Essays on Corporate Influence in Politics

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For my parents Gabriela and Jürgen,
and my brother Tom

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 work 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 warrant that this authorization does not, to the best of my belief, infringe the rights of any third party. I declare that my thesis consists of 43,478 words.

Statement of Conjoint Work

I confirm that Chapter 5 was jointly co-authored with Oleksandr Shepotylo (Aston Business School), and I contributed 50% of this work.

Statement of Use of Third Party for Editorial Help

I confirm that my thesis was proof-read for spelling and grammar by Florencia Pezzimenti.

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Abstract

Corporations are among the most important political and economic actors today, but the lack of firm-level data has thus far prevented researchers from answering long-standing questions on corporations in politics. I draw on new data to examine the micro-foundations of important political economy theories, to shed light on individual preference formation and the role of institutions and policy uncertainty for firm's international trade. The three papers which make up this dissertation answer the following three research questions:

1. Do political preferences of employees align with those of their employers?
2. Under what conditions do political preferences of employees align with those of their employers?
3. How does policy uncertainty affect firm-level trade?

In the first paper, I link big data on employee donations to their employer's Political Action Committee (PAC) donations using natural language processing to automatically identify individual employers and occupations. I show that employee and company contributions are highly correlated, and that firm- and occupation-level factors are significantly associated with firm-employee alignment. Contrary to existing datasets, this data can be easily linked to external data on industries, firms, and occupations. In the second paper, I investigate whether sectors, firms, or occupational asset specificity matter more for employee's political preferences. I find that firm and sectoral specificity are associated with higher firm-employee partisan alignment and that individuals donate more to firm-supported candidates, but no impact of occupations. The results have implications for research on coalition formation and preference formation. Work on uncertainty, institutions, and international trade overlooks the distributional consequences of uncertainty within sectors. In the last paper, I use Ukrainian firm-level data between 2003 and 2014 to show that a reduction in TPU has a positive and sizable effect on firms' imports of intermediate and capital goods. Our results have implications for the study of trade and uncertainty.

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Chapter 1

Introduction

Firms are among the most important political and economic actors today. Large corporations capture more and more economic activity. Since 1997, market concentration has increased in 3 out of 4 US industries (Grullon, Larkin and Michaely, 2018) and as a consequence, firms exert increasing market power. Since the 1980s, average markups increased from 21 to over 60 percent, a trend driven by few top firms reaping larger profits (De Loecker, Eckhout and Unger, 2018).[1] Similarly, the top 1 percent of 'superstar' firms alone account for over 80 percent of all US international trade (Bernard et al., 2018, p.34). At the same time, firms are pivotal players in politics. In the 2018 US electoral cycle, corporation donated over 194 million USD to federal candidates, more than double as much as trade associations, and more than three times as much as labor unions. And in 2017, public companies spent 1.48 billion USD on lobbying in Washington D.C., easily doubling the amounts spent on lobbying by industry-wide associations like the American Chamber of Commerce.

[1]The increases in market power mostly driven by the top percentile of firms reaping higher profits (as opposed to incorporating higher costs), and stems from within-industry rather than from between industry changes (De Loecker, Eckhout and Unger, 2018)[pp.1-5]. Those stylized facts are not unique to the US, with changes in similar magnitude apparent in Europe, Asia, and Oceania (De Loecker and Eckhout, 2018).

These empirical trends stand in stark contrast a large share of International (IPE) and Comparative Political Economy (CPE) research: while even recent work on preference formation relies on sector- and factor-based models (Kitschelt and Rehm, 2014; Owen and Johnston, 2017; Walter, 2017), research on the role of international institutions for trade and uncertainty uses crude aggregate trade flows at the country-level or broad sectoral level (Hollyer and Rosendorff, 2012; Kucik, 2012; Mansfield and Reinhardt, 2008*a*). Moreover, while existing work routinely highlights the importance of firms in theory, authors are quick to ignore them in their empirical analyses. The lack of firm-level empirical work is even more surprising given that new theories highlight the importance of distributional consequences of globalization within industries (Helpman, Melitz and Yeaple, 2004*a*; Melitz, 2003*b*). Thus, while firms are of increasing importance empirically and theoretically, "[...] their economic and political activities have not been fully incorporated into the field of international political economy" (Kim and Osgood, 2019, p.17).

In this dissertation, I pay close attention to the role of firms in International and Comparative Political Economy, providing answers to the guiding question: *how do firms influence politics and how do firms react to political change?* Overall, the papers of this dissertation provide answers to the following three research questions:

1. Do political preferences of employees align with those of their employers?
2. Under what conditions do political preferences of employees align with those of their employers?
3. How does policy uncertainty affect firm-level trade?

Understanding how corporations influence politics and respond to political change requires "more granular theory, data collection, and empirical methods" (Kim and Osgood, 2019, p.17). However, collecting firm-level data is inherently difficult. One the one hand, government-provided firm-level datasets require strict anonymity of individual firms, often making matching firms to political variables of interest impossible. Openly available data, on the other hand, is often un-structured, very large, and lacks unique identifiers for key levels of observation. Therefore, a large share of this dissertation is dedicated to the generation of original micro-level data. In the first two papers, I draw on big data of individual and corporate political donations to investigate how the workplace affects individual political preferences. Political Economy research shows that jobs and professions are crucial for the formation of political preferences, yet workplace or occupation are virtually absent from American Politics work on individual political donations. Therefore, in the first paper of this dissertation, *Political Alignment between Firms and Employees: Evidence from a New Dataset*, I construct a novel measure of partisan alignment between firms and employees. I link big data on employee donations to their employer's Political Action Committee (PAC) donations and construct a measure of partisan alignment between firms and employees. I accomplish this by using natural language processing to automatically identify individual employers and occupations. I show that employee and company contributions are highly correlated and that firm- and occupation-level factors are significantly associated with firm-employee alignment. Contrary to existing datasets, this data can be easily linked to external data on industries, firms, and occupations. Thus, the data enables scholars to better study the connections between corporate and employee donations and the impact of political change and economic shocks on individual contributions.

In the second paper *Political Alignment between Firms and Employees: The Role of Asset Specificity*, I use this newly created data linking firm and employee donations to answer the research question: when do political preferences of employees align with those of their employers? Comparative and International Political Economy scholars debate whether sectors, firms, or occupations matter more for preference formation, highlighting the importance of asset specificity. While some empirical work confirms the impact of sectoral and firm specificity, other research highlights occupational skill specificity. I investigate the impact of specificity on alignment using new data linking 1,691,790 campaign contributions by 85,109 employees to 874 corporate Political Action Committees between 2003 and 2016. I find that firm and sectoral specificity is associated with higher partisan alignment between firms and employees, but no evidence for the impact of occupational skill specificity. I also find that employees donate more to firm-supported candidates, which is driven by candidates likely to yield political returns like incumbents as well as House and Senate candidates. The results have implications for research on coalition formation, individual preference formation, and highlight that there might be important differences between the underlying motivations of political actions and stated preferences.

In the last paper, *Policy Uncertainty and Trade in Intermediate and Capital Goods*, co-authored with Oleksandr Shepotylo, I ask the question: how does policy uncertainty affect firm's decision to source intermediate goods? Despite the central role of uncertainty in political economy theories of trade cooperation, few studies have measured the impact of uncertainty between alternative trade policies on firm's expectations. Similarly, existing work focuses on the impact of uncertainty on firm's arm's length exports, notwithstanding the importance of global value chains. In this paper, we employ a new measure of trade policy uncertainty (TPU) by applying structural topic models to business-related news, and extend a heterogeneous firm model with policy uncertainty by introducing the decision to import intermediate inputs. Then, we empirically investigate the link between TPU and trade in intermediate goods using Ukrainian firm-level data between 2003 and 2014. We find that a reduction in TPU has a positive and sizable effect on firms' imports of intermediate and capital goods. Our results have important implications for the study of uncertainty in international trade.

The main contributions of my dissertation to the field of IPE are threefold. First, I generate novel micro-level data to shed light on the role of firms in politics. In the first paper, I produce a new dataset linking big data on firm and employee political donations in the US. This data uniquely allows for the comparison of firm *and* employee political preferences in terms of their political actions, rather than stated preferences. Moreover, contrary to existing datasets, this data contains widely-used identifiers for the firm, sector, and occupation. Thus, it enables researchers to merge the data with firm-, sector-, and occupation-level covariates of interest, and better investigate the impact of policy reforms and economic shocks on individual political behavior. Second, all papers in this dissertation use firm-level data to take a closer look at the micro-foundations underpinning established theories in IPE and CPE. In the second paper, I tackle a long-standing question about the role of asset specificity for political alignment between firms and employees, comparing the impact of specificity at the firm-, sector-, and occupational level. I find that *where people work seems to matter more for alignment than what they do*, providing an important contribution to the ongoing debate on the economic sources of political preferences. In the last paper, I investigate the micro-foundations underlying research on the role of institutions, trade, and uncertainty using detailed firm-product-destination-level trade data. Existing work assumes that signing international agreements reduces firm's uncertainty about future economic policies, and thus, boosts aggregate trade. I show that firms adjust their expectations dynamically during the negotiation phase of an agreement, and that a reduction in uncertainty affects firms unequally depending on the goods they trade as well as the design of the policy alternatives . Finally, this dissertation makes use of innovative quantitative methods to measure key concepts of interest for IPE and Political Economy more broadly. The first two papers make use of natural language processing tools to match individual donors to their firms and generate a measure of firm-employee political alignment. The last paper leverages structural topic models to measure the uncertainty between alternative trade policy options. The uncertainty measure varies intuitively along real-world political developments, and similar measures might be applied in other cases where firms face multiple, mutually exclusive policy options. Future work can also use the measure of alignment developed here to investigate important questions on the impact of alignment on corporate political activity and coalition formation.

In the next chapter, I provide a broader overview of the two main lines of research that this dissertation speaks to. I discuss the main assumptions of existing work, how these are challenged by the growing importance of the firm, and how exactly each of the papers addresses these challenges by zooming in on the corporation. The chapters three, four, and five present the papers, which constitute the main body of this dissertation. The last chapter discusses implications of the main findings, and provides a broad outlook for the future study of firms in politics.

Chapter 2

The Importance of Firms in Political Economy

Two of the most important lines of research in international political economy of trade are the work on preference formation and lobbying, and the research on the role of international institutions for trade cooperation (Martin, 2015; Milner, 1999). While both are at their core about the political and economic activity of firms, their analyses have traditionally concentrated on industries or the aggregate country-level. Notwithstanding their contributions, this abstraction from the firm goes contrary to new theories and empirical evidence in both Political Economy and International Economics which highlights the vast differences in economic and political activity *within industries*. In the following sections, I will review the sector- and country-centered literature on both research strands. Then, I will discuss how focusing on more aggregate levels of analyses might mask substantial heterogeneity at the firm level, leading researchers to draw partially misleading conclusions. Finally, I explain in detail how this dissertation fills the gaps in the literature by explicitly incorporating the firm in theorizing, and leveraging new micro-level data.

2.1 Preference Formation and Cleavages

What are the fundamental economic sources of political preferences leading to cleavages between societal actors? Based on economic self-interest of individuals, many political economy scholars argue the workplace exerts strong influence on political preferences for individuals, as the prime source of individual's livelihood.[1] Based on canonical trade theory, individual's sector of employment has been central to this line of research. Established models predict that political cleavages fall either along industry lines (Frieden, 1991) or along factors of production (Rogowski, 1989), leading to narrow sector-based or broad class-based cleavages, respectively. Whether sectoral or factor-based coalitions form depends on the degree of mobility of factors of production or specificity of assets (Alt et al., 1999, 1996; Alt and Gilligan, 1994; Hiscox, 2002*b*).

Since then, scholars of IPE have made vast progress in providing empirical evidence supporting these early theories. Mayda and Rodrik (2005) and Ardanaz, Murillo and Pinto (2013) show that individual trade preferences are in line with their sectoral exposure to trade. Similarly, Margalit (2011) finds that citizen's vote choices are responsive to sectoral trade-related layoffs. In addition, a plethora of studies also argues and tests that lobbying for free trade and protection depends on the degree of import competition

[1] There are also many studies which cast doubt on the idea that where people work or what they do determines preferences (Guisinger, 2009; Rho and Tomz, 2017) or that cultural factors matter more for preference formation (Bechtel, Hainmueller and Margalit, 2014; Mansfield and Mutz, 2009; Margalit, 2012). In this dissertation, I assume individuals and firms to be rational, self-interest maximizing actors.

of an industry, and hence, mostly plays out along sectoral lines (Gawande and Bandyopadhyay, 2000; Goldberg and Maggi, 1999; Grossman and Helpman, 1994; Irwin and Kroszner, 1999; Schattschneider, 1935; Trefler, 1993). While others, building on factor-based theories and new advances in labor economics (Autor, Levy and Murnane, 2003; Blinder, 2009; Blinder and Krueger, 2013) have been drawing attention to individual traits such as their skills (Hainmueller and Hiscox, 2006; Iversen and Soskice, 2001; Scheve and Slaughter, 2001) and occupational characteristics (Kitschelt and Rehm, 2014; Owen and Johnston, 2017; Walter, 2017), most studies still *implicitly or explicitly equate the sector of employment with the workplace*. Thus, apart from some occupational characteristics, sectors are still treated as uniform.[2] This goes contrary to the rhetoric in these studies: scholars routinely highlight the importance of firm-level differences within sectors, as in Walter (2017, pp. 3-5) or Owen and Johnston (2017, pp.668-670), but then resort to aggregate supposed firm differences at the sectoral level. Similarly, Margalit's landmark study on the impact of trade-related layoffs on US Presidential vote share (Margalit, 2011) draws on firm-level data but then aggregates at the county-level, and Margalit (2012) ignores firms or sectors altogether. In the same vein, the Varieties of Capitalism literature rightly distinguishes analytically between differences in sectoral or firm-level skill formation depending whether countries are classified as liberal or coordinated market economies (Hall and Soskice, 2001*a*), but then aggregates specificity of skills at the broad occupation (Iversen and Soskice, 2001) or country level (Iversen and Stephens, 2008).[3]

[2]For a good review of the individual-level literature on preferences for economic openness see Kuo and Naoi (2015).

[3]More recently, the idea that political preferences can be driven by sectoral exposure to globalization has gained renewed interest, as new studies which make use of fine-grained geographic data on industrial composition document large changes in party preferences and vote shares in Western democracies due to import competition from China or Eastern Europe (Autor, Dorn and Hanson, 2016*a*; Calantone and Stanig, 2018; Che et al., 2016;

Rodrik (1995, p.1459) summarized well over 20 years ago that a model of individual preferences need to contain a description of where individuals derive their preferences from, and how these individual preferences are aggregated and channeled into politics. The sectoral view of preference formation and cleavages has some theoretical and empirical shortcomings with respect to both parts.

First, with respect to preference aggregation, it is at odds with the more recent economics literature on heterogeneous firms which finds that firm productivity is unequally distributed within narrow economic sectors, with only a few firms exporting, importing, or investing abroad (Bernard et al., 2007, 2012). Driven by the inability of standard trade models to explain the large amount of intra-industry trade between developed countries, firm-level research finds that only a small minority of US firms actually exports (Bernard et al., 2007), and only 1 percent of US exporters is responsible for 81 percent of exports. Similar patterns of concentration of international activity among few firms are visible across a whole range of European (Mayer and Ottaviano, 2008) and non-Western countries (Freund and Pierola, 2015). These differences across firms translate into within-industry distributional consequences of trade openness (Melitz, 2003*b*). Thus, it seems unrealistic to assume that all firms in the same sector share the same preferences or are all equally easy to mobilize politically.[4]

Dippel, Gold and Heblich, 2015). The aggregation at the sector-level is less consequential in the work relying on geographic data, as there is only limited variation across firms within narrow and clearly-defined geographic units (i.e., there will not be many firms in the same industry, and many industries without any firms).

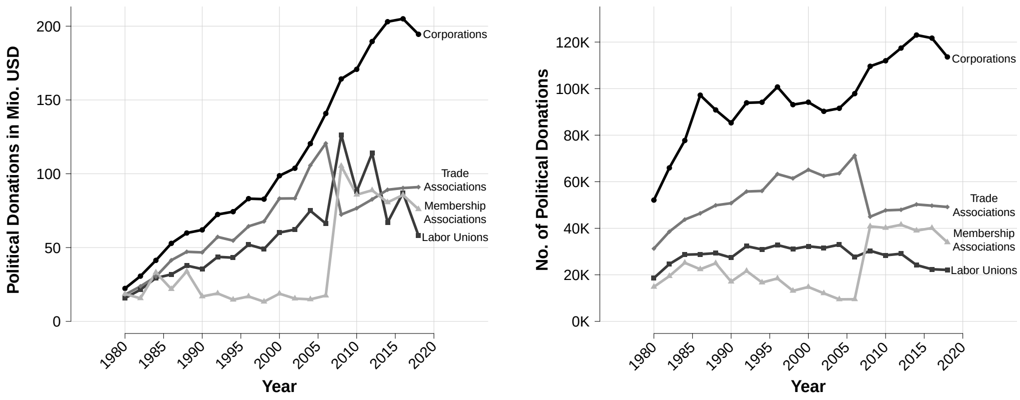
[4]This seems particularly obvious in most of the work building on the familiar Grossman-Helpman model on protection for sale as in Goldberg and Maggi (1999), Gawande and Bandyopadhyay (2000), or Gawande, Krishna and Robbins (2006). Often, an entire sectors is assumed to be 'mobilized' on trade policy if any firm or sectoral association is politically active, as measured by the presence of a Political Action Committee (PAC).

In addition, recent IPE work shows that intra-industry variation in political activity is driving support for free trade in the US (Kim, 2017) and that narrow industrial sectors are internally divided over trade (Osgood, 2017*a*). These findings are in line with stylized facts about lobbying and campaign finance which shows that firms are the most important political actors. In Figure 2.1 below, I show the growth of political donations in the US over time by types of donating groups between 1980 and 2018. The picture is striking: even though corporations always donate more than business associations, membership organizations, or labor unions, they have clearly outspent all of these other groups since 2003, as shown in Panel 2.1a. In 2018, firms spent 194.5 million USD in political donations, 3.3 times as much as labor unions, 2.6 times as much as membership associations, and 2.1 as much as trade associations. In terms of the number of donations, Panel 2.1b paints a similar picture: with 113.6K single donations, firm PACs comprise more donations than labor unions, membership associations, and trade associations together (105.2K). Thus, firms are the most important provider of campaign finance to federal political candidates in the US, as organized entities. Yet firms have received far less attention than labor unions, for instance, proportional to their amount of campaign donations (Ahlquist, Clayton and Levi, 2014; Feigenbaum, Hertel-Fernandez and Williamson, 2018; Kim and Margalit, 2017).[5]

Similarly, firms are among the most important actors lobbying politicians. In Figure 2.2, I show lobbying activity in the US and the European Union by different types of organizations.[6] US lobbying is depicted in Panel 2.2a

[5]Of course, PACs are not the only source of campaign finance in the US. Individual donations are another key source of funding for political candidates (Gimpel, Lee and Pearson-merkowitz, 2008; La Raya and Schaffner, 2015). For example, while all PAC types in Figure 2.1 donated around 467 million USD to federal candidates in 2016, individual donors spend a whopping 1.8 billion USD.

[6]While "Other" groups also spend as much as companies, this comprises a variety of different organizations, including issue groups, universities, *and* private companies. Public



(a) Dollars Spent **(b) Number of Donations**

Figure 2.1 Importance of Firm-level Political Donations in the US. This figure shows how US federal political donations by corporate Political Action Committees have been increasing from 1980 to 2018, and constitute the largest share of PAC donations today. Corporations donate more dollars (Panel 2.1a) and donate more frequently (Panel 2.1b) than trade associations, membership associations, and labor unions. Data: LobbyView.

showing that publicly traded firms spent more than double on lobbying than sector-based trade associations in 2017, with about 1.5 billion USD versus 0.65 billion USD, respectively. Moreover, this difference between firm and association lobbying has gotten larger over time. However, this pattern could also be particular to the US, given the outsized role of campaign finance and lobbying in the US context (Ansolabehere, de Figueiredo and Snyder, 2003; de Figueiredo and Richter, 2014). Therefore, in Panel 2.2b, I also display data on direct lobbying by different organization types in the European Union (EU), specifically, organized meetings with officials from the European Commission. While annual lobbying expenditure data is not available in the EU context, corporations clearly meet more frequently with the European Commission than trade associations. In 2018, corporations met 1669 times with the Commission, compared to 1207 trade association

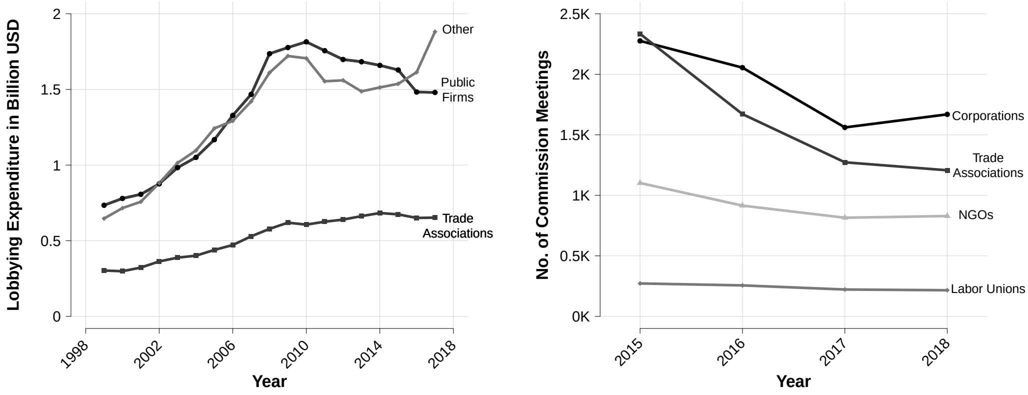
Firms are all firms from the Compustat database which lobby between 1999 and 2017. Trade associations are identified using all groups with a NAICS code 813910 (business associations) and other groups whose legal names include the character matches for "associations" or "ASSN.", as in (Huneeus and Kim, 2018).

meetings. This indicates more access for firms than for sectoral groups. Firms also meet more often with the Commission than labor unions or non-governmental organizations combined (1045 meetings in 2018). Thus, firms seem to lobby and donate more alone than via their industry associations, which casts doubt on the idea that political cleavages form along sectoral lines in favor of a view of *cleavages between firms within industries*.[7] These patterns are fully in line with new empirical evidence on corporate political activity. Kim (2017) shows that trade flows and variation in tariffs are at odds with both sectoral and factor-based views, and that highly productive firms producing differentiated products lobby more on specific trade bills. Similarly, Bombardini (2008) finds that sectors with more firm heterogeneity receive higher protection. Moreover, contrary to common perceptions of firms facing collective action problems, Huneeus and Kim (2018) provide some evidence on the targeted nature of lobbying in the US, showing that most bills introduced in a given Congress are only lobbied by one or two firms.

Second, the large differences in productivity and wages within industries (Helpman, Itskhoki and Redding, 2010) are likely to translate into differences in individual preferences based on their firm of employment, which is not reflected by the current literature on preference formation.[8] This omission is problematic because it assumes that within-sector heterogeneity of firms does not matter for political preferences. Indeed somebody's firm can shape preferences in a variety of ways. Workplaces can serve as an important social network where employees discuss politics, which can encourage

[7]While not part of this dissertation, an important question then is under which conditions corporations lobby alone or via umbrella organizations (Bombardini and Trebbi, 2012; Osgood, 2017*a*).

[8]The few exceptions are the work by Na-Kyung Lee and Liou (2019) which leverages a cross-sectional survey from Japan to test the impact of firm productivity on individual trade policy preferences, and the work by Hertel-Fernandez (2018) on employees as lobbyists.



(a) US Lobbying **(b) EU Lobbying**

Figure 2.2 Importance of Firm-level Lobbying in US and European Union. This figure shows that firms are very important entities lobbying the US federal government and the European Commission. Panel 2.2a shows that publicly traded firms spend more on lobbying than industry associations. The category "Other" comprises other groups, including private companies, issue groups, and universities. Panel 2.2b shows that corporations meet more frequently with the European Commission than other types of organizations, including business associations. Data: LobbyView and IntegrityWatch.

preference formation and political activity (Abrams, Iversen and Soskice, 2011; Mutz and Mondak, 2007). Labor unions also use the workplace to contact and mobilize employees to become union members or inform them about union stances on particular issues (Kim and Margalit, 2017). Finally, recent work by Hertel-Fernandez highlights that employers are increasingly mobilizing their own employees by distributing and monitoring dissemination of political information, mobilizing them to attend a political rallies, or to encourage turning out to vote. Given that for most individuals the workplace is the main source of their livelihood, employees seem to be more susceptible to employer mobilization if they feel at risk of losing their job (Hertel-Fernandez, 2018). In the United States, parallel trends towards union-weakening right-to-work legislation (Feigenbaum, Hertel-Fernandez and Williamson, 2018; Marx and Fleming, 2012; Starr, Prescott and Bishara, 2019), the fall of the labor share and the rise of market concentration(Autor et al., 2017), and simultaneous labor market monopsomy (Azar, Marinescu and Steinbaum, 2017) might increase dependence of individuals on their employer, even in the absence of the direct employer mobilization. Thus, it seems very unlikely that individuals in the same sector (given some occupational differences) will share the same preferences.[9] However, in order to micro-found firm level theories and take into account the stylized facts presented above, we need to actually measure the preferences of individual employees within firms, not within sectors.

To sum up, the work on cleavages and preference formation which puts the emphasis on industry sectors, overlooks the growing importance of corporations in politics. The theoretical and empirical differences between firms in the same sectors are likely to translate into firm-based patterns of preference formation, which require new micro-level data.

Therefore, in the first paper of this dissertation, *Political Alignment between Firms and Employees: Evidence from a new Dataset*, I construct a novel dataset linking big data on firm and employee political donations. I match 1,691,790 US federal campaign contribution filings of 85,109 individuals to the donations of 874 Political Action Committees (PACs) of publicly listed companies. The paper contributes to the extant literature on preference formation and cleavages in two ways. First, I actually measure the political preferences of individuals within firms, providing data to test the micro-foundations of the firm-level literature. The US as particularly interesting case where the prevalence of campaign donations allows for the measurement and comparison of firm and employee preferences. I show that employee and company contributions are highly correlated, and that firm- and occupation-level factors are significantly associated with

[9] In fact, there are likely significant differences between employees within the same firm. This is were occupational characteristics like task routineness, offshorability, and skills are useful complements to a firm-based approach (Hainmueller and Hiscox, 2006; Kitschelt and Rehm, 2014; Owen and Johnston, 2017; Walter, 2017).

firm-employee alignment. While this is expected from the perspective of firm-level political economy approaches, this is less than clear for American Politics work on campaign finance (Ansolabehere, de Figueiredo and Snyder, 2003; Tripathi, Ansolabehere and Snyder, 2002). Another big advantage of this data compared to existing datasets like the Database on Ideology, Money in Politics, and Elections (Bonica, 2016*b*), is that it contains widely-used identifiers for the firm, sector, and occupation. Thus, the data enables scholars to better study the connections between corporate and employee donations. Moreover, it allows future researchers in International Political Economy to match firm-, sector-, and occupational covariates of interest to the data, and better investigate the impact of policies and economic shocks on individual political behavior.

In the second paper *Political Alignment between Firms and Employees: The Role of Asset Specificity*, I use this newly created data to investigate when political preferences of employees align with those of their employers. I take up the long-standing literature on asset specificity of the firm, sector, and occupation, and derive clear predictions about when we should expect preferences of employees to align with their company. I find that firm and sectoral specificity is associated with higher partisan alignment between firms and employees, but no no evidence for the impact of skill specificity. In addition, I show that even within narrow sectors, there is huge variation in partisan alignment, which lends support to the firm-based view of political cleavages, and some to sector-based theories. While broad partisan alignment provides some evidence for firm-level theories, I also investigate a more direct link between individual and firm donations to specific candidates, and find that employees tend to donate more to the same candidates that their company PAC supports. The latter finding is not driven by sectoral or occupational differences, and provides suggestive evidence for patterns of workplace mobilization document in the American Politics context (Hertel-Fernandez, 2018; Li, 2018).

2.2 Institutions, Trade, and Policy Uncertainty

Another key research area in IPE concerns the role of international institutions for cross-national commerce and investment. In particular, this literature has highlighted the importance of the design of international agreements (Koremenos, Lipson and Snidal, 2001), such as the GATT/WTO, for reducing uncertainty about future economic policies of states. In principle, compliance with international agreements is costly because states might not be able to uphold their commitments in the case of domestic political pressure or an unexpected economic shock. These institutions contain flexible provisions which allow states to temporarily suspend their commitments to these agreements, and thus, reduce the uncertainty about future costs of compliance and the resulting time-inconsistency problem (Rosendorff and Milner, 2001). The conclusion from this line of research is that flexible provisions in international trade agreements, such escape clauses, rules on anti-dumping and countervailing duties, or limitations to the duration of these agreements (Koremenos, 2005), while suspending trade liberalization temporarily, promote international trade and cooperation. Empirical evidence shows that countries which already have flexible mechanisms such as anti-dumping in place are more likely to join the GATT/WTO and commit to lower applied tariffs and tariff bindings, with overall efficiency gains for private actors in the economy (Reinhardt and Kucik, 2008). Moreover, these institutions have been theorized to lock in current trade policies and therefore, reduce firm's uncertainty about future economic policy (Baccini and Urpelainen, 2015) or the unilateral removal of preferential market access (Manger and Shadlen, 2014), leading to lower volatility in exports and higher aggregate efficiency of trading firms (Mansfield and Reinhardt, 2008*b*). Some authors have also argued that Preferential Trade Agreements (PTAs) limit the policy discretion of political leaders and hence, increase in aggregate efficiency which helps political leaders to stay in power longer (Hollyer and Rosendorff, 2012).

This line of research implicitly or explicitly makes an argument about the uncertainty reducing impact of institutions on private actors, i.e. firms. Hence, the lion share of this work makes at least two assumptions about firm behavior. First, firms actually do adjust their expectations and react to swings in uncertainty before expectations are 'locked in' by the signing of an agreement. Mansfield and Reinhardt (2008*b*, p.648) close their study on trade volatility and institutions by conceding that this is an assumption that is not micro-founded. In fact their last sentence is that it "would be useful to analyze this micro-causal mechanism more directly in a study cast at the level of individual firms' responses to trade agreement formation", which Mansfield and Reinhardt leave for future research. Evidence for these micro-foundations would have to show that individual firms actually adjust their trading behavior in the face of varying trade policies.

