* The figure displays the results of the decomposition of the between-model variance defined in equation (2.3). The solid line refers to the overall between-model variance, whereas the dashed line refers to the component due to reallocation of expenditures across models, for fixed deviations of prices from their average. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

Figure 2.B.8: Decomposition of Average Price: Role of Expenditure Reallocation

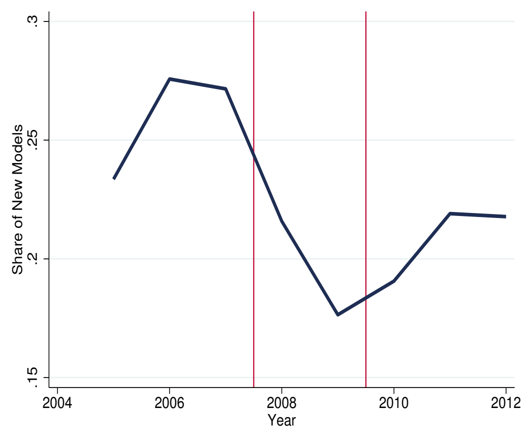



*Notes:* The figure displays the results of the decomposition of the average transaction price defined in equation (2.4). The solid line refers to the overall average price, whereas the dashed line refers to the component due to reallocation of expenditures across models, for fixed average prices at the model level. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

Figure 2.B.9: Transactions and Share of New Models




(a) Number of Transactions

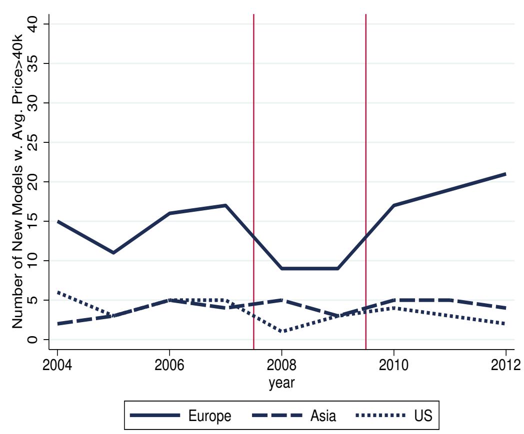



(b) Share of New Models

*Notes:* The left panel displays the number and compositions of new-car sales in the Dominion dataset during 2004-2012. The solid line refers to all sales; the dashed line refers to sales of new-car models only. The right panel displays the time series of the share of models we classify as new models. Horizontal axes report years (2004-2012); vertical lines highlight the recession years (2008 and 2009).

Figure 2.B.10: Introduction of New Models by Origin of Carmakers

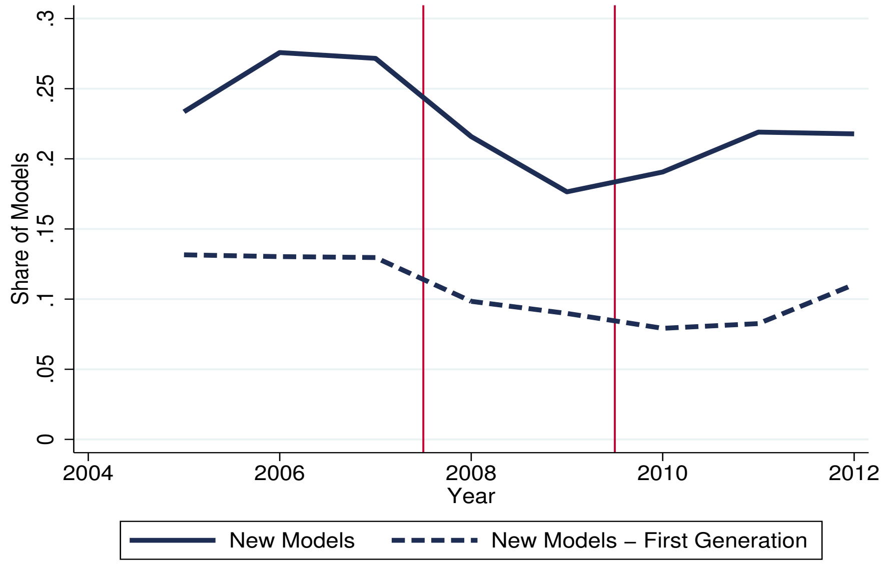

(a) All New Models




(b) High-Price New Models

*Notes:* The figure displays the volume of new-model introduction by origin of carmakers. The left panel refers to all new models, whereas the right panel refers to new models with a price above \$40,000. Solid lines denote European carmakers; dashed lines denote US carmakers; and dotted lines denote Asian carmakers. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

Figure 2.B.11: Introduction of New Model Names




*Notes:* The figure displays a decomposition of the volume of new-model introduction between new model names and new generations of existing model names. The solid line refers to the total share of models that we classify as new and the dashed line refers to the share of models with a new model name in the Dominion dataset. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

### 2.B.3 Dynamics of the Distribution of Quality

Table 2.B.1 reports the results of our hedonic-regression analysis. Specifically, column (1) in Panel A of Table 2.B.1 reports the hedonic prices of the main continuous attributes $X_{it}$ in the pre-recession subsample. Columns (2) and (3) in Panel A report the hedonic prices of the main continuous attributes $X_{it}$ in the recession and post-recession subsamples, respectively.

These hedonic regressions are well suited for accounting for the dispersion of expenditures. Car characteristics capture a large share of the between-model variance in prices: $R^2$ coefficients of the hedonic regressions exceed 0.93 in all subsamples.

The table shows that the coefficients of some attributes, most notably engine size, are not precisely estimated. The reason is that our regression equation (2.1) includes some discrete characteristics $W_{it}$, such as indicator variables for the number of cylinders, which absorb almost all variation in engine size. Hence, the residual variation in engine size is minimal and its coefficient estimate is noisy.

Panel B of the table reports the peak-to-trough dynamics of expenditures and quality of newly introduced models.

Table 2.B.1: Hedonic Regressions

| Panel A: Coefficient Estimates of Continuous Attributes | | | |
|---|---|---|---|
| | (1) Pre-Recession | (2) Recession | (3) Post-Recession |
| Log(Wheelbase) | 1.138 | 1.273 | 1.495 |
| | (0.133) | (0.168) | (0.162) |
| Log(Horsepower) | 0.487 | 0.488 | 0.612 |
| | (0.039) | (0.051) | (0.051) |
| Log(Weight) | 0.090 | 0.153 | 0.035 |
| | (0.060) | (0.078) | (0.077) |
| Log(Fuel Efficiency) | -0.080 | -0.058 | -0.062 |
| | (0.051) | (0.044) | (0.047) |
| Log(Engine Size) | 0.095 | 0.028 | -0.038 |
| | (0.051) | (0.066) | (0.064) |
| Observations | 2,055 | 1,084 | 1,671 |
| $R^2$ | 0.939 | 0.958 | 0.950 |

| Panel B: Quality of New Models | | | |
|---|---|---|---|
| | (1) Data | (2) Constant Prices | (3) Time-Varying Prices |
| Average 2008 – Average 2007 | -0.044 | -0.052 | -0.059 |
| St. Dev. 2008 – St. Dev. 2007 | -0.073 | -0.072 | -0.072 |

*Notes:* Panel A reports the estimated coefficients of the log of continuous characteristics $X_{jt}$ in equation (2.1), with standard errors in parentheses, in three subsamples: column (1) refers to the pre-recession subsample (2004-2007); column (2) to the recession subsample (2008–2009); and column (3) to the post-recession subsample (2010–2012). Panel B reports the peak-to-trough dynamics of expenditures and quality of newly introduced models, weighted according to their transaction shares in the IHS dataset. Column (1) reports the difference between the average log price of new models in the 2008 and the average log price of new models in 2007 (first row) and the difference between the standard deviation of log prices of new models in 2008 and the standard deviation of log prices of new models in 2007 (second row). Column (2) reports the difference between the average (first row) and the standard deviation (second row) of predicted log prices, based on constant hedonic prices estimated in the pre-recession subsample, applied to new models introduced in 2008 and to new models introduced in 2007. Column (3) reports the difference between the average (first row) and the standard deviation (second row) of predicted log prices, based on recession hedonic prices applied to new models introduced in 2008 and pre-recession hedonic prices applied to new models introduced in 2007.

Figure 2.B.12 displays the results of robustness analyses of average quality dynamics measured with hedonic regressions. Specifically, while we produce Figure 2.4 in Section 2.3.3 by aggregating continuous characteristics of different trims at the model level, but considering trims with different discrete characteristics—such as diesel, or

turbo injection—as distinct models, in these robustness analyses we aggregate both continuous and discrete characteristics of different trims of each model.

We consider two alternative specifications of the hedonic regressions. The first specification (top panels) is more flexible and uses indicator variables for discrete characteristics, as in equation (2.1). Within each model, we average the discrete characteristics weighting different trims according to their transaction shares. We then round the average to the closest discrete value, and set the corresponding indicator variable equal to one. The second specification (bottom panels) treats all characteristics that vary across trims—including discrete ones—as continuous variables and assumes a log-linear relationship between prices and all of these characteristics. Within each model, we average the discrete characteristics weighting different trims according to their transaction shares and treat the average as the value of a continuous characteristic. Because make and body type do not vary across trims within each model, we control for these two attributes with indicator variables as in equation (2.1).

The first specification has an overall better fit, because the indicator variables better capture the nonlinearities in the relation between discrete attributes—such as the number of cylinders—and prices, whereas the second specification features a finer measurement of discrete variables—as it does not rely on rounding—but imposes a linear relation between all attributes and prices.

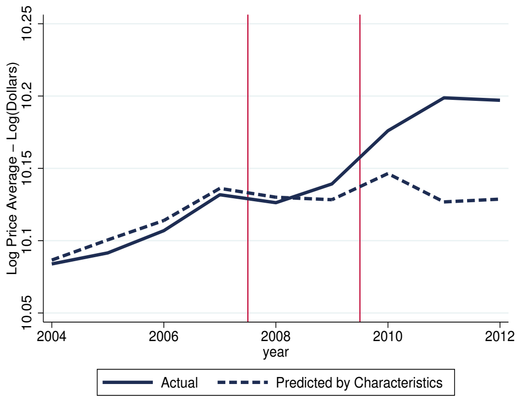
Critically, in both cases we find that quality growth is stagnant after the Great Recession when we measure it with pre-recession hedonic prices (left panels), whereas average quality tracks the average price more closely when we use time-varying hedonic prices (right panels). These results suggest that the level of aggregation of car characteristics, as well as the exact number of models, do not affect our main findings.

Table 2.B.2 reports selected coefficients of our hedonic regressions, with the same level of aggregation as in Section 2.3.3, when we focus exclusively on new models. Consistent with our baseline specification that pools all models (top panel of Table

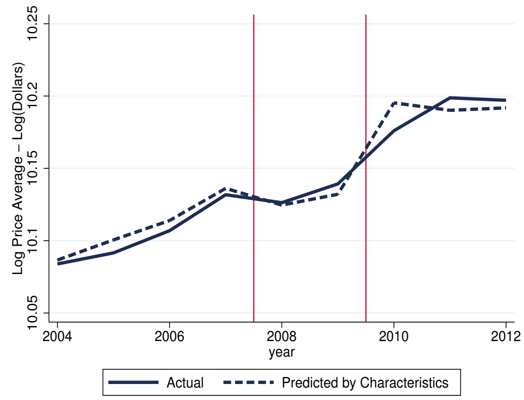
2.B.1), we measure an increase in several hedonic prices of characteristics associated with high quality between the pre-recession and the post-recession periods.

We also explore geographical heterogeneity in the dynamics of the distribution of car quality. To this end, we reproduce the hedonic-regression analysis separately for transactions in Ohio and Texas. We first estimate the hedonic prices of car characteristics in the pre-recession period for each state. We then use these hedonic prices to measure the quality of all cars sold during and after the recession. Both states experience a decline in average prices relative to their respective trends. However, our estimates reveal that in Ohio the substitution toward lower-quality models during the recession is stronger than in Texas: The peak-to-trough decline in average quality is approximately equal to 2% in Ohio and 1.4% in Texas. Moreover, starting during the recession, Ohio features a larger gap between price and quality than Texas.

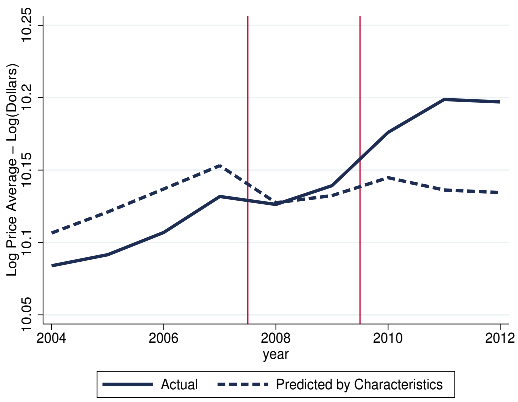
Figure 2.B.12: Hedonics and Vehicle Quality, Aggregating All Characteristics



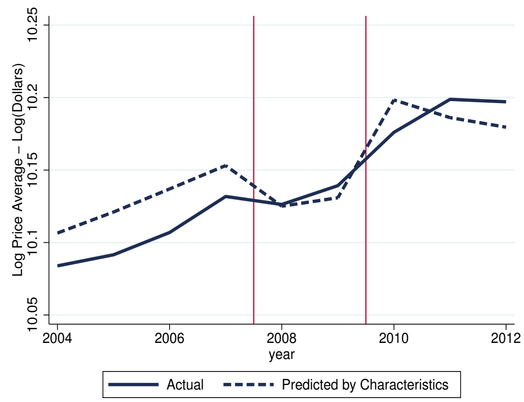

(a) Constant Hedonic Prices, Rounding




(b) Time-varying Hedonic Prices, Rounding




(c) Constant Hedonic Prices, Continuous




(d) Time-varying Hedonic Prices, Continuous

*Notes:* The figure displays the dynamics of average (log) transaction price in the merged Dominion-IHS dataset (solid lines) and the average (log) value predicted with a hedonic regression (dashed lines), when we aggregate both discrete and continuous characteristics of different trims at the model level. Top panels refer to a flexible specification with indicator variables for discrete characteristics, as in equation (2.1). Within each model, we average the discrete characteristics weighting different trims in proportion to their transaction shares. We then round the average to the closest discrete value, and set the corresponding indicator variable equal to one. Bottom panels refer to an alternative specification that treats all characteristics that vary across trims—including discrete ones—as continuous variables and assumes a log-linear relationship between prices and characteristics. Within each model, we average the discrete characteristics weighting different trims in proportion to their transaction shares and treat the average as the value of a continuous characteristic. Because make and body type do not vary across trims within each model, we control for these two attributes with indicator variables as in equation (2.1). Left panels refer to constant pre-recession hedonic prices (2004-2007); right panels to time-varying hedonic prices, estimated in three subsamples: pre-recession (2004-2007), recession (2008-2009), and post-recession (2010-2012). Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

Table 2.B.2: Hedonic Regressions: New Models

| | (1) Pre-Recession | (2) Recession | (3) Post-Recession |
|---|---|---|---|
| Log(Wheelbase) | 1.375 | 2.456 | 1.815 |
| | (0.272) | (0.456) | (0.511) |
| Log(Horsepower) | 0.409 | 0.324 | 0.483 |
| | (0.084) | (0.142) | (0.112) |
| Log(Weight) | 0.340 | 0.933 | 0.554 |
| | (0.143) | (0.205) | (0.216) |
| Log(Fuel Efficiency) | 0.051 | 0.307 | -0.253 |
| | (0.083) | (0.118) | (0.131) |
| Log(Engine Size) | 0.006 | -0.288 | -0.135 |
| | (0.104) | (0.166) | (0.130) |
| Observations | 457 | 215 | 306 |
| $R^2$ | 0.965 | 0.969 | 0.982 |

*Notes:* The table reports the estimated coefficients of the log of continuous characteristics $X_{jt}$ in equation (2.1), with standard errors in parentheses, using data on new models only in three subsamples: column (1) refers to the pre-recession subsample (2004-2007); column (2) to the recession subsample (2008–2009); and column (3) to the post-recession subsample (2010–2012).

### 2.B.4 New Models and Technological Progress

Figure 2.B.13 reports several robustness checks of our estimates of the technology level for new and old models. Specifically, the top-left panel reports the results we obtain by replacing the variable weight with three geometric dimensions—wheelbase, width, and height—in regression equation (2.2). Estimates of the technology level for new and old models are remarkably similar to the ones we show in Figure 2.2. Different from Knittel (2011), our dataset does not contain information about torque; thus, we measure engine power with horsepower across all of the specifications.

The top-right panel of Figure 2.B.13 displays our estimates of the technological level of new models and old models under the assumption of a translog cost function. Under this assumption, we recover the path of technological progress by estimating the following regression equation:

$$\begin{aligned}\log mpg_{it} &= \alpha'_{hp}\log hp_{it} + \alpha'_w \log w_{it} + \alpha'_Z Z^1_{it} + \alpha'_N \mathcal{I}^N_{it} + T_t + T_t \times \mathcal{I}^N_{it} + \\ &\quad \alpha'_{hp^2}(\log hp_{it})^2 + \alpha'_{w^2}(\log w_{it})^2 + \alpha'_{hp,w}\log hp_{it} \times \log w_{it} + \varepsilon_{it}.\end{aligned} \tag{2.5}$$

The results are qualitatively and quantitatively similar to those we obtain in Figure 2.5 under the assumption of a Cobb-Douglas cost function.

The bottom panel of Figure 2.B.13 displays our estimates of the technological level of new models and old models when we aggregate both continuous and discrete characteristics of different trims of each model, using their transaction shares in the IHS dataset, consistent with the hedonic analysis displayed in Figure 2.B.12. Our results are robust to this different level of aggregation of car characteristics, buttressing our argument that the level of aggregation of car characteristics and the exact number of models do not affect our results.

We also perform our estimation of the evolution of the technology frontier dividing carmakers by their geographical origin (Europe, Asia, and US). This strategy is useful for two main reasons. First, these groups of manufacturers are vertically differentiated in terms of average vehicle quality in the US market, as our hedonic-regression analysis confirms. Notably, European manufacturers specialize in higher-quality models. Second, these groups of manufacturers were likely differentially affected by the financial crisis. Specifically, US manufacturers were hit most directly by the crisis, which led to government bailouts.

Exploiting this heterogeneity, we find that European carmakers played a crucial role for the aggregate downward adjustment in the level of technology of new models that we discuss in Section 2.3.4. Notably, Figure 2.B.14 displays the estimates of the year fixed effects in the regression equation (2.2), which we estimate separately for European, Asian, and US carmakers. The level of technology of new models declined for all three groups during the recession, but European carmakers experienced the largest decline. This evidence suggests that the financial shock hitting US manufacturers is not a primary driver of the overall downward quality adjustment that we document.

We further estimate the level of embodied technology separately for new model names and new generations of existing model names. We find that the dynamics of average quality are similar for these two groups of models in all periods, including the quality drop during the recession. These results suggest that vertical and horizontal innovations contribute similarly to aggregate quality growth. We display the results of this new analysis in Figure 2.B.15.

Figure 2.B.16 displays the results we obtain by estimating regression equation (2.2) without an interaction term between year fixed effects and the indicator function for new models, without sales weights (left panel) and with sales weights (right panel). In this analysis, we effectively pool all models to estimate a common level of technology, and still find a substantial decrease in quality during the Great Recession.