Second, the literature assumes that firms will react positively to a reduction of uncertainty, on average, assuming away within-country or sector heterogeneity in the distributional consequences. In fact, Hollyer and Rosendorff (2012, p.750) note that "regardless of the distributional consequences of PTA formation, any given PTA will serve to reduce policy uncertainty, and this will have political effects". They go on and write that a "reduction in trade-policy uncertainty increases the volume of trade and generates gains to voters through the expansion of tradable sectors and the increase in demand for abundant factors". This welfare generation for voters then creates incentives for democratic leaders to sign trade agreements if they face less domestic opposition from veto players (Mansfield and Milner, 2012). However, if incentives for leaders work through the gains to voters, then the distributional consequences of trade cannot be ignored. This is because politicians care about the geography of their constituencies (Rodden, 2010) and distributional consequences of trade across constituencies will vary widely across geographies (Autor, Dorn and Hanson, 2016*b*). The distributional consequences, in turn, will depend on the trading partner and the design of the agreement, including the distribution of tariff reduction and non-tariff barriers (Dür, Baccini and Elsig, 2014; Horn, Mavroidis and Sapir, 2010; Kim et al., 2019). Moreover, the distributional consequences will differ across firms depending on their productivity levels (Melitz, 2003*b*) and how differentiated the goods they produce are (Kim, 2017; Osgood, 2016). It will also depend on whether firms trade at arm's length or with affiliates, in the case of multi-national corporations (Helpman, Melitz and Yeaple, 2004*a*; Manger, 2009), or whether they are import-dependent firms, relying on intermediate inputs from suppliers abroad (Amiti and Konings, 2007; Halpern, Koren and Szeidl, 2015; Johnson and Noguera, 2012).

In sum, the extant literature fails to test the micro-level foundations of their theories or to measure uncertainty before agreements are signed. In addition, existing work makes assumptions about the impact of uncertainty which might well depend on trading parter, degree of liberalization, and the firms themselves. However, as pointed out by Kim, Liao and Imai (2019, p.1), the studies above and related studies rely on aggregate trade flows or flows of a few specific goods between countries (Carnegie, 2014; Mansfield, Milner and Rosendorff, 2000; Rose et al., 2007). However, by aggregating trade at the country-level they ignore this heterogeneity, across firms, trading partners, and product types.

In the last paper of my dissertation, *Policy Uncertainty and Firm-level Trade in Intermediate and Capital Goods*, I attempt to tackle many of these shortcomings in the work on institutions, trade, and uncertainty. In the paper, I look at how policy uncertainty affects firm's decision to source intermediate goods when importers face uncertainty between mutually exclusive policies. The paper contributes to the existing literature in three ways. First, we provide a new measure of trade policy uncertainty between different policy alternatives based on quantitative text analyses of business news. Thus, we actually measure the uncertainty about future economic policy assumed by existing studies. Interacted with the tariff schedules of the respective policy alternatives, the measure provides clear implications for importers and exporters depending on the products they trade, contrary to aggregate trade flows (Mansfield and Reinhardt, 2008*b*; Reinhardt and Kucik, 2008) or broad industry sectors (Carnegie, 2014). Second, we highlight the importance of taking into account the type of products firms trade, particularly intermediate inputs. In our theoretical model, we recognize that intermediate goods are often key for technological upgrading of firms, and thus, require ex ante sunk investment on behalf of the company, similar to the decisions to export (Melitz, 2003*b*) or to serve foreign markets via horizontal foreign direct investment (Helpman, Melitz and Yeaple, 2004*a*). Moreover, recent political economy work stresses that the growth of trade in intermediates has been pivotal in driving firm support for recent trade agreements (Manger, 2009, 2012; Osgood, 2018), that firms actively lobby for the suspension of tariffs on specific intermediate goods (Ludema, Mayda and Mishra, 2018), and that tariffs on intermediate goods have been liberalized much faster via PTAs than final goods (Baccini, Dür and Elsig, 2018). Finally, we demonstrate empirically the distributional consequences of uncertainty between different policy alternatives for firms-level trade *before* an agreement is signed. In line with our model, the effects of uncertainty differ sharply according to the trading partner and degree fo liberalization, and are more pronounced for trade in intermediate and capital goods relative to consumer goods.

2.3 Summary of Contributions

To sum up, a large share of the existing literature on the preference formation and societal cleavages, and the impact of institutions on international trade, overlooks or assumes away the role of firm heterogeneity. I argue that this heterogeneity *within sectors* highlights two major problems inherent in the industry-based approaches.

First, the focus on the sector in the literature on individual preferences and trade policy lobbying is at odds with new theories and new empirical evidence on the importance of firms for lobbying and employee preferences. Sector-based approaches assume homogeneity of individual political preferences within sectors, but within-industry differences are most likely to translate into large variation of preferences, both across and within firms. This is likely exacerbated by declining bargaining power of employees vis-a-vis increasingly powerful corporate employers, and underlined by recent evidence on the workplace as a place of political mobilization. Second, the work on policy uncertainty and international institutions does not provide micro-level evidence underpinning the main assumption that institutions reduce uncertainty of firms about future economic policy. Moreover, reductions in uncertainty do not affect all firms equally: corporations will adjust their expectations according to the types of goods they trade and the trade-offs between policy alternatives they face.

In this dissertation, I take up these challenges to sector-based approaches to international and comparative political economy. The following chapters draw on firm-based theories and provide new firm- and individual-level evidence stressing the importance of the firm: both as political and as economic actors.

Chapter 3

Political Alignment between Firms and Employees: Evidence from a New Dataset

3.1 Introduction

In the field of Political Economy, an individual's workplace is viewed as one of the most fundamental determinants of a wide range of individual political preferences on diverse topics such as free trade (Margalit, 2011; Mayda and Rodrik, 2005; Scheve and Slaughter, 2001), redistribution, labor market risk (Iversen and Soskice, 2001; Kitschelt and Rehm, 2014; Walter, 2017), or foreign investment and offshoring of production (Margalit, 2012; Scheve and Slaughter, 2004). After all, where people work and what they do is the main source of their livelihood. However, data on the workplace is virtually absent from current research on individual campaign contributions, despite long-standing debates on whether donations by Political Action Committees (PACs) or individual donors are quid pro quo investments in expectation of political favors or merely consumption (Ansolabehere, de Figueiredo and Snyder, 2003; Bonica, 2014; Gordon, Hafer and Landa, 2007; Snyder, 1990).[1] If individuals are donating based on what is good for their employer, we would expect their donations to be strongly aligned with their company's political preferences. However, observing both individual and employer preferences at the same time is very difficult in practice.

In this paper, I create a measure of *political alignment between firms and their employees* based on novel data matching 1,691,790 federal campaign contribution filings of 85,109 individuals to the donations of 874 PACs of publicly listed US companies between 2003 and 2016.[2]. I use natural language processing to link individual donors to their company's PAC, and leverage donation shares to Democratic and Republican candidates to measure partisan alignment between firms and their employees. I then show that PAC- and employee donations are significantly correlated with each other. Moreover, I demonstrate that firm-level and occupational characteristics impact firm-employee alignment in predictable ways which are in line with expectations from political economy theories. Contrary to existing datasets, these novel data can be easily linked to external datasets on industry-, firm-, and occupational characteristics, enabling scholars to better study the connections between corporate and employee donations, or the impact of political change and economic shocks on individual contributions.

Whether individuals align with their employers has important implications for the political mobilization of firms, the formation of policy coalitions, and representation. Firms that are more aligned internally might be more

[1]The few exceptions looking explicitly at the workplace of individual donors are Hertel-Fernandez (2018), Li (2018), and Barber, Canes-Wrone and Thrower (2017).

[2]The overall number is actually 3,579,530 filings of 466,839 individuals working for 13,991 firms publicly listed firms. Since I look at the alignment between PACs and employees, I only use firms with data on both PAC and employee contributions in this paper.

likely to mobilize politically due to lower costs of collective action (Barber, Pierskalla and Weschle, 2014; Hansen, Mitchell and Drope, 2005; Olson, 1965). Since the corporate political strategy of firms is often determined by the senior management, less diverging views result in less frictions to arrive at a common political position (Unsal, Hassan and Zirek, 2016). For the same reason, we might expect corporations with similar employee political preferences to be more likely to form policy coalitions (Dean, 2016; March, 1962; Rogowski, 1989; Sabatier, 1988) or show greater unity in industry-wide associations like the American Chamber of Commerce or the American Legislative and Exchange Council (Hertel-Fernandez, 2016; Walker and Rea, 2014). Finally, an unequal distribution of preferences across firms and occupations might have severe consequences for unequal representation in the US Congress(Bartels, 2008; Gilens and Page, 2014). Scholars of money in politics should pay more attention to individual's workplace, their profession, and the activities of their employers when investigating motivations for political giving.

3.2 Linking Firm and Employee Campaign Donations

Observing both the political preferences of employees and employers at the same time is very difficult in practice. Individual-level surveys do only ask individuals but not their companies, and most firm-level data does not include individual-level attitudes of employees, leading to very little research investigating *both firm and employee preferences at the same time*. This stands in contrast to the abundance of studies investigating individual political preferences for free trade (Mayda and Rodrik, 2005;

Owen and Johnston, 2017; Rho and Tomz, 2017; Scheve and Slaughter, 2001), redistribution (Iversen and Soskice, 2001; Kitschelt and Rehm, 2014), labor market risk (Thewissen and Rueda, 2019; Walter, 2017), or other work looking at the preferences of individual firms (Bombardini and Trebbi, 2012; Kim, 2017; Osgood, 2017*b*; Plouffe, 2013). The notable exception is recent work on employees as lobbyists (Hertel-Fernandez, 2018), contributions to political action committees (PACs) (Li, 2018), and some work on chief executive's donations (Babenko, Fedaseyeu and Zhang, 2019; Bonica, 2016*a*). However, these do only cover few industries and occupations or do not focus on the potential impact of firm characteristics on firm-employee alignment or dis-alignment.

I match employee to corporate donations using US campaign finance data from the Federal Election Commission (FEC). The FEC data contains information on corporate PAC campaign contributions and individual donations to political candidates. The individual-level data contains information on a donor's name, employer, and occupation. However, linking employees' workplace or occupation to firm-, industry-, and occupation-level data or the contributions of their employers is challenging for two reasons. First, there are no unique employer names or identifiers. Rather, donors just manually enter employer names into a form, resulting in vastly different firm names across individuals working for *the same firm*. This problem is shown in Table 3.1 which depicts political contributions of five `MICROSOFT` employees, each of which provides a slightly different (and sometimes, orthographically incorrect) employer name. The same problem exists for individual occupations. Table 3.2 shows the problematic structure of occupation names in the FEC data for five senior managers of well-known US companies. Second, the sheer amount of the data precludes attempts to

Name	Employer	Occupation	...
Steven Ballmer	MICROSOFT	CEO	...
Jeff Teper	MICROSOFT CORP	Corporate CEO	...
Lisa Brummel	MICROSOFT CORPORATION	Executive Vice President	...
Rae Garret	MICROSOFT CORPORTATION	Consultant	...
Dorothy Dwoskin	MICROSOFT INC.	Trade Director	...
⋮	⋮	⋮	...

Table 3.1 Lack of Unique Employer Names for Individual Campaign Donations. The table shows the lack of unique employer names in the FEC individual donations data. In this example, all individuals are employees of Microsoft, but they use different versions of the company name when filing their contribution to the FEC.

Name	Employer	Occupation	...
John H. Myers	GENERAL ELECTRIC CO	PRESIDENT/C.E.O.	...
John H. Chambers	CISCO SYSTEMS INC	PRESIDENT/CEO	...
Richard Clark	MERCK & CO	PRESIDENT, CEO	...
Christopher M. Crane	EXELON CORP	PRESIDENT COO	...
Robert Marcus	TIME WARNER CABLE INC	PRESIDENT AND COO	...
⋮	⋮	⋮	...

Table 3.2 Lack of Unique Occupation Names for Individual Campaign Donations. This table shows examples of different employees of five companies, all of which have a very similar jobs. However, all individuals provide very different occupation names when filing their contributions to the FEC.

manually match individuals to employers or manually categorize individual occupations. Between 1980 and 2016, the FEC data contains 52,974,196 individual contributions, 4,085,773 unique employer names, and 825,697 unique occupation names.

Therefore, I need an automated way to match employer names to unique company identifiers and occupation names to unique occupations identifiers. I developed an automated script, written in the programming language Python, leveraging Python's computationally efficient natural language processing capabilities. The process by which the script links un-structured employer and occupation names to unique identifiers is portrayed in Figure 3.1 below. The script takes as input a list of un-structured employer names (from the FEC) and a list of unique firm (or occupation) names with unique firm IDs (or occupation codes). For company names, I use the full list of 35,672 publicly traded firms in the Compustat Capital IQ North America database. For occupation names, I use the 'direct match files' of occupation titles to Standard Occupational Classification Codes (SOC) by the US Census Bureau and the Bureau for Labor Statistics, as well as more fine-grained O∗NET codes, widely used in Labor Economics (Acemoglu and Autor, 2011).[3]

The script proceeds as follows: first, a number of different employer names is given to the script. Then, the names are cleaned up: they get lower-cased, additional whitespace and punctuation is removed, and company legal forms are canonicalized. Next, a term-document matrix is created from the names and terms are weighted by term frequency-inverse document frequency (tf-idf). Hence, terms that appear in many company names (like 'incorporated', 'inc', etc.) receive less weight in the matching step. Second, for each cleaned name, the cosine similarity between a given employer name and each name in the list of 35,672 publicly traded firms in the Compustat database is calculated. The similarity between company names d_1 and d_2 is then calculated as $sim(d_1, d_2) = \frac{d_1 \cdot d_2^T}{||d_1|| \, ||d_2||} = \frac{\sum_{i=1}^{n} d_{1i} d_{2i}}{\sqrt{\sum_{i=1}^{n} d_{1i}^2} \sqrt{\sum_{i=1}^{n} d_{2i}^2}}$, which is simply the angular distance between the two employer name vectors given to the script, normalized by vector length. Finally, the script picks the Compustat firm name with the highest cosine similarity, if above a set

[3]For the SOC codes, there are 89,000 occupation titles relating to 869 unique occupation codes. For O∗NET occupation codes 105,000 occupation titles are related to 1100 unique occupation codes. The US Census Bureau and US Bureau for Labor Statistics use the Standard Occupational Classification Codes (SOC), while O∗NET uses O∗NET SOC, a more fine-grained system based on but fully compatible to SOC codes.

threshold, and returns it together with its unique firm ID (GVKEY).[4]. This process is repeated for each of the individual employer names, as well as for 17,215 corporate PAC names between 2003 and 2016. The result can be seen below in Table 3.3 for `MICROSOFT`. All five employees are now matched to one unique firm name. Moreover, each individual and employer gets assigned a unique ID. In this paper, I use the GVKEY from Compustat in order to add firm financial information. The process for matching occupation titles to unique occupation titles and codes is identical to the procedure for employers. Only the inputs to the script differ.

[4]The similarity measure is between 0 and 1, where 0 means no match at all, and 1 indicates a full match. For employer names, I use a threshold of 0.81, and for occupations 0.72, based on similar record linkage problems in existing research (Raffo and Lhuillery, 2009).

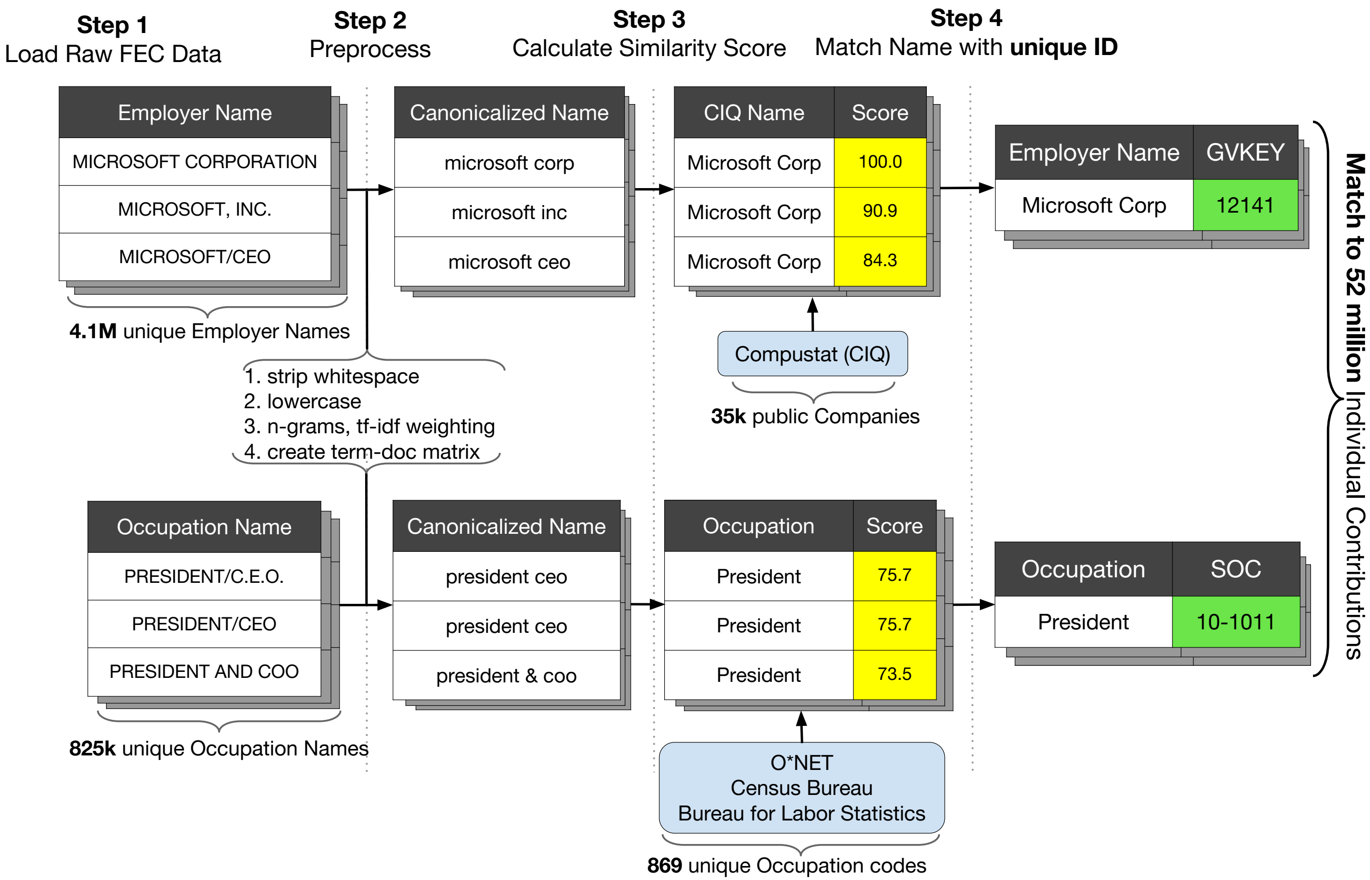


Figure 3.1 Script matching employees to unique employer IDs and occupation codes. The flow chart shows how employer names and occupations are matched to unique employer IDs (Compustat GVKEY) and occupation codes (Standard Occupational Classification (SOC) Codes) GVKEYs can be linked to firm- and industry level variables from financial databases, and SOC codes can be linked to official employment statistics.

Name	ID	Firm	Firm ID	SOC	Occup. Title	...
Steven Ballmer	I00301999	MICROSOFT CORP	12141	11-1011	Chief Executives	...
Jeff Teper	I06497673	MICROSOFT CORP	12141	11-1011	Chief Executives	...
Lisa Brummel	I00807330	MICROSOFT CORP	12141	11-1011	Chief Executives	...
Rae Garret	I01642142	MICROSOFT CORP	12141	13-1199	Consultant	...
Dorothy Dwoskin	I01780528	MICROSOFT CORP	12141	19-3011	Economists	...
⋮	⋮	⋮	⋮	⋮	⋮	...

Table 3.3 Result of Matching Employees to unique Employers and Occupation Codes: This table shows the result of the linkage process depicted in Figure 3.1 above. The individuals shown in Table 3.1 now have one unique firm name and firm ID (Compustat GVKEY), as well as unique occupation code (SOC) and individual IDs. Individual ID's are assigned by cleaning names, and using exact matching on first name, last name, and state of employee.

Overall, I match 3,537,187 filings of 466,840 individuals to 13,991 firms and 850 occupations between 2003 and 2016. I also match 274,106 out of 825,697 unique occupation names in the FEC data. Those occupations make up about 85 percent of the individuals contribution records matched to employers, excluding unemployed individuals and students.[5] I also match the zip codes of donors to Federal Information Processing Standard (FIPS) county codes. Individual identifiers were created using exact matching on the cleaned up versions of first name, last name, and state of residence of donors.[6]

[5]For this paper, I limit the period of investigation to the years between 2003 and 2016, because occupation data is only available from 2003 onwards. I also only use companies for which I observe both firm and employee donations, which are 1,691,790 campaign contribution filings of 85,109 individuals, working in 874 publicly listed firms and 850 occupations.

[6]The credit for the individual IDs goes to Mehmet Efe Akengin. The matching strategy is a compromise between having accurate individual IDs and being able to observe individuals changing workplaces or occupations. See below.

3.3 Advantages over Existing Datasets

These data provide some *significant advantages over existing databases* of US campaign donations like OpenSecrets.org (2018) or the Database on Ideology, Money in Politics, and Elections (DIME) (Bonica, 2016*b*). First, the dataset includes donations for all employees identified for a given publicly traded company. Existing research provides ample evidence on donations of individuals (Barber, Canes-Wrone and Thrower, 2017; Gimpel, Lee and Pearson-merkowitz, 2008; La Raya and Schaffner, 2015) or company executives (Babenko, Fedaseyeu and Zhang, 2019; Bonica, 2016*a*; Fremeth, Richter and Schaufele, 2013; Gupta, Nadkarni and Mariam, 2019; Richter and Werner, 2017; Unsal, Hassan and Zirek, 2016), but these studies do not differentiate between different positions of individuals within the same company or concentrate only on chief executives.

Second, the data uses commonly used identifiers for firms (Compustat GVKEY), industries (North American Industry Classification - NAICS) and occupations (Standard Occupational Classification - SOC), as depicted in Table 3.4. Those allow researchers to easily link companies and individuals to firm financial databases (e.g. Compustat or Orbis) and add industry and occupation level data from the Census Bureau, the Bureau of Labor Statistics, or other official data sources. In comparison, existing research uses the Open Secrets coding scheme for industry/occupation of donors which cannot easily be linked to any external data. Thus, the data makes it much easier for researchers to study the impact of sector- or occupation level reforms and economic shocks on the political behavior of donating firms and employees. The data also provides a clearer separation of occupation and industry of employment. Existing research often confuses occupation with industry, even though in economics (Acemoglu and Autor, 2011), CPE

Level	Identifer	Categories	CRP Identifier	CRP Categories
Occupation	SOC 2010	840	–	–
	O⋆NET SOC 2010	1010	–	–
Sector	NAICS 2012	1068	own scheme	400
Firm	GVKEY	13,766 (1980 - 2017)	–	–

Table 3.4 Unique Identifiers in Linked Employer-Employee Data: This table shows the unique identifiers available in the employer-employee data and the number of categories covered in comparison with the Center for Responsive Politics (CRP) data. Unique occupation and firm codes are missing from the CRP data, and sector codes cannot easily be linked to external datasets.

(Kitschelt and Rehm, 2014), or IPE (Owen and Johnston, 2017), researchers have developed different theoretical models with very different empirical implications for each of these levels of analysis. For example, Bonica (2014) uses 'Lawyers' as one and 'Mining' as another 'industry/occupation' category, based on the Open Secrets coding scheme. However, 'Lawyers' are not an industry but only one occupation which can be performed in many different industries, and 'Mining' is clearly not an occupation, but an industry comprising different occupations like miners, engineers, managers, and lawyers, among others. The same problem arises in the paper by Barber, Canes-Wrone and Thrower (2017) who also rely on the Center for Responsive Politics industry/occupation coding scheme.[7] Thus, my data makes a clearer distinction between firms, industries, and occupations which provides both analytical and empirical advantages over commonly-used data.

[7]In Bonica (2014) or Barber, Canes-Wrone and Thrower (2017) this is not particularly consequential, even though the former provides a misleading description of industry and occupation ideology. Bonica (2014) does not directly test theories on the impact of industry or occupation on donor behavior, and Barber, Canes-Wrone and Thrower (2017) do manually match Open Secrets occupation categories to committees with jurisdiction over said occupations.

3.4 Alignment across Firms and Occupations

I test three hypotheses that illustrate the potential usefulness of these data for scholars of political economy and political behavior. First, I test the hypothesis that all else equal, employees campaign contributions will be positively correlated with their employers contributions. This could be the case for multiple reasons. For instance, employees could self-select into firms because they live in areas dominated by the same party that the firm supports (Rodden, 2010). Alternatively, the nature of the workplace could tie the economic fortune of individuals to the firm and incentive them to donate to the same party (Alt et al., 1999; Alt and Gilligan, 1994). Lastly, the employers might mobilize employees to support similar candidates (Hertel-Fernandez, 2018).[8]

Second, I test the hypothesis that all else equal, firm-employee alignment will be lower in larger firms, as compared to smaller firms. Intuitively, we would expect alignment to be inversely related to firm size, because collective action is more difficult in large groups due to the higher likelihood of free riding (Barber, Pierskalla and Weschle, 2014; Hansen, Mitchell and Drope, 2005; Olson, 1965), and both the firm and their employees need to mobilize in order to support the same party[9] Also, while firms with a larger market share might be more likely to mobilize because political activity might yield more concentrated benefits, they are also more likely to have politically heterogeneous employees, which might in turn decrease overall alignment (Ostrom, 2010; Walker and Rea, 2014).

[8]Note that campaign donations are the least-used workplace mobilization mechanism according to Hertel-Fernandez (2018).

[9]They might also mobilize to support the same candidate, as shown in Chapter 4 of this thesis.

Third, I test the hypothesis that all else equal, high-ranking employees' contributions will be more aligned with their firm's contributions, as compared to lower-ranking employees.[10] Work on the political behavior of Chief Executives in Finance, Economics, and Management has documented that chief executives donate larger sums and more frequently than regular employees (Fremeth, Richter and Schaufele, 2013; Richter and Werner, 2017; Unsal, Hassan and Zirek, 2016). Moreover, CEO ideology has been shown to impact corporate decisions like downsizing or corporate social responsibility (Gupta, Briscoe and Hambrick, 2017; Gupta, Nadkarni and Mariam, 2019). CEOs should also have more incentives to donate to the same party as their company, since a large fraction of executive pay is based on bonuses or company shares which depend on the success of the company.[11]

Figure 3.2 plots Republican donations as a share of overall donations of publicly traded US corporations against the aggregate Republican donation share of the same companies' employees. It shows that employer and employee donations are indeed highly correlated: the higher the share of Republican donations by a corporate PAC, the higher the share of Republican donations by employees. There are also some companies deviating from the trend, especially in corporations that only have few employees or make few PAC contributions, but the average relationship is clearly positive. Further, this trend is driven by House and Senate candidates, and is strongest for

[10] Another possibility is that individuals become socialized into particular political views over time, via discussions with their co-workers (Abrams, Iversen and Soskice, 2011; Mutz and Mondak, 2007). In this dissertation, I concentrate on the economic reasons for partisan alignment between employees and their employers.

[11] Some part of corporate profits can be outside of CEO's control, such as external shocks to assets important to the company (Davis and Hausman, 2018). Gupta and Wowak (2017) shows that more conservative boards pay more to their CEOs, and that the connection between firm performance and CEO pay is stronger with more conservative boards. However, there is also evidence that CEOs are much more ideological donors than these reasons suggest (Bonica, 2016*a*), making it less clear whether they are more aligned with their company.

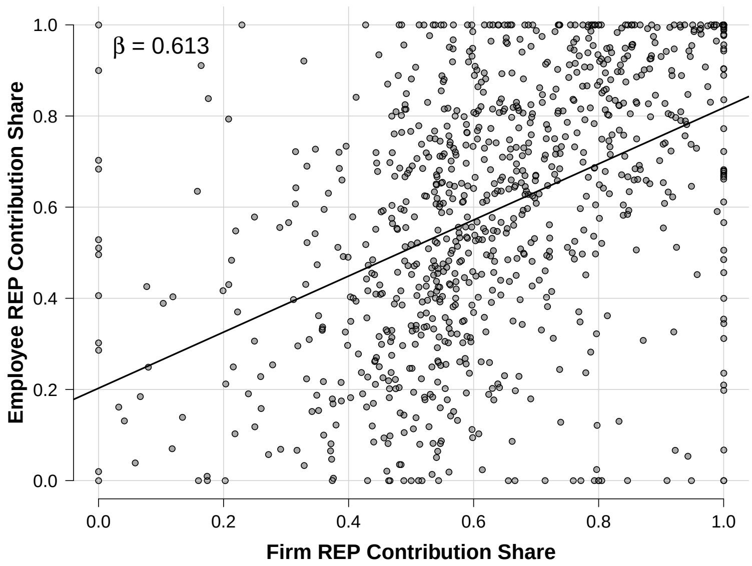


Figure 3.2 Positive Relationship between Firm and Individual Partisan Donations. This scatter plot shows that there is a positive association between the partisan donation share of firms and their employees.

incumbent candidates, followed by challengers and open seat candidates, as shown in Figures A.1 and A.2 in the appendix. This provides evidence that is more consistent with investment motives behind corporate donations rather than consumption.

Next, I aggregate the firm-employee donation data at the the firm-cycle level, and regress the Republican donation share of employees on the donation share of their corporate PAC. The result can be seen in Table 3.5 below. As expected, employee donation shares to Republicans are very responsive to firm donations. I then sequentially add time-varying firm control variables, cycle fixed effects, and firm fixed effects. In the most conservative specification in column 4 I only look at within-firm changes in employee donations as a function of the partisan donation share of their firm PAC. Moving from 0 to 1 on the PAC Republican donation share increases the employee share to Republicans by 18 percent, even after controlling for firm-and cycle unobservables. This association is large and surprising, given that a large portion of the campaign finance literature argues that individual donations are merely consumption (Ansolabehere, de Figueiredo and Snyder, 2003; Milyo, Primo and Groseclose, 2000). However, this finding is more in line with newer accounts of workplace coercion (Hertel-Fernandez, 2018) and individual donations to politicians which are members of Congressional committees regulating those employees' sector of employment (Barber, Canes-Wrone and Thrower, 2017).

Table 3.5 Regression Results: Employee and Firm Donations

	Dependent variable:			
	Employee REP Donation Share			
	(1)	(2)	(3)	(4)
Firm REP Donation Share	0.508***	0.511***	0.530***	0.178***
	(0.028)	(0.031)	(0.034)	(0.049)
Firm Controls		✓	✓	✓
Cycle FEs			✓	✓
Firm FEs				✓
Observations	3,871	3,009	3,009	3,009
Adjusted R^2	0.132	0.162	0.177	0.465

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm.

For testing the second and third hypothesis, I need a measure of alignment between firms and employees that incorporates the changes across electoral cycles. It also needs to represent the fact that most individuals only donate to one party, but that corporate PACs vary more in the partisanship of their donations, depending on who is in power, seniority of members, and whether they become members or chairs of powerful committees (Berry and Fowler, 2016; Fouirnaies and Hall, 2018). Hence, the main dependent variable for this paper, partisan alignment between employees and their employers, is calculated as:

$$Alignment_{ict} = 1 - \left| \left(\frac{R_{jt}}{(R_{jt} + D_{jt})} - \frac{R_{ijt}}{(R_{ijt} + D_{ijt})} \right) \right|$$

In Figure 3.3, I plot the distribution of partisan alignment between firms and employees which ranges from 0 (complete partisan dis-alignment) to 1 (complete partisan alignment). One can see that it is approximately normally distributed, with some peaks at both extremes of the distribution. This reflects that some corporations only donate to one party in some electoral cycles, and therefore, all individuals working for this company who donate to the opposite party score 0, and all employees donating to the same party score 1 on the alignment measure. For example, Blackstone Group LP donated only to Republican candidates from 2011 to 2015. Therefore, 408 employees of Blackstone donating to the Republican party will score 1 (full alignment), and 209 employees will score 0 (no alignment). This distribution translates into peculiar patterns across firms and industries which I show in Figure 3.4 below. Panel 3.4a depicts the 10 sectors with the most and the 10 sectors with least alignment, and panel 3.4b shows the same for the 10 most and 10 least aligned firms.

Figure 3.5 below provides some descriptive evidence in favor of both of the collective action and the chief executive hypothesis. Panel 3.5a depicts the bivariate relationship between aggregate alignment of all companies in my data and the logged number of employees. The relationship is moderately negative, with average alignment across all employees being

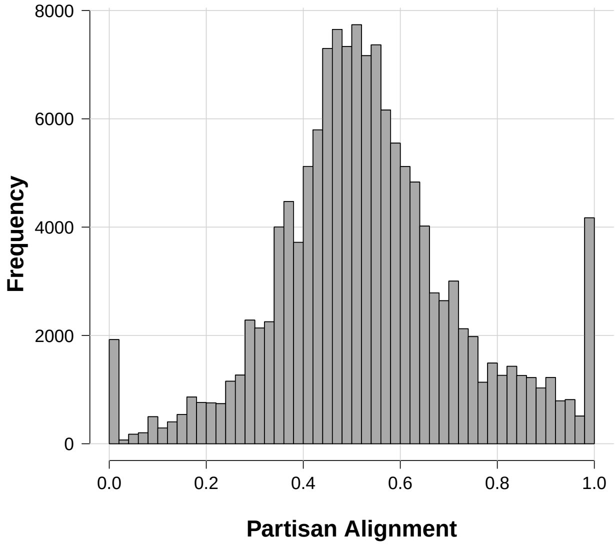
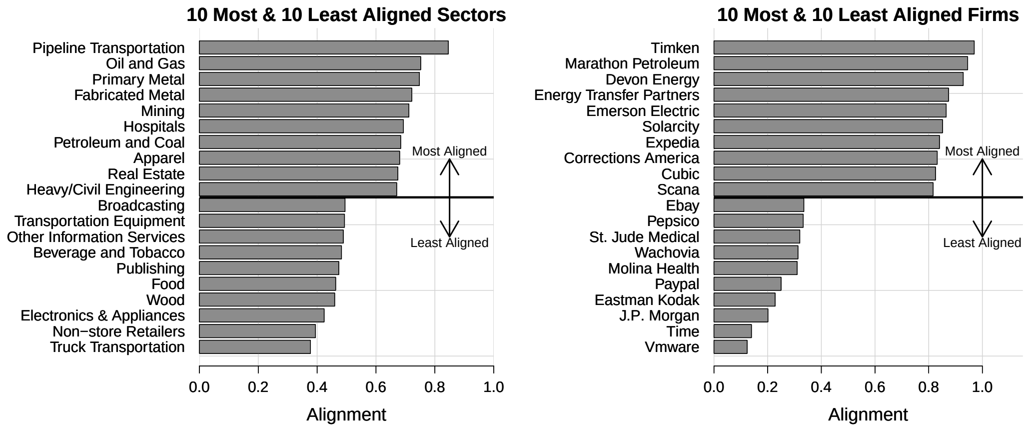


Figure 3.3 Distribution of Partisan Alignment. This histogram depicts the distribution of alignment from complete disalignment (0) to complete alignment (1) in the US campaign finance data. Complete (dis-) alignment happens when companies donate exclusvilely to one party and employees donate to the (other) same party.

about 0.63 for firms with the lowest number of employees, and about 0.45 for firms with the highest number of employees, supporting the expectation that larger firms are less aligned, on average. Panel 3.5b shows boxplots comparing average alignment of CEOs and regular employees. Executives have a median alignment score of 0.59 and rank- and file employees have an median alignment of 0.51. Hence, while CEOs tend to be more aligned with the partisan donations of the company PAC, rank-and-file employees seem to donate equally to both parties, on average. There is, however, a large variation in alignment, especially for non-executive employees. Over 75 percent of CEOs tend to align with the partisan donations of their PAC.

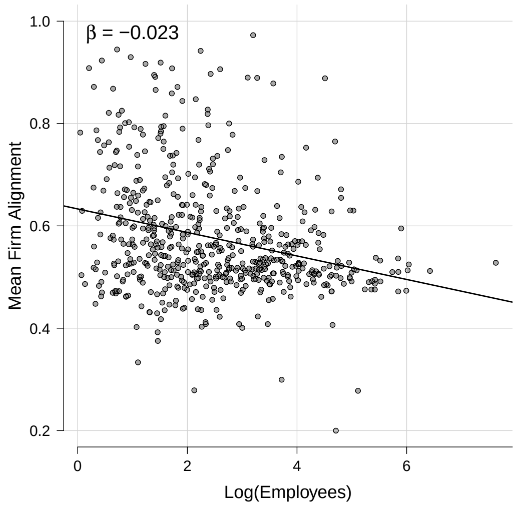
Next, in Table 3.6, I regress employee-firm-alignment in a given electoral cycle on the logged number of employees of a firm. The regression coefficient is negative, significant, and similar in size to the bivariate relationship in Figure 3.5. I then add a number of firm-election cycle control variables (natural log of capital expenditure, plant and property expenses, cost of



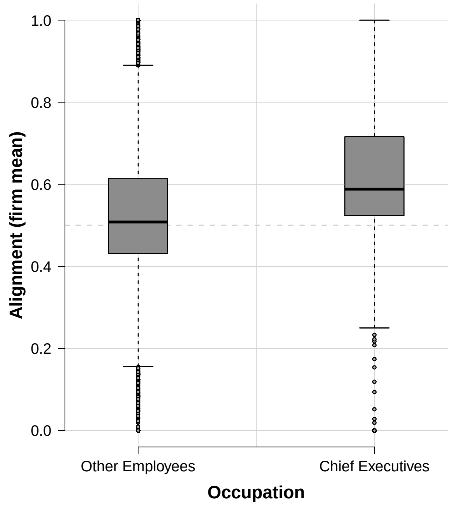
(a) Sectoral Alignment **(b) Firm Alignment**

Figure 3.4 Most and Least Aligned Firms and Sectors. This figure shows the ten sectors and firms with most and least alignment. Panel a) shows that extractive industries like oil, gas, and rubber are most aligned, while electronics and transportation manufacturers are least aligned. Panel b) shows that Timken and Marathon Petroleum are most aligned, while Vmware and Time show little alignment.

goods sold, sales), and the coefficient stays almost unchanged. Then, step by step, I add different fixed effects for electoral cycle, individual occupations at the 6-digit SOC level, and county fixed effects to control for geographic unobservables. At last, I also add broad industry fixed effects to control for the fact that some industries might be larger than others due to other factors, such as the necessity of a larger workforce or economies of scale (Chase, 2005). The strength of the coefficient on the number of employees decreases, especially when adding county fixed effects, but remains negative and significant. Holding constant occupation, electoral cycle, county, and industry, going from the minimum logged number of employees in the data (close to 0) to the 90th percentile is associated with a 0.059 increase in alignment which is substantive, given that most observations cluster closely around 0.5 (as shown in Figure 3.3 above). Even though these effects cannot be interpreted as causal, they support the notion of larger collective action problems in larger companies. There are several possible mechanisms



(a) Alignment and Firm Size



(b) Alignment and Occupations

Figure 3.5 Alignment and Firm- and Occupational Characteristics. Panel a) shows that there is a negative relationship between firm size and average alignment between firms and employees at the firm-level. Panel b) shows that chief executives are significantly more aligned with their firm, compared to all other firm employees.

behind this relationship that might be interesting to investigate further in the future: first, to the extent that it is important whom your colleagues donate to, it might be easier for employees in smaller companies to coordinate donations, or to converge on similar candidates via firm-internal discussions. Second, firms might find it easier to mobilize their employees to donate in smaller firms, especially if their workforce is more concentrated geographically (Hertel-Fernandez, 2018).

Finally, in Table 3.7, I regress firm-employee alignment on a binary indicator which is 1 if an employee is a top executive in a company (SOC 11-1011), and 0 otherwise. As expected, the coefficient is strongly significant and positive, indicating that CEOs are more aligned than other employees, on average. Thus, this provides some evidence that chief executives might have more incentives to support candidates which their firm supports. Like before, I then add firm controls and a host of fixed effects to the model. Holding constant electoral cycle, firm, county, and broad 2-digit

SOC occupations, CEOs are more aligned than other employees. In the most conservative specification, chief executives score 0.044 higher on my measure of alignment. This is less than a big increase in the number of employees but still substantively large, given that alignment centers around 0.5 for most employees.

Table 3.6 Regression Results: Firm Size and Alignment

	Dependent variable:					
	Align					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Employees)	-0.021^{***}	-0.023^{***}	-0.022^{***}	-0.019^{***}	-0.014^{***}	-0.011^{***}
	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Firm Controls		✓	✓	✓	✓	✓
Cycle FEs			✓	✓	✓	✓
Occupation FEs				✓	✓	✓
County FEs					✓	✓
NAICS 2-digit FEs						✓
Observations	113,110	112,405	112,405	112,405	100,910	100,910
Adjusted R^2	0.023	0.034	0.042	0.066	0.123	0.127

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm.

Table 3.7 Regression Results: Chief Executives and Alignment

	Dependent variable:					
	Align					
	(1)	(2)	(3)	(4)	(5)	(6)
CEO	0.073^{***}	0.058^{***}	0.055^{***}	0.045^{***}	0.045^{***}	0.044^{***}
	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)
Firm Controls		✓	✓	✓	✓	✓
Cycle FEs			✓	✓	✓	✓
Firm FEs				✓	✓	✓
County FEs					✓	✓
SOC 2-digit FEs						✓
Observations	126,686	112,405	112,405	112,405	100,910	100,910
Adjusted R^2	0.022	0.048	0.054	0.164	0.184	0.187

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm.

3.5 Summary and Future Applications

In this paper, I match big data on corporate and employee campaign contributions to each other, and create a measure of partisan alignment between firms and their employees. In line with Political Economy theories, firm and employee donations are highly correlated, and firm-employee alignment is significantly associated with firm size and one's position in the company. These data open up multiple avenues for further research to gain insights into coalition formation, individual motivations for political giving, and representation in US politics.

For example, how do economic shocks or policy reforms with distributional consequences on occupations and sectors affect individual contributions? There is good evidence that import competition influences vote shares of incumbent parties (Che et al., 2016), polarization (Autor, Dorn and Hanson, 2016*a*), and support for extreme right wing parties (Calantone and Stanig, 2018; Dippel, Gold and Heblich, 2015), or that the shale gas boom has benefited Republicans in terms of received donations (Sances and You, 2019). However, the presence of firm, sector, and occupational identifiers makes it possible to investigate the impact of policy reforms affecting only particular sectors or occupations, such as changes in occupational licensing requirements across US states, or firm-specific changes such as mergers and acquisitions on donor behavior.

Another important question is, what are the implications of alignment within sectors on the likelihood of firms to lobby alone or in business associations (Bombardini and Trebbi, 2012; Osgood, 2017*a*), and does alignment affect lobbying success? While both my data and Bonica (2016*a*) show that there is a large variation in partisanship of US top executives, I find that CEOs are still more aligned than rank- and file employees, on average. Apart from group size, heterogeneity of political preferences has been theorized to be an important factor inhibiting collective action (Ostrom, 2010). Thus, more internally aligned firms might be more likely to lobby in the first place, and firms more politically homogeneous sectors might be more likely to engage with politicians via umbrella associations.

Finally, how has the distribution of donations across and within sectors and occupations changed over time, and how has that affected representation (Gilens and Page, 2014; Schlozman, Verba and Brady, 2012) and polarization in US politics (Bafumi and Herron, 2010)? While it is well-known that donors are more likely to be white and male, older, more educated, and of higher income (Francia, 2003; La Raya and Schaffner, 2015), much less is known about how skewed are donations towards particular firms and occupations within firms.

These are only some of the questions which will be easier to answer with the linked employer-employee donations data presented in this paper. While here I show only one application from my ongoing work, this dataset will be a very useful resource for many different purposes in American Politics and Political Economy research.

Appendix A

Data Appendices on matched Firm-Employee Data

A.1 Accuracy of Information in FEC Data

How accurate are the FEC data files in terms of individual employers or occupations? Based on the 1974 Federal Election Campaign Act (FECA), disclosure of donations is mandatory for all individual contributions exceeding USD 200, a threshold which has not been changed since 1980 (McGeveran, 2003). While employers can and do report all contributions, even those smaller than USD 200 most candidates report only donations over USD 200.[1] Contribution limits differ by entity donated to, and change each electoral cycle.[2] Individuals who give to federal candidate must disclose their occupation and employer. Committees receiving donations must make their best effort to determine employer and occupation of donors before filing contributions to the FEC. Nevertheless, there is some mis-reporting, especially among occupation names. Some obviously incorrect or non-informative examples include:

- `ANTI-ISLAMOFASCISM EXPERT`
- `ANTI-ISLAM OF ASCIST CONSULTANT`
- `''MOBBED'' OCCUPATIONAL THERAPIST`
- `Mother :  )`
- `DINOSAUR EXPERT`
- `UNEMPLOYED LIKE 22% OF AMERICANS`
- `UNEMPLOYED & LOVING IT`
- `VP DICK CHENEY`

[1]Non-federal candidate disclosure rules are even stricter at times, but are not relevant for this paper which only uses federal contributions data.

[2]The 2017/2018 electoral cycle contribution limits within a given per election are: (1) USD 2,700 to individual candidates (2) USD 5,000 to PACs (3) USD 10,000 to non-national party committees (state, local, district), and (4) up to USD 33,900 to national party committees. Those limits are subject to adjustment for inflation every electoral cycle.

That being said, there are few ways to check the accuracy of each individual filing. Hence, I need to assume that committees are checking the accuracy of individual donations thoroughly, on average.

One downside of the data is that I have to compromise on the accuracy of individual identifiers. Bonica (2014, p.370) maximizes the precision of his identity-resolution algorithm by utilizing individual names, addresses, occupations, and employer names. Consequently, he loses the ability to follow individuals when they change occupation, address, or workplace. I only use first name, last name and state of residence for determining individual identifiers, to be able to observe changes in occupations and sectors.

A.2 Companies in Firm-Employee Data

Company Name	NAICS Code	NAICS Title	Frequency
MICROSOFT CORP	511210	Software Publishers	6294
GOLDMAN SACHS GROUP INC	523110	Investment Banking and Securities Dealing	5139
MORGAN STANLEY	523110	Investment Banking and Securities Dealing	5115
BOEING CO	336411	Aircraft Manufacturing	4360
BANK OF AMERICA CORP	522110	Commercial Banking	3293
MERRILL LYNCH & CO INC	523110	Investment Banking and Securities Dealing	2723
COMCAST CORP	515210	Cable and Other Subscription Programming	2665
RAYTHEON CO	334511	Aeronautical, and Nautical Manufacturing	2134
ORACLE CORP	511210	Software Publishers	2115
NORTHWESTERN MUTUAL LIFE INS	524113	Direct Life Insurance Carriers	1974
AMERICAN AIRLINES INC	481111	Scheduled Passenger Air Transportation	1973
PFIZER INC	325412	Pharmaceutical Preparation Manufacturing	1881
CISCO SYSTEMS INC	334210	Telephone Apparatus Manufacturing	1834
JOHNSON & JOHNSON	325412	Pharmaceutical Preparation Manufacturing	1618
GENERAL ELECTRIC CO	999977	Unknown/Other	1550
ACCENTURE PLC	541611	Management Consulting Services	1508
NEW YORK LIFE INSURANCE	524113	Direct Life Insurance Carriers	1243
INTEL CORP	334413	Semiconductor Manufacturing	1199
AMGEN INC	325414	Biological Product Manufacturing	1146
GENERAL DYNAMICS CORP	336411	Aircraft Manufacturing	1138
FORD MOTOR CO	33611	Automobile Manufacturing	1121
GENERAL MOTORS CO	33611	Automobile Manufacturing	1098
AMERICAN EXPRESS CO	522210	Credit Card Issuing	1082
UNITED AIRLINES INC	48111	Scheduled Air Transportation	997
MERCK & CO	325412	Pharmaceutical Preparation Manufacturing	995
MCDONALD'S CORP	722513	Limited-Service Restaurants	973
AMAZON.COM INC	454111	Electronic Shopping	951
LILLY (ELI) & CO	325412	Pharmaceutical Preparation Manufacturing	945
TARGET CORP	452990	All Other General Merchandise Stores	939
SOUTHWEST AIRLINES	481111	Scheduled Passenger Air Transportation	856
COCA-COLA CO	312111	Soft Drink Manufacturing	819
EXXON MOBIL CORP	324110	Petroleum Refineries	814
BLACKSTONE GROUP LP	523920	Portfolio Management	802
PROCTER & GAMBLE CO	325611	Soap and Other Detergent Manufacturing	783
DISNEY (WALT) CO	515120	Television Broadcasting	772
AMERICAN ELECTRIC POWER CO	2211	Electric Power Generation and Distribution	743
HOME DEPOT INC	444110	Home Centers	743
3M CO	322220	Paper Manufacturing	733
HARRIS CORP	334511	Aeronautical, and Nautical Manufacturing	733
EXPRESS SCRIPTS HOLDING CO	446110	Pharmacies and Drug Stores	724

Table A.1 Most Frequent Firms in Linked Firm-Employee Campaign Contributions Data. The table shows the distribution of 40 most common firms in the linked employer-employee data, their matched North American Industrial Classification System (NAICS) code, as well as their industry title.

A.3 Industries in Firm-Employee Data

NAICS Code	NAICS Title	Frequency
523	Securities, Commodity Contracts, and Other Financial Investments	15660
325	Chemical Manufacturing	11931
334	Computer and Electronic Product Manufacturing	10615
511	Publishing Industries (except Internet)	9826
336	Transportation Equipment Manufacturing	9514
522	Credit Intermediation	8538
524	Insurance Carriers	6229
221	Utilities	5723
515	Broadcasting (except Internet)	4869
541	Professional, Scientific, and Technical Services	4331
481	Air Transportation	4207
333	Machinery Manufacturing	2970
999	Unknown/Other	2167
211	Oil and Gas Extraction	1950
311	Food Manufacturing	1590
517	Telecommunications	1547
452	General Merchandise Stores	1359
722	Food Services and Drinking Places	1235
324	Petroleum and Coal Products Manufacturing	1186
621	Ambulatory Health Care Services	1153
446	Health and Personal Care Stores	1098
482	Rail Transportation	1038
561	Administrative and Support Services	1012
424	Merchant Wholesalers, Nondurable Goods	994
312	Beverage and Tobacco Product Manufacturing	986
454	Nonstore Retailers	951
339	Miscellaneous Manufacturing	935
444	Building Material and Garden Equipment and Supplies Dealers	849
322	Paper Manufacturing	778
721	Accommodation	764
445	Food and Beverage Stores	718
519	Other Information Services	712
236	Construction of Buildings	672
111	Crop Production	583
332	Fabricated Metal Product Manufacturing	571
512	Motion Picture and Sound Recording Industries	532
212	Mining (except Oil and Gas)	496
316	Leather and Allied Product Manufacturing	476
492	Couriers and Messengers	438
532	Rental and Leasing Services	437

Table A.2 Most Frequent Industries in Linked Firm-Employee Campaign Contributions Data. The table shows the distribution of 40 most frequent North American Industrial Classification System (NAICS) 3-digit industries in the linked employer-employee data.

A.4 Industries in Firm-Employee Data vs. US Economy

NAICS Code	Industry Name	% 2016 US Employment	% FEC Filings	Difference
31–33	Manufacturing	8.8	32.3	23.5
52	Finance and Insurance	4.1	14.0	9.9
22	Utilities	0.4	5.3	4.9
51	Information	2.0	6.7	4.7
48–49	Transportation/Warehousing	4.0	7.0	3.0
21	Mining, Oil & Gas	0.5	2.0	1.5
11	Agriculture, Forestry & Hunting	0.3	0.5	0.2
53	Real Estate, Rental & Leasing	1.5	1.2	-0.3
71	Arts & Entertainment	1.7	0.1	-1.6
42	Wholesale Trade	4.2	1.6	-2.6
81	Other Services	2.9	0.0	-2.9
54	Professional Services	6.2	2.5	-3.7
23	Construction	4.8	0.6	-4.2
56	Administrative & Support	6.5	0.9	-5.6
99	Unknown	6.8	0.3	-6.5
44–45	Retail Trade	11.4	4.0	-7.4
72	Accommodation & Food Services	9.5	0.9	-8.6
61	Educational Services	9.2	0.2	-9.0
62	Health Care & Social Assistance	13.7	1.9	-11.8

Table A.3 Differences between US Industry Employment and FEC Industry Filings. The table shows that there are large differences between 2016 US private Employment across 2-digit North American Industry Classification System (NAICS) industries and Filings per Industry in the FEC data. Source: Bureau for Labor Statistics and own calculations.

A.5 Occupations in Firm-Employee Data

SOC 2010	SOC 2010 Title	Frequency
11-1011	Chief Executives	24291
23-1011	Lawyers	9057
11-3031	Financial Managers	7726
11-9199	Managers, All Other	7375
17-2021	Agricultural Engineers	6079
15-1111	Computer and Information Research Scientists	3727
13-2052	Personal Financial Advisors	3719
11-2021	Marketing Managers	2880
41-3031	Financial Services Sales Agents	2748
41-4011	Sales Representatives, Wholesale and Manufacturing	2726
11-1021	General and Operations Managers	2357
11-9081	Lodging Managers	1636
11-9041	Architectural and Engineering Managers	1571
13-1199	Business Operations Specialists, All Other	1558
45-3011	Fishers and Related Fishing Workers	1486
13-2011	Accountants and Auditors	1335
11-3121	Human Resources Managers	1308
19-3094	Political Scientists	1259
11-2031	Public Relations and Fundraising Managers	1171
11-2022	Sales Managers	1168
29-1069	Physicians and Surgeons, All Other	968
11-9021	Construction Managers	947
15-1132	Software Developers, Applications	914
17-3029	Engineering Technicians, Except Drafters, All Other	890
11-3021	Computer and Information Systems Managers	888
41-3021	Insurance Sales Agents	826
13-1111	Management Analysts	742
15-1199	Computer Occupations, All Other	700
53-2031	Flight Attendants	630
41-1012	First-Line Supervisors of Non-Retail Sales Workers	624
11-9033	Education Administrators, Postsecondary	617
27-3031	Public Relations Specialists	578
15-1121	Computer Systems Analysts	569
13-2031	Budget Analysts	557
11-9111	Medical and Health Services Managers	546
29-1051	Pharmacists	507
15-1152	Computer Network Support Specialists	481
13-1161	Market Research Analysts and Marketing Specialists	419
13-1011	Agents and Managers of Artists, Performers, and Athletes	411
11-3061	Purchasing Managers	394

Table A.4 Unequal Frequency of Occupations in Linked Firm-Employee Campaign Contributions Data. The table shows the distribution of 40 most common Standardized Occupation Classification (SCO) codes in the linked firm-employee contributions data. The table shows that Management, Business and Financial, and Legal occupations comprise more than half of the individual contributions matched.

A.6 Occupations in Firm-Employee Data vs. US Economy

SOC Code	Occupation Name	% 2016 US Employment	% FEC Filings	Difference
11-0000	Management	5.1	34.0	28.9
23-0000	Legal	0.8	3.9	3.1
17-0000	Architecture & Engineering	1.8	4.1	2.3
13-0000	Business & Financial Operations	5.2	7.3	2.1
15-0000	Computer & Mathematical	3.0	5.1	2.1
19-0000	Life, Physical, & Social Science	0.8	2.0	1.2
45-0000	Farming, Fishing, & Forestry	0.3	0.6	0.3
27-0000	Arts, Design & Entertainment	1.4	1.1	-0.3
21-0000	Community and Social Service	1.4	0.1	-1.3
33-0000	Protective Service	2.4	0.2	-2.2
39-0000	Personal Care & Service	3.2	0.8	-2.4
31-0000	Healthcare Support	2.9	0.0	-2.9
37-0000	Building Cleaning & Maintenance	3.2	0.2	-3.0
49-0000	Installation, Maintenance, & Repair	3.9	0.3	-3.6
47-0000	Construction and Extraction	4.0	0.3	-3.7
29-0000	Healthcare Practitioners and Technical	5.9	1.1	-4.8
53-0000	Transportation and Material Moving	6.9	1.5	-5.4
25-0000	Education, Training, and Library	6.2	0.3	-5.9
51-0000	Production	6.5	0.6	-5.9
41-0000	Sales and Related	10.4	3.3	-7.1
35-0000	Food Preparation and Serving Related	9.2	0.6	-8.6
43-0000	Office and Administrative Support	15.7	1.4	-14.3

Table A.5 Differences between US Occupational Employment and FEC Occupation Filings. The table shows that there are large differences between 2016 US private Employment across 2-digit Standard Occupation Classification (SOC) categories and Filings per occupation in the FEC data. Source: Bureau for Labor Statistics and own calculations.

A.7 Examples of Firms Donating One-Sided

Only 1282 firm-year observations (out of 7844, or 16%) donate one-sided. 83% donate to both parties. There are some firms with consistent Republican-only donations, but not as many donating to the Democratic party only. Below, see examples of **Republican companies** (gvkey in parenthesis):

- XTO ENERGY INC (28256),
- WORTHINGTON INDUSTRIES (11600)
- WERNER ENTERPRISES INC (12266)
- SUN BANCORP INC (19420)
- REMINGTON ARMS COMPANY INC (9043)
- COOPER INDUSTRIES PLC (3497)
- CRYOLIFE INC (27823)
- LEGGETT & PLATT INC (6649)
- COLONIAL BANCGROUP (14201)

Below, see examples of **Democratic companies** (`gvkey` in parenthesis):

- JERRYS INC (6252)
- HOMESTREET INC (187164)
- MAUI LAND & PINEAPPLE CO (7117)
- PHOENIX COMPANIES INC (142462)
- REEBOK INTERNATIONAL LTD (9004)
- BANK OF HAWAII CORP (16200)
- BROWN & BROWN INC (117500)
- FUELCELL ENERGY INC (25430)

A.8 Alignment across Candidate Types and Incumbency Status

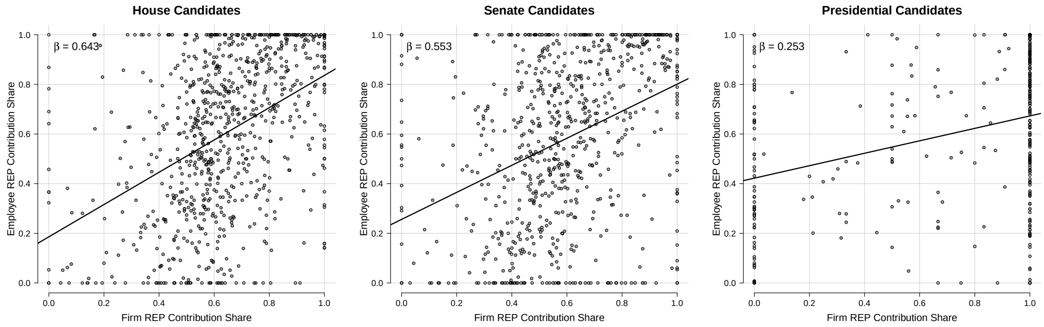


Figure A.1 Correlation between Firm- and Employee Donations across Candidate Offices: The plots show the correallation between employee and firm Republican donation share, aggregated at the firm-level between 2003 and 2016, across different offices donated to. It shows that donations of corporations and employees are more correlated for House and Senate candidates than for Presidential candidates.

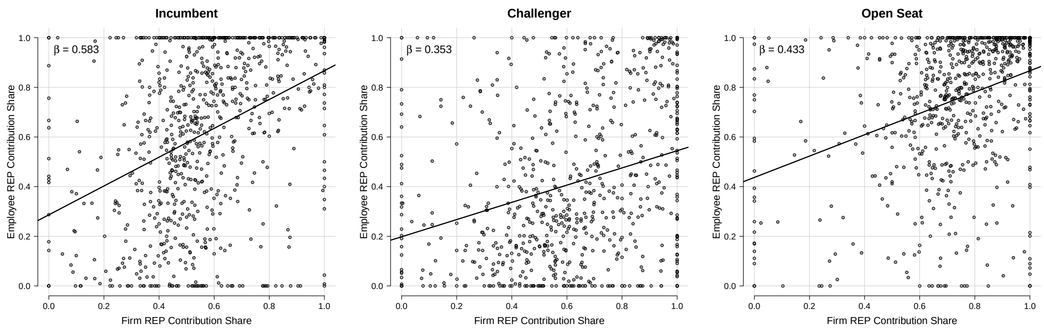


Figure A.2 Correlation between Firm- and Employee Donations and Candidate Incumbency Status: The plots show the correallation between employee and firm Republican donation share, aggregated at the firm-level between 2003 and 2016, for different candidate types. It shows that donations of corporations and employees are more correlated for Incumbent and Open Seat candidates than for Challengers.