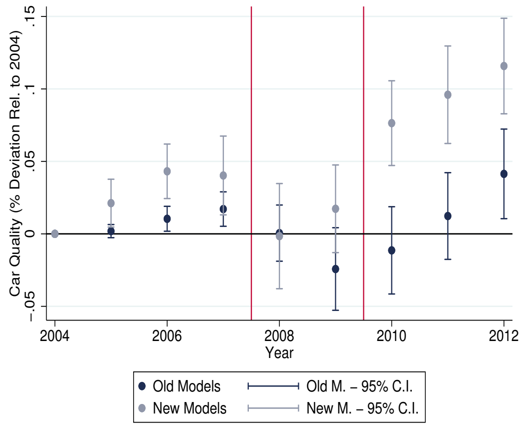
Finally, we perform a back-of-the-envelope calculation of the effects of low new-product quality during the recession for the quality of the overall stock of registered cars in the US. First, we leverage the estimates displayed in the right panel of Figure 2.B.16 to obtain a measure of the average annual growth rate in new-car quality, $x$, during 2004-2007, as well as the average technological level of new cars sold in year $t$, $q_t^N$. We normalize $q_{2004}^N = 1$ and assume that the economy in 2004 is on a balanced-growth path with constant inflow of new cars and constant growth in new-car quality equal to $x$. Thus, in 2004 the quality of cars of age $a$ is given by $q_{a,2004} = (1+x)^{-a}$. Between 2005 and 2012, we combine these assumptions with our estimates of new-car quality and update the quality of cars of age $a$ as follows: $q_{0,t} = q_t^N$ and $q_{a,t} = q_{a-1,t-1}$ for $a > 0$.

Second, we obtain data on new-vehicle registrations (automobiles and light trucks) from the Bureau of Economic Analysis during 2004-2012 (US Bureau of Economic Analysis, 2022). We assume that vehicles are scrapped at age $a = 15$ (our main findings are similar in a range of values for this parameter) and that the initial age distribution of vehicles is uniform. We update the distribution of vehicle age during 2005-2012 as follows. Let $n_{a,t}$ be the number of cars of age $a$ in year $t$. We set $n_{0,t}$ equal to the empirical flow of new registrations in year $t$ and $n_{a,t} = n_{a-1,t-1}$ for $a = 1, ..., 14$.

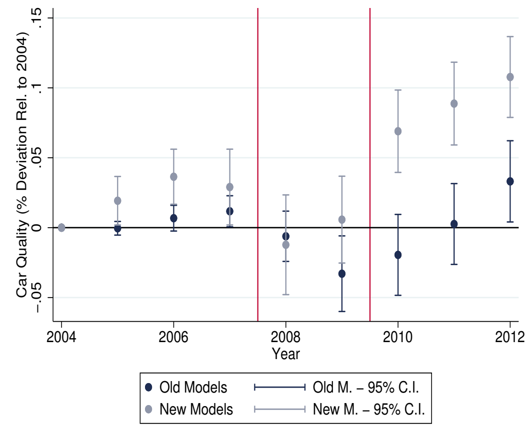
We then obtain the average quality of the stock, $q_t$, as follows: $q_t = \frac{\sum_{a=0}^{14} n_{a,t} q_{a,t}}{\sum_{a=0}^{14} n_{a,t}}$.

Figure 2.B.17 displays the time-series of $q_t$. We find that at the end of the sample the estimated quality of the stock (solid line) is 1.3% lower than if new-car quality and new-car sales had remained on their pre-recession trend (dashed-dotted line). We further decompose the difference between the estimated quality of the stock and its pre-recession trend in its two components—i.e., changes in the volume of new-car sales and changes in new-product quality. Specifically, the dashed line assumes that new-product quality $q_t^N$ remains on its pre-recession trend, whereas new-car sales follow their empirical path, dropping during the recession. As the figure shows, this counterfactual scenario accounts for approximately 0.4 percentage points of the overall decline in quality of the stock at the end of the sample, and thus almost one percentage point of the decline is due to the endogenous drop in new-product quality $q_t^N$.

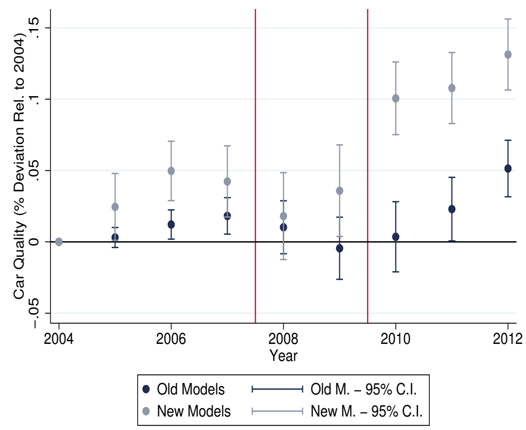
Figure 2.B.13: Technology of New and Old Models: Robustness




(a) Replacing Weight with Geometric Dimensions



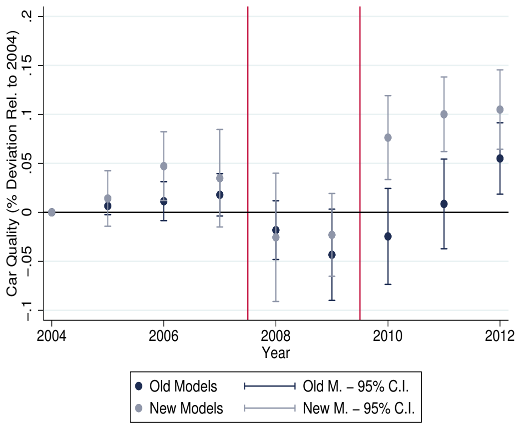

(b) Translog Cost Function



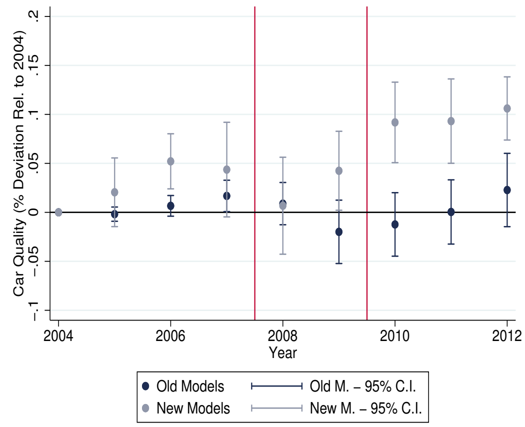

(c) Aggregating All Characteristics

*Notes:* The figure displays several robustness checks of our measure of technology level for new and old models. Specifically, the top-left panel displays the results we obtain by replacing the variable weight in equation (2.2) with the variables wheelbase, width, and height. The top-right panel displays the estimates we obtain for regression equation (2.5)—i.e., assuming a translog cost function. The bottom panel displays the estimates we obtain when we aggregate both continuous and discrete characteristics of different trims of each model using their transaction shares. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

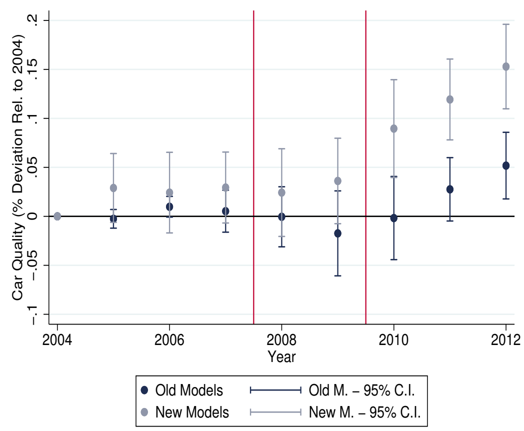
Figure 2.B.14: Technology of New and Old Models by Origin of Carmakers




(a) Europe



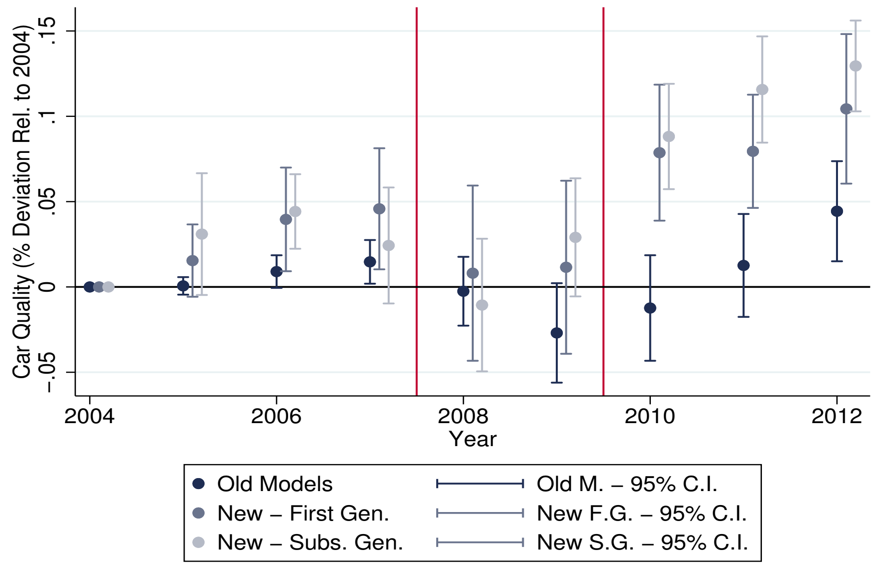

(b) Asia




(c) US

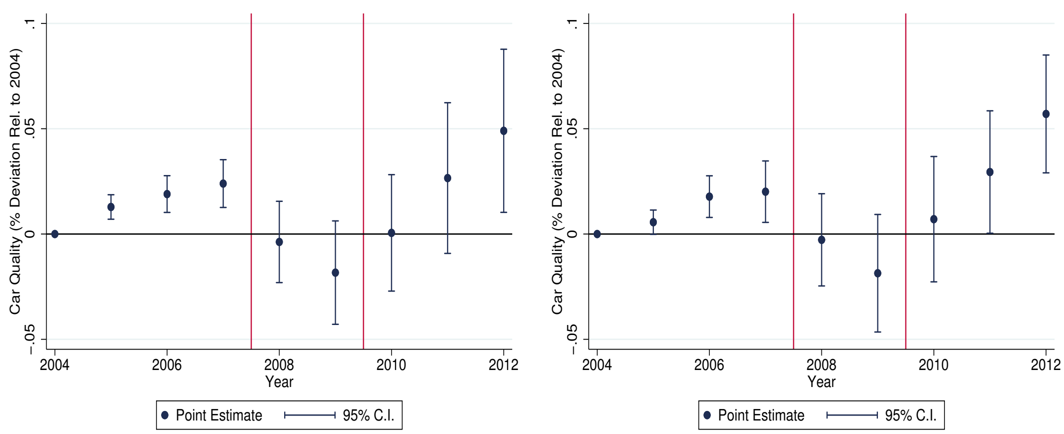
*Notes:* The figure displays the estimated average level of technological efficiency for new models (clear markers) and old models (dark markers), measured as the estimated time fixed effects in regression equation (2.2). The left panel refers to European carmakers; the middle panel to Asian carmakers; and the right panel to US carmakers. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

Figure 2.B.15: Technology of New Model Names and New Generations




*Notes:* The figure displays the estimated average level of technological efficiency for new generations of existing model names (clear markers), new model names (intermediate-darkness markers), and continuing models (dark markers). Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

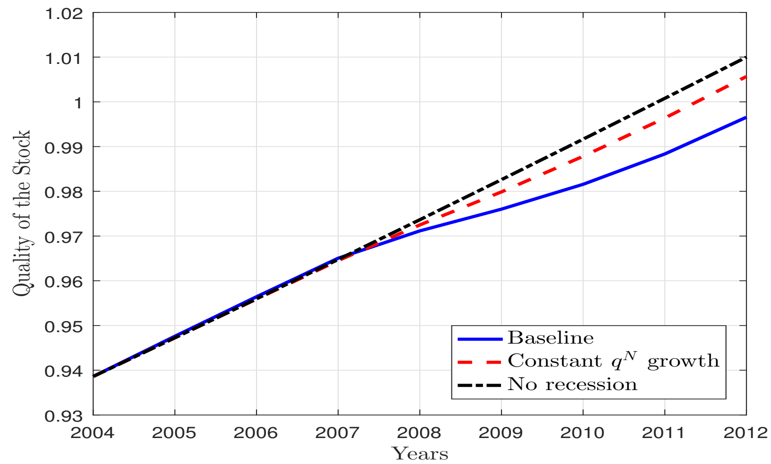
Figure 2.B.16: Technology of All Models




(a) Weighted by Sales (b) Not Weighted by Sales

*Notes:* The figure displays the estimated average level of technological efficiency for all models, based on equation (2.2), removing the interaction term between new models and time. The left panel refers to a regression with weights based on the number of transactions in the IHS dataset, whereas the right panel refers to a regression without weights. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

Figure 2.B.17: Evolution of the Quality of the Stock of Cars




*Notes:* The figure displays the results of our back-of-the-envelope calculations for the quality of the stock of registered cars, relative to the quality of new cars in 2004. The solid blue line refers to the quality of the stock $q_t$; the dashed red line refers to a counterfactual scenario with a constant growth in the quality of new cars, but the empirical inflow of new cars; the dashed-dotted black line refers to a counterfactual with a constant growth in the quality of new cars and a constant inflow of new cars. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

# Chapter 3

# The Good and the Bad of Patents Disclosures

**Abstract**

This paper investigates how the disclosure of "standard-essential" patents, which represent the technical content of technical standards like 5G, affects sectoral productivity growth. A Schumpeterian growth model is developed where innovation requires combining technological components owned by different firms (complementarity) that can disclose their patents to standards. In the model, disclosures enhance innovation efficiency and growth by helping combine existing technologies but also hinder implementation due to higher royalty payments. The first positive effect dominates if complementarity or bargaining power of disclosing firms are low enough. An empirical analysis of 16 industries in 10 European countries over 2000-2010 reveals that, on average, more disclosed patents are negatively related to TFP growth. The effect, however, varies across industries, with those with the strongest complementarity driving the average negative effect.

## 3.1 Introduction

Major technological upgrades, such as the shift from 4G to 5G communication technology, may require the integration of technical components owned by various firms, a feature known as "complementarity" in the innovation economics literature. Complementarity has increased over time, posing significant challenges to innovation and productivity growth, potentially due to the diffusion of Information Technologies (IT) over the 1980s and 1990s (Shapiro, 2001). Technological standards aim to overcome these challenges by specifying how firms can combine "essential" components that have been disclosed to create the standard. This paper focuses on the disclosed technologies and patents that determine the technological content of the standard and investigates their effect on productivity growth, both theoretically and empirically.[1]

This paper presents a Schumpeterian endogenous growth model that captures the fundamental trade-off between disclosures and growth as identified by the innovation and industrial organization literature. The model highlights that, while more disclosed patents contribute to building richer standards that increase the efficiency and effectiveness of the innovation process for the final technology, they also lead to larger royalty payments for all firms adhering to the standard. Since some disclosed components may not be genuinely essential from a technological standpoint, these higher royalty payments may be inefficient and could impede growth.

The model in this paper incorporates complementarity, disclosures, and two types of firms: those that innovate on specific technologies and those that innovate on generic technologies. Incumbent firms invest in R&D to improve the quality of their

[1] This topic gained relevance in the policy debate in both Europe and the United States. The European Commission included interoperability and standards in Pillar II of the "Digital Agenda for Europe", available online at http://ec.europa.eu/digital-agenda/en/ourgoals/pillar-ii-interoperability-standards. Standardization is also mentioned as a crucial component of the "Strategy for American Innovation" elaborated by the Executive Office of the President (2012) Memorandum for the heads of executive departments and agencies, Issued 17 January 2012, [Online], Available: http://www.whitehouse.gov/sites/default/files/omb/memoranda/2012/m-12-08.pdf

product, and to do so, they need to develop $k$ technological components specific to their variety, where $k$ represents the degree of complementarity. Alternatively, they can substitute the development of a new specific component by adapting generic technologies. The second category of firms, who do not have direct access to final customers, develop generic components for royalties paid by incumbent producers and decide whether to disclose them to the standard that forms in every period in the industry. Disclosed technologies help incumbents' R&D activity but require ex-ante royalty payments, while undisclosed technologies do not help final innovation and may generate royalties ex-post if they become a technological bottleneck. The split of monopolistic profits and R&D decisions are determined by Nash bargaining for royalties among firms, which subsequently impact innovation outcomes and productivity growth.

Using the model, I characterize the impact of disclosed technologies on Total Factor Productivity (TFP) growth in equilibrium. The direction of the effect depends on the degree of complementarity and the bargaining power of generic innovators when negotiating royalties with incumbent firms. When the latter have strong bargaining power, more disclosures have a negative effect on TFP growth because the excess-royalty effect dominates the efficiency improvement. The paper also shows that a higher degree of complementarity affects TFP growth through two channels in equilibrium. First, it has a direct negative effect because it makes innovation on final technologies more costly. Second, it affects growth by stimulating more disclosures, which can either foster or hinder growth, as explained earlier.

In the empirical application, a panel dataset is constructed to evaluate the relationship between disclosures, complementarity, and TFP growth using data from 10 European countries across 16 NACE 2-digit sectors between 2000 and 2010. The dataset is created by combining data from the dSEP database by Bekkers et al. (2012) for disclosed patents, PATSTAT for sectoral measures of complementarity based on patents backward citations, and the CompNet database for sectoral productivity growth estimates and other industry-specific aggregates for several European countries.

The empirical findings indicate that, on average, disclosures have a negative relationship with TFP growth across sectors. Specifically, an increase of 10 yearly and sectoral disclosures (equal to the sample mean of disclosed patents) is associated with a 0.045 percentage points increase in sectoral TFP growth, which is equivalent to 8% of the 0.54 percentage points sample mean. However, this average effect masks substantial cross-industry variation in the sign and magnitude of the coefficient. As predicted by the model, industries with the strongest degree of complementarity are more likely to exhibit a negative correlation between disclosures and TFP growth. For instance, the sign of the relation is markedly negative in the computer and machinery manufacturing sectors, where innovation complexity is high. Finally, the paper proposes an instrumental variable strategy that utilizes three distinct measures of complementarity, two of which are particularly related to the standardization process, to quantify the direct and indirect effects of complementarity on TFP growth. The results suggest that the direct effect of complementarity on TFP growth is negative, although imprecisely estimated, and the coefficient on disclosures remains unchanged in terms of sign and magnitude, as observed in OLS evidence.

### 3.1.1 Connection to existing literature

This paper contributes to multiple literature strands. Firstly, it examines the aggregate implications of complementarity and disclosures for growth in a general equilibrium model that formalizes some of the insights of the innovation economics and industrial organizations literature on the topic. Simcoe (2005) offers a comprehensive examination of the disclosure phenomenon, outlining the significant surge in disclosures since 1990 and exploring potential drivers, such as the fragmentation of the innovation process within certain industries and the emergence of small firms that specialize in patent licensing to larger companies that integrate their technology into products. These dynamics are integral to how complementarity and disclosure operate in my model. Moreover, several studies provide empirical evidence on the disclosure strategy of firms, including Simcoe, Graham and Feldman (2009) and Kang and Bekkers (2015), while others analyze the consequences of disclosures in terms of citations and litigation rates for patents, such as Rysman and Simcoe (2008). Additionally, Baron, Pohlmann and Blind (2016) examine the evolution of technical standards depending on the number of essential patents included. On the theoretical side, Shapiro (2001) is the first paper to study the negative consequences of complementarity in innovation, highlighting the existence of a "patent thicket", i.e., "an overlapping set of patent rights requiring that those seeking to commercialize new technology obtain licenses from multiple patentees", which becomes particularly harmful for innovation when combined with the risk of hold up.[2] This is the effect of complementarity in my model absent disclosure. Other authors, such as Lerner and Tirole (2015) and Lerner, Tabakovic and Tirole (2016), present game-theoretic models of the disclosure process, examining the incentives of different types of firms to opt for specific versus generic disclosures depending on the value of the patent they hold. In contrast, this paper's model provides a general equilibrium representation that abstracts from the specifics of the disclosure process. Finally, while patent pools are a related topic, they are not the focus of this work.[3]

Secondly, this paper contributes to the applied macroeconomics literature on the productivity growth. I focus on the effect of standard's technological content, i.e., disclosed patents, on TFP growth. To my knowledge, Baron and Schmidt (2014) is the closest paper to my empirical analysis. It builds a quarterly series of the number of technological standards released by American Standard Setting Organizations (SSOs)

[2] A thorough study of the effects of patent thickets and fragmentation is found in Galasso and Schankerman (2010).

[3] Lerner and Tirole (2004), Shapiro (2001), Dequiedt and Versaevel (2013) study patent pools.

in the field of Information and Communication Technologies and it includes this series in a Bayesian VAR with output, investment, and TFP. Identification assumes that shocks to the number of standards are genuine technology shocks–i.e., advancements to the technical state of the art that do not affect TFP and other aggregates on impact. Ordering the count of standards last in the VAR, the paper identifies technology shocks through a Choleski decomposition of the variance-covariance matrix. Their evidence shows that a shock to standards affects TFP negatively at first but positively in the long run, and that investment and output follow a similar S-shaped dynamics. They argue that new standards create a clash between new and old technologies, which initially translates into a fall in TFP that reverts once the new technology diffuses. Differently from Baron and Schmidt (2014), I provide more direct measurement of the technological content of standards and I use an empirical strategy that considers both the time-series and the cross-industry variation of the phenomenon.

Finally, the paper contributes to the macro theory literature explicitly introducing patenting in Schumpeterian growth models, such as O'Donoghue and Zweimüller (2004), or models of sequential innovations and blocking R&D as Cozzi and Galli (2014).

In the remainder of the paper, Section 3.2 presents details of the disclosure process, Section 3.3 presents the model and derives its key theoretical predictions, Section 3.4 discusses the data and illustrates the empirical analyses, Section 3.5 concludes.

## 3.2 Institutional setting

This section outlines the critical aspects of the standard-setting process and patent disclosure, which underlie the prominent features of the theoretical model discussed in Section 3.3.

Standard Setting Organizations (SSOs) strive to create comprehensive technical documents, or standards, that describe how to combine several technological components to implement a complex innovation. This requires both technological and informational coordination among firms due to complementarity. Multiple components must be developed and combined to operate efficiently in the same technology, and different firms may own intellectual property on different components. For example, the 3GPP standard consortium aimed to develop and maintain the 3G communication technology, which includes hundreds of components owned by dozens of firms.

During the standard formation process, firms that own a technology and consider it essential for the new upgrade may decide to disclose the patent that protects it to the SSO.[4] For instance, in 2009, Magnolia Broadband Inc. and VirnetX disclosed US patents 7,327,801 and 7,133,930, respectively, to build the 3G standard. After disclosures, the SSO selects relevant technological components and provides a detailed description of how to combine them to implement a major innovation. The technical components protected by disclosed patents represent the essential technological content of the standard.

Previous research in the fields of innovation economics and industrial organization has investigated the ways in which increased disclosures can both help and hinder innovation. In the former case, more disclosures can prevent bottlenecks that may obstruct the innovation process. Disclosed patents can provide information on which technological components have already been developed, thereby reducing R&D duplication costs and preventing relevant intellectual property rights from blocking the implementation of a major innovation ex-post. This, in turn, not only directly promotes innovation by removing roadblocks but also enhances the ex-ante incentive of firms to invest in R&D. Additionally, disclosures often come with a commitment from

[4] There are two types of disclosures. The first is "blanket" disclosures. They consist in a document where the disclosing firm declares to own intellectual property rights on one or more technologies essential for the standard, but omits the patent or patent application numbers thereof. The second category refers to "specific" disclosures, which differ from the blanket ones because the firm also specifies patent or patent application numbers that protect declared-essential technologies. The paper focuses on specific disclosures and Subsection 3.4.1.1 discusses measurement at length.

disclosing firms to license under Fair, Reasonable and Non-Discriminatory (FRAND) terms, which provides a secure negotiation environment that facilitates agreement on royalties and the implementation of the final innovation.

However, more disclosures may also have a negative impact on innovation and growth. Royalty-seeking firms may have an incentive to disclose patents that are not truly essential for the standard. If included, these patents may impose an additional burden on firms implementing the standardized technology, reducing their ex-ante R&D efforts and hindering innovation.

Therefore, the effect of disclosures on innovation and productivity growth is ambiguous. While more disclosed patents lead to richer standards that provide better technological coordination, they also impose a larger royalty burden on implementing firms. The next section presents a novel endogenous growth model that formalizes this trade-off.

## 3.3 Model

This section presents a novel Schumpeterian endogenous growth model that incorporates complementarity in innovation and patents disclosure. I first describe the model environment in Subsection 3.3.1, followed by the definition of the equilibrium in Subsection 3.3.2. I then derive two propositions in Subsection 3.3.3 that shed light on the impact of disclosures and complementarity on growth in the model. Appendix 3.B reports a detailed exposition of model's assumptions, optimization problems, and solution.

### 3.3.1 Environment

The model is an extension of the basic framework introduced by Aghion and Howitt (1997) that incorporates complementarity in innovation, modeled following Shapiro

(2001) and Simcoe (2005), and patents disclosure to standards. The conventional parts of the model, i.e., consumers and final good producers, are presented first, followed by the R&D activity and disclosure.

#### 3.3.1.1 Consumers

A representative consumer derives utility from consumption of a homogeneous final good $C_t$ according to the function $u(C_t)$, with $\lim_{C \to 0^+} u'(C) = +\infty$ and $u'(C) > 0$ and $u''(C) < 0 \ \forall C$. She is endowed with $L_t = L$ units of labor in every period $t$, which she supplies inelastically in the labor market. The consumer owns all the firms in the economy and gets income from profits and labor. Therefore, the time-0 utility maximization problem is

$$\begin{aligned} &\max_{C_t, A_{t+1}} \sum_{t=0}^{\infty} \left( \frac{1}{1+\rho} \right)^t u(C_t) \\ &\text{s.t.} \quad W_{t+1} = r_t W_t + \Pi_t + w_t L - C_t \end{aligned} \tag{3.1}$$

where $\rho$ is the discount rate, $r_t$ is the real interest rate, and $W_t$ is the value of asset holdings at the end of period $t$. Under the assumption that patent rights expire within the period, $W_t = 0 \ \forall t$ in equilibrium and the agent consumes all her income period-by-period.

#### 3.3.1.2 Final good production

A perfectly-competitive sector produces the final good $Y_t$ according to the production function

$$Y_t = L^{(1-\alpha)} \int_0^1 A_{i,t}^{1-\alpha} x_{i,t}^{\alpha} di$$

Production is Cobb-Douglas in labor $L$ and a unit measure of intermediate varieties indexed by $i$ whose quality is $A_{i,t}$ and whose quantity used in production is $x_{i,t}$. The price of the final good is normalized to one and profit maximization by final good producers generates demand for labor and demand for intermediate goods. The latter is

$$x_{i,t} = (\alpha z_{i,t})^{\frac{1}{1-\alpha}} A_{i,t} L \tag{3.2}$$

where $z_{i,t}$ is the price of intermediate variety $i$, which the final good producers take as given.

#### 3.3.1.3 Intermediate goods producers

In every intermediate product line $i$ there is an incumbent and a fringe of competitors. The production technology is common across the two groups and linear in the final good, with unit marginal cost. However, the incumbent can escape competition through innovation, i.e., by improving on the quality of the variety $A_{i,t}$ and obtaining a patent on this technological upgrade. Patents provide a legal monopoly to the incumbent for one period, after which fringe competitors can perfectly imitate the improved technology. The production problem of a monopolistic intermediate good producer is

$$\begin{aligned} &\max_{x_{i,t}} \quad z_{i,t} x_{i,t} - x_{i,t} \\ &\text{s.t.} \quad x_{i,t} = (\alpha z_{i,t})^{\frac{1}{1-\alpha}} A_{i,t} L \end{aligned} \tag{3.3}$$

which implies that total profits from variety $i$ are

$$\Pi_{i,t} = [\alpha^{\frac{1+\alpha}{1-\alpha}} - \alpha^{\frac{2}{1-\alpha}}] A_{i,t} L = \pi A_{i,t} L \tag{3.4}$$

in equilibrium. In contrast, if incumbents do not successfully innovate, Bertrand competition with fringe firms pushes the price $z_{i,t}$ to the unit marginal cost and profits to zero.

#### 3.3.1.4 R&D and innovation

**Types of innovations and complementarity**

The model distinguishes between two types of innovation: implementable and generic. Implementable innovation improves the existing quality $A_{i,t-1}$ of a specific variety $i$ by a step-size $\gamma > 1$ and is monopolized by the incumbent intermediate producer. All variables related to implementable innovations are denoted by $I$. I assume that $k > 1$ small technologies of step-size $\psi = \gamma/k$ are required to achieve an implementable upgrade, thus $k$ measures the degree of complementarity in innovation.

Generic innovation, denoted by $G$, results in a new technology that is $\psi$-times better than the average quality $\overline{A}_{t-1}$ of existing varieties, where

$$\overline{A}_t \equiv \int_0^1 A_{i,t} di \tag{3.5}$$

A measure $K$ of firms generates these innovations, but they cannot directly produce and sell them to final good firms due to their smaller step-size improvement and lack of contribution to the quality improvement of any specific variety $i$.

**Relation among innovation types, disclosure, and standards**

I assume that any generic innovation can replace one of the $k$ components of an implementable innovation, provided it is adapted to variety $i$. However, to achieve this, the incumbent firm on variety $i$ needs to "specialize" the generic technology, using its technical expertise to integrate it with its existing product. To compensate the generic innovator, the incumbent pays a royalty, determined through Nash bargaining.

The disclosure of generic innovations during the standard formation process significantly affects the substitution between specific components of implementable innovations and generic technologies. I model the disclosure process based on real-world standards formation, assuming that it occurs within a single period. A standard-setting organization encourages disclosure of technologies that may be essential for establishing a common technological basis for new implementable innovations. Since implementable technologies are specific to a variety, they are not suitable for inclusion in the standard. In contrast, generic innovations can be adapted to individual cases and replace specific components of any implementable bundle. As a result, generic R&D firms with successful patents must decide whether or not to disclose their technology, as this decision affects the use and profitability of the generic technology.

Undisclosed generic innovations are not visible to incumbent intermediate producers during the innovation process, so ex ante substitution is not possible. However, these generic technologies have an exogenous probability $\delta \in (0,1)$ of being ex post blocking for one of the $k$ components of any implementable innovation. In such a scenario, successful incumbents must pay royalties to the blocking generic innovator determined through Nash bargaining over profits. Negotiations often fail in this hostile environment, which I model by assuming a probability $\theta(m_t^u) \in [0,1]$ of breakdown, increasing with the total measure of undisclosed generic innovations $m_t^u$. If negotiations fail, the quality upgrade of intermediate varieties is blocked.

If a generic innovation is disclosed, it is included in the new standard with a probability that depends on the aggregate measure of disclosed technologies, denoted by $m_t^d$. The probability of inclusion of any disclosed innovation $j \in [0, m_t^d]$ is

$$\nu_{j,t} = \nu_t = \begin{cases} 1 & \text{if } \; m_t^d \leq k \\ k/m_t^d & \text{if } \; m_t^d > k \end{cases} \tag{3.6}$$

If the number of disclosed technologies is less than or equal to the number required to create an implementable innovation, then inclusion is certain. However, if the number of disclosed technologies exceeds this threshold, $k$ generic innovations are chosen with equal probability from the $m_t^d$ disclosed. The standard specifies the optimal way to combine these technologies to create implementable innovations for intermediate varieties $i \in [0,1]$ and provides a secure negotiation environment for incumbents and generic innovators. As disclosure usually involves a commitment to license the technology under Fair, Reasonable, and Non-Discriminatory (FRAND) terms, I assume that Nash bargaining over disclosed technologies never fails.

### Generic R&D problem and patents disclosure

A measure $K$ of identical firms indexed by $j$ invests $R^G_{j,t} \in \mathbb{R}^+$ units of the final good in R&D activity to generate generic innovations. Upon successful innovation, each firm decides whether to disclose ($d_{j,t} = 1$) their patent to the standard. Let $P^{e,d}_{j,t}$ and $P^{e,u}_{j,t}$ denote the expected royalties that a firm receives if it discloses or does not disclose, respectively. Firm $j$ solves

$$\max_{R^G_{j,t}, d_{j,t} \in \{0,1\}} \left\{ \phi\left(\frac{R^G_{j,t}}{\psi \overline{A}_{t-1}}\right) \left[ d_{j,t} P^{e,d}_{j,t} + (1-d_{j,t}) P^{e,u}_{j,t} \right] - R^G_{j,t} \right\} \tag{3.7}$$

where $\phi(\cdot)$ represents the probability to achieve the generic innovation as a function of generic R&D intensity $n^G_{j,t} \equiv R^G_{j,t}/(\psi \overline{A}_{t-1})$. The function $\phi(\cdot)$ satisfies standard assumptions: $\phi'(0) = 0$, $\lim_{n \to +\infty} \phi(n) = 1$, $\phi'(\cdot) > 0$, $\lim_{n \to 0^+} \phi'(n) = +\infty$, and $\phi''(\cdot) < 0$.

Once the generic innovation is disclosed and included in the standard, the firm engages in Nash bargaining with each incumbent that has developed an implementable innovation, with a probability of success $\sigma_i$ determined by incumbents' R&D. This results in the determination of a royalty payment $p_{i,j,t}$ for each incumbent. The expected royalty payments for the firm are then calculated as the product of the inclusion probability in the standard $\nu_{j,t}$ and the sum of expected royalties from each incumbent, i.e.,

$$P^{e,d}_{j,t} = \nu_{j,t} \int_0^1 \sigma_{i,t} p_{i,j,t} di \tag{3.8}$$

In contrast, if the generic innovation is not disclosed the expected royalty is

$$P^{e,u}_{j,t} = \delta(1 - \theta(m^u_t)) \int_0^1 \sigma_{i,t} p_{i,j,t} di \tag{3.9}$$

where $\delta$ is the exogenous probability that the generic innovation is blocking, $(1 - \theta(m^u_t))$ is the probability that ex-post Nash bargaining on royalties does not fail, and the integral represents the sum of expected royalties bargained with each incumbent.

The optimal policies for generic R&D firms are twofold: (i) to disclose the innovation if and only if the expected royalties from disclosing to the standard exceed the expected royalties from not disclosing, i.e., if $P^{e,d}_{j,t} > P^{e,u}_{j,t}$, and (ii) to choose $R^G_{j,t}$ such that R&D intensity satisfies the following first-order condition

$$\phi'(n^G_{j,t}) \max\{P^{e,d}_{j,t}, P^{e,u}_{j,t}\} = \psi \overline{A}_{t-1} \tag{3.10}$$

### Nash bargaining

I assume that Nash bargaining over royalties occurs among (i) any incumbent intermediate producer $i$ which successfully innovated and (ii) any generic innovator $j$ whose technology has either been employed ex-ante to develop an implementable upgrade or resulted ex-post blocking. Firms decide how to split total profits $\Pi_{i,t}$ in equation (3.4) with bargaining weights $\beta$ (incumbent) and $1 - \beta$ (generic innovator). The problem is

$$\max_{p_{i,j,t}} \Big(\Pi_{i,t} - p_{i,j,t}\Big)^{\beta} \Big(p_{i,j,t}\Big)^{1-\beta} \tag{3.11}$$

where $\Pi_{i,t} - p_{i,j,t}$ and $p_{i,j,t}$ are the payoffs of the incumbent and the generic innovator, respectively, and the outside option is null for both.

### Implementable R&D problem

Each incumbent intermediate producer can invest $R^I_{i,t}$ units of the final good in R&D to achieve an innovation that improves by a factor $\gamma = k\psi > 1$ the quality $A_{i,t-1}$ of her variety. In the process, the incumbent can integrate the $m^d_t$ disclosed generic technologies combined by the standard. This reduces the innovation step-size to autonomously achieve from $\gamma = k\psi$ to $(k - m^d_t)\psi$ but requires the payment of a mass of $m^d_t p_{i,t}$ royalties to generic innovators licensing the technologies.[5] If $m^d_t$ exceeds $k$, only $k$ generic innovations are used. Moreover, incumbents may ex-post discover that their implementable innovation infringes on a share $\delta$ of $m^u_t$ undisclosed generic technologies. If this is the case, negotiations with the blocking firm fail with an aggregate probability $\theta(m^u_t)$ or lead to a successful agreement on total royalties $\min\{\delta m^u_t, k\}p_{i,t}$ with probability $1 - \theta(m^u_t)$. Therefore, expected profits for a successful intermediate firm are

$$\Pi^e_{i,t} = (1 - \theta(m^u_t))[\Pi_{i,t} - \min\{m^d_t, k\}p_{i,t} - \min\{\delta m^u_t, k\}p_{i,t}] \tag{3.12}$$

and the optimal R&D investment decision solves the problem

$$\max_{R^I_{i,t}} \left\{ \phi\left( \frac{R^I_{i,t}}{(k - m^d_t)\psi A_{i,t-1}} \right) \max\{\Pi^e_{i,t}, 0\} - R^I_{j,t} \right\} \text{ s.t. } R^I_{i,t} \geq 0 \tag{3.13}$$

where the innovation probability function $\phi(\cdot)$ is the same as for the generic innovators.[6] The second term represents expected profits that the incumbent obtains through innovation, conditional on them being positive. In fact, equation (3.12) highlights that $\Pi^e_{i,t}$ may turn negative if the amount of royalty payments is too high, in which case the incumbent prefers to abandon the innovation. The last term represents the cost of R&D investment in units of the final good.

[5] I drop the subscript $j$ from $p_{i,t}$ because $p_{i,j,t} = p_{i,t}$ $\forall j$ due to the assumed symmetric of generic innovators.

[6] I assume throughout that functional forms and parameters of the model are such that, in equilibrium, $m^d_t$ is always strictly smaller than $k$.

Optimal R&D intensity $n_{i,t}^{I}$ defined as

$$n_{i,t}^{I} \equiv \frac{R_{i,t}^{I}}{\gamma A_{i,t-1}} = \frac{R_{i,t}^{I}}{k\psi A_{i,t-1}}$$

solves, if interior, the optimality condition

$$\phi'\Big(\frac{k}{k-m_t^d} n_{i,t}^{I}\Big)\Pi_{i,t}^{e} = (k-m_t^d)\psi A_{i,t-1} \tag{3.14}$$

### 3.3.2 Equilibrium

In this subsection, I define the model's equilibrium and I derive its key characteristics.

#### 3.3.2.1 Definition

The symmetric Cournot-Nash competitive equilibrium of the model is defined by quantities $\{C_t^*, W_{t+1}^*, \{x_{i,t}^*\}_{i\in[0,1]}, \{\{p_{i,j,t}^*\}_{i\in[0,1]}\}_{j\in[0,K]}, \{n_{j,t}^{G*}, d_{j,t}^*\}_{j\in[0,K]}, \{n_{i,t}^{I*}\}_{i\in[0,1]}, \nu_t^*, m_t^{d*}, m_t^{u*}, \{\sigma_{i,t}^*\}_{i\in[0,1]}, \Pi_t^*\}$ and prices $\{r_t^*, w_t^*, \{z_{i,t}^*\}_{i\in[0,1]}\}$ such that: (i) $\{C_t^*, W_{t+1}^*\}$ solves problem (3.1); (ii) $\{x_{i,t}^*\}$ solves problem (3.3) for all monopolistic $i$'s and equation (3.2) for all competitive $i$'s; (iii) royalties $\{\{p_{i,j,t}^*\}_i\}_j$ solve problem (3.11) $\forall i \in [0,1]$ and $\forall j \in [0,K]$; (iv) $\{n_{j,t}^{G*}, d_{j,t}^*\}_j$ solves problem (3.7) $\forall j \in [0,K]$; (v) $\{n_{i,t}^{I*}\}$ solves problem (3.13) $\forall i \in [0,1]$; (vi) $\nu_t^*$ satisfies (3.6); (vii) $m_t^{d*} = \int_0^K d_{j,t}^*\phi(n_{j,t}^{G*})dj$; (viii) $m_t^{u*} = \int_0^K (1-d_{j,t}^*)\phi(n_{j,t}^{G*})dj$; (ix) $\sigma_{i,t}^* = (1-\theta(m_t^{u*}))\phi\Big(\frac{k}{k-m_t^d}n_{i,t}^{I*}\Big)$ $\forall i \in [0,1]$; (x) $\Pi_t^* = \int_0^1 \sigma_{i,t}^*\Pi_{i,t}^* di$, where $\Pi_{i,t}^*$ satisfies (3.4) $\forall i \in [0,1]$ (xi) the asset market clears $W_t^* = 0$; (xii) the resource constraint of the economy (3.15) holds.

$$L^{(1-\alpha)}\int_0^1 A_{i,t}^{1-\alpha}(x_{i,t}^*)^{\alpha}di = C_t^* + \int_0^1 n_{i,t}^{I*}k\psi A_{i,t-1}di + \int_0^K n_{j,t}^{G*}\psi\overline{A}_{t-1}dj \tag{3.15}$$

#### 3.3.2.2 Characterization of the equilibrium

In this subsection, I will discuss the equilibrium allocations' distinctive features and their influence on productivity growth. Appendix 3.B provides all the derivations.