Chapter 4

Political Alignment between Firms and Employees: The Role of Asset Specificity

4.1 Introduction

When do political preferences of employees align with those of their employers? Research in Comparative (CPE) and International Political Economy (IPE) states that sectors (Mayda and Rodrik, 2005; Scheve and Slaughter, 2004), firms (Ardanaz, Murillo and Pinto, 2013; Naoi and Urata, 2013), or occupations (Kitschelt and Rehm, 2014; Owen and Johnston, 2017) are an important source of political preferences. In particular, the existing literature identifies asset specificity as a key factor determining which level of analysis should dominate individual preference formation (Alt and Gilligan, 1994; Iversen and Soskice, 2001): high specificity should tie the fate of individual jobs more closely to their firm, and hence make employees more likely to share the economic preferences of their company. Therefore, they should also be more likely to align politically with their employer. However, while some empirical work confirms the impact of specificity at the level of the firm or sector (Alt et al., 1999; Dean, 2016; Hiscox, 2002*a*) other scholars highlight the role of occupational skill specificity on preferences (Iversen and Soskice, 2001; Rehm, 2009). Thus, the jury is still out with regards to whether firm, sectoral or occupational specificity matters more for preference formation. Moreover, observing both individual and employer political preferences at the same time is very difficult in practice, so that most work relies on either firm or individual preferences. In addition, measurement mostly focuses on stated preferences of individuals instead of political actions.[1]

This paper provides three main contributions. First, I uniquely test the relationship between specificity and alignment at the firm-, sector-, and occupational level, comparing the impact of all three levels of analysis against each other. Thus, I provide an important contribution to the debate on the economic sources of political preferences. I find that employees in companies and sectors with high asset specificity are more aligned with their employer, holding constant individual occupation and location, and controlling for firm and sectoral characteristics. However, I find no evidence for the impact of skill specificity on alignment. Hence, *where people work seems to be more important for their preferences than what they do*. Second, I am able to measure alignment in terms of firm's and employee's political actions instead of relying on stated preferences. I accomplish this by exploiting a novel dataset matching the donations of corporate Political Action Committees (PACs) to employee donations, using 1,691,790 campaign contribution filings of 85,109 individuals working in 874 publicly listed firms and 850 oc-

[1] For some examples of work in IPE focusing either on firm preferences (Kim et al., 2019; Osgood, 2017*b*; Plouffe, 2013) or individual preferences (Mayda and Rodrik, 2005; Rho and Tomz, 2017; Scheve and Slaughter, 2001), without comparing employers' and employees' preferences.

cupations between 2003 and 2016.[2]. Third, I explore further the mechanism linking firm-level factors to employee donations. If employees pay attention to their company's political activities, they should change their donation patterns in conjunction with their firm. I focus on within-individual variation in donations and find that employees increase donations to specific candidates by 4.4 to 4.5 percent once their company political action committee (PAC) contributes to the same candidate. Moreover, they are more reactive to PAC donations to candidates where donations are more likely to yield political benefits, such as congressional candidates, incumbents, and candidates running for open seats. Thus, I provide evidence on PAC donations as a possible informational mechanism linking firm and sectoral characteristics to employee political contributions, and suggestive evidence on an investment motive behind this connection (Li, 2018).

The results of this paper have important implications for the study of collective political action, coalition formation, and individual preference formation. If structural firm characteristics are associated with more homogeneous political preferences of employees, then overcoming collective action problems might be much easier for these firms. In particular, corporations might be more likely to lobby together in associations as coordination on common political goals becomes easier. Alternatively, firms with politically coherent workforce might just engage in political action if gains from taking action are private (Bombardini and Trebbi, 2012; Hansen, Mitchell and Drope, 2005). Moreover, this paper adds to our understanding of indi-

[2]The overall number is actually 3,579,530 filings of 466,839 individuals working for 13,991 firms publicly listed firms. Since I look at the alignment between PACs and employees, I only use firms with data on both PAC and employee contributions in this paper. There is very little research combining campaign contributions data by firms and individuals. Bonica (2016*a*) only compare donations of CEOs to company PACs, and Babenko, Fedaseyeu and Zhang (2019) investigate whether CEO contributions influence donations of individuals working in the same firm.

vidual preference formation. Contrary to existing studies relying on stated preferences of employees, occupational characteristics such task routineness or offshorability are not associated with firm-employee alignment while sectoral and firm characteristics are (Iversen and Soskice, 2001; Owen and Johnston, 2017; Rehm, 2009; Rho and Tomz, 2017; Scheve and Slaughter, 2001). This does not invalidate the results of existing studies, but points towards qualitative differences between the factors influencing stated preferences often used in political economy research, and the rationales for political actions of already politically active individuals.

The rest of this paper proceeds as follows: the first part describes the literature relating firm, sectoral, and occupational characteristics to firm-employee alignment, and derives testable hypotheses. The second part describes the process of matching individual campaign contributions to firms and occupations. The third part shows descriptively the main dimensions of variation in the data and demonstrates that most of the meaningful variation is along industry lines and not across occupations. Then, I empirically analyze the relationship between asset specificity and employer-employee partisan alignment, and zoom in on donations to specific candidates. The final part concludes, discusses implications, and describes avenues for future research.

4.2 Theory

4.2.1 Asset Specificity and Firm-Employee Alignment

In Comparative and International Political Economy, a long line of research has tried to determine whether firms, sectors, or occupational characteristics are most decisive for the formation of individual political preferences on redistribution (Bechtel, Hainmueller and Margalit, 2014; Walter, 2017), risk assurance (Thewissen and Rueda, 2019), trade openness (Mayda and Rodrik, 2005; Scheve and Slaughter, 2001) or foreign direct investment (Margalit, 2012; Scheve and Slaughter, 2004). One of the most-debated factors in the literature has been *asset specificity* at the sectoral level, the occupational level, or the firm level (Alt et al., 1999; Alt and Gilligan, 1994; Iversen and Soskice, 2001).

First, In International Political Economy (IPE), canonical trade models predict that individual preferences will be determined by one's *sector of employment* (Frieden, 1991; Grossman and Helpman, 1994) or according to individual factor endowment (Rogowski, 1989). A combination of the Heckscher-Ohlin and Stolper-Samuelson theorem assumes that factors of production (labor and capital) are mobile across sectors and hence, all owners of the same factor are equally affected by changes in goods prices. The Ricardo-Viner model assumes that factors are highly specific to a particular industry and therefore, the fate of factor owners is closely tied to economic sectors. The extent to which we see coalitions in favor of or in opposition to free trade depends on the degree of asset specificity (Alt and Gilligan, 1994).[3] Asset specificity refers to the degree to which an asset can be redeployed to alternative uses without sacrificing its production value (Alt et al., 1999). For instance, if workers (labor) would have to sacrifice a sector-specific wage premium due to skills that are only useful in a particular sector, sectoral specificity is high and workers will find it costly to move to a job in a different industry. Workers are more 'stuck' in their workplace, more vulnerable to economic and political changes affecting their sector, and

[3]While the IPE literature refers to factor mobility (Hiscox, 2002*b*; Rogowski, 1989), the CPE literature uses the term asset specificity (Iversen and Soskice, 2001). Since one is the inverse of the other, I use both interchangeably from here on.

their economic interest will be more aligned with their employer. Therefore, under low mobility of labor, employee economic interests are more tied to their industry, and employees will be more likely to share the political preferences of their employer. Hence, the first hypothesis for this paper is the following:

> **Hypothesis 1**: *The higher specificity in a sector, the more politically aligned individuals are with their firm in terms of their campaign donations, all else equal.*

Most evidence on the impact of inter-sectoral specificity (low mobility) comes from the realm of trade policy. Hiscox (2002*a*) finds that congressional voting patterns on trade policy better reflect class-based cleavages during times of low specificity, and that sector-based considerations dominate in times of higher specificity. Mukherjee, Smith and Li (2009) extend this work and provide cross-national evidence that trade protection in majoritarian democracies is higher under low labor mobility because interests of voters are more aligned with the sector they work in. Similarly, Rickard (2009) shows that lower labor mobility (high labor specificity) is associated with more narrow distributive transfers and Zahariadis (2001) finds that more specificity is associated with more sector-specific subsidies.[4] There is also anecdotal evidence linking worker mobility to firm-employee political alignment. Hertel-Fernandez (2018, p.66) notes that companies who attempt to mobilize their workforce need to be careful when employees are highly skilled and mobile, as they might resist mobilization efforts and leave the

[4] Imai and Tingley (2012, pp. 230) use more sophisticated mixture models but find little evidence that factor mobility distinguishes well between class- and sector-based voting in Hiscox's original study, but concede that this could easily be due to the low number of bills under investigation. A more recent study by Zhou (2017) argues that labor mobility is (plausibly) not exogenous to political outcomes, but the result of left-wing parties seeking higher mobility when unions are decentralized.

company: “Managers are simply not in the position to send potentially controversial messages to [these] highly mobile workers”.

Second, the CPE and IPE literature equally identifies *firm-level* asset specificity as an important factor that might facilitate or hinder firm-employee political alignment. Based on research in transaction cost economics, the literature further distinguishes between physical specificity (the physical asset has specific design characteristics), site specificity (the value of assets is tied to the location), human asset specificity (relationship-specific human capital acquired via learning-by-doing), and dedicated assets (of a seller to a particular customer) (Joskow, 1988, pp.106-107). As before, more firm-level asset specificity means that firms are more vulnerable to changes in the regulatory environment and economic shocks since redeploying immobile assets is more costly. If firms are more vulnerable to regulatory changes due to high asset specificity, they are more likely to engage in corporate political activity such as lobbying, donations, or workplace mobilization, to minimize the risk that policies will hurt their economic interests (Sawant, 2012).[5] Moreover, if both labor and capital are firm-specific, both workers and managers potentially benefit more from the rents obtained through corporate political activity, and both realize higher losses in the case of adverse shocks. If employees are aware of the vulnerability of their firm to regulatory change (or economic shocks), they might support similar political candidates as their company to guarantee a friendly regulatory environment. Therefore, I expect that employees of firms with more specific assets are more likely to share the political preferences of their employer, leading to the following second hypothesis:

[5]Even though mobilizing employees to donate is not the most prevalent strategy of US firms documented by Hertel-Fernandez (2018), his survey results could under-estimate the mobilization of senior managers and executives, who are the most represented donor group in federal elections (Francia, 2003).

> **Hypothesis 2**: *The higher the share of specific assets of a firm, the more politically aligned employees are with their firm in terms of their campaign donations, all else equal.*

Alt et al. (1999) investigate the impact of asset specificity on firm-level lobbying and find that firms with more specific assets are more likely to engage in lobbying for subsidies. Given the immobility of their assets, firms are more likely to invest in corporate political activity to insure against un-wanted policies. Sawant (2012) argues that firms with high asset specificity have larger incentives to engage in corporate political activity when uncertainty or transaction costs in the political market are low.[6] Qualitative evidence also shows that firms with large investment in non-mobile physical assets are more likely to mobilize their employees. For example, an Ohio coal mining company required their employees take an unpaid day off to attend a rally of 2012 Republican Presidential candidate Mitt Romney. Participation was not formally enforced, but the company noted on lists who attended and who did not (Hertel-Fernandez, 2018, p.2).

Third, there is now a rich literature differentiating *occupational characteristics* from sectoral and firm characteristics as explanations for political preferences. More recent research has taken up the findings from labor economics on skill-biased technological change which disproportionally affects routine tasks occupations (Autor, Levy and Murnane, 2003), or used offshorability of occupations (Blinder, 2009; Blinder and Krueger, 2013) to predict individual preferences about redistribution, labor market risks,

[6]For example, Gehl and Porter (2017) analyze the US political system from a market competition perspective and argue that it is a duopoly that serves only the two major US parties. With most House and Senate elections being uncontested, one could argue that the current US political system is provides such a low-uncertainty environment. Kim and Kung (2017) also demonstrate that after shocks or uncertainty-inducing events, firms with less specific assets find it much easier to redeploy capital to more productive uses and recover faster.

and trade policies (Kitschelt and Rehm, 2014; Owen and Johnston, 2017; Thewissen and Rueda, 2019; Walter, 2017).[7] The varieties of capitalism (VoC) literature also puts skill specificity at the core of its theoretical edifice (Iversen and Soskice, 2001). Under certain institutional conditions (Hall and Gingerich, 2009), workers and firms tend to invest in so-called co-specific skills that can only be used in a particular industry or firm. Having invested in these co-specific skills, workers cannot easily move to other sectors without a pay-cut.[8] While skills that can be employed in any firm are considered general, those that cannot be carried from one firm to another are specific (Becker, 1993, pp.33-40). The investment in specific skills makes it rational for employees to demand more redistribution as an insurance against longer unemployment spells, demand more job security, and for employers to offer longer job tenure to benefit from the investment in skill formation. This leads to more strategic coordination between firms and employees in coordinated market economies, and more market-based coordination in liberal market economies (Hall and Soskice, 2001*a*).[9] While the original VoC argument is about cross-national variation in specificity, the same argument can easily be applied to variation within countries (Hall and Gingerich, 2009, p.452). Individuals with specific skills are more closely tied to the fate of their sector or firm and are thus more likely to support similar political candidates as their employer.[10] Hence, my third hypothesis is the following:

[7]Note that at its core, offshorability can also be seen as a case of low asset specificity since it implies mobility of capital across borders. In separate empirical tests I also include widely-used measures of offshorability (Blinder, 2009) and task routineness (Acemoglu and Autor, 2011), and do not find any impact on partisan alignment.

[8]According to the VoC literature, the early investment in specific skills of employees was decisive for consensus between workers and employers in the introduction of proportional representation in coordinated market economies (Cusack, Iversen and Soskice, 2007). See Korpi (2006) for dissenting views highlighting conflictual nature of the cleavage between capital and labor (Lipset and Rokkan, 1967).

[9]See Streeck (2011) for a critique of the distinction between general and specific skills, and the political economic implications thereof outlined by the VoC literatire.

[10]This is an extension of the sector-based argument made above. In sectors with high specificity (e.g. low labor mobility), occupational skills will tend to be more specific.

> **Hypothesis 3**: *The higher the skill specificity of individual's occupation, the more politically aligned individuals are with their firm in terms of their campaign donations, all else equal.*

There is ample evidence on the impact of occupational characteristics on political preferences. Individuals with more specific skills demand more employment protection (Iversen and Soskice, 2001) and more redistributive social policies (Rehm, 2009). With regards to the impact of occupations in general, Owen and Johnston (2017) find that occupations focusing on routine tasks are more inclined to oppose free trade if they are more easy to offshore, and Walter (2017) shows that education and occupational offshorability shape labor market risk perceptions. Hertel-Fernandez (2018, pp.65-66) notes that within companies, occupations and positions in the firm hierarchy are associated with how susceptible employees are for mobilization efforts of employers. For example, high-demand occupations like research scientists are described as being less responsive to company political messages than more easily replaceable administrative and support staff.

Finally, even though I propose a positive relationship between asset specificity and partisan alignment, the relationship might not be the same for Democratic and Republican partisan alignment. In the US, the Democratic party has historically been the party that was more supportive of the interests of labor, whereas the Republican party has been more representing capital interests. For example, Democrats have a long-standing positive relationship with labor unions (Dark, 2001) while Republicans have historically opposed unions (Ahlquist, 2017). Most recently, Republican states have been quite active in passing right-to-work laws which have effectively weakened unions across the US (Feigenbaum, Hertel-Fernandez and Williamson, 2018). Moreover, even though most US companies split their donations between both parties, they also tend to have a slight Republican bias (Tripathi, Ansolabehere and Snyder, 2002), on average.[11] Therefore, I expect there to be a stronger positive relationship between firm-level asset specificity and Republican alignment, and a stronger, negative relationship between sectoral labor mobility and Republican alignment than with Democratic alignment.[12]

4.2.2 Employee and Firm Motivations for Political Donations

Individuals might have different motivations to donate than their company PACs. While the donations of PACs are typically conceived to be more strategic, with companies often splitting donations more or less equally between parties, individuals are often seen as merely expressing their personal ideology. However, for individuals to base contributions on their firm, sector, or occupation, I need to assume that employees are at least somewhat rational and self-serving in their donations.

On the one hand, a prominent line of research on campaign contribution argues that donations are too small (Milyo, Primo and Groseclose, 2000) and that there is too little evidence of political returns on donations for them to be strategic investments (Ansolabehere, de Figueiredo and Snyder, 2003). Similarly, Bartels (2008) contends that individuals routinely vote against their objective economic preferences. In addition, Rho and Tomz (2017) show that individual preferences on free trade and protectionism are less in line with their economic interest if they are not educated about the potential

[11] In the data used for this paper, firms spend on average 60% of donations on Republican candidates, and 40% on Democrats.
[12] This is not the main focus of this paper, but I provide additional evidence on the specific partisan direction in the appendix.

negative or positive effects of trade. On the other hand, there are reasons to believe that (donating) employees are at least somewhat rational. I focus on individual donations, and donors are not a random sample of the US population. On average, they have higher income and are more educated (Francia, 2003). Moreover, there is ample evidence that politically organized employers communicate their political preferences to their employees, or mobilize them to contact legislators or accompany company lobbyists on visits to Washington DC (Hertel-Fernandez, 2018). Further, recent research on campaign donations shows that donations strategically flow across state borders to competitive districts (Gimpel, Lee and Pearson-merkowitz, 2008), and that donors tend to give to politicians with similar political views or with jurisdiction over their sector of employment (Barber, Canes-Wrone and Thrower, 2017). Considering these findings, it increasingly difficult to support the notion that donations of individuals are merely consumption.

Employees also need to be aware of the donations of their company PACs to donate to the same party or the same candidates. While public opinion scholars often highlight the ignorance of voters (Zaller, 1992), work on chief executives has shown that employees start donating to candidates after their company CEO donated to the same candidate, pointing to signaling by well-known company representatives (Babenko, Fedaseyeu and Zhang, 2019).Li (2018) also provides evidence that employees react to the donations of their company PAC. She finds that donors reduce the contributions to their firms' PAC if their firm donates too much to candidates that are at odds with those employees' ideology. This work highlights the different strategic and ideological incentives faced by firms and employees, but also shows that employees pay attention to PAC donations.[13]

4.3 Empirics

4.3.1 Data Linking Firm and Employee Campaign Donations

For this paper, I use new data matching employee to corporate political donations using US campaign finance data from the Federal Election Commission (FEC). The FEC data contains information on corporate PAC contributions to federal candidates and individual donations to candidates. Moreover, the individual data contains the donor name, employer, occupation, and address. I describe in detail how I match individuals to their companies in Chapter 3 of this dissertation. The matched firm-employee donations data contains 3,537,187 filings of 466,840 individuals, working for 13,991 firms in 850 occupations between 2003 and 2016. For this paper, I limit the investigation to the time period from 2003 to 2016, because occupation data is only available from 2003 onwards. I only use companies for which I observe both firm and employee donations, which leaves me with 1,691,790 campaign contribution filings of 85,109 individuals, working in 874 publicly listed firms and 850 occupations.

The data has two unique features that make them well-suited for analyzing the impact of specificity on firm-employee alignment. First, they contain unique identifiers at the level of the firm (Compustat GVKEY),

[13]One important limitation of Li's study is that the study does not specify which kind of employees react to changes in PAC donations. For example, senior managers might be more aware of changes in PAC donations than rank-and-file employees.

the sector (NAICS), and the occupation (SOC). Thus, the data allow for clear differentiation of levels of analysis which are treated as analytically and empirically different in the Political Economy (Owen and Johnston, 2017; Walter, 2017) and Labor Economics (Acemoglu and Autor, 2011), but not in American Politics (Barber, Canes-Wrone and Thrower, 2017; Bonica, 2014). The availability of both firm and occupation-level identifiers allows me to test the impact of occupational-, firm- as well as sector-level asset specificity on political alignment between firms and employees. Second, the data enable me to identify of individual preferences via employee actions (donations). Thus, I do not rely on stated preferences as does virtually all the IPE and CPE research on individual preferences on trade, investment, or redistribution.[14]

4.3.2 Alignment across Firms, Sectors, and Occupations

I use the matched firm-employee campaign finance data to measure the partisan preferences of employees and their employers. I approximate these preferences with the party of the candidates that they donate to. Then, I calculate from these donations a time-varying measure of alignment. I use partisanship for two reasons: first, especially in the US context, partisanship is highly correlated with many specific policy preferences of interest in IPE and CPE, such as preferences for redistribution, regulation, health care, or trade policy (Bafumi and Shapiro, 2009; Cusack, Iversen and Rehm, 2006; Mansfield and Mutz, 2009). Thus, the partisanship of donations can be viewed as indicative of the broad policy preferences of individuals. More-

[14]For a selection of this literature see, among others, Ardanaz, Murillo and Pinto (2013); Baker (2005); Bechtel, Hainmueller and Margalit (2014); Iversen and Soskice (2001); Margalit (2011, 2012); Mayda and Rodrik (2005); Naoi and Kume (2015); Rehm (2009); Scheve and Slaughter (2001, 2004), and Thewissen and Rueda (2019). Kuo and Naoi (2015) provides an excellent overview on the literature on individual-level trade preferences.

over, donors are usually one-sided partisan supporters (Bonica, 2014; La Raya and Schaffner, 2015). Only two percent of the individuals in my sample donate to both sides of the isle, which makes partisanship a good indicator for broad policy positions. Second, there are severe limitations with regards to the availability of data on specific policy positions of candidates. While there is some data on policy reforms or individual issues such as support for North American Free Trade Agreement[15], issue position data are only available for a limited number of candidates. Moreover, even simple measures like left-right ideology are problematic. DW-Nominate scores are only available for current Senate and House members, but not for challengers and new candidates. The ideology scores by Adam Bonica (Bonica, 2016*b*) cover both elected and non-elected candidates, but are themselves a function of individual and PAC donations, and thus, are of limited use to explain donations themselves.

Therefore I focus on partisanship in this part of the paper and analyze donations to specific candidates in a later section. The main dependent variable, partisan alignment between firms and their employees, is calculated as:

$$Alignment_{ict} = 1 - \quad \frac{R_{jt}}{(R_{jt} + D_{jt})} - \frac{R_{ijt}}{(R_{ijt} + D_{ijt})}$$

[15]Some of those are available at On the Issues (http://www.ontheissues.org/) or Project Vote Smart (https://votesmart.org/), but issue position data is not available for most candidates, or in the case of voting records for key bills, only available for candidates who make it into office. Barber, Canes-Wrone and Thrower (2017, p.275) used various sources to determine the positions of candidates in 22 races. Unfortunately, this would be impossible to do manually for the 4667 candidates in my sample.

where R_{jt} and D_{jt} are Republican and Democratic donations of firm j in year t, while R_{ijt} and D_{ijt} are Republican and Democratic donations of individual i working for firm j in year t, respectively. This variable ranges from zero to one, where larger values indicate more partisan alignment between employee and a firm in a given year. Intuitively, some company PACs donate more to one of the two parties while some PACs donate equally to both parties. The measure will be larger if an employee donates to one party and the employer gives a higher proportion of donations to the same party, and less so if they donate to the opposite sides of the isle. Figure 3.3 in Chapter 3 showed the distribution of alignment in my data. Alignment is approximately normally distributed, with most observations around the mean of 0.53 (median 0.52). Around 2000 observations show complete non-alignment (corresponding to 1531 individuals) and 4000 observations (corresponding to 2906 individuals) show complete alignment.[16]

This means there can be very high alignment when PACs donate very one-sided, but also very low alignment if most employees of the same company donate to the opposite party. What are the patterns of partisan alignment across sectors, firms and occupations in the matched employer-employee data? First, as Figure 3.4 in Chapter 3 shows, average alignment is highest in extractive and primary resources industries like metal and rubber, while the lowest alignment can be seen in publishing, food, and information services. This translates into specific companies in panel b). Timken, Marathon Petroleoum, and Devon Energy are most alignment between employees and company PAC, and J.P. Morgan, Time Warner, and Vmware are least aligned. It seems quite striking that the companies and sectors with large sunk investment in site-specific structures and physical assets

[16] In Tables B.3 and B.4 I show that all the main results of this paper hold excluding the extreme cases in the data where alignment is 0 or 1.

(machinery) are the ones that are most aligned, while services industries seem to be less aligned, on average.[17]

Second, how does alignment between individual and firm contributions vary across all industries? In Figure 4.1, I plot the distribution of average individual alignment for each 3-digit NAICS industry in the data. The plot reveals that there is substantive variation in alignment across and within sectors. Heavy industries and extractive industries are much more aligned, with alignment larger than 0.6, on average. Many services industries like information services, merchandise stores, broadcasting, but also some manufacturing industries like food or chemical manufacturing seem to be much more split between the two parties, with alignment scores closer to 0.5.

Third, how does the large variation across industries compare to the variation across occupations? Below in Figure 4.2, I plot the distribution of alignment across 23 two-digit SOC occupations. There is actually little variation in alignment across occupations as different as management, legal services, construction, extraction workers, or personal care.

In Figure B.2 in the appendix, I show the same pattern of non-variation across 96 more fine-grained three-digit SOC occupations. While there is more variation in Figure , there is still much less divergence in alignment between different occupations than between industries. Some might argue that the differences across industries might simply be driven by geography: certain sectors might be located in red (or blue) states, and these states might happen to have a more politically aligned population of donors.[18]

[17]The exception is Expedia wich is also very aligned. Both Expedia's PAC and employees donate mostly to Democratic candidates.

[18]In Figure B.3 in the appendix, I show that even though there might be a role for geography in determining alignment, it might not be as large one might think. There is less variation in alignment across the 50 US states than across industries. Despite some states like Oklahoma, South Carolina, and Wyoming showing more alignment between employees and firms than other states, most states are closer to alignment scores of 0.5.

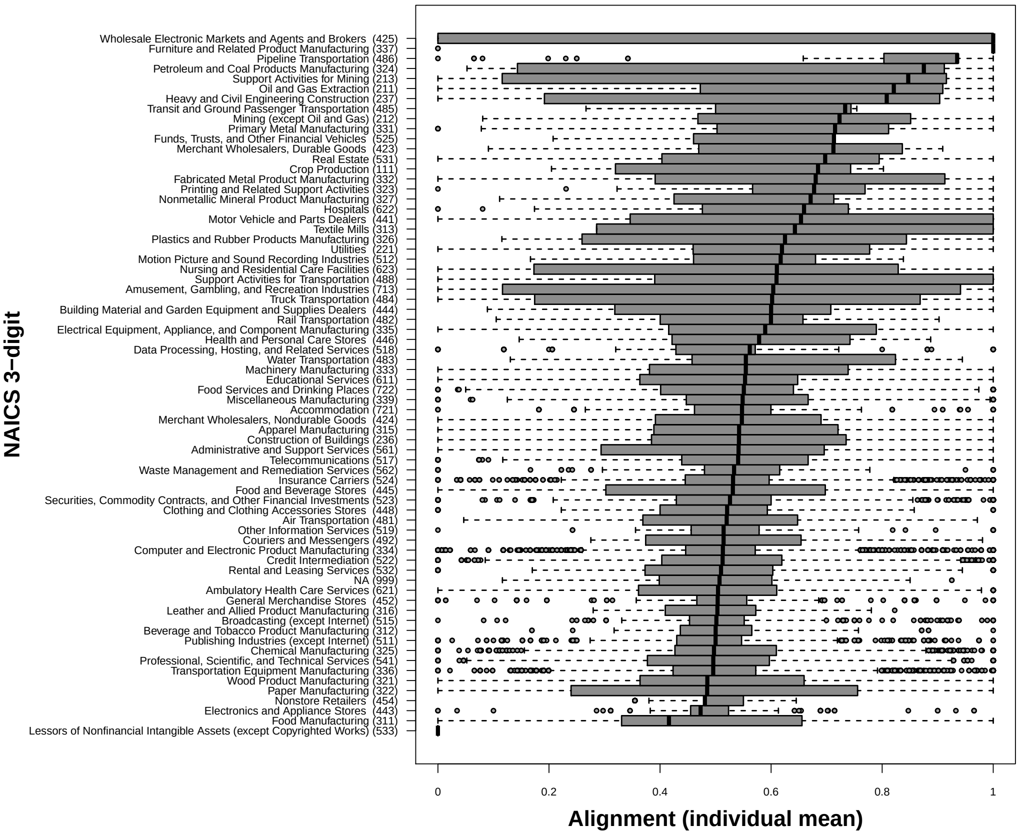


Figure 4.1 Strong Variation in Alignment across 3-Digit NAICS Industries. The boxplot shows that there is strong variation in alignment across 3-digit NAICS industries (3-digit industry codes in parentheses) Heavy and extractive industries are most aligned while most services industries are less aligned. Data: own calculations.

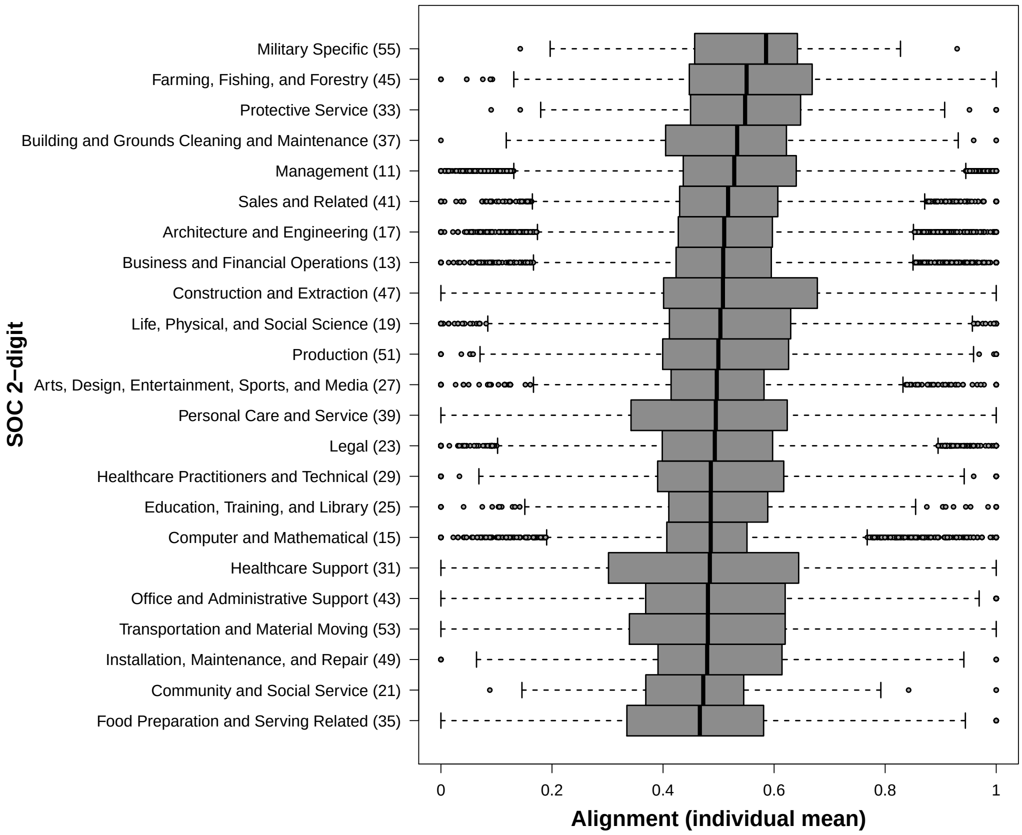


Figure 4.2 Weak Variation in in Alignment across Occupations. The plot shows that there is very little variation in alignment across 2-digit SOC occupations of donors. Data: own calculations.