First, R&D intensity is symmetric across incumbent innovators $i \in [0,1]$, and royalties paid by incumbent $i$ are linear in $\Pi_{i,t}$ and symmetric across generic innovators. Nash bargaining results in a fraction $\beta$ of profits $\Pi_{i,t}$ going to the incumbent, and the remainder going to the generic innovator. Additionally, profits are linear in $A_{i,t} = \gamma A_{i,t-1}$ conditional on innovation. Thus, $\Pi^e_{i,t}$ is linear in $A_{i,t-1}$, and the optimal R&D intensity on implementable innovations does not depend on $i$.

Second, all generic innovations are disclosed. Under the assumption that for any chosen functional forms and parameters the measure of generic firms $K$ is small enough, the probability of being included in the standard conditional on disclosure is larger than the probability of blocking implementable innovations ex-post without disclosure.[7] Additionally, with disclosure, Nash bargaining is not subject to failure. Evaluating expression (3.8) for expected royalties and optimality condition (3.10) for generic R&D intensity in the equilibrium reveals that both are independent of $j$, thus verifying the symmetry assumption.

Therefore, an interior equilibrium in the R&D sector solves the equations

$$
\begin{aligned}
&\phi'(n_t^{G*})(1-\beta)\nu_t^*\mu_t^*\pi L = \psi \\
&m_t^* = m_t^{*d} = \phi(n_t^{G*})K \\
&\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)(1-(1-\beta)\min\{m_t^{*d},k\})\pi L = (k-m_t^{*d})\psi \\
&\mu_t^* = \phi\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)
\end{aligned}
$$

where $\mu_t^*$ represents the equilibrium share of intermediate varieties on which innovation occurs and $\nu_t^*$ is determined by equation (3.6).

Furthermore, analyzing two extreme cases sheds light on the equilibrium outcomes. The first case represents an equilibrium where the disclosure process successfully coordinates technical and information aspects, thereby overcoming complementarity hur-

[7] The formal condition on $K$ and parameters is formalized by Assumption 1 in Appendix 3.B.1.

dles and avoiding R&D duplication costs across varieties. If $m_t^d > k$ and $k \leq \frac{1}{1-\beta}$, intermediate firms are willing to pay royalties to implement a quality upgrade on all intermediate varieties, and $n_t^I = 0$ but $\mu_t^* = 1$. The second case features $m_t^d > k$ but $k > \frac{1}{1-\beta}$. Therefore, incumbents find it unprofitable to pay royalties on generic technologies ($\Pi_{i,t}^e < 0$), resulting in $\mu_t^* = 0$. However, this is not an equilibrium because this outcome contradicts $m_t^{*d} > k$, and the degree of complementarity is too strong, leading to a failure to innovate through disclosure.

In the next subsection, I will employ these findings to demonstrate how the disclosed innovations relate to productivity growth.

#### 3.3.2.3 Productivity growth

I define TFP growth for this economy as the growth rate of the average productivity level, i.e.,

$$g_t \equiv \overline{A}_{t+1}/\overline{A}_t - 1 \tag{3.16}$$

For the interior equilibrium, it is possible to write $g_t$ as

$$g_t = \phi\Big(\frac{k}{k - m_t^{d*}} n_t^{I*}\Big)(\gamma - 1) \tag{3.17}$$

where $n_t^{I*}$ solves

$$\phi'\Big(\frac{k}{k - m_t^{d*}} n_t^{I*}\Big)(1 - (1-\beta)\min\{m_t^{*d}, k\})\pi L = (k - m_t^{*d})\psi \tag{3.18}$$

Equation (3.17) shows that productivity growth depends on the net quality improvement $(\gamma - 1)$ and the success probability of incumbents' innovative effort $n_t^{I*}$, as determined by equation (3.18). The latter expression reveals two channels through which disclosed technologies $m_t^{d*}$ impact growth. Firstly, more disclosures increase the innovation probability $\phi(\cdot)$, thanks to technical coordination. Secondly, they induce higher R&D intensity by reducing its marginal cost, as shown on the right-hand side of (3.18). However, more disclosures also reduce the effective payoff for incumbents, as they have to pay more royalties, which can decrease R&D intensity. Depending on the relative strength of these channels, disclosures may either enhance or hinder productivity growth. Proposition 1 in Subsection 3.3.3 characterizes the sign of the effect based on the model's parameters.

Moreover, disclosures endogenously depend on the degree of complementarity $k$, which motivates the standard-setting process because the proliferation of small technologies increases the risk of hold up. To highlight the separate effect of complementarity and disclosures, I examine TFP growth in two alternative economies nested in the current model. Firstly, in a setting with complementarity ($k > 1$) and potentially blocking innovations ($K > 0$) but without disclosures to standards ($d_{j,t} = 0 \; \forall j \in [0, K]$), growth satisfies

$$\begin{cases} g_{ns,t} = (1 - \theta(m_t^u))\phi(n_t^I)(\gamma - 1) \\ \phi'(n_t^I)(1 - \theta(m_t^u))[1 - (1 - \beta)\min\{\delta m_t^u, k\}]\pi L = k\psi \end{cases} \tag{3.19}$$

Secondly, in an economy without complementarity ($k = 1$) and without blocking innovations and, hence, disclosures ($K = 0$), growth is

$$\begin{cases} g_{nc,t} = \phi(n_t^I)(\gamma - 1) \\ \phi'(n_t^I)\pi L = \psi \end{cases} \tag{3.20}$$

The comparison of conditions (3.19) and (3.20) reveals that complementarity, in the absence of disclosure, unambiguously reduces growth due to several reasons. First, it directly increases the cost of innovation for intermediate firms. Second, it creates a hold-up probability as undisclosed generic technologies may block the adoption of implementable innovations ex post. Third, it lowers implementers' ex-ante R&D intensity as hold-up risk and royalties reduce its expected payoff from innovation.

Furthermore, the comparison of equations (3.17) and (3.18) with (3.19) highlights the role of technologies disclosed to standards in promoting growth. Firstly, they eliminate the possibility of failed negotiation because disclosing firms commit to license. Secondly, they reduce the implicit marginal cost of the incumbent's R&D intensity thanks to technical coordination. Thirdly, they may reduce the expected incumbent's payoff by inflating royalty payments. The first and second forces promote growth, while the third hinders it.

Finally, the comparison of (3.17) and (3.18) with (3.20) emphasizes the same channels, but also highlights that their relative strength may depend on the value of $k$. The next subsection formalizes this intuition with two propositions.

### 3.3.3 Theoretical predictions

Proposition 1 provides a simple condition to determine the effect of disclosures on growth and derives this effect.

**Proposition 1.** *At interior equilibria, the effect of the mass of disclosed patents on TFP growth satisfies*

$$\frac{dg_t}{dm_t^{d*}} = -\frac{(\phi_I')^2}{\phi_I''}\left[\frac{1}{k} - \frac{k - m_t^{d*}}{k}\frac{(1-\beta)}{(1-(1-\beta)m_t^{d*})}\right](\gamma - 1)$$

*where* $\phi_I' = \phi'\left(\frac{k}{k-m_t^{d*}}n_t^{I*}\right)$ *and* $\phi_I'' = \phi''\left(\frac{k}{k-m_t^{d*}}n_t^{I*}\right)$.

*Moreover,* $\frac{dg_t}{dm_t^{d*}}$ *is negative if* $k(1-\beta) > 1$, *i.e., if product of complementarity* $k$ *and generic innovators' bargaining power* $(1-\beta)$ *is large enough.*

Intuitively, when complementarity is strong, the cost of paying royalties to use generic technologies is more likely to outweigh the technological benefits, particularly if the bargaining weight of generic innovators is high.

Proposition 2 investigates the impact of complementarity on growth, which prior research has identified as a key driver of technical and informational coordination needs that underlie disclosures to standards. As discussed earlier, the proposition confirms that stronger complementarity directly reduces growth. Moreover, it also has an indirect effect on $g_t$ by affecting firms' incentives to invest in R&D and disclose generic innovations. Similar to Proposition 1, the direction of this effect depends on the values of $k$ and $\beta$.

**Proposition 2.** *The degree of complementarity $k$ affects TFP growth $g_t$ both directly and indirectly through disclosure of patents. The direct effect is unambiguously negative. The indirect effect is negative if $k(1-\beta) > 1$.*

$$\frac{dg_t}{dk} = \underbrace{\frac{(\phi_I')^2}{\phi_I''} \frac{m_t^{d*}}{k(k - m_t^{*d})}(\gamma - 1)}_{\textit{Direct Effect} < 0} - \underbrace{\frac{(\phi_I')^2}{\phi_I''}(\gamma - 1)\left[\frac{1}{k - m_t^{*d}} - \frac{1-\beta}{1-(1-\beta)m_t^{*d}}\right]\frac{dm_t^{*d}}{dk}}_{\textit{Indirect Effect}}$$

*where* $\phi_I' = \phi'\left(\frac{k}{k - m_t^{d*}} n_t^{I*}\right)$ *and* $\phi_I'' = \phi''\left(\frac{k}{k - m_t^{d*}} n_t^{I*}\right)$.

Proofs of both propositions are in Appendix 3.C.

## 3.4 Empirical analysis

This section provides an empirical investigation of the relationship between productivity growth, patent disclosure to technological standards, and complementarity. In Subsection 3.4.1, I present the data and describe the key variables used in the analysis. Subsection 3.4.2 adapts Propositions 1 and 2 to the panel data dimension and maps theoretical insights to empirical applications. Subsections 3.4.3 and 3.4.4 present the main results and additional insights.

### 3.4.1 Data

To build measures of patents disclosure, complementarity, and productivity growth for the empirical analysis, I rely on multiple data sources that cover industries, countries, and time periods. The following subsection provides a description of these sources.

#### 3.4.1.1 dSEP database: Patents disclosure

The Disclosed Standard Essential Patents (dSEP) Database, compiled by Bekkers et al. (2012), includes 46,906 disclosure documents to 13 major Standard Setting Organizations (SSOs) from 1975 to 2012. The data consist of two types of disclosures: blanket disclosures and specific disclosures. Blanket disclosures involve a document where the disclosing firm declares owning intellectual property rights on one or more technologies essential for the standard, without specifying the patent or patent application numbers. In contrast, specific disclosures provide patent or patent application numbers that protect declared-essential technologies. For the empirical analysis, we focus on specific disclosures.

The specific disclosures in Bekkers et al. (2012) identify 14,057 US Patent Office (USPTO) or European Patent Office (EPO) patents or patent applications, which have unique identifiers in PATSTAT–a worldwide patent database described in Subsection 3.4.1.2. PATSTAT provides information on each patent's technological content, summarized by International Patent Classes (IPCs) that patent examiners attribute to the protected technology. By utilizing Eurostat's concordance tables between IPCs and NACE industries, I assign each disclosed patent to specific industrial sectors.[8]

To construct my preferred measure of patents disclosure for industry $l$ in year $t$, I count the number of patents whose technological content refers to NACE industrial

[8] I use Eurostat's concordance table IPCV8-NACE Rev.2 Update (version 2.0) available at https://ec.europa.eu/eurostat/ramon/documents/IPC_NACE2_Version2_0_20150630.pdf. Table downloaded in February 2023. If a patent covers more than one IPC and/or if the IPCs link to more than one NACE industry, I count one disclosed patent in each of the NACE industries.

sector $l$ and whose first disclosure event occurs in year $t$. The final sample consists of 5,805 such patents covering 16 2-digit NACE industrial sectors from 2000 to 2012.[9] On average, there were 28 disclosed patents per year and sector, with a standard deviation of approximately 120.

Figure 3.1 displays the time-series of disclosed patents in each industry. Across all sectors, disclosures increased over time. Additionally, the figure highlights that industries related to Information and Communication Technologies (ICT) and machinery had the highest number of disclosed patents.[10] For instance, manufacturing of computer, electronic, and optical products had an average yearly count of 388 disclosed patents, reflecting the numerous technological components that these products comprise, with intellectual property owned by various firms.

The sectoral focus of the disclosure process does not diminish its overall significance, as the industries in question represent 17% of GDP in my sample and make a substantial contribution to overall investment dynamics. Additionally, the proliferation of "smart" systems is expected to increase the demand for technological coordination in other industries, expanding the potential for disclosure and standardization.

I will now discuss three limitations of the proposed disclosure measure. First, the measure may not capture potential consequences of blanket disclosures or patents that are essential for the standard but not disclosed. Unfortunately, appropriate measurement of these unobserved factors is unavailable, which may introduce a downward bias in the estimated effect of disclosed patents on productivity growth. To partly address this issue, the instrumental variable strategy discussed in Subsection 3.4.3.3 is used. Second, the classification of disclosed patents into NACE sectors based on

[9] The sample starts in 2000 because TFP growth measures will be available starting from this year. The number of patents in the final sample is lower than the total patent count in the dSEP database because of this sample restriction and because for some patents IPC classes or disclosure year are missing. Moreover, Table 3.A.2 in Appendix 3.A.2 reports covered sectors.

[10] I classify as ICT industries NACE codes 26, 27, 28, and 62, i.e., "Manufacture of computer, electronic and optical products", "Manufacture of electrical equipment", "Manufacture of machinery and equipment n.e.c.", "Computer programming, consultancy and related activities", respectively.

IPCs may generate measurement error and, hence, attenuation bias in the empirical estimates of the effect of disclosures on growth. The strategy discussed in Subsection 3.4.3.3 makes some progress in this direction.[11] Third, the raw count of disclosed patents may merely reflect heterogeneous patenting trends across industries rather than differences in disclosure intensity. To account for this, I construct an alternative disclosure intensity measure that re-scales the raw count of disclosed patents by the total number of patent applications per year and industry.[12] I use it in Section 3.4.3 alongside the preferred measure and in Appendix 3.D, and all empirical findings are equivalent. Figure 3.2 presents disclosure intensity over time and across industries graphically.

#### 3.4.1.2 PATSTAT: Patenting and complementarity measures

PATSTAT is a global patent database that provides bibliographic information on published patent documents from major patent offices worldwide. To measure complementarity in innovation, I use data on patent citations between patents.

However, there is no agreement in the innovation literature on how to measure complementarity in innovation. Based on the definition of complementarity in the theoretical framework of Section 3.3, I propose a method that relies on backward citations between patents. I will first describe my preferred measures and then discuss their drawbacks.

In the model, the degree of complementarity is determined by the number of small technologies required to develop a larger, implementable innovation. This creates technological links among patented technologies, which are measured through cita-

[11] Moreover, in an additional analysis available upon request, I check that empirical evidence is robust to using an alternative classification scheme based on the sector of activity of the patent owner. I use the disclosed patent number to match the patent to its owner in "ORBIS - Bureau Van Dijk", which reports firm's industry of activity. Next, I assign each patent to the its owner's NACE industrial sector. Results are broadly consistent with the those presented in the paper.

[12] I compute the total number of applications by NACE-year by combining the tls201 and the tls229 PATSTAT tables. The robustness analysis using "scaled" disclosure measures refers just to the Eurostat IPC-based classification case used in PATSTAT.

tions among patent documents in the innovation literature. Specifically, a citation from patent $x$ to a previous patent $y$ is believed to indicate the use of technical knowledge contained in $y$ for the creation of $x$. Given the model's definition, small generic innovations would be represented as $y$, and implementable innovations would be represented as $x$. Thus, a larger number of backward citations would indicate more links and a higher degree of complementarity ($k$).

As Proposition 2 demonstrates, complementarity has both direct and indirect effects on TFP growth. Therefore, I construct three alternative measures of complementarity that serve two purposes: (i) to control for the direct effect and (ii) to generate variation in disclosures to estimate the indirect effect.

To capture cross-industry heterogeneity in the overall number of links among patents over time and differential trends in innovation complexity due to the penetration of "smart" technologies across sectors, I first calculate the industry- and year-specific average number of backward citations per patent, denoted by $AvgCit_{l,t}$.

For the second and third measures, I focus on narrower subsets of backward citations that reflect two important aspects of complementarity for the disclosure process. The first aspect relates to the within-industry dimension of the standardization process, which has been emphasized by previous literature in innovation economics and industrial organization. Accordingly, the second measure, denoted by $WCit_{l,t}$, counts the number of backward citations that occur among patents classified within the same industry $l$ at time $t$.

The second distinctive aspect of disclosure is the need to consider patents that are essential for the development and implementation of a new broader technology. Therefore, for the third measure of complementarity, I use the World Intellectual Property Organization (WIPO) classification of patent citations into "non-derivative" and "derivative" to isolate backward citations capturing technical links vital for the creation of the citing innovation.[13] Specifically, I calculate the average number of derivative backward citations per patent made within the same industry $l$ at time $t$, denoted by $AvgWDCit_{l,t}$.[14]

Figures 3.3, 3.4, and 3.5 provide a visual representation of the evolution of the first, second, and third complementarity measures, respectively, over time and across industries. Across all industries, there is a substantial increase in the average number of backward citations per patent over time. The growth rate significantly accelerates in most industries between 2000 and 2005, leading to a doubling or tripling of the measure in 2005 compared to 1990. However, for most sectors, there is a slowdown, if not a reversal of this increase between 2005 and 2012. Figure 3.4 displays a similar trend for within-industry citations, although the evolution is less noisy and does not decline after 2005. On the other hand, Figure 3.5 reveals a more irregular evolution of average within-industry derivative citations per patent. In certain industries such as "Manufacture of wearing apparel", the third complementarity measure is low and stable over time, whereas in others such as "Manufacture of machinery and equipment", $AvgWDCit_{l,t}$ grows markedly until 2000 and declines thereafter. The heterogeneous evolution of complementarity measures across industries and over time indicates that they indeed capture different characteristics of the innovation process.

[13] The WIPO classifies citations into several categories. The main are "A", which denotes "non-derivative" citations, and "X" and "Y", which denote a "derivative" citations. A citation is classified in category "A" if the document cited in the European search report represents state of the art not prejudicial to the novelty or inventive step of the invention claimed by the citing document. In contrast, if a document cited in the European search report is particularly relevant, it is indicated by the letters "X" and "Y". Category "X" applies if the invention claimed by the citing patent cannot be considered novel or involving a sufficient inventive step absent the citing document. Category "Y" applies where the invention claimed by the citing document cannot be considered to involve an inventive step if the cited document is combined with one or more other documents of the same category, such combination being obvious to a person skilled in the art.

[14] Appendix Subsection 3.A.4 provides detailed information on how the three measures are constructed.