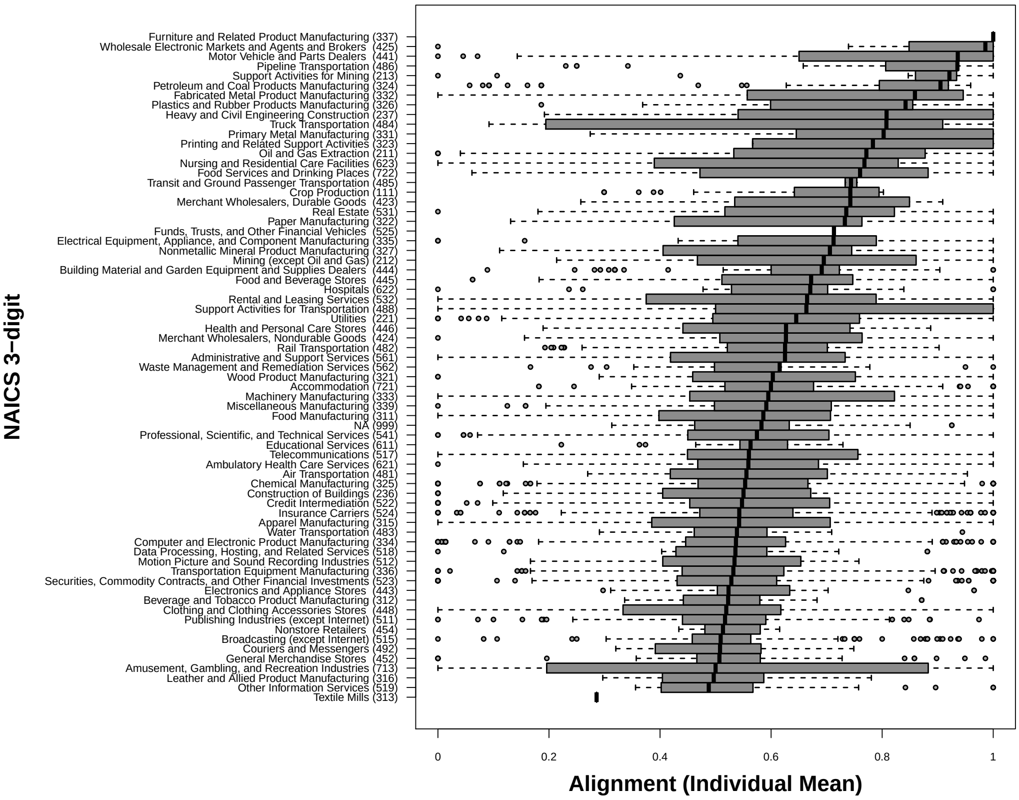


Figure 4.3 Strong Within-Occupation Variation in Alignment across Industries. The boxplot depicts the strong within-occupation variation in alignment for one specific occupation (chief executives, SOC Code 11-1011) across 3-digit NAICS industries (3-digit industry codes in parentheses). Data: own calculations.

Finally, there is significant variation *within* individual occupations *across* industries. Figure 4.3 depicts the same three-digit NAICS distribution of alignment as before, but this time for only one occupation, in this case chief executives and presidents (SOC 11-1011). In fact, the differences in alignment are even starker than pooled across occupations, ranging from approximately equal donations of companies and employees to both sides of the isle in broadcasting and couriers services (median alignment of 0.5) to more than a 0.8 alignment in petroleum, coal, and pipeline transportation. This goes partly against the argument put forward by Bonica (2016*a*) that CEOs are mostly ideological and not strategic in their contributions. In fact, heir contributions seem to vary systematically with the industry in which they are employed.[19]

This pattern becomes even clearer if we only concentrate on manufacturing industries (NAICS 31 - 33). Figure 4.4 below shows that even within manufacturing industries and within the same occupation, there is a trend towards more alignment in industries related to resource extraction and raw materials, i.e. in industries with highly specific physical assets. Further, in Figure B.1 in the appendix, I show that this pattern is not specific to chief executives. Very similar alignment distributions can also be observed in other occupations like lawyers, agricultural engineers, and (with some limitations) IT specialists.

This initial inspection of the data reveals that there is significantly more variation in alignment across industries (and only a bit more across states) than there is across individual occupations. Hence, *where people work seems to matter more than what people do*, in terms of whether they share the same parti-

[19]This is more coherent with strategic CEO donations as observed by Babenko, Fedaseyeu and Zhang (2019), even though they do not hypothesize about differences in strategies across different industries.

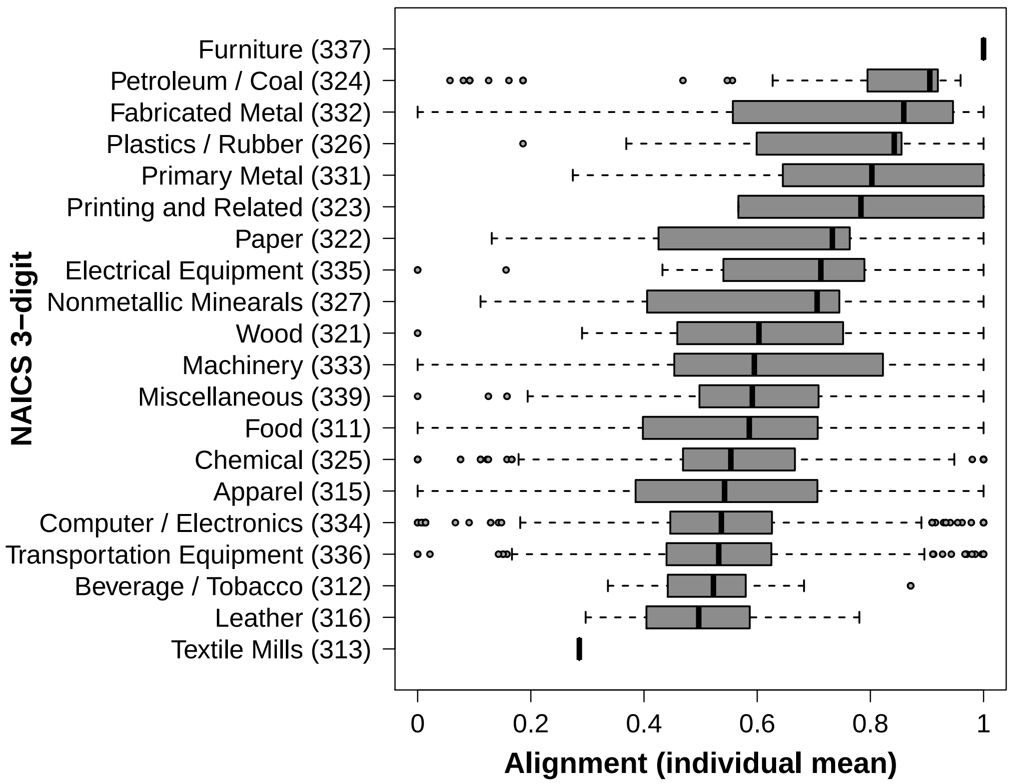


Figure 4.4 Strong within-Occupation Variation in Alignment across Manufacturing Industries. The graph shows that within one narrow occupational group (chief executives, SOC Code 11-1011) there is substantive variation in alignment across 3-digit manufacturing industries. CEOs in extractive industries and energy industries tend to be most aligned, and computer and chemical industries less. Data: own calculations.

sanship with their employer. This is in itself a surprising finding considering the long line of research which argues that occupational characteristics are important sources of political preferences. However, individual occupational characteristics within firms seem not to be as important for donation-based partisan alignment. In sum, the main message from the data is that sectoral models of individual preference formation might still be valuable, despite a recent push towards occupation-based models.[20]

4.3.3 Measuring Specificity: Firms, Sectors & Occupations

For measuring sector-level asset specificity, I use a measure of labor mobility (Alt et al., 1999) which is calculated as $LM_{kt} = \frac{JG_{kt}+JL_{kt}}{L_{kt}}$, where JG_{kt} are job gained in industry k in year t, JL_{kt}, are job lost, and L_{kt} are overall jobs in a sector, taken from the Statistics of US Businesses (SUSB) tables, published by the US Census Bureau. Hence, LM_{kt} measures the overall relative job turnover in a given sector-year, one important indicator of specificity (Cusack, Iversen and Soskice, 2007; Hall and Soskice, 2001*a*). The measure ranges from 0 to 1, where 0 indicates the absence of mobility and 1 indicates full mobility. Hence, more mobility implies less human capital specificity. I show the distribution of this variable in Panel a) in Figure 4.5 below. One can see that it is approximately normally distributed, if somewhat right-skewed.[21] The average labor mobility is 0.28 in the sample, which is slightly higher than the country-wide average of 0.26 between 2003 and 2015. The most mobile 3-digit NAICS sectors across 2003 and

[20]In separate tests, I did not find a significant relationship between partisan alignment in donations and different measures of offshorability and job routineness from Acemoglu et al. (2015) or Blinder and Krueger (2013), both used in the study by Owen and Johnston (2017). If there is any relationship in the aggregate, it is driven by CEOs (low offshorability in the data) and disappears once I control for this single occupation.

[21]One caveat of this measure is that the SUSB tables only become available after some delay, so the measure ends in 2015 at the moment.

2015 in the data are Information Services and Data Processing Services (514), Broadcasting and Telecommunications (513), Data processing, hosting, and related services (518), and Construction of Buildings (236). The least mobile are Central Banks and Monetary Authorities (521), Hospitals (622), Paper Manufacturing (322), and the Petroleum Sector (324). One can easily identify some of the most (e.g. Petroleum) and least (e.g. Data Processing) aligned sectors from the descriptive analysis above.[22]

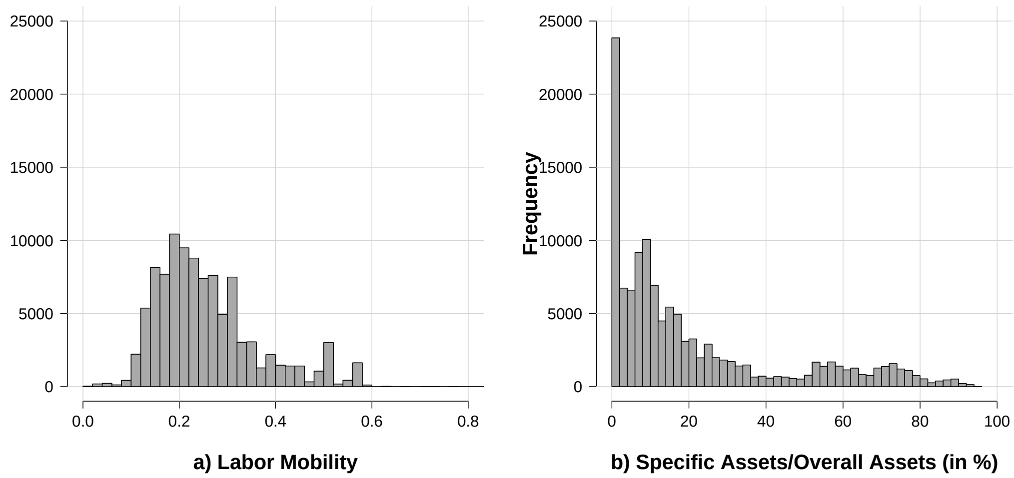


Figure 4.5 Distribution of Sector- and Firm Specificity. Panel a) shows the distribution of Labor Mobility across 4-digit NAICS sectors. Panel b) depicts the distribution of specific assets as a share of overall assets at the firm level. Source: Compustat Capital IQ North America, Statistics of US Businesses (SUSB).

For firm-level specificity, I use a combination of site specificity and physical specificity (Joskow, 1988, pp.106-107). I measure asset specificity as firm-level plant, property and equipment expenses as a share of overall firm assets, $(PPENT_{jt}/AT_{jt})$, both taken from Compustat.[23] Below in Panel

[22]Note that I also found highly aligned information technologies firms above (Expedia), while most of the information technology firms have rather low alignment. Therefore, this measure might underestimate specificity in sectors with stringent occupational licensing (hence, high specificity) but not necessarily long-term contracts (such as hospitals), or in sectors with high use of non-compete contracts (such as technology firms).

[23]I do not use R&D expenditures as a measure of asset specificity, as does former work Alt et al. (1999). R&D expenditure data are missing for over 60% firm-year observations in Compustat. Moreover, at the industry level R&D expenditure is often only available at the very rough 2-digit NAICS level or it is missing altogether. Ideally, I would also use

b) of Figure 4.5, I show the distribution of asset specificity in my data. Which companies have high and low specificity, respectively? Companies with a very high share of specific assets in the data include oil and gas extraction companies like Whiting Petroleum (alignment: 0.79, asset specificity: 91.3) and Chesapeake Energy (alignment: 0.69, asset specificity: 87.7), or the pipeline transportation firm Energy Transfer Partners (alignment: 0.84, asset specificity: 68.1). Firms with very low asset specificity include Fannie Mae (alignment: 0.53, asset specificity: 0), the insurance carrier MetLife (alignment: 0.52, asset specificity: 1.2), chemical manufacturer Celegne (alignment: 0.5, asset specificity: 3.7), or the professional services consultancy SRA International (alignment: 0.53, asset specificity: 4.1).

Level	Explanatory Variable	Measurement	Source	Expected Sign
Sector	*Labor Mobility*	$LM_{kt} = \frac{JG_{kt}+JL_{kt}}{L_{kt}}$	SUSB	$-$
Firm	*Asset Specificity*	$(PPENT_{jt}/AT_{jt})$	Compustat	$+$
Occupation	*Skill Specificity*	Skill Specificity	Iversen and Soskice (2001) Cusack, Iversen and Rehm (2006)	$+$

Table 4.1 Main Explanatory Variables and Expected Signs: This table depicts the measures for asset specificity at the sector-level, firm-level, and occupation-level, their sources, and the expected signs. LM_{kt} is labor mobility, where JG_{kt} are job gains in industry k in year t, JL_{kt} are job losses, and L_{kt} are overall jobs. $(PPENT/AT)$ are plant, property and equipment expenses as a share of overall firm assets.

Finally, I measure specificity at the occupational-level using the measure of skill specificity by Iversen and Soskice (2001) and Cusack, Iversen and Rehm (2006), calculated from individual-level response data from the International Social Survey Project and OECD labor force statistics. It measures the specialization of individual skills in an occupation relative to total skills or general skills. The original measure is at the ISCO-88 classification of occupations and matched to US SOC codes for this paper. I use the stan-

firm-specific investment in training and skills of employees but such data is not available either.

dardized version of the measure which ranges from zero to 4.5, and recode it into a binary measure which scores 1 if specificity is above the mean value of the continuous skill specificity measure, and 0 if it is below the mean. All the results shown below are identical using the continuous measure instead. Overall, 30 percent of my sample exhibit a high skill specificity, and 70 percent have a low occupational skill specificity. The main independent variables at the sectoral-, firm-, and occupational level used in the analysis part are summarized in Table 4.1.

4.3.4 Analysis: Specificity and Individual Alignment

In this section, I empirically analyze the impact of asset specificity on partisan alignment between employees and their company in terms of their campaign contributions. First, I show that employees in sectors with high asset specificity are more inclined to share the partisan preferences of their employer. I do not find the same result for skill specificity at the occupational level, indicating that where individuals work seems to matter more for the partisan alignment with their employer than the jobs they have in a company. Second, I explore in more detail the mechanism behind the observed firm-employee alignment, and test the impact of firm donations on employee donations to specific candidates.

Figure 4.6 shows the relationship between specificity at the sectoral-, firm-, and occupational level and alignment between firms and employees. Panel a) depicts a negative association between labor mobility and alignment as hypothesized above. However, the correlation between the two variables is also rather weak (-0.137). Panel b) plots firm-level asset specificity as defined above against average firm alignment showing a stronger, positive relationship. In Figure B.5 and B.6 in the appendix, I partition alignment by

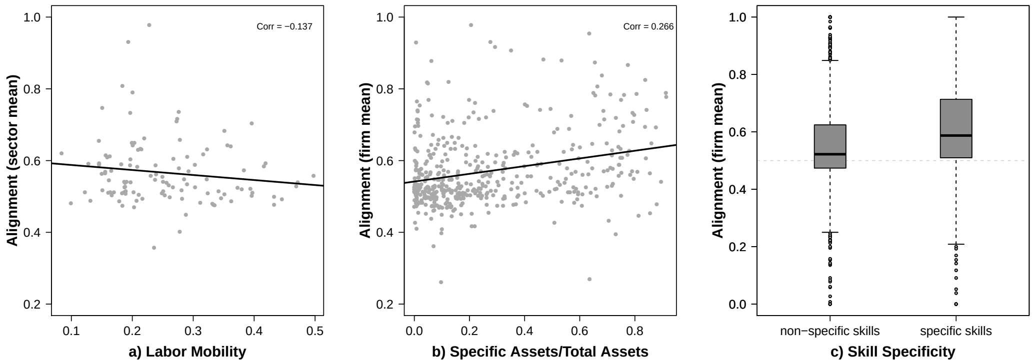


Figure 4.6 Relationship between Specificity and Partisan Alignment across Sectors, Firms, and Occupations. These plots shows the relationship between the three main explanatory variables and partisan alignment between firms and employees. While labor mobility as an inverse measure of specificty shows a weak negative relationship, both firm-level asset specificity and skill specificity are positively related to firm-employee alignment. Source: Iversen and Soskice (2001) and own calculations.

partisanship and show that the negative relationship between mobility and alignment and the positive correlation between asset specificity and alignment are driven by Republican alignment. Labor mobility (asset specificity) and aligning on a Republican candidate are strongly negatively (positively) related. Conversely, Democratic alignment correlates positively (negatively) with labor mobility (firm asset specificity). While I do not explore the partisan mechanism here, a plausible explanation could be that the Democratic Party has historically been more aligned to labor-intensive industries and labor unions. Moreover, since corporate PACs have a conservative bias, on average, it seems intuitive that a larger portion of firm-employee alignment is Republican and hence driving results. Panel c) shows that skill specificity is associated with a a 6% increase in alignment. Across all individuals, the mean level of alignment is 0.51 when skill specificity equals 0 and 0.57 when skill specificity equals 1.

Table 4.2 includes descriptives of the main variables used in the following analysis. Motivated by the initial descriptive results shown above, I am

Table 4.2 Summary Statistics

Statistic	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Year	138,549	2010.39	4.04	2003	2016
Partisan Alignment	138,539	0.53	0.19	0.00	1.00
Democratic Alignment	138,549	0.20	0.40	0	1
Republican Alignment	138,549	0.35	0.48	0	1
Share Specific Asset	122,657	0.21	0.23	0.00	0.94
Labor Mobility	101,133	0.26	0.11	0.00	0.94
Skill Specificity	117,885	0.31	0.46	0	1
log(Median Annual Income)	111,634	11.39	0.45	9.58	12.24
log(Employees)	121,601	3.77	1.31	0.00	7.74
log(Sales)	126,109	9.90	1.41	−0.28	13.09
log(Capital Expenditure)	124,645	6.41	2.00	−0.06	10.44
log(Cost of Goods Sold)	126,110	9.15	1.52	0.00	12.78
log(Expenses for Plant/Property)	122,267	8.26	1.87	0.00	12.44
Productivity	120,601	−0.10	0.69	−4.89	6.19
Union Membership (in %)	124,419	8.30	11.19	0.00	72.90
log(# Regulatory Restrictions)	84,068	7.93	1.56	5.27	10.49
Herfindahl-Hirschman (geographic)	120,057	0.16	0.20	0.00	1.00
Red State (Presidential Vote)	123,272	5.82	2.05	1.50	28.80

interested in the relationship between partisan alignment between firms and employees and specificity at the sectoral-, firm-, and occupational level. I expect that more specificity at a given level of analysis will be related to more alignment between employees and companies, holding constant the other levels of analysis. Therefore, for the first empirical specification, I estimate the following linear model, regressing individual alignment on firm- and sectoral asset specificity, using occupation and year fixed effects:

$$Alignment_{iojst} = \alpha_o + \theta_t + \gamma Specificity_{jt} + \beta Z_{jt} + \delta I_{iot} + \tau R_{st} + \epsilon_{iojst}$$

where alignment is measured for employee i in occupation o working in firm j living in county c in state s, with t denoting year. The α_o refers to occupation fixed effects, and θ_t to year fixed effects. My coefficient of interest is γ, the degree of asset specificity. In the initial specification, I control for a host of firm-level factors like log sales, employment, cost of goods sold, capital expenditure, and firm productivity[24], contained in the matrix Z_{jt}. Moreover, I control for the log of the occupation-specific median income from the Bureau of Labor Statistics, I_{iot}, and for R_{ist}, whether the state an employee lives in is Republican or Democratic, according to the presidential vote share from the respective election.

The main specification in column 1 in Table 4.3 shows that there is a strong positive relationship between the share of firm-specific assets and individual partisan alignment. Holding constant SOC occupation and several controls, a one-standard-deviation increase in asset specificity (a 0.23 increase) means a 0.015 (or 1.5%) increase in alignment. This is a significant increase given that most firms are located around the 0.5 alignment score mark. A larger two-standard deviation increase in asset specificity would be associated with a 3% increase in alignment. Conversely, the relationship between labor mobility (as an inverse measure of specificity) is shown in Column 4 in Table 4.3 and is negative and significant, as expected. The substantive effect is smaller than the firm-level asset specificity. A one-standard deviation increase in labor mobility is associated with a 0.007 decrease in alignment. I sequentially introduce 2-digit industry and county-level fixed effects, to account for unobserved and time-invariant geographic factors and larger industry-level differences, respectively. The results are remarkably stable, even though controlling for geography slightly reduces the impact of firm-level asset specificity and sectoral labor mobility. The coefficient for Republican states is positive and significant, indicating that living in a Republican-voting state increases alignment by 0.031, on

[24]Productivity is measured by estimating the Solow-residual, i.e. by regressing (logged) sales on employment and expenditures for plant, property and equipment, as well as industry and year fixed effects (Bilir, 2014). The resulting residual is my measure of productivity.

average. As expected from the theoretical discussion and descriptives in Figures B.6 B.5, this result seems to be driven by firms and employees being aligned on Republican candidates. In sum, being in a firm with high asset specificity is almost as predictive of alignment as the state individuals live in. Furthermore, I test for the impact of skill specificity on alignment between firms and employees in Table 4.4 below. Controlling for firm- and county-level fixed effects, the results suggest a positive effect of skill specificity on alignment. Within the same firm and county, employees employed in a skill-specific occupation are approximately 2% more aligned than employees in a non-specific occupation. However, because there is a strong correlation between skill specificity and the occupational category of chief executives (SOC 11-1011), I include a binary measure for whether an employee is a chief executive in columns 3 and 4. This eliminates virtually all the relationship between skill specificity and alignment. While I find a strong association between sectoral and firm-level specificity and alignment, I do not find support for occupational skill specificity.[25]

I also find that firms with more employees are less aligned, on average. This is an interesting result in itself that is in line with the expectation that collective political actions is more difficult in larger groups because of higher likelihood of free riding (Hansen, Mitchell and Drope, 2005; Olson, 1965). While larger firms might be potentially more powerful, they are also more likely to have more politically heterogeneous employees which would reduce alignment, confirming work on how group size and heterogeneity (or cohesiveness) of preferences inhibit or foster collective action (Ostrom,

[25]Because their compensation most often depends on company profits, it is not surprising that CEOs and Presidents of companies are significantly more aligned with their company, as also shown in the descriptives above.

Table 4.3 Regression Results: The Effect of Specificity on Partisan Alignment, Firms and Sectors

	Dependent variable:					
	Align					
	(1)	(2)	(3)	(4)	(5)	(6)
Share Specific Assets (firm)	0.068***	0.070***	0.036**			
	(0.017)	(0.026)	(0.015)			
Labor Mobility (sector)				−0.063**	−0.098***	−0.043*
				(0.029)	(0.035)	(0.024)
log(Capital Expenditure)	0.003	0.002	0.002	0.008***	0.002	0.004*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
log(Sales)	−0.005	−0.005	−0.002	−0.012**	−0.007	−0.003
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
log(Employees)	−0.016***	−0.015***	−0.014***	−0.023***	−0.023***	−0.019***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.006)	(0.004)
log(Cost Goods Sold)	0.003	0.002	−0.001	0.010**	0.009	0.003
	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)	(0.004)
Productivity	−0.0001	−0.004	−0.001	−0.007	−0.017***	−0.007**
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
log(Med. Income)	−0.045	−0.047	−0.032	0.029	0.029	0.042
	(0.031)	(0.031)	(0.030)	(0.033)	(0.034)	(0.035)
Red State (1/0)	0.031***	0.030***		0.037***	0.032***	
	(0.005)	(0.004)		(0.006)	(0.006)	
Year FEs	✓	✓	✓	✓	✓	✓
Occupation FEs	✓	✓	✓	✓	✓	✓
NAICS 2-digit FEs		✓			✓	
County FEs			✓			✓
Observations	95,220	95,220	85,524	74,576	74,576	67,117
Adjusted R^2	0.085	0.089	0.133	0.065	0.073	0.120

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm are in parentheses.

Table 4.4 Regression Results: The Effect of Skill Specificity on Partisan Alignment, Occupations

	Dependent variable:			
	Align			
	(1)	(2)	(3)	(4)
Skill Specificity (1/0)	0.019***	0.019***	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Chief Executive (1/0)			0.042***	0.042***
			(0.005)	(0.005)
log(Capital Expenditure)	0.009***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
log(Sales)	0.021	0.026	0.021	0.025
	(0.018)	(0.019)	(0.019)	(0.019)
log(Employees)	−0.010	−0.009	−0.011	−0.010
	(0.032)	(0.033)	(0.032)	(0.033)
log(Cost Goods Sold)	−0.023	−0.027	−0.022	−0.026
	(0.016)	(0.017)	(0.017)	(0.017)
Productivity	−0.014	−0.014	−0.014	−0.014
	(0.023)	(0.023)	(0.023)	(0.023)
log(Med. Income)	0.020***	0.022***	0.006	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Red State (1/0)	0.023***		0.023***	
	(0.003)		(0.003)	
Year FEs	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓
County FEs		✓		✓
Observations	94,951	85,284	94,951	85,284
Adjusted R^2	0.164	0.187	0.167	0.189

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by firm are in parentheses.

2010). For future research, it would be interesting to investigate the potential interaction between political preference heterogeneity in firms and firm size.

Of course, there are *alternative explanations* for why individuals might donate to the same party as their employer, which I explore in Table B.1 and B.2 in the appendix, using the main specification from Column 1 and 4 above. Hertel-Fernandez (2018) notes that when individuals live in a region with higher unemployment, they are more likely to become politically active for the company because they are more fearful of retaliation if they do not follow company demands. Therefore, I control for the annual county-level unemployment rate taken from the Local Area Unemployment Statistics (LAUS), published by the Bureau of Labor Statistics.[26] The coefficient on the unemployment rate is negative and significant, which suggests that the mechanism proposed by Hertel-Fernandez does not hold for donations. The results in this paper indicate that those employees who are living in more affluent counties are more aligned with their company, on average. Moreover, geographic concentration of an industry has been shown to be positively related to political mobilization (Busch and Reinhardt, 2000). In column 3 of Table B.1 and B.2, I control for industry concentration using a local Herfindahl-Hirschmann Index (HHI). I do not find that including this control variable changes the result for my main independent variable of interest. While the coefficient on the HHI is negatively signed, opposite to what I would expect from existing research, it is not significantly different from zero.[27] Related to the argument of this paper, employees in sectors

[26]The mean unemployment rate in the linked firm-employee data is 5.82 percent, which is slightly lower than the US-wide mean unemployment rate of 6.53 between 2003 and 2016.
[27]The HHI is measured as $\sum_{k=1}^{K} s_{ik}^2$ where s_{ik}^2 are the squared employment shares of each industry k in county i, which are subsequently summed over all counties. Intuitively, if all employees in an industry are located in one county, this measure is one, indicating full geographic concentration, and approaches zero as the number of employees is distributed across more and more counties. The geographic HHI has a mean of 0.16 in the sample analyzed which is higher than the US-wide 0.12, on average. This makes sense as I am only

with stronger profit-sharing institutions like unions could be more likely to align politically with their employer, because their own wages are more closely linked to company profits (Dean, 2016). Controlling for union membership as in column 4 does not change the strong positive relationship between asset specificity and alignment. Furthermore, the coefficient on union membership is not significantly different from zero, suggesting no impact of profit sharing institutions on partisan alignment. Finally, Hertel-Fernandez (2018) also finds that companies are more likely to mobilize their employees in highly regulated industries, i.e. in sectors where there is a tighter connection between regulation and company profits. In column 5 of Table B.1 and B.2, I control for regulatory exposure using the number of regulatory restrictions from the RegData database as a measure of regulatory exposure, measured at the 6-digit NAICS level (McLaughlin et al., 2017). I do not find any relationship between the extent to which an industry is exposed to regulation and the degree of partisan alignment between firms and employees.[28] Finally, Table B.5 and B.6 replicate the main results from above, splitting alignment by partisanship. While the effect of labor mobility (firm asset specificity) Republican alignment is always negative (positive) and highly significant, the signs are reversed for Democratic alignment. In sum, these results point to a positive relationship between sectoral and firm-level specificity and partisan alignment, but not for occupational skill specificity. However, both from the descriptive graphs in Figures B.5 and

looking at companies which are politically organized (i.e. which have a PAC). Industry concentration has been shown to be positively related to the existence of corporate political activity at the firm and industry level, although with mixed results (Hansen, Mitchell and Drope, 2005).

[28]Note that labor mobility becomes insignificant when introducing the measure of regulatory restrictions. However, this measure is also missing for many observations and shrinks the sample used for estimation by 1/3. Thus, those last results are not as conclusive as other robustness tests.

B.6 and the below analysis, this relationship seems to be driven by firms and employees aligning on a Republican candidate.

4.3.5 Employee Responsiveness to PAC Donations

Above, I find a strong positive relationship between different measures of specificity at the sector-level and firm-level and firm-employee alignment. This suggests that individuals support the party or the candidates that their company supports. But do employees pay attention to their company donations, and then change their contribution patterns when their company PAC does? An alternative mechanism could be that individuals self-select into particular employers due to individual characteristics like unobserved skills, education, or their own political preferences, despite controlling for occupation, broad industry, or geography. Unfortunately, I do not observe many donors changing employers in my dataset, but I do observe the candidates that company PACs donate to, as well as those that individuals support. Therefore, I can test whether employees change candidate-specific donations when their company PAC changes contribution patterns. This would provide stronger evidence for the claim that employees follow their company political activities. Hence, I aggregate the linked employer-employee donations data at the employee-candidate-cycle level and add information on whether the PAC of on individuals' employer donated to the respective candidate in a given election cycle. I estimate the following linear regression model:

$$log(Donations_{ijt}) = \alpha_i + \theta_j + \gamma_t + \delta Firm\ Donation_{ijt} + \epsilon_{ijt}$$

where the dependent variable is the log of individual *i*'s donations to candidate *j* in electoral cycle *t*, and the independent variable of interest $Firm\ Donation_{ijt}$ equals one if an employees *i*'s company PAC donates to candidate *j* in cycle *t*. Firms donating to the same candidate as an employee happens 47,316 times in my sample of 432,474 individual-candidate-cycle donations, for about 10.9 percent of donations. I include individual-, candidate-, and cycle-specific fixed-effects. Therefore, I estimate only the effect of firm donations on within-individual and within-candidate donations amounts. Thus, I control for all unobserved time-invariant individual and candidate characteristics, and cycle-specific shocks that affect all donors equally.

Table 4.5 Regression Results: Effect of Firm Donations on Employee Donations

	Dependent variable:	
	log(Donations)	
	(1)	(2)
Firm Donation	0.044***	0.043***
	(0.015)	(0.016)
Cycle FEs	✓	
individual FEs	✓	✓
Candidate FEs	✓	
Candidate-Cycle FEs		✓
Observations	432,474	432,474
Adjusted R^2	0.566	0.572

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by firm in parentheses.

Column 1 in Table 4.5 shows the results. There is indeed a positive and very significant relationship between PAC donations to specific candidates and employee donations to the same candidates. In Column 2, I substitute the candidate-specific fixed effects for candidate-cycle fixed effects, since some candidates run for multiple offices over time. For example, some candidates run for the House in one cycle and for Senate in the next cycle, which could affect both company and employee donations, because these candidates might be more well-known to the public and more valuable for corporations. The effects are almost identical and still highly significant. Substantively, the coefficients indicate a 4.4 and 4.5 percent increase in employee donations to specific candidates in a given cycle, if the employees' company PAC donates to the same candidate. This is equivalent to an additional 59 USD to 60 USD donated per employee.[29] Since I include individual fixed effects, this effect is not driven by individual occupations (like CEOs or other top executives).[30] This provides quite strong evidence that employees pay attention to the donations of their employer PAC, providing a mechanism for the aggregate correlations found in the previous section.

I proceed by investigating which types of candidates are driving the increases in individual donations following PAC donations. If the motivation behind the changes is to support one's company, then the relationship should be stronger for candidates that are more likely to be politically valuable. These include House and Senate representatives (versus Presidential candidates), well-entrenched incumbents, and candidates running for open seats. In Table 4.6, I drop the candidate-specific fixed effects to investigate which kind of candidates or elections contribute more to the average positive effect of PAC donations on individual donations. I interact $\textit{Firm Donation}_{ijt}$ with dummy variables for whether the respective candidate is running for the House, Senate, or trying to become President. Given that PACs donate strategically, one would expect them to be more likely to contribute to House and Senate candidates, because they can affect actual legislation

[29]The average individual donation in my sample is \$1335, and the median donation \$500.
[30]Of course, occupations can change over time. In separate regressions I interact the donation dummy with a dummy for chief executives and find no effect.

Table 4.6 Regression Results: Effect of Firm Donations on Employee Donations by Election Types

	Dependent variable:		
	log(Donations)		
	(1)	(2)	(3)
Firm Donation	-0.070^{***}	-0.103^{***}	0.065^{***}
	(0.020)	(0.022)	(0.016)
House	-0.281^{***}		
	(0.010)		
Senate		-0.021^{*}	
		(0.011)	
President			0.495^{***}
			(0.013)
Firm Donation × House	0.099^{***}		
	(0.025)		
Firm Donation × Senate		0.144^{***}	
		(0.026)	
Firm Donation × President			-0.031
			(0.048)
Cycle FEs	✓	✓	✓
individual FEs	✓	✓	✓
Observations	432,474	432,474	432,474
Adjusted R^2	0.534	0.524	0.543

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by firm in parentheses.

once elected. Hence, one would expect stronger effects for Senatorial and House races. This indeed what I find: when a firm donates to a House or a Senate candidate, employees of the firm donate more to the same candidate, on average, indicated by the positive and significant interaction terms on *Firm Donation* $\times$ *House* as well as *Firm Donation* $\times$ *Senate*. The same does not hold for Presidential candidates, for which the interaction term is negative and insignificant. Moreover, the effect is stronger for Senate candidates than for House candidates. This makes intuitive sense because individual Senators are more powerful legislators than individual House Representatives which receive larger donations, on average, and are more targeted by PACs. Substantively, the effects are slightly lower, but similar to the baseline results shown above. Employees increase donations by 2.9 percent to House candidates and by 4.2 percent to Senate candidates if their employer's PAC donates to the same candidate.[31]

Finally, I repeat the same for the incumbency status of the candidate, shown in Table 4.7. Again, the results point towards an investment motive for individual donations. Employees donate more to challengers and less to open seats and incumbents, showing that their are probably more ideological, on average, than institutional donors like PACs (La Raya and Schaffner, 2015). However, the negative effect of incumbency status on individual donations narrows down significantly when the employer donates to the same candidate, as indicated by the significant interaction term *Firm*

[31] Note that above, I only estimate the intensive margin, or how much individuals donate more to candidates supported by their company. I do not estimate, however, the extensive margin, or whether they donate to a candidate or not. At the moment, creating this dataset takes up too much computing resources because it would require a prohibitively large dataset. For instance, only creating a company-candidate-cycle dataset with all possible combinations of firms, candidates, and cycles, would result in 12799 firms $\times$ 4667 candidates $\times$ 7 cycles, or a dataset with 418,130,531 rows. The data used above contains information on approximately 240,000 individuals, which would result in a dataset of 78,642,776,942 rows.

Table 4.7 Regression Results: Effect of Firm Donations on Employee Donations across Seat Types

	Dependent variable:		
	log(Donations)		
	(1)	(2)	(3)
Firm donated	-0.018	-0.045^{**}	-0.067^{***}
	(0.017)	(0.019)	(0.021)
Challenger	0.057^{***}		
	(0.010)		
Open Seat		-0.019^{*}	
		(0.011)	
Incumbent			-0.042^{***}
			(0.011)
Firm donated x Challenger	-0.077^{***}		
	(0.030)		
Firm donated x Open Seat		0.007	
		(0.026)	
Firm donated x Incumbent			0.062^{***}
			(0.024)
Cycle FEs	✓	✓	✓
individual FEs	✓	✓	✓
Observations	432,474	432,474	432,474
Adjusted R^2	0.524	0.523	0.523

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by firm are in parentheses.

Donation $\times$ *Incumbent*. Vice versa, the positive effect of firm donations on employee donations is not driven by open seats and incumbents, as visible in the negative and significant interaction *Firm Donation* $\times$ *Challenger*, and the insignificant interaction term *Firm Donation* $\times$ *Open Seat*.

Overall, this section shows that employees follow their company political activities, and donate more to candidates that their corporate PAC supports. Moreover, this positive relationship between employee donations and company contributions is driven by incumbents as well as House and Senate candidates. This provides evidence that individuals seem to pay attention to the information provided by company PAC donations, and more so if these donations are more likely to be politically valuable.[32]

4.4 Discussion of Limitations

There remain important limitations and qualifications with regards to the findings of this paper. In terms of case selection and external validity of findings, it is not clear that the US allows very broad conclusions about firm-employee alignment in other countries. The out-sized role money in politics in the US is quite exceptional, compared to other developed countries which typically have stricter limits on campaign finance. I am also limited to a sample of firms which choose to have a PAC and employees who decide to donate to political candidates in the first place. Hence, there can be doubt with regards to how far the findings concerning the firm-employee link travel outside of the US and how much we can learn about

[32]Note that the firm and individuals donating to the same candidate is not determined by individual occupation. In the appendix in Table B.7 I show that the chief executives, even though more likely to support the same party, are not more likely to donate to the same candidate. Senate and House Candidates are more likely to be supported by employees and PACs, as are incumbents and open seat candidates (in that order, decreasing), relative to Presidential candidates and challengers.

non-donation-based forms of alignment. First, I want to stress that open data on employee donations is not readily available in many other countries, and usually not easily linked to their employer.[33] Second, similar questions can indeed be investigated elsewhere using firm- and employee surveys as in Hertel-Fernandez (2018), but but would likely require more resources than are available for a PhD dissertation. Third, while I show that the sample of employees in publicly-traded companies is not representative of the US as a whole in terms of sectoral and occupational composition, the data might still allow conclusions about the overall US donor population, or donors in public firms. Publicly traded firms are important because they make up a large share of US economic activity, and the abundance of financial data on them will facilitate future work.[34]

With regards to *measurement of alignment*, I assume in the first two papers of this dissertation that individual donations are expressions of employee ideology, and that firm donations are expressions of the corporate political leanings. While individual donations are often regarded as purely ideological (Ansolabehere, de Figueiredo and Snyder, 2003; La Raya and Schaffner, 2015)[35], this is assumption can be challenged for corporate PACs, which have been shown to donate strategically (Fouirnaies and Hall, 2018). However, since PACs depend on donations from their employees for funding, we know that PACs face a trade-off between donating to the candidates that promise the most return on investment and potentially scaring off donations

[33] In cases like Brazil in which this data is indeed available, similar analyses might be possible though, in principle (Colonnelli, Prem and Teso, 2018).
[34] In addition, we know that donors are different from the rest of the population (Francia, 2003; La Raya and Schaffner, 2015), and the skewness to certain sectors and occupations is likely a feature of the data.
[35] Of course, this is also a simplifying assumption, given that individual donors donate to many candidates across the US (Gimpel, Lee and Pearson-merkowitz, 2008), and seem to target committees based on the sector they work in (Barber, Canes-Wrone and Thrower, 2017).

from ideological employees if the PAC donates too strategically on both sides of the aisle (Li, 2018). Thus, PACs cannot solely donate based on investment motives, and must (at least partially) represent the make-up of their employees. This is also partly visible in the distribution of my alignment measure, which, despite being fairly normally distributed around 0.5, seems quite left-skewed, towards more rather than less alignment. Hence, simple partisan alignment might not be the perfect measure of political alignment, but it seems to provide an approximation of individual and corporate preferences.

Lastly, I cannot claim *causality* of the findings in this paper. This is mostly due to the observational nature of the data. I try to address some of the endogeneity problems by ruling out a host of plausible alternative explanations and by leveraging within-individual variation in donations. Further, while causal inference and big data do not need to be mutually exclusive (Grimmer, 2015; Monroe et al., 2015; Varian, 2014), the strength of both this paper and the first paper in this dissertation lies in the development of new micro-level data, and the measurement of the theoretically and empirically important variable firm-employee political alignment. Good identification is impossible, though. I see better causal identification as a key challenge which I want to address more explicitly in future work. I will take up and discuss these issues in more detail in the concluding chapter of this dissertation.

4.5 Conclusion

There is an ongoing debate on the impact of individuals' sector, firm, or occupation on preferences, but no clear consensus has emerged yet.

Leveraging big data on firm and employee donations, I find that employees in firms and sectors with more specific assets show more partisan alignment with their employer, but I find no impact of occupations-specific effects. Hence, *where individuals work seems to matter more for partisan alignment than what they do*. Moreover, I find that employee donations are reactive to the donations of their company's PAC. This suggests that PAC contributions inform employees about company-preferred politicians, and provides a potential mechanism linking employee and firm political activities.

These results have important implications for the study of collective political action, coalition formation and future work on preference formation. First, meaningful corporate political action might be much easier in firms that are internally aligned, particularly if top executives share the same political views (Bonica, 2016*a*). Aligned firms might be more likely to engage in other corporate political activity like lobbying if benefits from this activity are private (Bombardini and Trebbi, 2012; Kim, 2017; Osgood, 2016). Alternatively they might be more likely to engage in collective political activity in ad-hoc policy coalitions or established business associations like the American Chamber of Commerce or the American Legislative and Exchange Council (Hansen, Mitchell and Drope, 2005; Hertel-Fernandez, 2016; Olson, 1965) because coordination on common political goals is easier. Future work should explore whether ideological coherence is a factor affecting individual or collective political action of corporations.

Second, I find that sectoral and firm characteristics are more important than occupations as predictors of alignment between firms and employees in terms of their donations. These results go against the literature on individual preferences on trade, foreign direct investment, redistribution, and economic risk. This line of work most often finds no coherent impact of sectoral factors (Mansfield and Mutz, 2009; Rho and Tomz, 2017), and instead highlights occupational characteristics (Iversen and Soskice, 2001; Kitschelt and Rehm, 2014; Owen and Johnston, 2017; Rehm, 2009; Thewissen and Rueda, 2019). Why do occupational factors provide little explanatory power for firm-employee alignment? Theoretically, the VoC literature notes that the US is characterized by general skills, as opposed to specific skill (Hall et al., 2001; Iversen and Stephens, 2008). Hence, skills might be less specific to the occupation in the US, and therefore be less predictive of partisan alignment with employers. On the other hand, occupational licensing and training varies markedly across US states and could be a much better indicator of occupational immobility than general or specific skills. Moreover, the results do not mean that occupations do not matter at all for alignment. CEOs are one of the few occupations that stands out in terms of partisan alignment, and I do find some (if less) variation in alignment across occupations (Bonica, 2016*a*). More importantly, this paper departs from existing studies in leveraging actual political action of employers and their employees as opposed to stated preferences of individuals in surveys, which could explain partly why the findings differ from the existing literature. In fact, there might be a qualitative difference between the factors explaining stated policy preferences in the general population, as measured in surveys and survey experiments, and the drivers behind political actions of those individuals which have already overcome barriers to political engagement. Thus, future work should try to tease out which factors lead to meaningful variation in political activity among those citizens who are already active to begin with.

Finally, the observed relationship between firm and individual donations to specific candidates suggests that donating employees are aware of their employer's contributions, and might be able to use them as informational cues partly guiding their own decisions to donate. Thus, the results are in line with work highlighting that employees pay attention to the donations of their company PAC when their firm solicits money from them (Li, 2018), and other research highlighting the informational role CEO donations for employee donations (Babenko, Fedaseyeu and Zhang, 2019). Given the strict regulations on campaign finance, firms might not be able to force their employees to donate to specific candidates, but they could highlight which particular candidates their firm support, which might in turn influence politically active employees (Hertel-Fernandez, 2018). When employees are more susceptible to these signals by their employers is also an open question which future work should try to answer.

Appendix B

Data Appendices and Additional Analyses

B.1 Within-Occupation Alignment across 3-Digit NAICS Industries

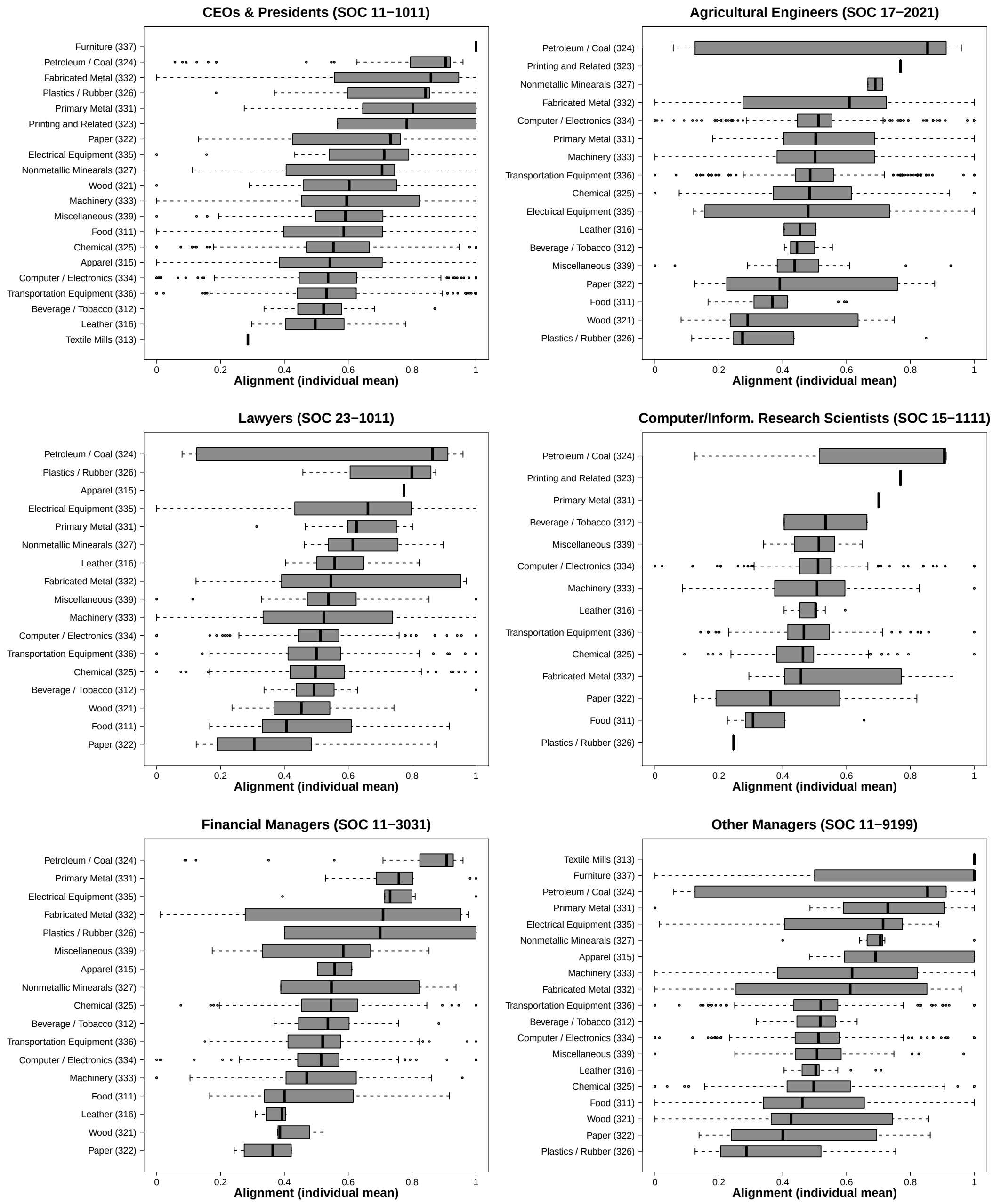


Figure B.1 Strong Within-Occupation Variation in Alignment in Manufacturing Industries. These boxplots show that there is strong within-occupation variation in alignment for six very different different six-digit SOC occupations across industries. Data: own calculations.

B.2 Alignment across 3-Digit SOC Occupations

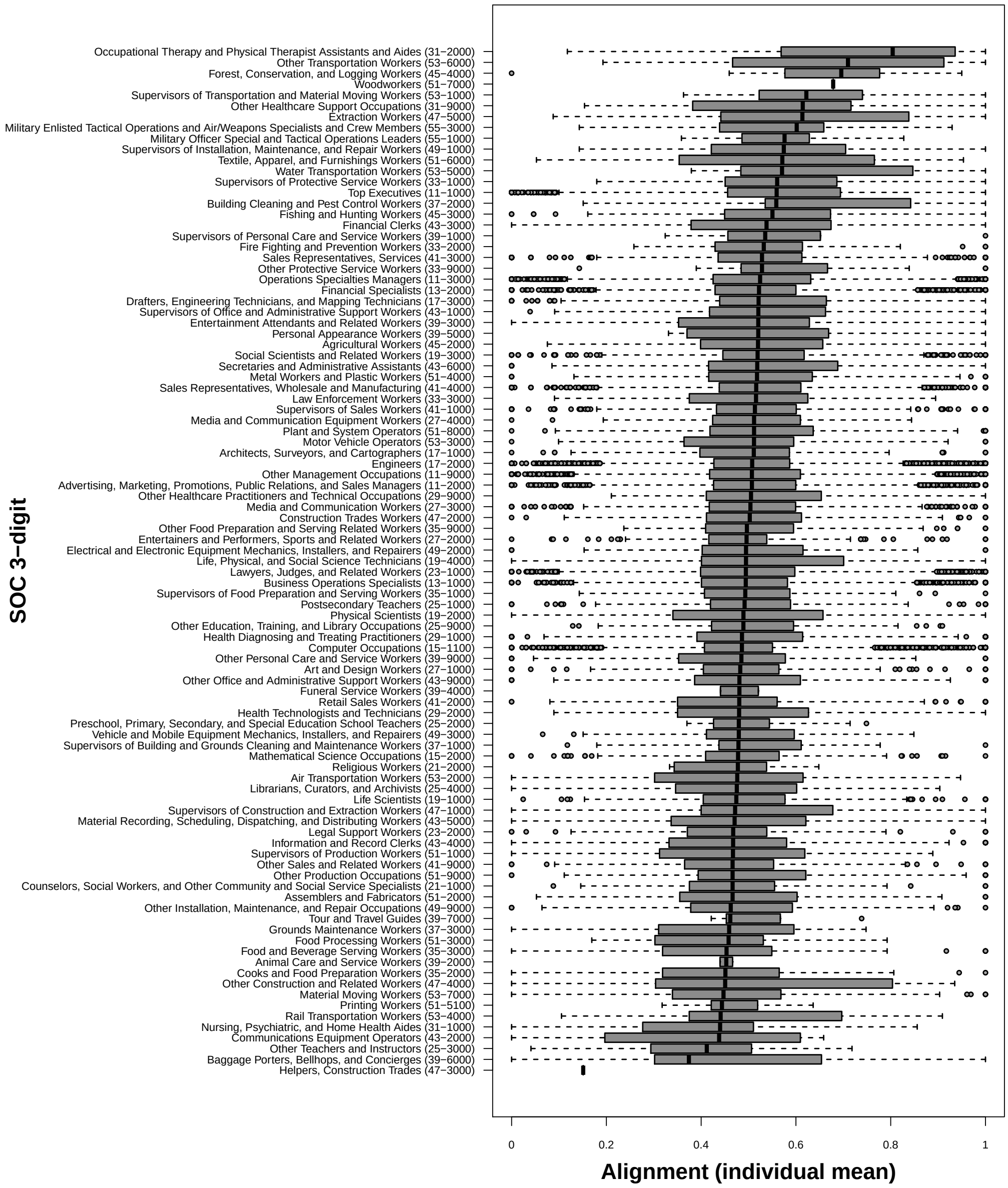


Figure B.2 Weak Variation in Alignment across 3-Digit Occupations. The graph shows that there are much less differences in alignment across very fine-grained occupations, compared to variation across industries. Data: own calculations.

B.3 Alignment across US States

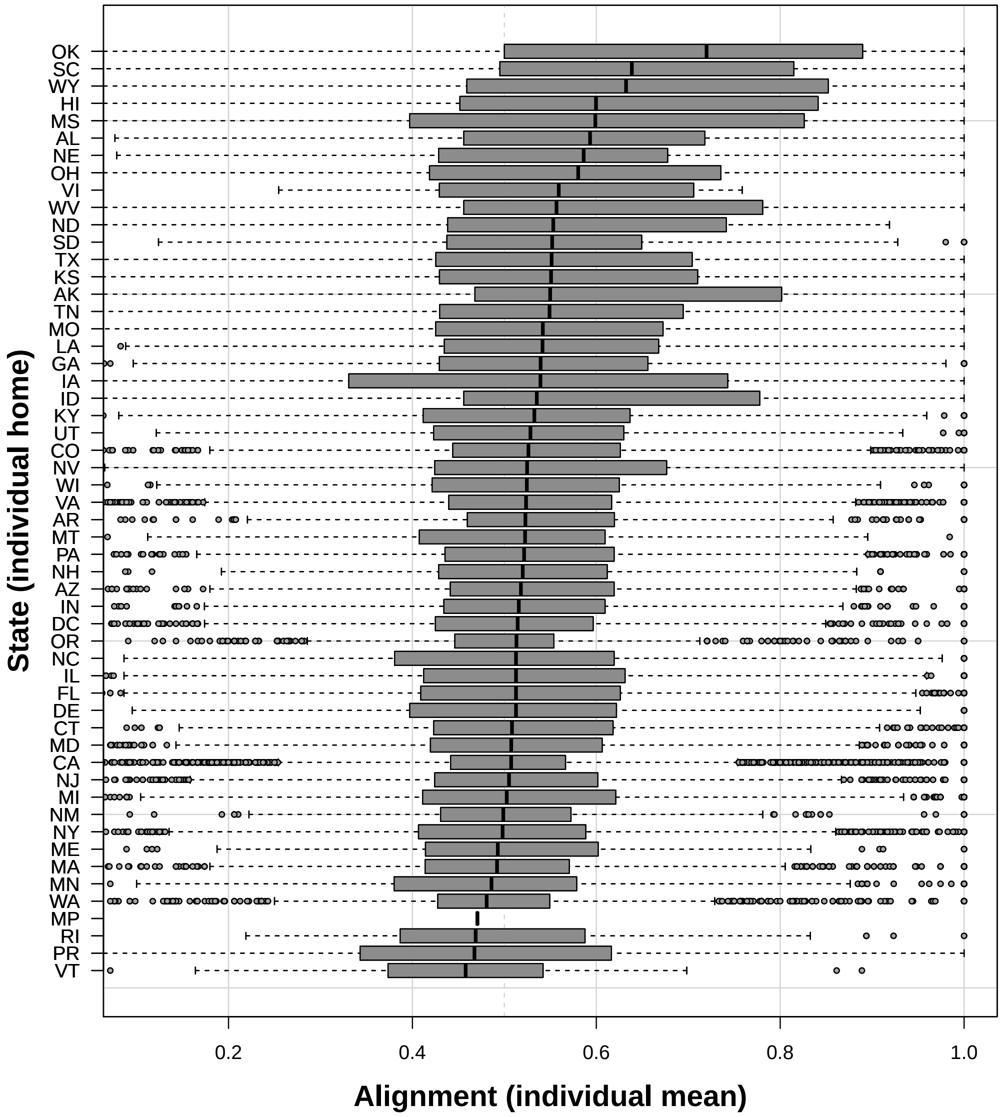


Figure B.3 Variation in Alignment across US States. The boxplot shows that there is some variation in alignment across US states, albeit not as much as across industry sectors. Data: own calculations.

B.4 Asset Specificity and Partisan Alignment over Time

In Figure B.4 below, I show the aggregate (mean) alignment between employees and their firms in my data between 2003 and 2016, the time period under investigation. One can see that for most of the time, it is close to 0.5 (firms and employees donate to both parties equally), with occasional up and down swings. The plot also depicts the share of alignment in donations by party, with more Republican alignment except for the time between 2007 and 2009. This seems to be driven by strategic changes in partisan donations by corporations (Fouirnaies and Hall, 2018) during the Obama campaign, as traditionally more conservative companies donated more to Democracts than usual. The graph also includes the mean asset specificity across all firms in my sample. Even though the changes in asset specificity are not large, they seem to tick up in tandem in 2005, 2009, and 2013 with alignment, and decrease in years of lower alignment (correlation of 0.44).

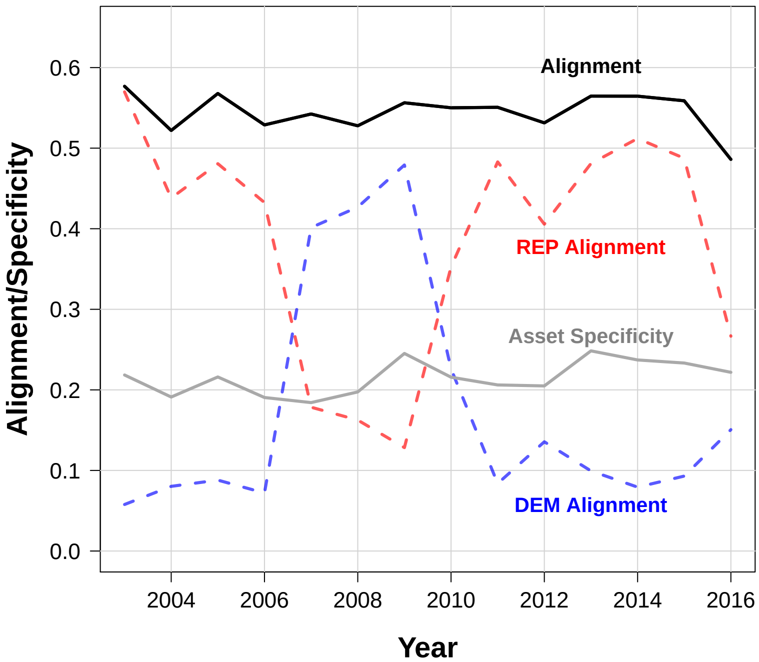


Figure B.4 Alignment and Asset Specificity over Time. The graph depicts average alignment across all firms in the sample between 2003 and 2016. It shows that average asset specificity moves in tandem with overall alignment, and that the share of Republican and Democratic Alignment changes with election years. Data: own calculations and Compustat Capital IQ North America.

B.5 Sectoral Labor Mobility and Partisan Alignment

Figure B.5 plots the average alignment in each 4-digit NAICS sector in my data against this labor mobility measure. There is only a weakly negative relationship in terms of overall alignment at the industry level. However, the middle and the rightmost scatter plot show that there seems to be a negative relationship between Republican alignment and labor mobility, while there is a positive relationship between labor mobility and Democratic alignment.

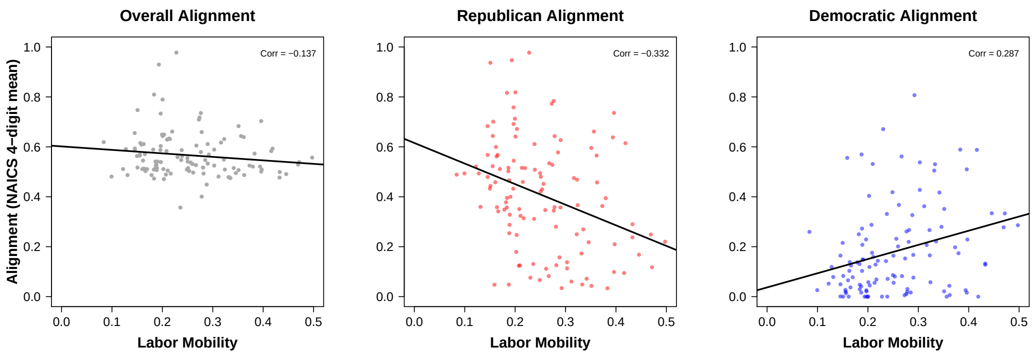


Figure B.5 Party-Specific Relationship between Alignment and Labor Mobility. For robustness, these plots show the relationship between labor mobility at the 4-digit NAICS level and mean sectoral alignment. Labor mobility shows a strong negative relationship with Republican alignment, and a strong negative relationship with Democratic alignment. Data: own calculations and Census Bureau Statistics of U.S. Businesses (SUSB).

Controlling for year- and occupation fixed effects, Table B.6 replicates the main results from this paper using labor mobility as an inverse measure of firm-level asset specificity. The results show that there is a slight negative relationship between mobility and higher partisan alignment. Moreover, the regressions reflect the asymmetric impact of mobility on Republican and Democratic alignment shown in the scatter plots in Figure B.5, using different combinations of fixed effects.

B.6 Firm Asset Specificity and Partisan Alignment

How does the relationship between specificity and alignment look like at the firm level? Figure B.6 (left panel) shows that there is indeed a positive association between asset specificity and alignment. However, there is still a large variation in the alignment within firms with high and low asset specificity, respectively. The center and right panel of the same figure depict another interesting pattern in the data. The relationship shown in the left panel seems to be driven by the share of Republican alignment at the firm-level which is more positively related to asset specificity. Democratic alignment, on the other hand, is indeed weakly negatively related to asset specificity. This partly supports my expectation that specificity is more strongly associated with Republican alignment, based on historic relationships between labor- and capital intensive industries and US parties.