#### 3.4.1.3 CompNet: Productivity and other industry characteristics

I use data from the European Central Bank CompNet database (4th round) to obtain industry-specific measures of Total Factor Productivity (TFP) growth and other sectoral characteristics across ten European countries over time. The time-coverage of the data varies by country (Austria: 2000-2012; Belgium: 2000-2011; Finland: 2000-2012; Germany: 2000-2012; Estonia: 2000-2012; Italy: 2001-2012; Lithuania: 2000-2011; Portugal: 2006-2012; Romania: 2003-2012; Slovenia: 2000-2012), resulting in a yearly unbalanced panel with a cross-sectional unit of country $\times$ NACE industry pair.

To estimate TFP, CompNet employs Wooldridge (2009)'s approach, which involves estimating a Cobb-Douglas production function on firm-level data using real value added as output and controlling for capital measurement error through a GMM framework. The resulting TFP estimates have a yearly sectoral average growth rate of 0.54% in the sample, with a standard deviation of 0.2 percentage points.

In addition to TFP, I include industry-specific measures of labor productivity, capital productivity, hours worked, real capital stock, real value added, the Herfindahl–Hirschman index of market concentration, and the price-cost margin as controls in the empirical analysis of Section 3.4.3. These additional characteristics are also obtained from the CompNet database.

#### 3.4.1.4 Estimation sample

To obtain my empirical estimates, I merge disclosure and complementarity measures from dSEp and PATSTAT with productivity and other industry characteristics from CompNet. While disclosure and complementarity measures vary at the industry $\times$ year level, productivity and other characteristics vary at the country $\times$ industry $\times$ year level. To address this, I assign the same industry- and year-specific values of disclosure and complementarity measures to all countries in the CompNet sample.

This reflects the global nature of the disclosure process and the industry-specific nature of complementarity, which is unlikely to vary significantly across countries. Appendix 3.A provides industry coverage in the merged sample in Table 3.A.2, as well as industry-specific summary statistics for the main variables used in the analysis. Finally, I limit the estimation sample to years up to 2010 due to truncation problems observed in the disclosure measures after that year.

### 3.4.2 Adapting theoretical predictions to the empirical setting

In this subsection, I adapt Propositions 1 and 2 to the variation present in the data. In fact, while the theoretical model includes one industry and a single country, the empirical setting features cross-industry variation in complementarity and disclosures as well as additional cross-country heterogeneity in productivity growth. This allows me to connect theoretical predictions to the empirical analyses of Subsection 3.4.3.

I index industries by $l$ and I assume that aggregate final output $C_t$ is an equal-shares Leontief aggregate of industry-specific consumption $C_{l,t}$. As market clearing requires $C_{l,t} = Y_{l,t}$ at any time, the model of Section 3.3 now describes production of industry-specific output $Y_{l,t}$ and innovation in industry $l$.[15]

As a consequence, Proposition 1 can be specialized to each industry $l$ and we can write the relation between industry-$l$ TFP growth and disclosed patents as

$$\frac{dg_{l,t}}{dm_{l,t}^{d*}} = -\frac{(\phi_{l,I}')^2}{\phi_{l,I}''}\left[\frac{1}{k_l} - \frac{k_l - m_{l,t}^{d*}}{k_l}\frac{(1-\beta_l)}{(1-(1-\beta_l)m_{l,t}^{d*})}\right](\gamma_l - 1) \tag{3.21}$$

whose implication is that the effect of disclosures on growth is more likely to be negative if the industry-specific degree of complementarity is large.[16] Moreover, the

[15]This simple adaptation of the model abstracts from cross-industries effects, which might be relevant in the real world. The advantage of keeping the model tractable is that it features a closed form solution that has intuitive theoretical predictions. As to the drawbacks, I try to control for cross-industry effects in the empirical analysis directly.

[16]I express this relationship in probabilistic terms because, differently from the setup of Section 3.3, in the multi-industry framework also $\beta$ may vary across sectors.

linearization of the industry-specific version of equations (3.17) and (3.18) around the time-average of growth ($g_{l,\cdot}$) and disclosures ($m^d_{l,\cdot}$), yields the implementable specification

$$g_{l,t} = g_{l,\cdot} + \omega_l(m^d_{l,t} - m^d_{l,\cdot}) \tag{3.22}$$

which motivates the initial OLS specification (3.23) of Subsection 3.4.3.1.

The empirical analysis is divided into three steps. Firstly, in Subsection 3.4.3.1, I estimate a cross-industry average of equation (3.22) with additional controls, using a common $\omega$ coefficient across industries. Secondly, Subsection 3.4.3.2 investigates the heterogeneity in $\omega_l$ highlighted by equation (3.22), by leveraging cross-country variation in TFP growth data. This heterogeneity in $\omega_l$ is then related to the degree of complementarity across industries, with Proposition 1 suggesting that industries with stronger innovation complementarity are more likely to have a negative estimated $\omega_l$. Finally, Subsection 3.4.3.3 explores the direct effect of complementarity and its indirect impact through disclosures, in line with the insight of Proposition 2. To achieve this, I propose an empirical strategy that uses measures of complementarity presented in Subsection 3.4.1.2 to (i) control for the direct effect and (ii) induce variation in sectoral disclosures plausibly related to complementarity only. Proposition 2 predicts a negative direct effect and an indirect effect with the same sign as the one estimated by OLS on (3.23).

### 3.4.3 Empirical Evidence

This subsection provides empirical results that demonstrate the relationship between the number of disclosed patents and productivity growth.

#### 3.4.3.1 Preliminary findings

Table 3.1 shows OLS estimates for different extensions of equation (3.22). These extensions demonstrate a consistent negative relationship between TFP growth and the number of disclosed patents across industries.

The benchmark specification, whose results are reported in the first column of the table, includes sector-, year-, and country-fixed effects as controls, i.e.,

$$g_{i,l,t} = c_t + c_i + c_l + \beta(\text{Disclosures}_{l,t})/10 + +\varepsilon_{i,l,t} \tag{3.23}$$

where the left hand side is TFP growth in country $i$, sector $l$, and year $t$ ($g_{i,l,t}$); $c_t$, $c_i$, and $c_l$ are year-$t$, country-$i$, and sector-$l$ fixed effects; and disclosed patents in sector $l$ and year $t$ are rescaled by 10. The estimates in the second, third, and fourth columns of the table refer to specifications where I incrementally add to (3.23) (i) a rich set of industry-specific time-varying controls including concentration, price-cost margin, value added, growth in profit margin, turnover, average wage share on total costs, investment ratio, hours worked, and leverage; (ii) country×year fixed effects, and (iii) country×sector fixed effects. In all columns, standard errors are clustered by sector.[17]

The estimated $\hat{\beta}$ coefficient is consistently negative and statistically significant across all specifications. The most conservative estimate indicates that a 10-unit increase in disclosures corresponds to an approximate 0.045 percentage point decrease in TFP growth by country-industry pair. In other words, a 35% increase in disclosed patents is associated with an 8% reduction in TFP growth, relative to their sector- and year-specific averages, respectively (corresponding to 28 disclosures and 0.54 percentage points). These findings suggest that, on aggregate, the negative complementarity effect between disclosures and TFP growth dominates the positive coordination effects

[17] I check the robustness of the results to using two-way clustered standard errors by sector×year or heteroskedasticity robust standard errors. Results are available upon request.

of disclosing technical information to standards. Furthermore, the estimated effect remains stable across specifications, even when controlling for time-varying measures of profitability, which may jointly increase both implementable innovations (i.e., TFP growth) and disclosures.

However, this evidence may obscure significant heterogeneity across industries. As shown in equation (3.22), the relationship between disclosures and TFP growth is contingent upon complementarity and other sector-specific factors. In the next subsection, I address this issue by examining cross-industry heterogeneity.

#### 3.4.3.2 Sectoral heterogeneity

I investigate sectoral heterogeneity in the relation between disclosures and TFP growth by re-estimating the following modification of (3.22)

$$g_{i,l,t} = c_t + c_i + c_l + \beta_l(\text{Disclosures}_{l,t})/10 + +\varepsilon_{i,l,t} \tag{3.24}$$

where $\beta_l$ can now vary across industries. Figure 3.6 plots estimates of $\hat{\beta}_l$'s for 16 industries in my sample. For a better graphical comparison, I re-scale estimates so they represent the effect of a 1% increase in the yearly and industry-specific average of disclosed patents.[18]

The figure demonstrates the notable heterogeneity in the sign and magnitude of the relationship between disclosures and TFP growth across industries. The results are consistent with the aggregate evidence, as the number of industries with a statistically significant negative relationship between disclosures and TFP growth is larger than those with a positive $\hat{\beta}_l$ (6 and 3, respectively). Furthermore, the observed empirical patterns align with Proposition 1's prediction on the sign of the effect based

[18] The proposed re-scaling affects the relative magnitude of plotted coefficients across sectors, but not the sign. This allows to better highlight industries with a small marginal effect of one additional disclosed patent but with a large number of disclosures, while preserving the possibility to evaluate model's prediction on the direction of the effect.

on complementarity. Figure 3.6 shows a substantial positive relationship in manufacturing of basic metals and manufacturing of rubber and plastic products, where new innovations typically do not require the combination of multiple technological components. In contrast, the opposite is evident in industries where innovation is more complex and complementarity is expected to be stronger. For example, the estimated $\hat{\beta}_l$ is significantly negative in computers manufacturing, where a final product comprises several technological parts, and intellectual property rights on the components are often dispersed. Similarly, the construction of airplanes or vessels, which falls into the category of "other transportation", involves a high degree of complexity and software components that may contribute to the estimated negative $\hat{\beta}_l$.

The results of a formal test support the insight that the sign of the estimated relationship between TFP growth and disclosures is more likely to be negative in industries with a high degree of complementarity. The test estimates the correlation between the indicator variable $\mathbf{1}_{\hat{\beta}_l>0}$, which takes a value of 1 if the estimated $\hat{\beta}_l$ is positive for industry $l$ and 0 otherwise, and sector-specific measures of complementarity that were computed before the estimation sample. To leverage the greater informativeness of sectors where disclosure is more intense, a least squares estimator is used that weighs sectors by the sample average of yearly disclosures. The results, shown in Table 3.2, indicate that for all measures of complementarity–i.e., backward citations per patent, derivative backward citations, and within-sector derivative backward citations per patent–the estimated correlation is statistically negative. This finding provides empirical support for Proposition 1.

#### 3.4.3.3 Direct and indirect effects of complementarity

In this subsection, I propose an empirical strategy that aims to disentangle the direct effect of complementarity on TFP growth, which theory predicts to be negative, and the indirect effect through disclosure, whose sign should retain that estimated in specification (3.22). To achieve this, I focus on the first measure of complementarity, i.e., average backward citations per patent ($AvgCit_{l,t}$), and use it as a control for the direct effect. Additionally, I use long lags of two alternative proxies, i.e., the number of within-sector backward citations $WCit_{l,t-5}$ and the average number of within-sector derivative backward citations $AvgWDCit_{l,t-5}$, to generate variation in disclosures that is related to sectoral complementarity and less influenced by other factors.[19] The proposed instrumental variable approach also addresses two major endogeneity concerns: measurement error in the disclosure variable, as discussed in Subsection 3.4.1.1; and reverse causation, as disclosing firms' expectations on productivity growth may directly influence their disclosure decisions. Moreover, I ensure that the external instruments have a mutual correlation of 0.09, which avoids collinearity concerns and allows the implementation of overidentification tests on the first-stage regression.

First and second stage regressions are

$$\frac{Discl_{l,t}}{10} = d_l + d_t + d_i + \psi AvgCit_{l,t} + \delta_1 \frac{WCit_{l,t-5}}{10^3} + \delta_2 AvgWDCit_{l,t-5} + u_{i,l,t} \tag{3.25}$$

$$g_{i,l,t} = c_l + c_t + c_i + \beta \frac{\widehat{Discl_{l,t}}}{10} + \gamma AvgCit_{l,t} + \varepsilon_{i,l,t} \tag{3.26}$$

where the baseline specification includes country, sector, and year fixed effects. Standard errors are clustered by sector. Table 3.3 shows the estimation results.

In the first column of Table 3.3, I present the results of the first stage regression (3.25). The external instruments used to instrument for disclosures are strong and positively related to the number of disclosed patents, with an F-statistic of joint significance of 27.54. In the second column, I report the results of the second stage regression (3.26). The estimated relationship between disclosed patents and TFP growth is negative and statistically significant. Notably, the magnitude of the effect is

[19] Results are robust to the use of alternative lags. Shorter lags may have more power, but they are also more prone to endogeneity concerns. Using a 5-year lag strikes a reasonable balance between the two trade-offs.

very similar to the OLS estimate of Subsection 3.4.3.1. To further test the robustness of the results, I report additional specifications in columns 3-5 of Table 3.3. Column 3 adds industry-specific time-varying controls specified in Subsection 3.4.3.1, column 4 adds country×year fixed effects, and column 5 includes country×sector fixed effects. Across all specifications, the estimated effect of disclosed patents on TFP growth remains similar in size and statistically significant. As for the direct effect of complementarity on TFP growth, it is generally negative, although not statistically significant.

In addition, I conduct overidentification tests to examine the validity of the IV strategy. Table 3.4 reports the test statistics and the associated p-values for the Sargan and the Basmann tests for overidentifying restrictions. The tests do not reject the null hypothesis that either of the two instruments is exogenous conditional on the exogeneity of the other, providing further support for the validity of the IV approach.

### 3.4.4 Additional results and robustness

In this subsection, I present additional results that both complement previous findings and verify their robustness. I investigate the heterogeneity in the impact of disclosures on TFP growth over the firm-level distribution of disclosures. I find that the negative relationship between disclosures and average TFP growth is primarily driven by firms with the fastest productivity growth, whereas TFP growth for firms at the bottom of the distribution is positively related to disclosures. To conduct this analysis, I use CompNet's data on selected percentiles of the TFP growth distribution, which I employ as the second-stage dependent variable in the IV strategy of Subsection 3.4.3.3. Table 3.5 shows the estimation results. The first column pertains to the average of the TFP growth distribution, confirming a negative and statistically significant relation between disclosures and productivity.[20] Subsequent columns refer to selected

[20]The estimated coefficient is different from Table 3.3 because the dependent variable changes in the two specifications. In Subsection 3.4.3.3, the outcome variable was the growth rate of the average

percentiles, indicating that the effect of disclosures is positive for firms with the lowest TFP growth and it turns sizably negative at the top of the distribution.[21] These findings suggest that the aggregate negative effect is due to a drag on firms with very fast productivity growth, which is consistent with the narrative of the proposed model.

I also present additional robustness results to further support the findings. In Appendix 3.D.1, Tables 3.D.1 and 3.D.2 replicate the analyses of Subsections 3.4.3.1 and 3.4.3.3, but this time using a measure of disclosed patents re-scaled by the sectoral flow of new patents as the regressor of interest. Results are broadly consistent with the main analysis, with re-scaled disclosures losing their statistical significance in the OLS estimation, but retaining it in the IV analysis.

Moreover, Tables 3.D.3 and 3.D.4 in Appendix 3.D.2 show the results of the analyses of Subsections 3.4.3.1 and 3.4.3.3 using labor-productivity growth as an alternative dependent variable. Results are qualitatively very similar to those in the main paper.

## 3.5 Conclusions

This paper presents a novel endogenous growth model that incorporates innovation complementarity and patents disclosure to technological standards. It identifies a crucial trade-off of disclosed technologies for productivity growth, where more disclosures lead to richer standards that enhance the effectiveness and efficiency of implementing major technological improvements, but also impose potentially unnecessary royalty payments on firms implementing the new technology, thus harming innovation and growth. The net effect can be negative if complementarity and/or the bargaining power of licensors are high enough.

of the TFP distribution, while here, it is the average of the TFP growth distribution.

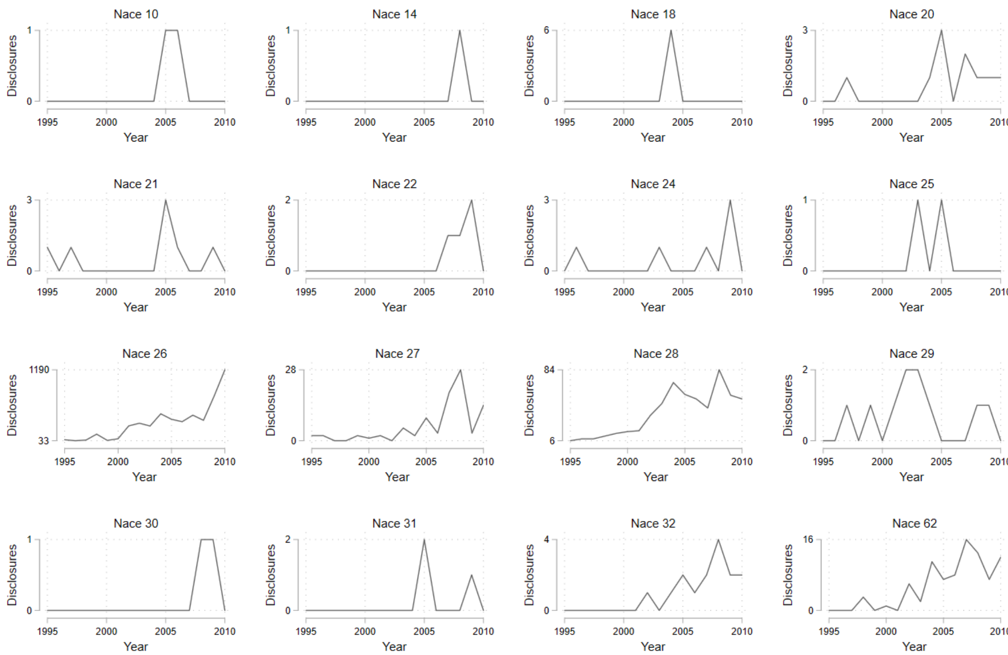
[21]The sample mean of the $99^{th}$ percentile of the growth-rate distribution is around 2.5%, and therefore, each disclosed patent reduces the within-firm TFP growth of "star" firms by around 10% of its value.

The empirical results show that, on average, more disclosures are negatively related to TFP growth across industries. However, there is considerable sectoral heterogeneity, which is consistent with the model's theoretical predictions. Sectors with low complementarity tend to exhibit a positive relationship between disclosures and TFP growth, while the opposite is true for sectors with high complementarity. These findings have important implications for the desirability of rich disclosure in sectors with high complementarity.

While the model has some simplifications, it generates insights that are supported by the data. Moreover, the model provides a useful general equilibrium framework to study the growth-effect of standards and disclosures, which will be increasingly important in the future due to the diffusion of smart systems in many industries.