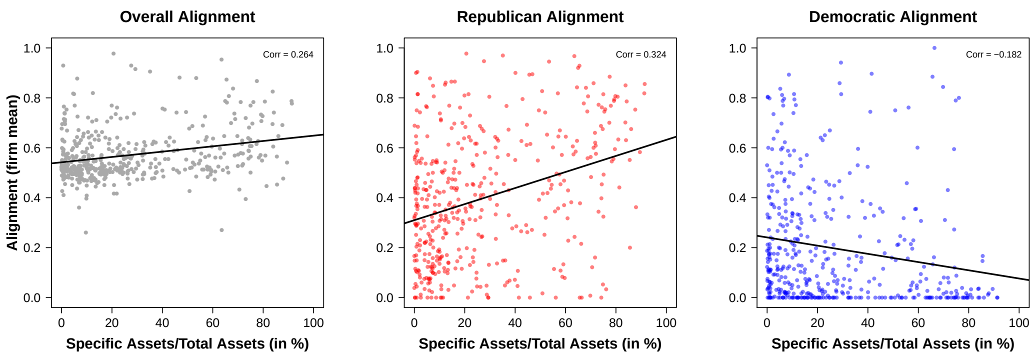


Figure B.6 Positive Relationship between Alignment and Specific Assets. These scatter plots show that there is a positive relationship between specific assets and average firm-employee partisan alignment. Moreover, the relationship is negative for Democratic aignment, but strongly positive for Republican alignment. Data: own calculations and Compustat Capital IQ Annual Updates North America.

B.7 Robustness Checks and Additional Models

Table B.1 Regression Results: The Effect of Firm Asset Specificity on Partisan Alignment, Extended Controls

	Dependent variable:				
	Partisan Alignment				
	(1)	(2)	(3)	(4)	(5)
Share Specific Assets	0.068***	0.065***	0.072***	0.079***	0.078***
	(0.017)	(0.018)	(0.020)	(0.020)	(0.020)
log(Capital Expenditure)	0.003	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(Sales)	−0.005	−0.004	−0.005	−0.007	−0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
log(Employees)	−0.016***	−0.017***	−0.016***	−0.016***	−0.017***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
log(Cost of Goods Sold)	0.003	0.003	0.003	0.005	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Productivity	−0.0001	−0.0003	0.00005	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
log(Median Income)	−0.045	−0.044	−0.045	−0.046	−0.064**
	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)
Red State (1/0)	0.031***	0.032***	0.030***	0.031***	0.027***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Unemployment Rate		−0.003**			
		(0.001)			
HHI			−0.005		
			(0.015)		
Union Membership				−0.0004	
				(0.0004)	
# Regulatory Restrictions					0.001
					(0.002)
Year FEs	✓	✓	✓	✓	✓
Occupation FEs	✓	✓	✓	✓	✓
Observations	95,220	85,110	90,293	93,543	62,881
Adjusted R^2	0.085	0.085	0.084	0.084	0.083
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors clustered by firm are in parentheses.				

Table B.2 Regression Results: The Effect of Labor Mobility on Partisan Alignment, Extended Controls

	Dependent variable:				
	Partisan Alignment				
	(1)	(2)	(3)	(4)	(5)
Labor Mobility	-0.043^{*}	-0.043^{*}	-0.042^{*}	-0.051^{*}	-0.044
	(0.024)	(0.024)	(0.024)	(0.026)	(0.033)
log(Capital Expenditure)	0.004^{*}	0.004^{*}	0.004^{*}	0.004^{*}	0.005^{**}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(Sales)	-0.003	-0.003	-0.003	-0.004	-0.0004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
log(Employees)	-0.019^{***}	-0.019^{***}	-0.020^{***}	-0.020^{***}	-0.023^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
log(Cost of Goods Sold)	0.003	0.003	0.004	0.004	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Productivity	-0.007^{**}	-0.007^{**}	-0.008^{**}	-0.007^{**}	-0.007
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
log(Median Income)	0.042	0.038	0.039	0.042	0.021
	(0.035)	(0.036)	(0.035)	(0.035)	(0.039)
Red State (1/0)	0.017^{**}	0.016^{**}	0.016^{**}	0.017^{**}	0.031^{***}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Unemployment Rate		-0.006^{***}			
		(0.002)			
HHI			-0.020^{**}		
			(0.010)		
Union Membership				-0.0003	
				(0.0003)	
# Regulatory Restrictions					0.002
					(0.002)
Year FEs	✓	✓	✓	✓	✓
Occupation FEs	✓	✓	✓	✓	✓
Observations	67,117	66,781	65,753	67,117	46,227
Adjusted R^2	0.120	0.121	0.122	0.120	0.106
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$				
	Standard errors clustered by firm are in parentheses.				

Table B.3 Regression Results: The Effect of Specificity on Partisan Alignment, Outliers Dropped

	Dependent variable:					
	Align					
	(1)	(2)	(3)	(4)	(5)	(6)
Share Specific Assets (firm)	0.073***	0.065**	0.045***			
	(0.017)	(0.026)	(0.015)			
Labor Mobility (sector)				−0.066**	−0.088***	−0.048**
				(0.028)	(0.033)	(0.023)
log(Capital Expenditure)	0.002	0.002	0.002	0.007***	0.001	0.003*
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
log(Sales)	0.003	0.003	0.006	−0.003	0.002	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
log(Employees)	−0.017***	−0.014***	−0.014***	−0.023***	−0.021***	−0.018***
	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)
log(Cost Goods Sold)	−0.0001	−0.002	−0.005	0.007	0.005	−0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.004)
Productivity	−0.001	−0.004	−0.004	−0.007*	−0.016***	−0.009***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
log(Med. Income)	−0.046	−0.047	−0.040	0.020	0.019	0.031
	(0.030)	(0.031)	(0.029)	(0.032)	(0.032)	(0.033)
Red State (1/0)	0.028***	0.027***	0.014**	0.033***	0.028***	0.017**
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.008)
Year FEs	✓	✓	✓	✓	✓	✓
Occupation FEs	✓	✓	✓	✓	✓	✓
NAICS 2-digit FEs		✓			✓	
County FEs			✓			✓
Observations	91,615	91,615	82,255	71,430	71,430	64,271
Adjusted R^2	0.087	0.091	0.137	0.065	0.074	0.123

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm are in parentheses.

Table B.4 Regression Results: The Effect of Skill Specificity on Partisan Alignment, Outliers Dropped

	Dependent variable:			
	Align			
	(1)	(2)	(3)	(4)
Skill Specificity (1/0)	0.019***	0.018***	0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Chief Executive (1/0)			0.038***	0.038***
			(0.004)	(0.004)
log(Capital Expenditure)	0.010***	0.010***	0.009***	0.009***
	(0.003)	(0.004)	(0.003)	(0.004)
log(Sales)	0.024	0.027	0.024	0.026
	(0.018)	(0.019)	(0.018)	(0.019)
log(Employees)	−0.007	−0.006	−0.007	−0.006
	(0.033)	(0.034)	(0.034)	(0.034)
log(Cost Goods Sold)	−0.028	−0.031*	−0.027	−0.030*
	(0.018)	(0.018)	(0.018)	(0.018)
Productivity	−0.013	−0.012	−0.014	−0.013
	(0.024)	(0.024)	(0.024)	(0.024)
log(Med. Income)	0.018***	0.019***	0.005	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)
Red State (1/0)	0.022***	0.014**	0.022***	0.014**
	(0.003)	(0.006)	(0.003)	(0.006)
Year FEs	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓
County FEs		✓		✓
Observations	91,361	82,029	91,361	82,029
Adjusted R^2	0.155	0.182	0.157	0.184

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by firm are in parentheses.

Table B.5 Regression Results: The Effect of Asset Specificity on Partisan Alignment, by Party

	Dependent variable:					
	Align	REP	DEM	Align	REP	DEM
	(1)	(2)	(3)	(4)	(5)	(6)
Share Specific Assets	0.070***	0.181**	−0.089	0.036**	0.156***	−0.146**
	(0.026)	(0.073)	(0.100)	(0.015)	(0.051)	(0.057)
log(Capital Expenditure)	0.002	0.004	0.004	0.002	0.008	0.00004
	(0.002)	(0.006)	(0.010)	(0.002)	(0.007)	(0.010)
log(Sales)	−0.005	−0.078***	0.087**	−0.002	−0.034*	0.038
	(0.006)	(0.024)	(0.035)	(0.005)	(0.019)	(0.031)
log(Employees)	−0.015***	0.007	−0.032	−0.014***	−0.018	−0.005
	(0.005)	(0.014)	(0.020)	(0.003)	(0.012)	(0.015)
log(Cost Goods Sold)	0.002	0.064***	−0.079***	−0.001	0.038**	−0.048*
	(0.005)	(0.017)	(0.025)	(0.004)	(0.015)	(0.026)
Productivity	−0.004	−0.014	−0.003	−0.001	−0.003	−0.013
	(0.005)	(0.019)	(0.019)	(0.004)	(0.020)	(0.018)
log(Med. Income)	−0.047	−0.142*	0.047	−0.032	−0.124	0.043
	(0.031)	(0.086)	(0.049)	(0.030)	(0.085)	(0.051)
Red State (1/0)	0.030***	0.139***	−0.071***	0.014**	0.032**	−0.006
	(0.004)	(0.011)	(0.011)	(0.006)	(0.016)	(0.019)
Year FEs	✓	✓	✓	✓	✓	✓
Occupation FEs	✓	✓	✓	✓	✓	✓
NAICS 2-digit FEs				✓	✓	✓
County FEs	✓	✓	✓			
Observations	95,220	95,230	95,230	85,524	85,533	85,533
Adjusted R^2	0.089	0.200	0.208	0.133	0.243	0.230

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm are in parentheses.

Table B.6 Regression Results: Labor Mobility and Partisan Alignment, by Party

	Dependent variable:								
	Align	REP	DEM	Align	REP	DEM	Align	REP	DEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor Mobility	-0.063^{**}	-0.352^{***}	0.301^{***}	-0.043^{*}	-0.203^{**}	0.200^{**}	-0.098^{***}	-0.277^{**}	0.147
	(0.029)	(0.089)	(0.091)	(0.024)	(0.079)	(0.089)	(0.035)	(0.121)	(0.131)
log(Capital Expenditure)	0.008^{***}	0.025^{***}	-0.015^{**}	0.004^{*}	0.021^{***}	-0.016^{**}	0.002	0.014^{**}	−0.006
	(0.003)	(0.007)	(0.006)	(0.002)	(0.006)	(0.006)	(0.002)	(0.006)	(0.008)
log(Sales)	-0.012^{**}	-0.087^{***}	0.061^{***}	−0.003	-0.051^{***}	0.041^{*}	−0.007	-0.088^{***}	0.075^{***}
	(0.006)	(0.017)	(0.022)	(0.005)	(0.015)	(0.024)	(0.006)	(0.022)	(0.029)
log(Employees)	-0.023^{***}	-0.032^{***}	0.007	-0.019^{***}	-0.032^{***}	0.010	-0.023^{***}	−0.013	−0.016
	(0.005)	(0.012)	(0.013)	(0.004)	(0.011)	(0.013)	(0.006)	(0.014)	(0.017)
log(Cost of Goods Sold)	0.010^{**}	0.080^{***}	-0.058^{***}	0.003	0.051^{***}	-0.040^{*}	0.009	0.075^{***}	-0.062^{***}
	(0.005)	(0.015)	(0.021)	(0.004)	(0.014)	(0.023)	(0.006)	(0.018)	(0.022)
Productivity	−0.007	−0.021	−0.010	-0.007^{**}	−0.018	−0.011	-0.017^{***}	-0.036^{**}	−0.002
	(0.005)	(0.017)	(0.016)	(0.004)	(0.018)	(0.018)	(0.004)	(0.017)	(0.017)
log(Median Income)	0.029	0.049	0.028	0.042	0.056	0.037	0.029	0.037	0.046
	(0.033)	(0.117)	(0.064)	(0.035)	(0.116)	(0.063)	(0.034)	(0.116)	(0.064)
Red State (1/0)	0.037^{***}	0.166^{***}	-0.092^{***}	0.017^{**}	0.026	0.018	0.032^{***}	0.145^{***}	-0.076^{***}
	(0.006)	(0.014)	(0.011)	(0.008)	(0.019)	(0.018)	(0.006)	(0.013)	(0.011)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occupation FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FEs				✓	✓	✓			
NAICS 2-digit FEs							✓	✓	✓
Observations	74,576	74,576	74,576	67,117	67,117	67,117	74,576	74,576	74,576
Adjusted R^2	0.065	0.185	0.203	0.120	0.246	0.239	0.073	0.203	0.219

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by firm are in parentheses.

Table B.7 Regression Results: Candidate Characteristics and Same-Candidate Donations

	Dependent variable:		
	Donation to Same Candidate		
	(1)	(2)	(3)
Chief Executive	0.004	0.006	0.002
	(0.004)	(0.004)	(0.004)
House	0.127***		0.108***
	(0.020)		(0.017)
Senate	0.144***		0.122***
	(0.025)		(0.021)
Republican	0.009	0.005	0.009
	(0.008)	(0.008)	(0.008)
Incumbent		0.095***	0.067***
		(0.019)	(0.015)
Open Seat		0.043***	0.032***
		(0.010)	(0.009)
Cycle FEs	✓	✓	✓
individual FEs	✓	✓	✓
Observations	432,474	432,474	432,474
Adjusted R^2	0.372	0.364	0.377

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by firm are in parentheses.

Chapter 5

Policy Uncertainty and Trade in Intermediate and Capital Goods

5.1 Introduction

How does policy uncertainty affect manufacturing firm's decision to source intermediate inputs from abroad? Uncertainty is of central importance to both Political Economy Research on international cooperation and Economics work on trade and investment. In International Political Economy (IPE), research has focused on the uncertainty-reducing role of international institutions for private actors and political leaders. Flexibility in international agreements promotes cooperation by reducing uncertainty about future costs of compliance and decreases the resulting time-inconsistency problem (Rosendorff and Milner, 2001). Empirically, countries with anti-dumping mechanisms which allow temporary escape from free trade commitments are more likely to join the GATT/WTO, and have lower tariff bindings and applied tariffs (Reinhardt and Kucik, 2008). Some authors also argue that the reduced policy uncertainty leads to higher economic efficiency which helps democratically elected leaders to stay in office longer (Hollyer and Rosendorff, 2012). Preferential trade agreements (PTAs) and the GATT/WTO also lower export volatility by locking in existing trade policies, and thus reduce uncertainty of economic actors about future policy (Baccini and Urpelainen, 2015; Mansfield and Reinhardt, 2008*a*).

Demand uncertainty stemming from trade policies has also long been recognized as an important question in Economics (Fishelson and Flatters, 1975; Helpman and Razin, 1978; Hillman and Katz, 1986; Rodrik, 1995). Recent work on trade policy uncertainty (TPU) departs from country-level analyses and shows that even within narrowly-defined sectors, only few firms are able to pay the sunk necessary to start exporting (Bernard et al., 2007, 2012). Building on the insights of 'new-new' trade theory, this work integrates policy uncertainty into models of heterogeneous firms (Helpman, Melitz and Yeaple, 2004*b*; Melitz, 2003*a*) and provides evidence of the effect of uncertainty on firm-level export decisions (Feng, Li and Swenson, 2017; Handley, 2014; Handley and Limao, 2015; Limao and Maggi, 2015).[1] This work highlights that country-level or sectoral analyses might overlook large variation in the distributional consequences of TPU on firms *within sectors*.

Notwithstanding their important contributions, both lines of research suffer from particular empirical and theoretical shortcomings. On the one hand, even though theories of trade cooperation assume that there is substantive uncertainty about future trade policy *before* uncertainty-reducing

[1]Handley and Limao (2015) show that Portugal's accession to the EEC increased firm export entry and sales even before it came into effect. Feng, Li and Swenson (2017) show that China's WTO accession increased Chinese firm export entries, while Liu and Ma (2017) demonstrate that TPU reduction encourages firm patent applications. Manger and Shadlen (2014) find that FTAs 'lock in' preferential market access for developing countries since Generalized System of Preferences (GSP) tariffs can be unilaterally suspended. For work looking at the effect of WTO tariff bindings on exports see also Handley (2014), Osnago, Piermartini and Rocha (2015), Francois and Martin (2004), and Groppo and Piermartini (2014). Uncertainty has also been a major theme in macroeconomics (Bernanke, 1983; Dixit, 1989) and industrial organization (Bloom, Bond and Van Reenen, 2007).

agreements are enacted, almost no effort has been put into *actually measuring* trade policy uncertainty between alternative policies during the negotiation phase. Moreover, the few existing measures of economic uncertainty are based on word dictionary approaches (Baker, Bloom and Davis, 2016) which can be prone to researcher bias (King, Lam and Roberts, 2017). In addition, existing work assumes that on average, private actors will prefer trade openness (Mansfield and Reinhardt, 2008*a*) and that political leaders negotiate and sign trade agreements because they are welfare-enhancing. However, there are well-known distributional consequences of liberalization which will differ according to the design of the agreements that states can choose from, like their depth and scope (Dür, Baccini and Elsig, 2014). The distributional effects can also differ sharply within industries (Baccini, Pinto and Weymouth, 2017; Kim, 2017), depending on what types of products firms trade, and can be realized before the respective policies are in place, as firms adjust their expectations. In contrast, the existing IPE literature on trade and uncertainty treats all agreements as equal using binary measures for signing of PTAs, and results mask the distributional consequences because of the use of aggregate trade flows. In short, we lack a good measure of uncertainty between different trade-liberalizing policy alternatives during the negotiation phase that also takes into account the diverging distributional consequences across firms.

On the other hand, while economics studies focus on the role of policy uncertainty for firm exports, there is a remarkable absence of research on the impact of trade policy uncertainty for firm's decisions to source important intermediate inputs from abroad. This absence is surprising given the importance of high-quality inputs for productivity-increasing technological upgrading of firms, especially in developing economies (Amiti and Konings, 2007; Halpern, Koren and Szeidl, 2015). Moreover, political economy research has shown that firms integrated in global production networks are particularly engaged in shaping trade policies. For example, firms relying on import of intermediate inputs have been most actively lobbying in favor of PTAs in order to opening up and retaining access to global supply chains (Manger, 2009; Osgood, 2018), which is also reflected in the faster liberalization of intermediate goods relative to final goods in PTAs (Baccini, Dür and Elsig, 2018). Thus, despite the prominence of policy uncertainty and intermediate inputs in work on international trade, it remains unclear how uncertainty between different trade policies affect firm-specific decisions to source intermediate inputs.

In this paper, we attempt to fill both gaps in the literature and provide three main contributions. First, we employ a new measure of TPU by applying machine learning tools to textual data. We use structural topic models (Roberts et al., 2014) to analyze over 2000 news releases on Ukrainian economic policy to approximate the uncertainty between two particular trade policies: a free trade agreement with the European Union (EU FTA) and a customs union with Russia (RU CU).[2] Interacted with differing tariff schedules for the EU FTA and the RU CU, our measure picks up the distributional consequences of both policies across Ukrainian firms. This approach is almost fully automated and can be easily applied to a broad range of other cases involving multiple, mutual exclusive policies. We demonstrate that our TPU measure picks up real-world policy swings between Ukraine, the EU, and the Russian Federation. We also show that our TPU measure is related to (but different from) general economic uncertainty

[2]In that respect, our approach is similar to that by Baker, Bloom and Davis (2016). However, we do not purposely select keywords such as 'uncertainty' but use a method which requires less decisions by the researcher.

(Baker, Bloom and Davis, 2016), and not driven by changes in tone or sentiment, or how articles talk about the EU FTA or the RU CU.

Second, we extend a heterogeneous firm model with monopolistic competition and trade policy uncertainty (Handley and Limao, 2015) by introducing an additional decision on the choice of intermediate inputs. These intermediate goods can be sourced from domestic and foreign suppliers, with wider choice increasing productivity (Ethier, 1982). In the spirit of heterogeneous firm models, importing is costly and requires irreversible sunk investments.[3] The connection between TPU and imported intermediate inputs is especially important for developing countries, since these inputs have been shown to improve firm productivity via technological upgrading (Amiti and Konings, 2007; Halpern, Koren and Szeidl, 2015; Ramanarayanan, 2017), which in turn impacts the intensive margin of exports.

Finally, we empirically investigate the link between changes in TPU and imports of intermediate inputs. We test our model predictions by combining Ukrainian manufacturing census and firm-product-destination-level trade data between 2003 and 2014. Ukraine faced an unusually volatile trade policy with regards to both Russia and the EU over the last two decades, being torn between two *mutually exclusive* policy options: an FTA with the EU (EU FTA) or a Customs Union with Russia (RU CU) (Hoekman, 2014). We conceptualize TPU as the probability of Ukraine signing either the EU FTA or joining the CU with Russia. In this binary decision, each of those two options implies increased uncertainty with regards to the alternative policy, because both policies could not have been implemented at the same

[3]This is similar to the TPU model with intermediate inputs by Novy and Taylor (2014), but contrary to their paper, we emphasize the heterogeneity across firms, and the technology upgrading channel for intermediate goods.

time.[4] The shifts in TPU between the RU CU and the EU FTA were difficult to predict for Ukrainian firms and driven by the foreign policies of the EU and Russia.[5] We find that a reduction in TPU with EU FTA has a positive and sizable effect on export to and imports from EU countries. Moreover, a reduction in the probability of joining the RU CU is associated with more imports from the EU. This is because the CU would have increased Ukrainian MFN tariffs compared to the status quo, whereas the EU FTA left MFN tariffs untouched.[6]

In line with our theoretical model, we also show that different types of goods respond differentially to reductions in uncertainty. While exports and imports of intermediate and capital goods which require higher sunk investments respond strongly to TPU, we do not find any effect of TPU on trade in consumer goods. Further, imports of products that are more protected in the CU relative to Ukrainian MFN tariffs expand more once TPU with respect to the EU FTA is reduced. According to our results, full elimination of TPU (signing an EU FTA), would increase Ukrainian exports to EU countries by 8.3 percent and imports to Ukraine from the EU by 10.1 percent, while tariff reduction would increase exports by 1.3 percent and imports by 6 percent, respectively. Additionally, we leverage the 2014 transition following the Euro-Maidan demonstrations as a shock to TPU

[4]Being part of the RU CU would have made it impossible for Ukraine to negotiate an FTA with the EU on its own due to the common external tariff, and joining the RU CU after concluding the EU FTA was impossible due to incompatibility of the RU CU tariff structure with the EU FTA trade regime and with the WTO commitments of Ukraine.

[5]Moreover, the decision between closer economic ties with the West (EU) or the East (Russia) resulted in multiple political turnovers in Ukraine in 2004 and early 2014 (Earle and Gehlbach, 2015), leading up to the Russian annexation of Crimea in early 2014.

[6]Russia threatened to withdraw from the free trade agreement with Ukraine, apply MFN tariffs, and impose some arbitrary bans on sensitive items of Ukrainian imports to Russia (milk, cheese, chocolate, railway carriages), but as previous cases related to the Eastern European countries joining EU (i.e Estonia, Poland) demonstrated, those sanctions were short-lived. While trade policy retaliation from Moscow might have been credible, firms could not reasonably believe that a decision to join EU FTA could lead to a full-scale conflict between Ukraine and Russia, annexation of Crimea, and war in the Eastern Ukraine.

which made the EU FTA more likely and rendered the CU with Russia politically infeasible. Using a difference-in-difference approach, we show that imports of intermediate products, which are more protected under the status quo or under the alternative RU CU, expanded more in the aftermath of the transition. Our results are not driven by other uncertainty-inducing events, such as the military conflict in Eastern Ukraine, the Global Financial Crisis, or Ukrainian accession to the WTO.[7] Our results also stay robust when we control for a host of alternative measures of uncertainty, overall trade policy salience, and general economic uncertainty.

Our results have important implications for the study of uncertainty in international trade. We show how quantitative text analysis can be fruitfully applied to the study of trade and uncertainty between clearly-defined policies without resorting to more ambiguous dictionary approaches. Further, contrary to studies assuming that on average, policies locking in trade liberalization are welcomed by private interests, we show that even during the negotiation phase, there are clear distributional consequences within sectors depending on the trading partner and the degree of liberalization. Moreover, while lots of existing work relies on aggregate trade flows between countries, we show that at the level of the firm, not all types of goods react uniformly to swings in uncertainty, emphasizing the added value of micro-level data. We also add to an emerging literature on how trade policies affect firm's expectations and decisions to export *and* import even before they are signed or implemented (Handley, 2014; Handley and Limao, 2015). Finally, the paper shows a mechanism by which uncertainty between policies can dampen productivity growth in emerging economies, by reducing imports of key inputs necessary for technological upgrading.

[7]Limiting our analysis to 2013-2014 or excluding the Luhansk, Donetsk, and Crimea regions does not affect our findings

The next section outlines our theoretical model of heterogeneous firms under monopolistic competition and trade policy uncertainty. The third section introduces the reader to the trade policy context of Ukraine, discusses our approach for measuring TPU, and shows our data sources. Section four describes our empirical results. The last section concludes and discusses implications for further research.

5.2 Theoretical Model

As our point of departure, we use a partial equilibrium model of monopolistic competition with heterogeneous firms (Melitz, 2003*b*). The firms face a costly and irreversible export decision and uncertainty in the foreign demand (Handley and Limao, 2015). Firms are risk neutral and care only about expected profits. Therefore, market volatility does not influence firm's behavior. We add two important features to the model. First, we modify the trade policy uncertainty process to account for a binary and mutually exclusive choice between two policy alternatives. In our case, an increase in uncertainty of exporting to the EU is represented by a higher probability of joining the RU CU. Likewise, uncertainty of exporting to the CU increases in a probability of signing the EU FTA. Second, we incorporate a decision about imports of intermediate and capital goods into the production process. Assuming that this decision involves costly and irreversible investment, we show that uncertainty negatively influences imports of intermediate and capital goods.

An extensive literature shows that the purchase of imported intermediate and capital goods is an important mechanism for increasing total factor productivity (TFP). Amiti and Konings (2007) disentangle the effect of trade liberalization on productivity into output competition vs. input liberalization effects. Fernandes and Paunov (2012) demonstrate that opening up to FDI in the services sector increases productivity in the manufacturing sector. The theoretical underpinnings of the input tariff liberalization effect on productivity are divided into static and dynamic gains. The static gains include gains from increased variety of inputs (Ethier, 1982; Markusen, 1989) and gains from better quality imported inputs (Hallak and Sivadasan, 2013). The dynamic gains come from learning from importing (Grossman and Helpman, 1991).

A recent empirical literature compares the relative importance of these gains. Halpern, Koren and Szeidl (2015) demonstrate that gains from variety amount to two-thirds of productivity gains, while one-third comes from better quality of imported inputs. Zhang (2017) further finds that importing increases productivity in the next period by 0.5-5.8 %. Finally, Ramanarayanan (2017) adds sunk costs with irreversibility to the model. Matching the model predictions to Chilean plant level data, the introduction of irreversible costs of importing improves the model fit by about two thirds. We use these findings to model the impact of uncertainty on imports.

5.2.1 Basic Model of Exporting

An exporting firm from a small open economy produces a variety ω. The firm is small relative to the market size of differentiated varieties in importing countries (more generally, trade blocks or customs unions) and "believes" that it is too small to impact aggregate statistics. Assuming a standard constant elasticity of substitution utility function across varieties, the firm is facing demand

$$q(\omega) = p(\omega)^{-\sigma} E \times P^{\sigma-1} \tag{5.1}$$

where σ is the elasticity of substitution across varieties, $p(\omega)$ is price of variety ω, E is the total expenditures on goods in the differentiated sector, and $P = \left(\int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$ is the price index, where Ω is the set of available varieties. We further assume that σ is common across all markets. In order to start production, the firm has to pay a fixed cost and learn its marginal cost $c(\omega)$, which is drawn from a known distribution $\Phi(c)$, defined over $(0, \infty)$. Once the firm learns its marginal cost, it decides whether to produce or not.

To enter a new export market j, the firm incurs an irreversible cost, I_{EX}, which is pair-specific and cannot be applied to another country. If the firm exports, there is an exogenous probability of exporting continuation, $\beta < 1$. An exporting firm is subject to country j's import tariffs, $\tau^j_{EX,s} \geq 1$, which depends on the trade policy state, s. Given market conditions and trade policy state, this uniquely determines the profitability cutoff of the marginal exporting firm which is given by

$$c^j_{EX,s} = \left(\frac{(1-\beta) I_{EX}}{a^j_s} \right)^{1/(1-\sigma)}. \tag{5.2}$$

where $a^j_s = (\tau^j_{EX,s}\sigma)^{-\sigma}[(\sigma-1)P]^{\sigma-1}E$.

5.2.2 Imported Inputs and Productivity

Now, consider a firm which sources inputs domestically or imports them from abroad. We introduce the following production function

$$q = \varphi L^{\alpha_L} K^{\alpha_K} M^{\alpha_M} \tag{5.3}$$

where q is output, φ is productivity, L is labor, K is capital, and M is composite intermediate input. We assume that productivity is firm specific and drawn from a known distribution function $F(\varphi)$, defined over $(0, \infty)$. We also assume constant returns to scale, $\alpha_L + \alpha_K + \alpha_M = 1$.

Further suppose that intermediate inputs are a composite good, such that

$$M = \left(X_D^{\frac{\theta-1}{\theta}} + X_F^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}$$

where X_D is a domestic intermediate input, X_F is an imported intermediate input, and $\theta > 1$ is elasticity of substitution across domestic and foreign intermediate inputs. Further, there are varieties of domestic and foreign suppliers of intermediate inputs given by $X_D = [\sum^{n_D} x_D^{\epsilon}]^{1/\epsilon}$and $X_F = [\sum^{n_F} x_F^{\epsilon}]^{1/\epsilon}$, where $\sigma_\epsilon = 1/(1-\epsilon)$ is the elasticity of substitution across inputs and $0 < \epsilon < 1$.

We assume that factor prices w_L, w_K, w_D, and w_F are exogenous. To incorporate a foreign intermediate input into the production process, a firm incurs irreversible investment I_{IM} per foreign variety, which is partner-specific and cannot be recovered by switching to another intermediate good supplier. In addition, there is an ad-valorem tariff $\tau_{IM,s}$, that is paid by importers. Solving the cost minimization problem yields

$$c(\varphi) = \frac{1}{\varphi} \quad \frac{w_L}{\alpha_L}^{\alpha_L} \quad \frac{w_K}{\alpha_K}^{\alpha_K} \quad \frac{P_M}{\alpha_M}^{\alpha_M}$$

where $P_M = \quad n_F(\tau_s^{IM} w_F)^{1-\theta} + n_D w_D^{1-\theta} \quad ^{\frac{1}{1-\theta}}$ if the firm imports and $P_M = (n_D)^{1/(1-\theta)} w_D$ if it uses domestic inputs only. Given a productivity level φ, the ratio of the unit costs for a firm with foreign inputs c_{IM} and a firm with domestic inputs c is given by

$$\mu(\tau_{IM,s}, n_D, n_F) = \frac{c_{IM}}{c} = \left[1 + \frac{n_F}{n_D} \quad \frac{w_D}{\tau_{IM,s} w_F}^{\theta-1} \right]^{\frac{-\alpha_M}{\theta-1}} \leq 1 \tag{5.4}$$

There are two sources of cost advantage of importing firms. First, prices may not be fully aligned and hence, imported inputs may provide an advantage if $\tau_s^{IM} w_F < w_D$.[8] Second, even if $\tau_s^{IM} w_F = w_D$, the importing firm has a cost advantage due to the imperfect substitutability of inputs: $c_{IM} = c \times (1 + \frac{n_F}{n_D})^{\frac{-\alpha_M}{\theta-1}} = c \times \mu$. If $n_F \gg n_D$, which is very likely to be the case for a small open economy, and hence $c_{IM} \ll c$.