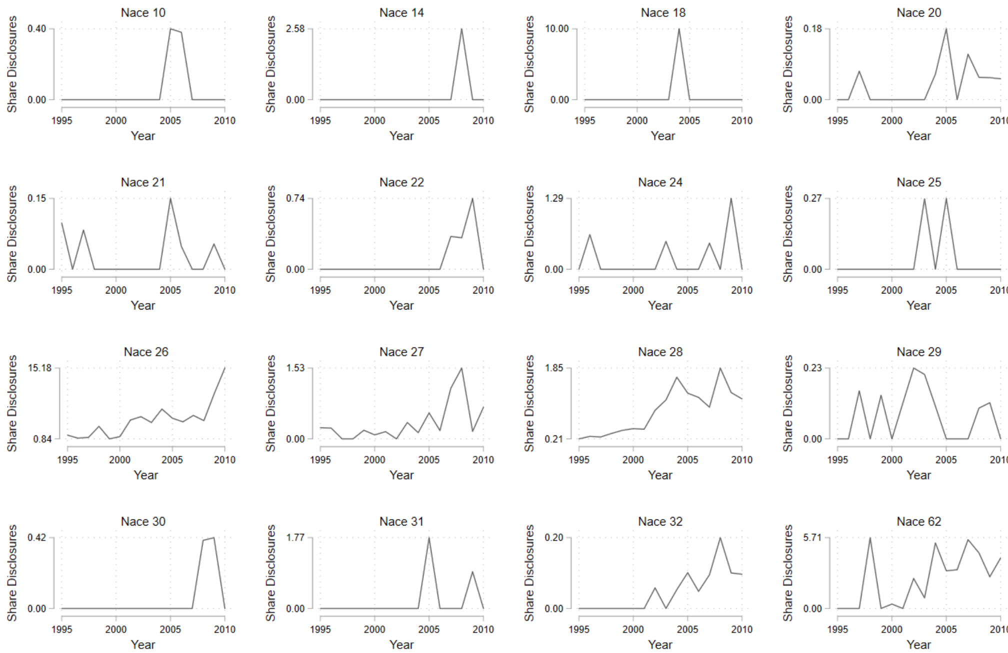
## 3.6 Tables and Figures

Figure 3.1: Total number of disclosed patents by industry



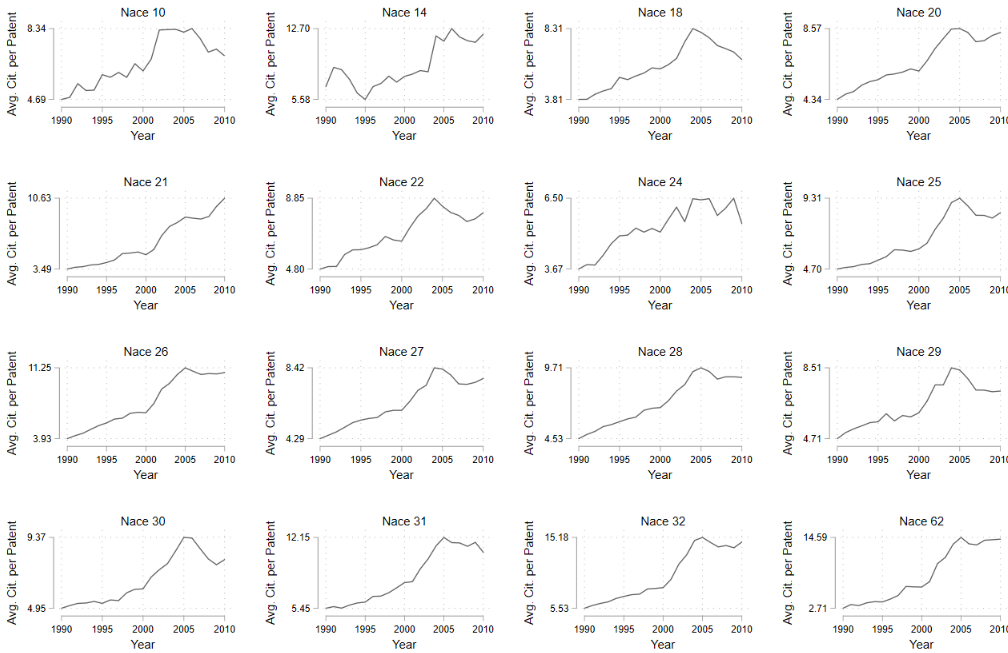

The figure shows the evolution of the number of disclosed patents by industry. The measure if build by counting the number of disclosed patents by 4-digit IPC class and year and then using the 4-digit IPC–NACE Rev.2 industry crosswalk provided by Eurostat to convert the series from patents classes to industrial sectors. NACE legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

Figure 3.2: Scaled measure of disclosed patents by industry




The figure shows the evolution of the scaled number of disclosed patents by industry. The variable represents the number of disclosed patents per year and industry relative to the total number of patent applications in the same year and industry. NACE legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

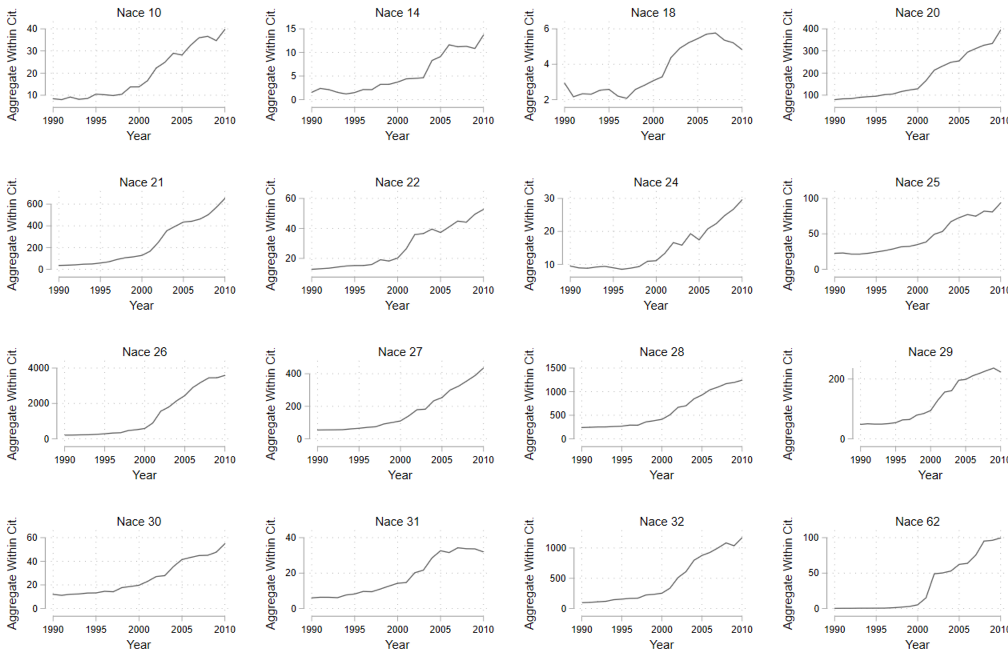
Figure 3.3: Average number of backward citations per patent




by industry

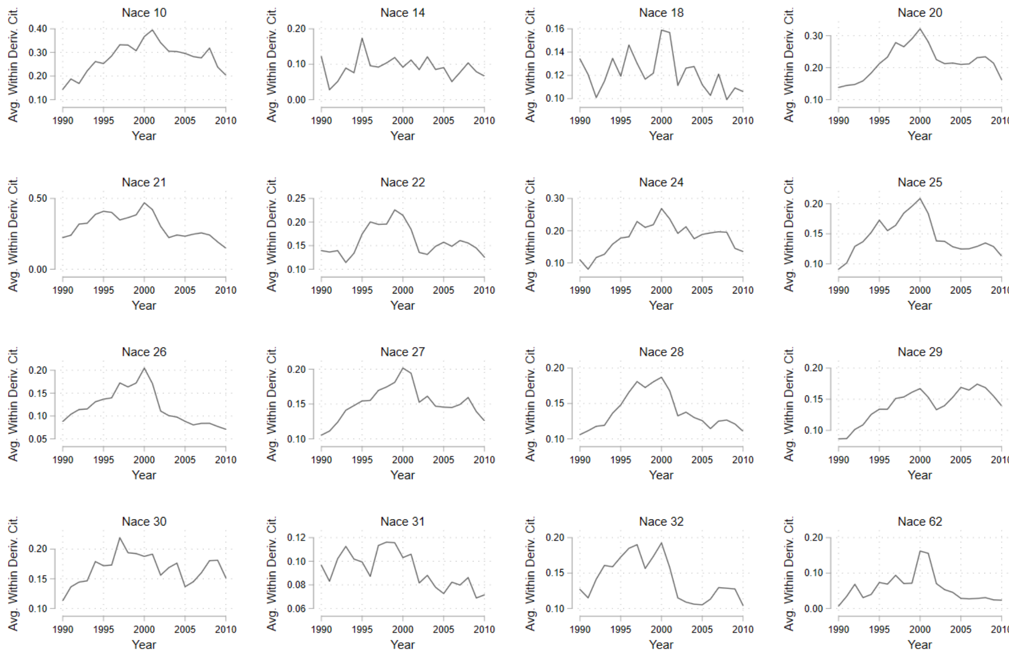
The figure shows the evolution of the average number of backward citations per patent by industry. The count of citations includes both citations to patents classified in the same industry of the citing patent and citations to patents classified in different industries. In formulae, $AvgCit_{l,t} = \frac{\sum_{p=1}^{N_{l,t}} c_{p,l,t}}{N_{l,t}}$, where $l$ indexes industries, $p$ indexes patents, and $t$ years. $N_{l,t}$ is the cardinality of the set of patents classified in industry $l$ published in year $t$, and $c_{p,l,t}$ is the number of backward citations made by patent $p$. NACE industry legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

Figure 3.4: Aggregate number of within-industry backward citations by industry




The figure shows the evolution of the aggregate number of within-industry backward citations by industry. The plotted measure is computed by summing, for all the patents classified in a given industry $l$, the number of backward citations directed to patents classified in the same industry $l$. The year time dimension is obtained from the publication year of the citing patent. In formulae, $WCit_{l,t} = \sum_{p=1}^{N_{l,t}} c^{l}_{p,l,t}$, where $l$ indexes industries, $p$ indexes patents, and $t$ years. $c^{l}_{p,l,t}$ is the number of patent-$p$ backward citations to other patents classified in industry $l$ and $N_{l,t}$ is the cardinality of the set of patents classified in industry $l$ and published in year $t$. The plots express quantities in thousands. NACE industry legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

Figure 3.5: Average within-industry derivative backward citations per patent




The figure shows the evolution of the average number of within-industry derivative citations, by industry. The latter is computed as $AvgWDCit_{l,t} = \frac{\sum_{i=1}^{N_{l,t}} c_{i,l,t}^{l}(d)}{N_{l,t}}$, where $l$ indexes industries, $p$ indexes patents, and $t$ years. $c_{i,l,t}^{l}(d)$ is the total number of derivative citations made by patent $p$ to patents classified in the same industry $l$ as $p$. $N_{l,t}$ is the cardinality of the set of patents classified in industry $l$ and published in year $t$. NACE industry legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

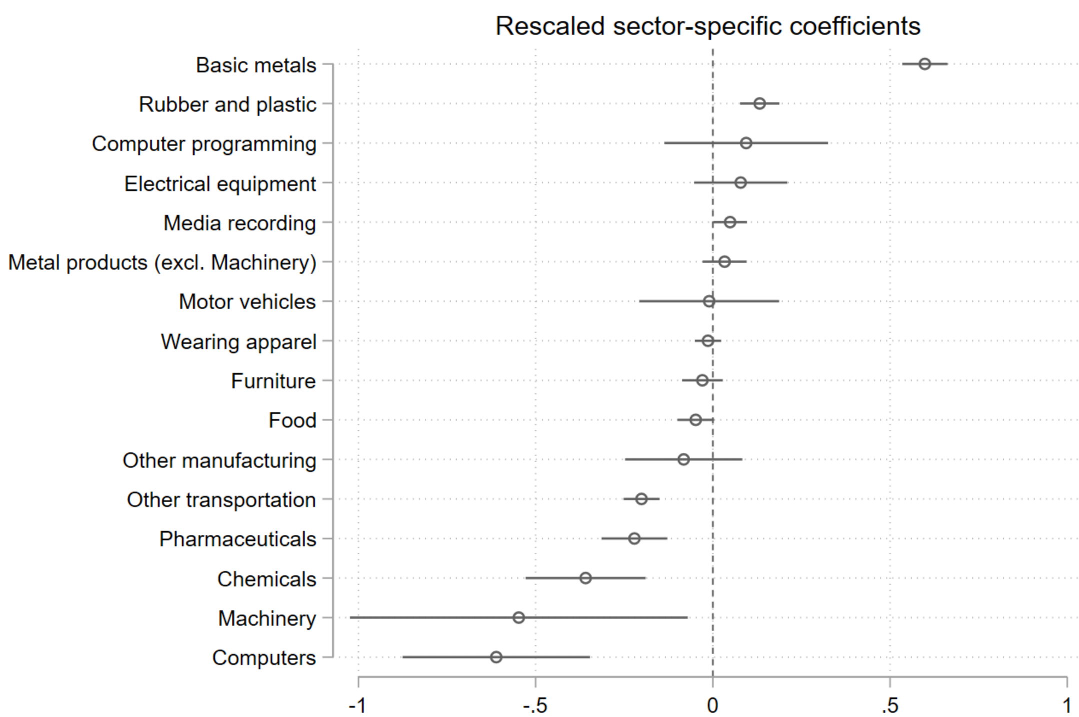
Table 3.1: Correlation between disclosed patents and TFP Growth

| | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ |
|---|---|---|---|---|
| Disclosures$_{l,t}$/10 | -0.0517** | -0.0458** | -0.0452** | -0.0452** |
| | (0.0178) | (0.0158) | (0.0166) | (0.0166) |
| Country F.E. | Y | Y | Y | Y |
| Year F.E. | Y | Y | Y | Y |
| Sector F.E. | Y | Y | Y | Y |
| Controls | | Y | Y | Y |
| Country×Year F.E. | | | Y | Y |
| Country×Sector F.E. | | | | Y |
| Observations | 1386 | 1170 | 1170 | 1170 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table shows the OLS estimates of the correlation between disclosed patents and the growth rate of the mean of the firm-level TFP distribution. The first column refers to specification (3.22). The second, third, and fourth column reports estimates of specification (3.22) incrementally augmented by (i) time-varying sector-specific controls described in Subsection 3.4.3.1; (ii) country×year fixed effects; (iii) country×sector fixed effects, respectively. Standard errors clustered at the industry-level are shown in parenthesis.

Figure 3.6: Industry-specific correlation between TFP growth and disclosures




The figure shows the industry-specific estimates of the correlation between the number of disclosed patents and TFP growth from specification (3.24), scaled by the inverse of the industry-specific average number of disclosed patents. Therefore, every dot represents the effect of a 1% increase in disclosures at the industry level. Bands reports 95% rescaled confidence intervals.

Table 3.2: Marginal effect of disclosed patents and sectoral complementarity measures

| | Sign of NACE-specific $\beta$ |
|---|---|
| Mean Aggr. Within Cit. (‘75-‘80) | -0.0066$^{***}$ |
| | (0.0008) |
| Mean Aggr. Within Cit. (‘81-‘85) | -0.0052$^{***}$ |
| | (0.0005) |
| Mean Aggr. Within Deriv. Cit. (‘75-‘80) | -1.0370$^{***}$ |
| | (0.1719) |
| Mean Aggr. Within Deriv. Cit. (‘81-‘85) | -0.0855$^{***}$ |
| | (0.0106) |
| Mean Average Within Deriv. Cit. (‘75-‘80) | -105.5851$^{***}$ |
| | (15.9304) |
| Mean Average Within Deriv. Cit. (‘81-‘85) | -7.3854$^{***}$ |
| | (1.6027) |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The table shows the estimated correlations between long lags of sectoral complementarity measures and the sign of the sector-specific correlation between disclosures and TFP growth. The regression coefficients reported in the table result from the weighted least-squares estimation–with frequency weights being the sample average of the industry-specific number of disclosures–of a linear specification where the dependent variable is a dummy variable taking value one if the sign of estimated $\hat{\beta}_l$ from specification (3.24) is positive and the regressor of interest is either of the past complementarity measures reported in the first column. The latter are computed on the periods 1975-1980 and 1981-1985. Each row refers to a separate regression including just one of the regressor at a time.

Table 3.3: Direct and indirect effects of complementarity on TFP growth

| | $\text{Discl}_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ |
|---|---|---|---|---|---|
| $\text{Disclosures}_{l,t}/10$ | | -0.0571** | -0.0522** | -0.0521** | -0.0521** |
| | | (0.0269) | (0.0251) | (0.0252) | (0.0252) |
| $AvgCit_{l,t}$ | -0.2133 | -0.1845 | -0.1721 | -0.1719 | -0.1719 |
| | (0.3891) | (0.2257) | (0.2161) | (0.2252) | (0.2231) |
| $WCit_{l,t-5}$ | 0.0301*** | | | | |
| | (0.0024) | | | | |
| $AvgWDCit_{l,t-5}$ | 31.2911** | | | | |
| | (11.3491) | | | | |
| Country F.E. | Y | Y | Y | Y | Y |
| Year F.E. | Y | Y | Y | Y | Y |
| Sector F.E. | Y | Y | Y | Y | Y |
| Controls | | | Y | Y | Y |
| Country×Year F.E. | | | | Y | Y |
| Country×Sector F.E. | | | | | Y |
| Observations | 1386 | 1386 | 1170 | 1170 | 1170 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table shows the estimation results of specifications (3.25) and (3.26). The first column reports the results of first stage estimation. The second column refers to the second stage estimates. The third, fourth, and fifth column reports the second stage estimates from specifications (3.25) and (3.26) augmented by (i) time-varying industry-specific controls described in Subsection 3.4.3.1; (ii) country×year fixed effects; and (iii) country×sector fixed effects, respectively. Standard errors clustered at the industry level are reported.

Table 3.4: Overidentification tests

| Test Statistic | Value | $p$-value |
|---|---|---|
| Sargan $\chi^2_{(1)}$ | 1.3949 | 0.2376 |
| Basmann $\chi^2_{(1)}$ | 1.3560 | 0.2442 |

Standard errors in parentheses

The table reports the test statistics and p-values for Sargan and Basmann tests for overidentifying restrictions, based on the 2SLS estimates of specifications (3.25) and (3.26).

Table 3.5: Direct and indirect effects of complementarity on TFP growth

| | Mean | $1^{st}$ perc. | $10^{th}$ perc. | Median | $90^{th}$ perc. | $99^{th}$ perc. |
|---|---|---|---|---|---|---|
| Disclosures$_{l,t}/10$ | -0.1003$^{*}$ | 0.0597 | 0.0811$^{**}$ | -0.0311 | -0.2028 | -2.5841$^{***}$ |
| | (0.0633) | (0.0499) | (0.0394) | (0.0346) | (0.1617) | (1.0789) |
| $AvgCit_{l,t}$ | -0.1345 | 0.8613$^{**}$ | 0.1815 | -0.0474 | -1.7520 | 4.4443 |
| | (0.3327) | (0.3751) | (0.3632) | (0.2131) | (1.2691) | 8.8391 |
| Country F.E. | Y | Y | Y | Y | Y | Y |
| Year F.E. | Y | Y | Y | Y | Y | Y |
| Sector F.E. | Y | Y | Y | Y | Y | Y |
| Controls | | | | | | |
| Country$\times$Year F.E. | | | | | | |
| Country$\times$Sector F.E. | | | | | | |
| Observations | 1386 | 1386 | 1386 | 1386 | 1386 | 1386 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The table reports estimation results of specification (3.25) having as dependent variable the growth rates of TFP at different points of its year-, industry-, and country-specific firm-level distribution. The first column reports the results for the growth rate of average TFP, the second column for the growth rate of the $1^{st}$ percentile, the third column for the growth rate of the $10^{th}$ percentile, the fourth column for the growth rate of the median, the fifth column for the growth rate of the $90^{th}$ percentile, and the sixth column for the growth rate of the $99^{th}$ percentile. All regressions include industry-, year- and country-fixed effects. Standard errors are clustered at the industry level.

# Appendices

## Appendix 3.A Data Description

### 3.A.1 Disclosures by Standard Setting Organization

Table 3.A.1: Disclosures by Standard Setting Organization

| Standard Setting Organization | $N$ Disclosures | % Disclosures |
|---|---|---|
| ANSI | 911 | 2.01 |
| ATIS | 675 | 1.49 |
| BBF | 142 | 0.31 |
| CEN | 22 | 0.05 |
| CENELEC | 17 | 0.04 |
| ETSI | 28,940 | 63.82 |
| IEC | 367 | 0.81 |
| IEC - JTC1 | 1,368 | 3.02 |
| IEEE | 2,507 | 5.53 |
| IETF | 2,723 | 6.00 |
| ISO | 503 | 1.11 |
| ISO - JTC1 | 2,256 | 4.97 |
| ITU | 2,962 | 6.53 |
| OMA | 1,001 | 2.21 |
| TIA | 955 | 2.11 |

The table reports in the first column the names of the 13 SSOs covered by the dSEP database. The second and third columns report the number of disclosures and their percentage over the total by SSO.

## 3.A.2 Industry Coverage

Table 3.A.2: Industries in the sample based on IPC classification

| NACE Code | Description |
|---|---|
| 10 | Manufacture of food products |
| 14 | Manufacture of wearing apparel |
| 18 | Printing and reproduction of recorded media |
| 20 | Manufacture of chemicals and chemical products |
| 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| 22 | Manufacture of rubber and plastic products |
| 24 | Manufacture of basic metals |
| 25 | Manufacture of fabricated metal products, except machinery and equipment |
| 26 | Manufacture of computer, electronic and optical products |
| 27 | Manufacture of electrical equipment |
| 28 | Manufacture of machinery and equipment n.e.c. |
| 29 | Manufacture of motor vehicles, trailers and semi-trailers |
| 30 | Manufacture of other transport equipment |
| 31 | Manufacture of furniture |
| 32 | Other manufacturing |
| 62 | Computer programming, consultancy and related activities |

NACE Rev.2 2-digit represented in the merged sample where the classification criterion used to build the disclosure measure is based on the International Patent Classification Codes associated to each patent. NACE legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

## 3.A.3 Summary Statistics

Table 3.A.3 reports industry-specific summary statistics for disclosed patents, complementarity measures, and productivity. The table reveals high variability in the productivity variables as well as in the disclosure measure. The sector with the highest disclosure measure is "Manufacture of computer, electronic and optical products" and the one with lowest disclosure intensity is "Manufacture of wearing apparel". The ranking of industries by intensity of the disclosure phenomenon reflects that innovation complementarity is stronger for Information and Comunication Technologies (ICTs), where a large number of technological components must be combined and must jointly operate in any individual innovation.

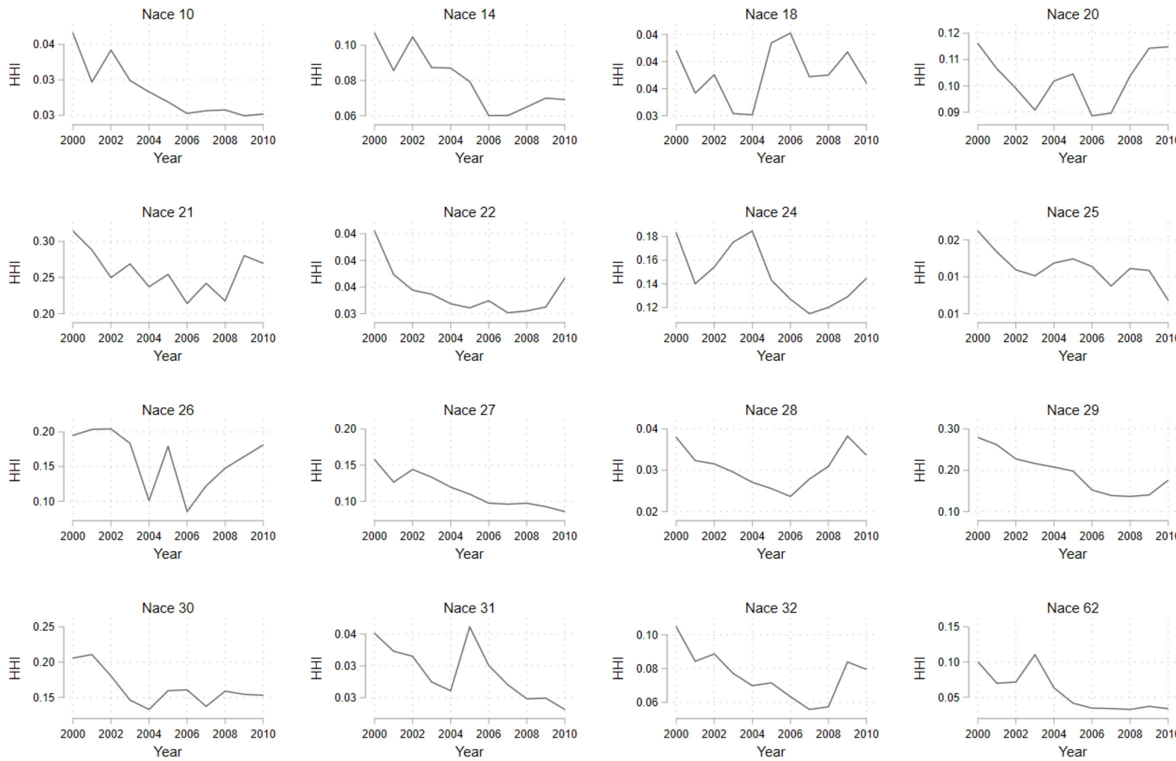
Table 3.A.3: Summary statistics for IPC-based classification sample

| | 10 | 14 | 18 | 20 | 21 | 22 | 24 | 25 | 26 |
|---|---|---|---|---|---|---|---|---|---|
| | mean | mean | mean | mean | mean | mean | mean | mean | mean |
| Disclosures | 0.053 | 0.026 | 0.184 | 0.289 | 0.184 | 0.105 | 0.158 | 0.079 | 143.421 |
| Share of patents disclosed (p.p.) | 0.021 | 0.068 | 0.313 | 0.019 | 0.011 | 0.037 | 0.076 | 0.027 | 2.132 |
| Aggr. Within-Ind. Cit. (Thousands) | 21.009 | 4.633 | 2.853 | 168.550 | 202.973 | 23.924 | 16.036 | 41.322 | 1175.552 |
| Aggr. W. Deriv. Cit. (Thousands) | 3.768 | 0.290 | 0.322 | 20.984 | 23.619 | 2.823 | 2.071 | 3.505 | 66.434 |
| Avg. W. Deriv. Cit. per patent | 0.236 | 0.079 | 0.107 | 0.163 | 0.223 | 0.126 | 0.139 | 0.111 | 0.092 |
| Avg. Cit. per patent | 5.308 | 7.358 | 4.992 | 5.525 | 5.239 | 5.688 | 4.458 | 5.690 | 6.167 |
| Avg. Sectoral TFP Growth (p.p.) | 0.064 | 0.077 | 0.131 | -0.265 | 1.575 | 0.691 | 0.693 | 0.225 | 1.821 |
| Avg. Labor Prod. Growth (p.p.) | 1.777 | 3.836 | 2.447 | 2.457 | 6.435 | 3.639 | 2.812 | 3.641 | 8.493 |
| Avg. Capital Prod. Growth (p.p.) | 3.607 | 4.964 | 4.138 | 8.063 | 10.921 | 6.995 | 6.384 | 4.172 | 8.513 |
| Within-firm Avg. TFP growth (p.p.) | 0.094 | 0.060 | 0.071 | 0.087 | 0.071 | 0.087 | 0.084 | 0.085 | 0.123 |
| Observations | 410 | 410 | 410 | 410 | 410 | 410 | 410 | 410 | 410 |

| | 27 | 28 | 29 | 30 | 31 | 32 | 62 |
|---|---|---|---|---|---|---|---|
| | mean | mean | mean | mean | mean | mean | mean |
| Disclosures | 2.553 | 16.053 | 0.289 | 0.053 | 0.079 | 0.421 | 2.263 |
| Share of patents disclosed (p.p.) | 0.166 | 0.394 | 0.033 | 0.022 | 0.071 | 0.022 | 0.987 |
| Aggr. Within-Ind. Cit. (Thousands) | 163.020 | 524.792 | 105.843 | 23.569 | 14.294 | 392.658 | 28.144 |
| Aggr. W. Deriv. Cit. (Thousands) | 16.564 | 41.496 | 9.019 | 2.269 | 0.906 | 24.644 | 1.213 |
| Avg. W. Deriv. Cit. per patent | 0.123 | 0.108 | 0.113 | 0.125 | 0.083 | 0.113 | 0.043 |
| Avg. Cit. per patent | 5.393 | 5.980 | 5.641 | 5.793 | 7.160 | 8.179 | 6.292 |
| Avg. Sectoral TFP Growth (p.p.) | 1.106 | 1.191 | 1.788 | -0.168 | 0.292 | 0.527 | -0.226 |
| Avg. Labor Prod. Growth (p.p.) | 3.733 | 4.007 | 5.590 | 2.917 | 2.682 | 2.864 | 2.220 |
| Avg. Capital Prod. Growth (p.p.) | 6.453 | 3.679 | 8.548 | 8.003 | 3.412 | 2.831 | 7.650 |
| Within-firm Avg. TFP growth (p.p.) | 0.089 | 0.114 | 0.143 | 0.220 | 0.086 | 0.115 | 0.106 |
| Observations | 410 | 410 | 410 | 410 | 410 | 410 | 410 |

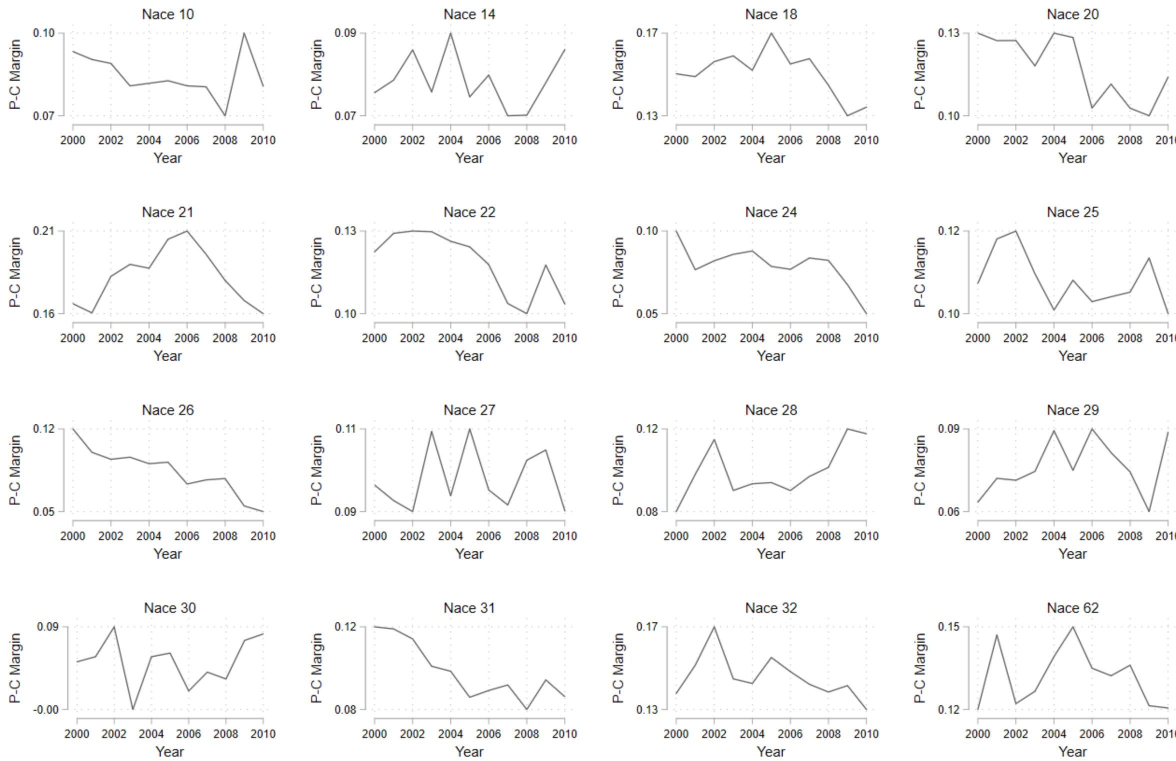
The table reports the industry-specific averages (over time and across countries) for the main variables used in the empirical analysis. NACE industry legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

Figure 3.A.1: Herfindahl-Hirschman Index




HH Index of concentration at the industry level. Values closer to 1 imply more concentration in the industry. Source: CompNet. NACE industry legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

Figure 3.A.2: Price-Cost margin




Price-Cost Margin at the industry level. Source: CompNet. NACE industry legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

## 3.A.4 Construction of complementarity variables

**3.A.4.0.1 Average number of backward citations per patent** Let $c_{p,l,t}$ be the total number of patents cited by patent $p$ published in year $t$ and classified in industry $l$, and let $N_{l,t}$ be the total number of patents published in year $t$ and classified in industry $l$. I compute the variable as

$$AvgCit_{l,t} = \frac{\sum_{p=1}^{N_{l,t}} c_{p,l,t}}{N_{l,t}}$$

#### 3.A.4.0.2 Total number of within-industry citations

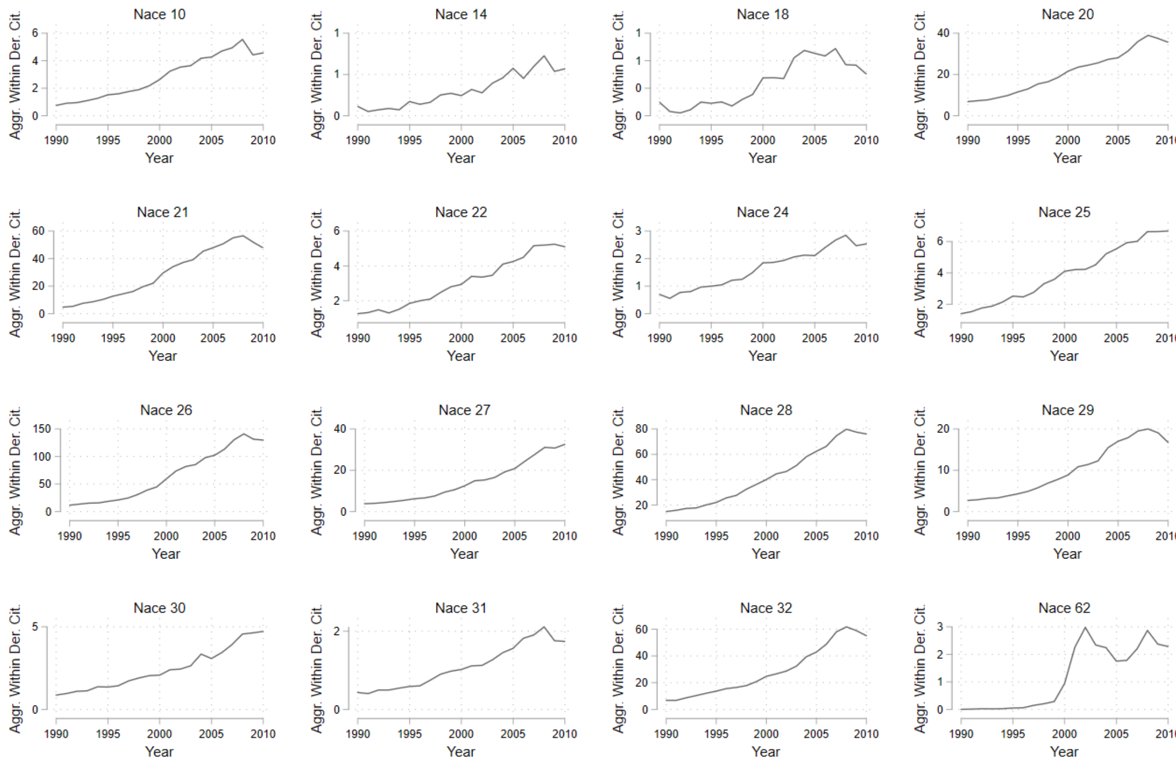
Let $c^l_{p,l,t}$ be the number of industry-$l$ patents cited by patent $p$ published in year $t$ and classified in industry $l$. Also, let $N_{l,t}$ be the number of patents published in year $t$ and industry $l$. I compute the variable as

$$WCit_{l,t} = \sum_{p=1}^{N_{l,t}} c^l_{p,l,t}$$

and it represents a measure of the absolute intensity of within-sector connections among technologies. This is one of the two variables whose long-lags are used as excluded instruments for disclosed patents.

Similarly I build a variable measuring the aggregate number of within-industry "derivative" citations by counting by NACE and year only those citations that are classified as either type "X" or "Y". I call this variable $WDCit_{l,t}$ and plot its evolution by industry in Figure 3.A.3. I verify that the results of Subsection 3.4.3.3 of the paper are robust to using $WDCit_{l,t}$ rather than $WCit_{l,t}$ as an excluded instrument. Results of this robustness check are available upon request.

Figure 3.A.3: Aggregate within-industry derivative citations




The figure plots the industry-specific evolution of the aggregate number of derivative citations among patents classified in the same industry. NACE industry legend: 10 Food; 14 Wearing apparel; 18 Printing; 20 Chemicals; 21 Pharmaceutical; 22 Rubber and plastic; 24 Basic metals; 25 Fabricated metal products (except machinery and equipment); 26 Computer, electronic and optical products; 27 Electrical equipment; 28 Machinery and equipment; 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing; 62 Computer programming, consultancy.

**3.A.4.0.3 Average number of within-industry derivative citations** Let $c_{p,l,t}^{l,d}$ be the number of patents classified in industry $l$ that are cited with a type "X" or "Y" citation by patent $p$ granted in year $t$ and classified in industry $l$. Also, let $N_{l,t}^{d}$ be the total number of patents granted in year $t$, classified in industry $l$, and making at least one type "X" or "Y" citation. I build the variable as

$$AvgWDCit_{l,t} = \frac{\sum_{p=1}^{N_{l,t}^{d}} c_{p,l,t}^{l,d}}{N_{l,t}^{d}}$$

It represents an industry-specific measure of the intensity of within-industry complementarity in innovation. This measure is meant to capture variation in complementarity that is particularly relevant for the patents disclosure process and standardization.

Figure 3.3 shows the industry-specific evolution of average citations per patent. The increasing trend observed for most industries confirms that there is a general rise in the degree of complementarity in innovation. Differences in slope and in level suggest that such increase, possibly induced by the spread of Information and Communication Technologies, is very heterogeneous across sectors. Figure 3.4 plots the aggregate number of within-industry patents citations and it shows that, for most industries, the relevance of within-industry complementarity is also growing over time. Finally, Figure 3.5 plots the average number of within-industry "derivative" citations by patent. In this case, the behavior observed across different industries is more mixed and, while it shows an increase up to 2000, it seems to be generally declining thereafter.

# Appendix 3.B Assumptions, optimization problems, and solution

## 3.B.1 Assumptions

**Assumption 1.** *Parameters $(k, K, \alpha, L, \beta)$ and the function $\phi(\cdot)$ are such that $(n_t^{I*}, n_t^{G*})$ solving the system*

$$\begin{cases} \phi'\left(\frac{k}{k-\phi(n_t^{G*})K} n_t^{I*}\right)(1-(1-\beta)\phi(n_t^{G*}))\pi L = (k-\phi(n_t^{G*})K)/k \\ \phi'(n_t^{G*})\phi\left(\frac{k}{k-m_t^{d*}} n_t^{I*}\right)(1-\beta)\pi L k = 1 \end{cases}$$

*verify the condition $\phi(n_t^{G*}) < \min\{k, (1-\beta)^{-1}\}$*

### 3.B.2 Bargaining Problem

The bargaining problem between an intermediate firm $i \in [0,1]$ and a generic innovator $j \in [0,K]$ is

$$\max_{p^p_{i,j}} \quad (\Pi^*_{i,t} - p^p_{i,j})^{\beta}(p^p_{i,j})^{1-\beta}$$

where $\Pi^*_{i,t}$ are total monopolistic profits in industry $i$ and $p^p_{i,j}$ is the royalty payment from $i$ to $j$ for the use of a generic innovation patented by $j$. Equilibrium royalty is

$$p^{*,p}_{i,j,t} = p^{*,p}_{i,t} = (1-\beta)\Pi^*_{i,t} \tag{3.27}$$

which is the same across every $j \in [0,K]$. By assumption, the bargaining problem is the same whether or not the generic technology is disclosed. Therefore, the royalty payment is the same. The difference between the two cases is that, in the absence of disclosure, bargaining may fail with exogenous probability $\theta(m^{d*}_t)$, in which case the transfer is zero.

### 3.B.3 Final good production problem

$$\begin{aligned}&\max_{x_{i,t},L} \quad Y_{i,t} - p_{i,t}x_{i,t} - w_t L\\ &\text{subject to} \;\; Y_t = L^{(1-\alpha)} \int_0^1 A^{1-\alpha}_{i,t} x^{\alpha}_{i,t} di\end{aligned}$$

which pins down equilibrium wages and the inverse demand function faced by monopolistic producers of each variety $x_{i,t}$ according to:

$$\begin{aligned}p^*_{i,t} &= \alpha L^{1-\alpha} A^{1-\alpha}_{i,t} x^{\alpha-1}_{i,t}\\ w^*_t &= (1-\alpha) L^{-\alpha} A^{1-\alpha}_{i,t} x^{\alpha}_{i,t}\end{aligned} \tag{3.28}$$

### 3.B.4 Intermediate good production problem

The profit maximization problem of the producer of intermediate input $i$ conditional on being a monopolist on it is

$$\begin{aligned} &\max_{x_{i,t}} \quad p^*_{i,t}x_{i,t} - x_{i,t} \\ &\text{s.t.} \quad p^*_{i,t} = \alpha L^{1-\alpha} A^{1-\alpha}_{i,t} x^{\alpha-1}_{i,t} \end{aligned} \tag{3.29}$$

which implies the following equilibrium quantities

$$\begin{aligned} x^*_{i,t} &= \alpha^{\frac{2}{1-\alpha}} A_{i,t} L \\ \Pi^*_{i,t} &= [\alpha^{\frac{1+\alpha}{1-\alpha}} - \alpha^{\frac{2}{1-\alpha}}] A_{i,t} L = \pi A_{i,t} L \end{aligned} \tag{3.30}$$

For a competitive producer of intermediate $i$, the constraint on profit maximization is different from (3.29). In fact, Bertrand competition drives the price to the unitary marginal cost, thus $p^*_{i,t} = 1$ and $\Pi^*_{i,t} = 0$ in the absence of successful innovation ob variety $i$.

### 3.B.5 Characterization of the Cournot-Nash symmetric balanced growth path equilibrium

From the discussion of Subsection 3.3.1 of the paper and using the solution to the bargaining problem (3.27) and equilibrium profits (3.30) conditional on innovation, we know that optimal R&D intensity for intermediate innovators is positive conditional on

$$\Pi^e_{i,t} = (1 - \theta(m^u_t))[1 - \min\{m^d_t, k\}(1-\beta) - \min\{\delta m^u_t, k\}(1-\beta)]\Pi^*_{i,t} > 0$$

where $\Pi^*_{i,t} = \pi L \gamma A_{i,t-1}$, as productivity improves by a factor $\gamma$ conditional on innovation. $\Pi^e_{i,t} > 0$ requires that $m^u_t$ and/or $m^d_t$ are small enough in equilibrium.

Assumption 1 ensures that this is the case. Then, optimal R&D intensity $n_{i,t}^{I*}$ is interior and satisfies the condition

$$\phi'\Big(\frac{k}{k-m_t^d}n_{i,t}^I\Big)\Pi_{i,t}^e = (k-m_t^d)\psi A_{i,t-1} \tag{3.31}$$

which, given the linearity of $\Pi_{i,t}^e$ in $A_{i,t-1}$ and the independence of all other terms from $i$, implies that R&D intensity is symmetric across intermediate innovators, i.e., $n_{i,t}^{I*} = n_t^{I*}\ \forall i \in [0,1]$. Therefore, since R&D outcomes are independent across $i$'s, by a suitable law of large number the equilibrium measure of varieties where a successful quality upgrade is potentially feasible is $\mu_t^* = \phi\Big(\frac{k}{k-m_t^d}n_t^{I*}\Big)$.

I assume that identical innovators on generic technologies are atomistic and take the behavior of other generic innovators and of intermediate firms as given. Therefore, the comparison of equations (3.8) and (3.9) shows that, for any given equilibrium decisions of intermediate firms and other generic innovators, it is individually optimal to disclose as long as $k/m_t^{d*} > \delta(1-\theta(m_t^{*u})$. In a symmetric equilibrium featuring full disclosure, this requires $k/m_t^{d*} > \delta$, which is verified under Assumption 1. As a result, combining equations (3.8), (3.10), equilibrium royalties, and intermediate innovation rate, it is possible to express generic R&D intensity as

$$\phi'(n_{j,t}^{G*})\nu_t^* \int_0^1 \phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)(1-\beta)\pi L\gamma A_{i,t-1}di = \psi\overline{A}_{t-1}$$
$$\phi'(n_{j,t}^{G*})\nu_t^* \phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)(1-\beta)\pi L\gamma \overline{A}_{t-1} = \psi\overline{A}_{t-1}$$

which shows that generic R&D intensity is also symmetric across $j \in [0,K]$ and satisfies

$$\phi'(n_t^{G*})\phi\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)(1-\beta)\pi Lk = 1 \tag{3.32}$$

because $\gamma = k\psi$ and $\nu_t^* = 1$ under assumption 1.

Given equation (3.32) and full disclosure, the equilibrium measure of disclosed generic technologies is

$$m_t^{d*} = \phi(n_t^{G*})K \tag{3.33}$$

and expected profits for implementing firms are

$$\Pi_{i,t}^{e*} = (1 - (1-\beta)m_t^{d*})\Pi_{i,t}^{*} \tag{3.34}$$

which is strictly positive as long as $(1 - (1-\beta)m_t^{d*}) > 0$, i.e., $m_t^{d*} < (1-\beta)^{-1}$. Therefore, at the interior equilibrium optimal symmetric R&D intensities $(n_t^{I*}, n_t^{G*})$ solve the system of equations

$$\begin{cases} \phi'\Big(\frac{k}{k-\phi(n_t^{G*})K} n_t^{I*}\Big)(1-(1-\beta)\phi(n_t^{G*}))\pi L = (k - \phi(n_t^{G*})K)/k \\ \phi'(n_t^{G*})\phi\Big(\frac{k}{k-m_t^{d*}} n_t^{I*}\Big)(1-\beta)\pi L k = 1 \end{cases} \tag{3.35}$$

Under Assumption 1, in the equilibrium intermediate innovators still need to invest in R&D despite disclosed technologies and have the incentive to implement the final innovation even after paying royalties. At the same time, innovators on generic technologies find it profitable to invest in R&D because they have a profitable outlet for their inventions and prefer to disclose them to the standard.

# Appendix 3.C Proofs

## 3.C.1 Proof of Proposition 1

From

$$g_t = \phi\Big(\frac{k}{k - m_t^{d*}} n_t^{I*}\Big) \tag{3.36}$$

I get

$$\frac{dg_t}{dm_t^{d*}} = \Bigg[\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k}{(k-m_t^{d*})^2}n_t^{I*} + \\ +\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k}{k-m_t^{d*}}\frac{dn_t^{I*}}{dm_t^{d*}}\Bigg](\gamma-1) \tag{3.37}$$

Next, I derive $\frac{dn_t^{I*}}{dm_t^{d*}}$ from the intermediate innovator's R&D first order condition. Differentiating (3.18) I get:

$$\phi''\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k}{(k-m_t^{d*})^2}n_t^{I*}\frac{k}{k-m_t^{d*}}(1-(1-\beta)m_t^{d*})\pi L + \\ +\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k}{(k-m_t^{d*})^2}(1-(1-\beta)m_t^{d*})\pi L + \\ -(1-\beta)\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k}{k-m_t^{d*}}\pi L + \\ +\phi''\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k^2}{(k-m_t^{d*})^2}(1-(1-\beta)m_t^{d*})\pi L\frac{dn_t^{I*}}{dm_t^{d*}} = 0 \tag{3.38}$$

Denote $\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)$ by $\phi_I'$ and $\phi''\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)$ by $\phi_I''$. Then

$$\frac{dn_t^{I*}}{dm_t^{d*}} = -\frac{n_t^{I*}}{k-m_t^{*}} - \frac{1}{k}\frac{\phi_I'}{\phi_I''} + \frac{(1-\beta)}{(1-(1-\beta)m_t^{d*})}\frac{k-m_t^{d*}}{k}\frac{\phi_I'}{\phi_I''} \tag{3.39}$$

Using (3.39) into (3.37), I get a final expression for $\frac{dg_t}{dm_t^{d*}}$.

$$\frac{dg_t}{dm_t^{d*}} = \Bigg\{\phi_I'\frac{k}{(k-m_t^{d*})^2}n_t^{I*} + \phi_I'\frac{k}{k-m_t^{d*}} \\ \Bigg[-\frac{n_t^{I*}}{k-m_t^{d*}} - \frac{1}{k}\frac{\phi_I'}{\phi_I''} + \frac{(1-\beta)}{(1-(1-\beta)m_t^{d*})}\frac{k-m_t^{d*}}{k}\frac{\phi_I'}{\phi_I''}\Bigg]\Bigg\}(\gamma-1) = \\ = -\frac{(\phi_I')^2}{\phi_I''}\Bigg[\frac{1}{k} - \frac{k-m_t^{d*}}{k}\frac{(1-\beta)}{(1-(1-\beta)m_t^{d*})}\Bigg](\gamma-1) \tag{3.40}$$

which is negative as long as:

$$\frac{1}{k} - \frac{k - m_t^{d*}}{k} \frac{(1-\beta)}{(1-(1-\beta)m_t^{d*})} < 0$$

which can be rewritten as:

$$1 - (1-\beta)m_t^{d*} < (1-\beta)(k - m_t^{d*})$$

which is equivalent to

$$k > \frac{1}{1-\beta}$$

which ends the proof.

### 3.C.2 Proof of Proposition 2

I start from

$$g_t = \phi\Big(\frac{k}{k - m_t^{d*}} n_t^{I*}\Big)(\gamma - 1)$$

and I differentiate both sides by $k$, obtaining:

$$\frac{dg_t}{dk} = \phi_I'(\gamma - 1)\left[-\frac{m_t^{d*}}{(k - m_t^{d*})^2} n_t^{I*}\right] + \phi_I'(\gamma - 1)\frac{m_t^{d*}}{k - m_t^{d*}} \frac{dn_t^{I*}}{dk} \tag{3.41}$$

Also, differentiating equation (3.18) by $k$ on both sides I get

$$
\begin{aligned}
-\phi''\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\left[\frac{m_t^{d*}}{(k-m_t^{d*})^2}n_t^{I*}\right]\frac{k}{k-m_t^{d*}}(1-(1-\beta)m_t^{d*})\pi L+ \\
-\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\left[\frac{m_t^{d*}}{(k-m_t^{d*})^2}n_t^{I*}\right](1-(1-\beta)m_t^{d*})\pi L+ \\
+\phi''\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\left[\frac{m_t^{d*}}{k-m_t^{d*}}\right]^2\frac{dn_t^{I*}}{dk}(1-(1-\beta)m_t^{d*})\pi L+ \\
+\Bigg[\phi''\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k^2}{(k-m_t^{d*})^3}n_t^{I*}(1-(1-\beta)m_t^{d*})\pi L+ \\
+\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k}{(k-m_t^{d*})^2}(1-(1-\beta)m_t^{d*})\pi L+ \\
-\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)\frac{k}{k-m_t^{d*}}(1-\beta)\pi L\Bigg]\frac{dm_t^{d*}}{dk}=0
\end{aligned}
\tag{3.42}
$$

which gives $\frac{dn_t^{I*}}{dk}$ as a function of $\frac{dm_t^{d*}}{dk}$:

$$
\begin{aligned}
\frac{dn_t^{I*}}{dk}=\Big[\frac{m_t^{d*}}{k(k-m_t^{d*})}n_t^{I*}+\frac{\phi_I'}{\phi_I''}\frac{m_t^{d*})}{k^2}\Big]+ \\
-\Big[\frac{n_t^{I*}}{k-m_t^{d*}}+\frac{\phi_I'}{\phi_I''}\frac{1}{k}-\frac{\phi_I'}{\phi_I''}\frac{k-m_t^{d*}}{k}\frac{1-\beta}{1-(1-\beta)m_t^{d*}}\Big]\frac{dm_t^{d*}}{dk}
\end{aligned}
\tag{3.43}
$$

where again $\phi'\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)$ is denoted by $\phi_I'$ and $\phi''\Big(\frac{k}{k-m_t^{d*}}n_t^{I*}\Big)$ by $\phi_I''$.

Using equation (3.43) into (3.41) I get:

$$
\frac{dg_t}{dk}=\underbrace{\frac{(\phi_I')^2}{\phi_I''}\frac{m_t^{d*}}{k(k-m_t^{d*})}(\gamma-1)}_{\text{Direct Effect } < 0}-\underbrace{\frac{(\phi_I')^2}{\phi_I''}(\gamma-1)\left[\frac{1}{k-m_t^{d*}}-\frac{1-\beta}{1-(1-\beta)m_t^{d*}}\right]}_{\text{Indirect Effect}}\frac{dm_t^{d*}}{d}
$$

which gives the key relation presented in Proposition 2. As to the sign of the indirect effect, notice that since $\phi_I''<0$ by assumption, then the term $-\frac{(\phi_I')^2}{\phi_I''}(\gamma-1)$ is positive. Therefore, the indirect effect is negative as long as:

$$\frac{1}{k - m_t^{d*}} - \frac{1-\beta}{1-(1-\beta)m_t^{d*}} < 0$$

which rearranged becomes:

$$(1-\beta)k - (1-\beta)m_t^{d*} > 1 - (1-\beta)m_t^{d*} \Leftrightarrow k > \frac{1}{1-\beta}$$

which concludes the proof.

# Appendix 3.D Additional Empirical Results

## 3.D.1 Scaled Disclosure Measures

Table 3.D.1: Correlation of scaled disclosures with TFP growth

| | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ |
|---|---|---|---|---|
| Scaled Disclosures$_{l,t}$ | -0.1024 | -0.0981 | -0.0970 | -0.0970 |
| | (0.1887) | (0.1583) | (0.1711) | (0.1720) |
| Country F.E. | Y | Y | Y | Y |
| Year F.E. | Y | Y | Y | Y |
| Sector F.E. | Y | Y | Y | Y |
| Controls | | Y | Y | Y |
| Country×Year F.E. | | | Y | Y |
| Country×Sector F.E. | | | | Y |
| Observations | 1386 | 1170 | 1170 | 1170 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Correlations of the scaled disclosure variable with growth rate of the mean and selected percentiles of the firm-level distribution of TFP, labor productivity and capital productivity. The regression specification is $g_{i,l,t} = c_0 + \beta * (ShDisclosures_{l,t})/10 + c_t + c_i + c_l + \epsilon_{i,l,t}$. Industry classification is based on firm's sector of activity. Coefficient shows the marginal effect of 10 more disclosures on percent growth rates of the dependent variable. All the coefficients shown refer to a linear regression with country-, industry- and year-fixed effects. Standard errors clustered at the industry-level are shown in parenthesis.

Table 3.D.2: Direct and indirect effects of complementarity on TFP growth

| | Scaled Discl$_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ |
|---|---|---|---|---|---|
| Scaled Disclosures$_{l,t}$ | | -0.5751** | -0.5351** | -0.5191** | -0.5202** |
| | | (0.2649) | (0.2501) | (0.2527) | (0.2528) |
| $AvgCit_{l,t}$ | 0.2694 | -0.0112 | -0.0231 | -0.0220 | -0.0228 |
| | (0.1831) | (0.2757) | (0.2800) | (0.2752) | (0.2876) |
| $WCit_{l,t-5}$ | 0.0021*** | | | | |
| | (0.0005) | | | | |
| $AvgWDCit_{l,t-5}$ | 4.6741 | | | | |
| | (3.6711) | | | | |
| Country F.E. | Y | Y | Y | Y | Y |
| Year F.E. | Y | Y | Y | Y | Y |
| Sector F.E. | Y | Y | Y | Y | Y |
| Controls | | | Y | Y | Y |
| Country×Year F.E. | | | | Y | Y |
| Country×Sector F.E. | | | | | Y |
| Observations | 1386 | 1386 | 1170 | 1170 | 1170 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Correlations of the scaled disclosure variable with growth rate of the mean and selected percentiles of the firm-level distribution of TFP, labor productivity and capital productivity. The regression specification is $g_{i,l,t} = c_0 + \beta * (ShDisclosures_{l,t})/10 + c_t + c_i + c_l + \epsilon_{i,l,t}$. Industry classification is based on firm's sector of activity. Coefficient shows the marginal effect of 10 more disclosures on percent growth rates of the dependent variable. All the coefficients shown refer to a linear regression with country-, industry- and year-fixed effects. Standard errors clustered at the industry-level are shown in parenthesis.

### 3.D.2 Labor productivity growth

This appendix subsection replicates the main analyses of Subsections 3.4.3.1 and 3.4.3.3 of the paper using as dependent variable labor productivity growth rather than TFP growth. The former is computed as the yearly growth of country-specific sectoral values added divided by number of workers.

Table 3.D.3: Correlation of scaled disclosures with labor productivity growth

| | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ |
|---|---|---|---|---|
| $\text{Disclosures}_{l,t}/10$ | -0.1345*** | -0.1017*** | -0.1019*** | -0.1019*** |
| | (0.0173) | (0.0156) | (0.0171) | (0.0172) |
| Country F.E. | Y | Y | Y | Y |
| Year F.E. | Y | Y | Y | Y |
| Sector F.E. | Y | Y | Y | Y |
| Controls | | Y | Y | Y |
| Country×Year F.E. | | | Y | Y |
| Country×Sector F.E. | | | | Y |
| Observations | 1498 | 1355 | 1355 | 1355 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Correlations of the scaled disclosure variable with growth rate of the mean and selected percentiles of the firm-level distribution of TFP, labor productivity and capital productivity. The regression specification is $g_{i,l,t} = c_0 + \beta * (ShDisclosures_{l,t})/10 + c_t + c_i + c_l + \epsilon_{i,l,t}$. Industry classification is based on firm's sector of activity. Coefficient shows the marginal effect of 10 more disclosures on percent growth rates of the dependent variable. All the coefficients shown refer to a linear regression with country-, industry- and year-fixed effects. Standard errors clustered at the industry-level are shown in parenthesis.

Table 3.D.4: Direct and indirect effects of complementarity on labor productivity growth

| | $\text{Discl}_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ | $g_{i,l,t}$ |
|---|---|---|---|---|---|
| $\text{Disclosures}_{l,t}/10$ | | -0.1237*** | -0.1137*** | -0.1159*** | -0.1158** |
| | | (0.0279) | (0.0294) | (0.0295) | (0.0295) |
| $AvgCit_{l,t}$ | -0.2133 | -0.2833 | -0.2437 | -0.2420 | -0.2421 |
| | (0.3891) | (0.2156) | (0.2471) | (0.2472) | (0.2470) |
| $WCit_{l,t-5}$ | 0.0301*** | | | | |
| | (0.0024) | | | | |
| $AvgWDCit_{l,t-5}$ | 31.2911** | | | | |
| | (11.3491) | | | | |
| Country F.E. | Y | Y | Y | Y | Y |
| Year F.E. | Y | Y | Y | Y | Y |
| Sector F.E. | Y | Y | Y | Y | Y |
| Controls | | | Y | Y | Y |
| Country×Year F.E. | | | | Y | Y |
| Country×Sector F.E. | | | | | Y |
| Observations | 1386 | 1386 | 1355 | 1355 | 1355 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Correlations of the scaled disclosure variable with growth rate of the mean and selected percentiles of the firm-level distribution of TFP, labor productivity and capital productivity. The regression specification is $g_{i,l,t} = c_0 + \beta * (ShDisclosures_{l,t})/10 + c_t + c_i + c_l + \epsilon_{i,l,t}$. Industry classification is based on firm's sector of activity. Coefficient shows the marginal effect of 10 more disclosures on percent growth rates of the dependent variable. All the coefficients shown refer to a linear regression with country-, industry- and year-fixed effects. Standard errors clustered at the industry-level are shown in parenthesis.

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