Consider a change in import tariffs from τ_0 to $\tau_1 > \tau_0$, which does not have an impact on w_F and w_D. Keeping the number of foreign and domestic suppliers fixed, this scenario would result in an increase in the unit cost of an importing firm

$$\ln \frac{c_{IM,1}}{c_{IM,0}} = \ln \frac{\mu_1}{\mu_0} = \frac{\alpha_M}{\theta - 1} \times \frac{n_F}{n_D} \quad \frac{w_D}{w_F}^{\theta-1} \left[\quad \frac{1}{\tau_0}^{\theta-1} - \quad \frac{1}{\tau_1}^{\theta-1} \right] > 0 \tag{5.5}$$

[8] Another interpretation is that imported goods may provide an advantage because they are cheaper in quality adjusted price.

5.2.3 Introducing Trade Policy Uncertainty

The firm in the small open economy trades with two large trade blocs, one of which is the EU and one of which is the Russian CU. The three feasible policy states are a free trade agreement with the EU (EU FTA), the status quo policy (MFN), and the customs union membership (RU CU), shown in Table 5.1. In the case of the EU FTA, exporters from the small open economy face the tariff schedule $\tau_{EX,FTA} = \{\tau^{EU}_{EX,FTA} = 0, \tau^{CU}_{EX,FTA}\}$, which refers to a zero import tariff schedule imposed by the EU, and MFN import tariffs imposed by the CU.[9] The status quo trade policy means that EU MFN tariff rates are applied to exports to the EU and zero tariffs to exports to the CU: $\tau_{EX,MFN} = \{\tau^{EU}_{EX,MFN}, \tau^{CU}_{EX,MFN} = 0\}$.[10] Finally, in the case of the CU, the tariff schedule is $\tau_{EX,CU} = \{\tau^{EU}_{EX,CU}, \tau^{CU}_{EX,CU} = 0\}$. Even though the EU applies the same MFN tariff rates to both Ukraine and CU countries, by joining the CU, Ukraine would worsen the access of its firms to EU countries ($\tau^{EU}_{EX,MFN} \leq \tau^{EU}_{EX,CU}$) for two reasons. First, the current WTO bindings of import tariffs of Ukraine are lower than the CU applied import tariffs. Therefore, if Ukraine joined the CU and adjusted its import tariffs to the CU levels, it would violate its WTO commitments and trigger a lengthy and unpredictable process of renegotiating its bilateral trade relationships with all WTO members, including EU countries. Second, it would have to harmonize its technical standards and phytosanitary norms with the RU CU. These differ substantially from the EU standards, making it harder for

[9] It was repeatedly mentioned by CU representatives that if Ukraine signed the EU FTA, it would lose its free trade status with CU countries. However, one might argue that such a threat was not considered as credible before 2014. Moreover, the EU FTA is compatible with Ukrainian free trade with CU countries. Therefore, it is not clear whether Ukrainian firms attached a high probability to a scenario where CU withdrew from the free trade with Ukraine.

[10] Until recently, the Ukrainian exports to Russia were mostly tariff free with several exceptions. At the same time, Russia frequently introduced non-tariff measures that essentially blocked Ukrainian exports to Russia.

Ukrainian firms to export to the EU. The trade policy states for exports to the EU and the CU are summarized in columns (1) and (2) of Table 5.1.

State, s	Export to EU (1)	Export to CU (2)	Imports from EU (3)	Imports from CU (4)
EU FTA	0	$\tau^{CU}_{EX,MFN}$	0	$\tau^{UKR}_{IM,MFN}$
MFN	$\tau^{EU}_{EX,MFN}$	$0^{b)}$	$\tau^{UKR}_{IM,MFN}$	$0^{c)}$
RU CU	$\tau^{EU}_{EX,CU} \geq \tau^{EU}_{EX,MFN}$ $^{a)}$	0	$\tau^{UKR}_{IM,CU} > \tau^{UKR}_{IM,MFN}$	0

a) May be higher due to potential WTO disputes and non-tariff measures
b) There are some exceptions. See text.
c) Some restrictions apply. See text.

Table 5.1 Ukrainian Tariff Schedules for Exports and Imports to/from EU and CU under different Trade Policies. The table shows that exporting to the EU would be more expensive for Ukrainian exporters than under MFN rules or the EU FTA, as would be importing from the EU.

Firms from the small open economy can also import intermediate inputs from the CU and the EU. Columns (3) and (4) of Table 5.1 present import tariffs that would be imposed on domestic producers importing from the EU or the CU under the different policy states. In the EU FTA state, the import tariffs for goods from EU countries equal zero, $\tau^{UKR}_{IM,FTA} = 0$, and for goods from the CU equal Ukrainian MFN import rates, $\tau^{UKR}_{IM,MFN} > 0$. In the MFN state, the tariff rates for goods from EU are positive $\tau^{UKR}_{IM,MFN} > 0$, and hence, larger than in the FTA state. In the CU state, the import tariffs for imports from EU are $\tau^{UKR}_{IM,CU} > \tau^{UKR}_{IM,MFN} > 0$.[11] For imports from the CU countries, Ukrainian tariffs are zero for both MFN and CU states.

The state of the trade policy is a Markov process with a transition probability matrix

[11] This follows from the fact that the CU tariffs are higher than the Ukrainian tariffs. We discuss this issue in details in the data section.

$$\Lambda = \begin{pmatrix} \Lambda_{FTA} \\ \Lambda_{MFN} \\ \Lambda_{CU} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ p_{EU} & p_{MFN} & p_{CU} \\ 0 & 0 & 1 \end{pmatrix} \tag{5.6}$$

with $p_{EU} + p_{MFN} + p_{CU} = 1$. The small open economy starts in the MFN state. Once the economy moves to either the FTA or CU state, it remains in that state indefinitely. Also, we can rank policy states according to the ease of access to the EU markets as $CU \preceq MFN \preceq FTA$. Hence, Λ_{FTA} stochastically dominates Λ_{MFN}, which in turn stochastically dominates Λ_{CU} in terms of their ease of access to the EU markets.

5.2.4 Exporting under Uncertainty with Intermediate Imported Inputs

The baseline model under uncertainty is considered in the appendix C.1.1. This section discusses how the introduction of intermediate goods changes the expectations from the baseline model. Let us denote $c_{IM,s} = \mu(\tau_{IM,s}, n_{D,s}, n_{F,s}) \times c = \mu_s c$, where $0 < \mu \leq 1$ and $\frac{\partial \mu}{\partial \tau_s^{IM}} > 0$. In addition we denote $\widetilde{I}_{IM} = I_{IM} \times n_F$. Under certainty, a firm imports intermediate inputs if

$$c \leq c^j_{IM,s} = \left[\frac{(1-\beta)\widetilde{I}_{IM}}{a^j_s(\mu^{1-\sigma} - 1)} \right]^{\frac{1}{1-\sigma}} \tag{5.7}$$

Comparing (5.7) with (5.2), all exporting firms would invest in imported inputs if $I_{EX} > \tilde{I}_{IM}(\mu^{1-\sigma} - 1)$. However if $I_{EX} \leq \tilde{I}_{IM}(\mu^{1-\sigma} - 1)$, only a subset of exporting firms invests in intermediate inputs, and the two cutoffs are related as given by

$$c^j_{IM,s} = c^j_{EX,s} \times \left[\frac{\tilde{I}_{IM}}{I_{EX}} \right]^{\frac{1}{1-\sigma}} \times (\mu^{1-\sigma} - 1)^{\frac{1}{\sigma-1}}$$

5.2.5 Importing under Uncertainty

We now consider the case when there is uncertainty in import tariffs, but no uncertainty in export tariffs, $a_s^j = a^j$.[12] In order to optimally chose the mix of inputs, a firm solves the following stopping problem

$$\Pi_s^{IM} = \max\left\{\Delta\Pi_s^e - \widetilde{I}_{IM}, \beta E_s \Pi_{s'}^{IM}\right\}$$

where $\Delta\Pi_s^e = \pi(a^j, \mu_s \times c) - \pi(a^j, c) + E_s \sum \beta^t[\pi(a^j, \mu_{s'}c) - \pi(a^j, c)]$. The detailed discussion of this problem is provided in Appendix C.1.2. Proposition 1 summarizes our main results about the relationship between uncertainty and importing.

Proposition 1 (TPU and import of intermediate inputs) *Under uncertainty about the future trade policy state, where an increase in import tariff rates is possible (moving from MFN to CU state), the cost cutoff for imports from the EU is unique and lower than the cost cutoff under certainty. A reduction in the probability of moving to the CU state leads to more imports of intermediate inputs from the EU. The relationship between the import cutoffs under certainty and uncertainty is given by*

$$\tilde{c}_{IM,MFN}^{EU} = \left(\frac{1 - \beta(1 - p_{CU})}{1 - \beta(1 - \frac{\mu_{CU}^{1-\sigma} - 1}{\mu_{MFN}^{1-\sigma} - 1} \times p_{CU})}\right)^{\frac{1}{1-\sigma}} \times c_{IM,MFN}^{EU} \tag{5.8}$$

[12] This assumption can be relaxed to $a_{MFN} = a_{CU}$, meaning there is no possibility of fundamentals decline in some state of the future trade policy. We can also consider a model with uncertainty in export and import tariffs, which would not change our conclusions, but would considerably complicate discussion.

As in Handley and Limao (2015), the uniqueness of the cutoff follows from the fact that a) the option value of waiting declines with an increase in the gains from importing intermediate inputs $\pi(a^j, \mu_s \times c) - \pi(a^j, c)$ and b) policy states are ordered in terms of likelihood of good access to the EU: Λ_{FTA} stochastically dominates Λ_{MFN}, which in turn stochastically dominates Λ_{CU}. From (5.8), we can see that uncertainty matters only if $\mu_{CU} \neq \mu_{MFN}$, meaning that the value of waiting is positive only if a firm regrets its decision to start importing from the EU. Reducing the probability of joining the customs union to zero eliminates uncertainty and makes $\tilde{c}^{EU}_{IM,MFN} = c^{EU}_{IM,MFN}$, which indicates zero value of postponing importing when there is no risk of a negative impact of the decision. A higher elasticity of substitution lowers the uncertainty cutoff, making it harder for firms to import from the EU, which is another way to test how uncertainty has a differential effects on firms with different elasticity of substitution – uncertainty effects more substitutable goods more strongly.

To sum up, if the use of imported inputs involves irreversible sunk costs, firms in small open economies react to changes in TPU when considering to use imported intermediate inputs. A reduction in TPU encourages companies to import intermediate inputs by investing in technology upgrading and increase their productivity, which can be observed as an increase in imports of capital goods, but should not matter for consumer goods.

5.3 Data

5.3.1 Firm Balance Sheet and Trade Data

We obtain firm-year-level characteristics from statistical forms that all Ukrainian firms have to submit to Ukrstat, the State Statistical Service of Ukraine. From the Financial Results Statements, we measure firm output as total sales revenues net of excise and other indirect taxes. The statement also contains data on material costs, which is measured as the firm's expenditures on materials, supplies, and utilities. The Balance Sheet Statements contains data on the end-of-year value of fixed assets, which we use as our measure of capital endowment of each firm. We measure firm employment as the full-time equivalent of the labor force, calculated as the average number of employees weighted by their time involvement. We then use these data to calculate important firm-level variables like employment and total factor productivity (TFP). The estimation methodology and main results are described in Shepotylo and Vakhitov (2015).

We limit our sample to manufacturing firms (Section D of NACE, Revision 1 of Statistical Classification of Economic Activities) from 2003 to 2014. First, manufacturing industries are better described as monopolistically competitive relative to mining and quarrying where companies produce more homogeneous goods and markets tend to be oligopolistic, or utility companies where state regulation is strong. Second, productivity is better defined in manufacturing and more precisely measured than in services. Finally, manufacturing firms are more likely to be importers of intermediates than other types of firms.[13]

We use the transaction-level database of foreign trade in goods by the Ukrainian Customs Service for generating firm-level exports and imports. The data contain comprehensive information on all export and import transactions at the firm level during a given year. They also contain information on the value and quantity of trade, country of origin and destination, and the product classification at the four-digit level of the Harmonized System

[13]For example, firms in wholesale and retail trade import mostly to resell goods.

(HS-4). The comprehensive transaction level data set enables us to link firm-level exports and imports to MFN tariffs at the HS-4 level, which we describe in the following subsection. We identify intermediate goods and capital goods by mapping the HS6 2012 codes to BEC Ver.4 classification codes, and using the respective BEC categories for both types of goods[14]. Then, we aggregate products from HS6 to HS4 using their median value. Table 5.2 below shows the mapping of BEC goods to intermediate goods, capital, and consumer goods.

Good Type	BEC Ver.4 Code	Number of HS4 Codes
Intermediate Goods	111*, 121*, 21*, 22*, 31*, 322*, 42*,53*	974
Capital Goods	41*, 521*	175
Consumption Goods	112*, 122*, 321*, 522*, 61*, 62*, 63*	523

Table 5.2 Intermediate, Capital, and Consumption Goods: This table depicts the mapping of intermediate, capital, and consumption goods to BEC Ver.4 codes according to the UN Comtrade classification. BEC Ver.4 codes are mapped to HS-codes using the UN concordance tables at the HS4-digit level.

Table 5.3 shows exports and imports of manufacturing firms by Ukrainian regions and destinations in 2010 and 2013. The East and Crimea regions were the major exporting regions, both in 2010 and 2013. Firms from this region exported mostly to CU countries in 2010, but had diversified to the rest of the world by 2013. Exports to the EU dominate the Western region, and expanded markedly between 2010 and 2013. In terms of imports, the South region, East, and Crimea imported heavily from CU countries in 2010, while by 2013 all regions imported more from the EU than from any other origin. The data illustrate that by 2013, Ukrainian firms were already re-orienting towards European markets. Ukrainian exports still mostly went

[14]The respective concordance tables can be found under the UN Comtrade Correspondence Tables. The mapping of BEC to intermediate goods, capital, and consumption goods follows the UN definition for Intermediate Goods in Trade.

to CU countries, but started to expand to other emerging economies by 2013.

	Year and Partner							
	2010				2013			
Region	**CU**	**EU**	**ROW**	**Total**	**CU**	**EU**	**ROW**	**Total**
	A Exports, in billion USD							
Center	2.05	1.03	1.64	4.71	2.96	1.39	5.89	10.24
East&Crimea	4.13	2.43	3.43	9.99	5.91	1.88	8.11	15.90
South	2.82	1.11	3.70	7.64	4.44	1.49	6.20	12.13
West	0.41	1.14	0.25	1.79	1.12	1.94	0.36	3.43
Total	9.41	5.72	9.01	24.14	14.44	6.70	20.56	41.70
	B Imports, in billion USD							
Center	0.83	1.89	0.56	3.28	1.36	4.09	1.49	6.95
East&Crimea	3.63	0.83	0.48	4.93	1.65	6.73	2.57	10.95
South	2.19	0.87	1.27	4.32	1.24	2.94	1.79	5.97
West	0.26	2.00	0.10	2.36	0.22	3.86	0.31	4.39
Total	6.90	5.59	2.41	14.90	4.46	17.63	6.16	28.25

Table 5.3 Ukrainian Regional Manufacturing Exports and Imports by Destination, 2010 and 2013. The table depicts the regional trade of Ukrainian manufacturing firms from different regions in Ukraine with the the CU, the EU, and the Rest of the World (ROW) in 2010 and 2013. Overall Ukrainian manufacturing firms trade more with the EU and the ROW than with the CU. While all regions gradually shifted towards EU imports from 2010 to 2013, Ukrainian exports were still mostly focused on the CU and the ROW.

5.3.2 Tariff Data

One of our key predictions is that a reduction in TPU has a larger impact on trade in products with higher MFN tariff rates, as shown in proposition 1. We obtain year-varying data on CU tariffs from Shepotylo and Tarr (2013), and data on Ukrainian MFN tariffs from the TRAINS database. The applied MFN rates of Ukraine are very close to the binding rates, so in the analysis that follows, we compare the applied MFN rates of Ukraine and the CU. It is important to emphasize that, as a WTO member, Ukraine accepted a multilateral schedule of binding tariff rates which is not compatible with the CU MFN tariff schedule. Thus, *Ukraine would have violated its WTO commitments by joining the CU, and would have faced large increases of tariff rates for most finished and intermediate goods*. Table C.3 in the appendix shows the changes in applied Ukrainian tariffs and Russian Customs Union tariffs between 2003 and 2013. Russia import bans on on beer, vodka, juice, wallpaper and confectionery from mid-2013 do not affect our analysis, because we are only focusing on manufacturing products.

Figure 5.1 illustrates the differences in tariff rates between Ukrainian MFN rates and the CU by major product categories in 2012. Except for a couple of products, the CU tariffs are much higher than Ukrainian MFN rates, particularly in foodstuff, textiles, transportation, and wood products. If Ukraine had joined the CU in 2012, this *would have increased Ukrainian applied MFN rates for more than 90 percent of all product lines, by 6.5 percentage points, on average*. This would be a substantive increase in the levels of tariffs compared to the baseline MFN scenario. In contrast, the EU FTA would have left Ukraine's MFN tariffs untouched (i.e. still lower than the CU tariffs), and would have set most of Ukraine's tariffs vis-a-vis EU countries to zero.

5.3.3 Trade Policy Uncertainty Measure

We conceptualize TPU as the probability of Ukraine signing either the EU FTA or joining the CU with Russia. In this binary decision, each of these policies means increased uncertainty with regards to the alternative, because *both policies could not have been implemented at the same time*. While the common external tariff of the RU CU would have made the conclusion of the EU FTA impossible, an FTA with the EU would have rendered the

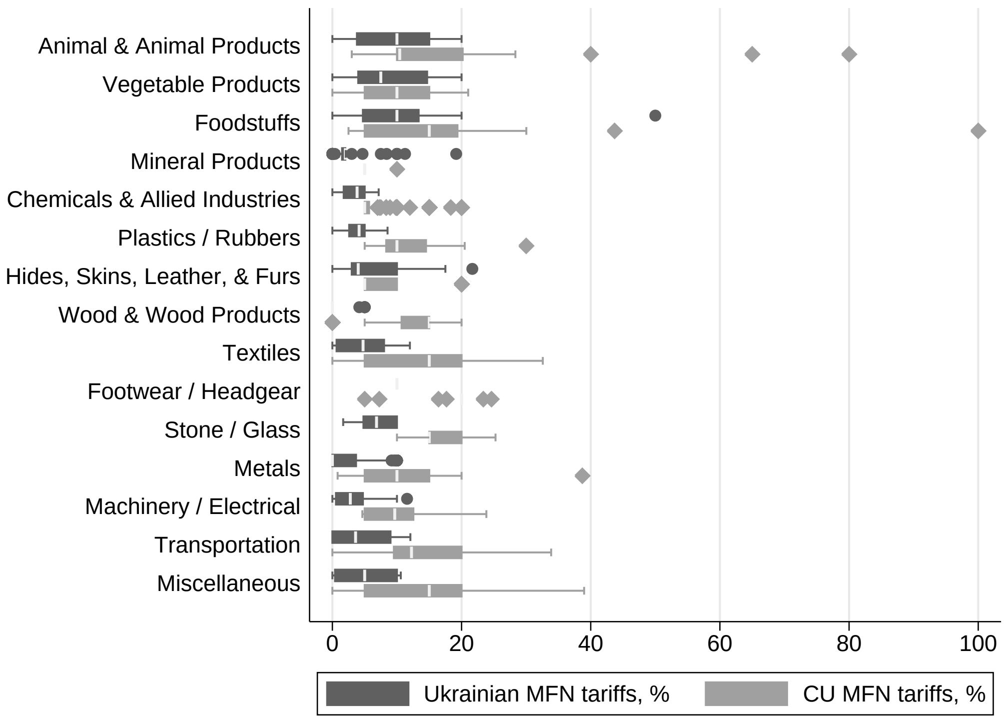


Figure 5.1 Differences in Applied MFN Tariff Rates between Ukraine and the RU CU in 2012. This graph illustrates the differences in the distribution of applied MFN tariff rates between Ukraine and the CU. The figure shows that the CU MFN tariffs are higher than Ukraine's MFN tariffs in all product categories, particularly in foodstuff, transportation, textiles as well as wood and wood products.

CU with Russia politically unfeasible. To measure TPU, we use automated quantitative text analysis for large-scale, unstructured collections of texts.

The measure is based on relative salience of the respective policy in Ukrainian business news. Our main source for measuring TPU consists of approximately 2200 trade-related[15] news briefs from Ukraine Business Weekly (UBW). Operated by Interfax, UBW is a press release service that provides summaries of business and financial news in Ukraine. UBW is available over a long period of time, from January 2003 to today, and it concerns business news only, which makes it more relevant to our investigation than broadsheet newspapers. To estimate TPU from UBW articles, we use so-called "topic models", developed by computer scientists for the analysis and organization of large-scale collections of texts. Topic models analyze relative word occurrences in un-labeled documents in order to infer "themes" that run through them.[16] It is crucial to understand that topics *are not defined ex ante* by the researcher, like in hand-coding of words or documents based on pre-defined dictionaries.[17]

Estimation of the topic models works as follows: a topic K is defined as a distribution over a fixed vocabulary V. We assume that documents (press releases) are created by K topics. Across documents, we first randomly choose a distribution over topics β_k. Each document is modeled as a distribution over K topics, θ_d. Within each document, words are generated by a two step process. First, for each word $z_{d,n}$, one draws one topic for that

[15]See Appendix C.2.1 for a detailed description of how we selected the text collection, or "corpus".
[16]These models have been successfully applied in both Political Science (Grimmer, 2010; Roberts et al., 2014) and Economics (Mueller and Rauh, 2018), and many more fields such as Genetics or Information Science (Blei, 2012).
[17]For a good description of the basics of dictionary-based text analysis see Neuendorf (2002, Chapter 6). A well-known application of dictionary-based methods keywords representing left-right ideology in order to estimate scores of party positions using their election manifestos (Laver and Garry, 2000). In economics, Baker, Bloom and Davis (2016) use pre-defined dictionaries to measure their Economic Policy Uncertainty index.

word from a multinomial distribution $z_{d,n} \sim Mult(\theta_d)$ (with $z_{d,n}$ indexing the topic assignment for the n-th word in document d). Second, a word $w_{d,n}$ is drawn from a distribution over the vocabulary $w_{d,n} \sim Mult(\beta_{z_{d,n}})$ where $\beta_{k,v}$ is the probability of drawing the v-th word in the vocabulary for topic k. The likelihood of a word for a given topic is then the probability of a topic within a given document times the probability of a term in the overall word distribution, $p(z_{d,n}) \cdot p(w_{d,n})$. This joint distribution of the latent and observed parameters (Blei, Ng and Jordan, 2012) is formally given by

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \quad \prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \quad .$$

Finally, the model assumes a Dirichlet prior for the topic proportions over documents, so that $\theta_d \sim Dirichlet(\alpha)$ (Blei, Ng and Jordan, 2003). This joint probability distribution can be used in order to calculate the latent parameter of interest, the posterior topic probabilities θ_d for each document. Higher posterior likelihoods of a topic mean that a high proportion of terms in document is assigned to that topic. The intuition is that *documents* in a collection of documents contain multiple *topics* or themes, but they exhibit these topics in different proportions, depending on which words (each assigned to one topic) are used more or less in these documents. Bigrams like “Association Agreement” or “Eastern Partnership” are related to the topic “EU-Ukraine FTA” , while terms like “customs union” or “EACU” would be related to the topic “Russia-Ukraine Customs Union”. Topic models do not require any prior information about the text - only the number of topics K needs to be specified. We use *Structural topic models* (STMs) which allow the introduction of document-level covariates, in our case, the publication date, allow for topics to vary over time (Roberts et al., 2014).[18]

Figure 5.2 shows the topics estimated by an STM with $K = 10$, and the five terms mostly associated with them.[19] The x-axis shows the overall topic proportions across all articles from all 10 topics, which sum up to 1. One can clearly identify the two topics which we are interested in: *Topic 1* is about Ukraine approaching the EU, about the Eastern Partnership process and the Association Agreement ("easternpartnership", "euukrain", "association-agr"). *Topic 8* is about the Ukraine joining the CU with Russia. Documents with high proportions of this topic use terms like "economicspace", "zone", or "customsunion" score high on this topic. We can also differentiate the EU FTA and the CU topic from other trade topics which might be discussed in UBW, but which are not directly related to the EU FTA and the CU.[20]

Figure 5.3 below shows the EU FTA and the RU CU topics over time, including 95% confidence intervals. It measures the relative salience of the two mutually exclusive policies. Thus, it is similar to the economic policy uncertainty measure developed by Baker, Bloom and Davis (2016). However, we do not use a pre-defined dictionary, as the topics are estimated from the textual data.[21] Empirically, we are interested in the up-and-down swings between the two non-compatible policies. As long as none of the policies

[18] A well known application in Political Science are party manifestos, which contain information about the election year, the type of election (federal, subnational), and the author (the party). See Volkens et al. (2015).

[19] Here, we report the so-called "FREX" terms. These are words associated with the topic which appear with high probability *and* most exclusively this topic, but not other topics. However, all words *can* in principle occur in all topics, as the top assignment to words *n* is not deterministic but probabilistic.

[20] For instance, topic 3 is about steel and cheese quotas ("quota, "pipe", "dairy",...) and topic 10 is about Russian gas imports ("gazprom", "russiangas", "gastransit",...), two topics which are also very contentious in Ukrainian trade relations. In Figure C.6 in the appendix, we also provide snippets of articles that score high on our two topics of interest.

[21] The raw monthly and weekly topic prevalences are presented in Figure C.5 in Appendix A6.

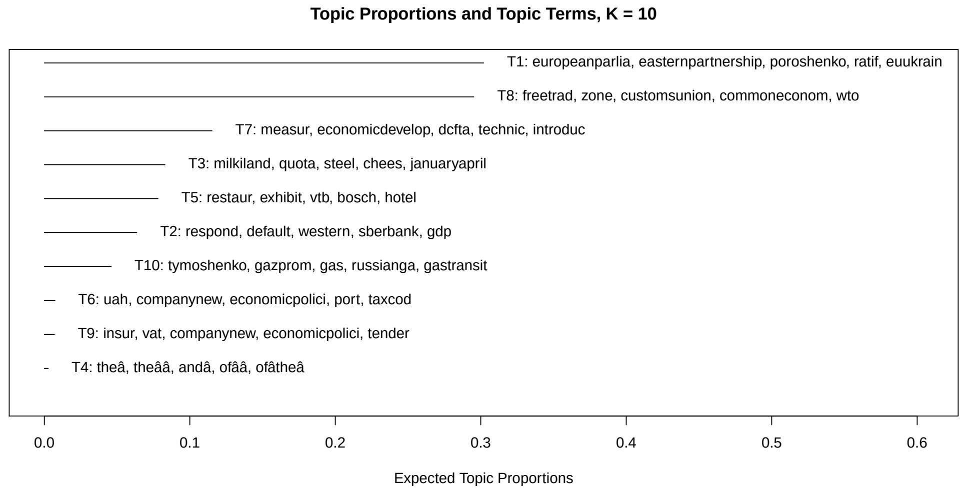


Figure 5.2 Mean Topic Proportions across $K = 10$ **Topics**. This graph shows the distribution of 10 topics estimated from 2200 Ukraine Business Weekly news briefs. The proportions across all topics sum up to 1 and indicate the prevalence of a given topic in a the collection of news briefs. The words are terms that are mostly associated with the respective topic. Topic 1 is abput the EU FTA and Ukraine-EU relations, whereas Topic 8 is about the RU CU and Ukraine-Russia relations.

has been realized (i.e. $p_{EU} = 1$ or $p_{CU} = 1$), larger values in one topic can be interpreted as uncertainty with regards to the other topic. The smoothed time trend shows both the increasing prevalence of the EU FTA, and the simultaneous decline of the CU salience over time. It also highlights the short but sharp decline in EU FTA prevalence in 2013, when the Ukrainian president Yanukovich declined to sign the EU FTA. After Yanukovich is ousted from office, the EU FTA becomes more salient again.[22]

The latent topics estimated from the UBW articles are therefore good representations of the long-run policy process and the relative probabilities

[22] See the next section for a more thorough description. The graph also includes vertical lines for other events in the following order: 1) 08/2006: Announcement of plans for Eurasian Customs Union; 2) 07/2008: Inauguration of Eastern Partnership between EU and post-Soviet states; 3) 01/2010: Launch of Eurasian Customs Union with Belarus, Kazakhstan and Russia; 4) 03/2012: Start of negotiations between EU and Ukraine on Association Agreement; 02/2013: EU Commission President Jose-Manuel Barroso announces Ukraine needs to decide between EU AA and CU with Russia; 01/2014: Yanukovich ousted from office following Euro-Maidan demonstrations; 03/2014: AA between EU and Ukraine signed; 04/2016: Ukraine signs Deep and Comprehensive Free Trade Agreement with the EU; 04/2016: Dutch Referendum rejects the EU-Ukraine DCFTA, which enters into force regardless in January 2017.

of the two trade policy options. Inspection of the words associated with topics, the documents associated with the topics, and the long-run trend resembling real-world events provide validity to our TPU measure.[23] Moreover, in appendix A7, Figures C.9 and C.10 we provide evidence that our measure is not driven by changes in tone, or *how* UBW reports about the FTA and the CU. In another validation exercise, in Figure C.8 in appendix A6, we plot our measure against the widely-used Economic Policy Uncertainty (EPU) measures by Baker, Bloom and Davis (2016) for Russia.[24] In line with our expectations, we find that our EU FTA measure is positively correlated with Russian EPU and that our RU CU measure is negatively correlated with Russian EPU.

5.4 Empirical Analysis

5.4.1 Ukrainian Trade Policy vis-a-vis the EU and Russia

Since the fall of the Iron Curtain, Eastern European countries had to re-orient their foreign economic policies and sought either closer ties with the EU or the Russian Federation. By 2011, 12 former communist countries had joined the EU. Since 2000, Russia pursued the Eurasian Economic Union (EACU) , a customs union with Belarus and Kazakhstan. In 2003, Russian president Valdimir Putin officially invited Ukraine to join the customs union project, and publicly supported the pro-Russian candidate Victor Yanukovich in the Ukrainian presidential elections. However, Ukraine had already applied for EU membership in 1995, and most Ukrainian voters supported the Western-friendly candidate Victor Yushchenko.

[23]In Appendix A5, we provide tests of non-stationarity of our measure, and reject it for both time-series.
[24]We use Russia since there is no separate EU or Ukrainian EPU measure.

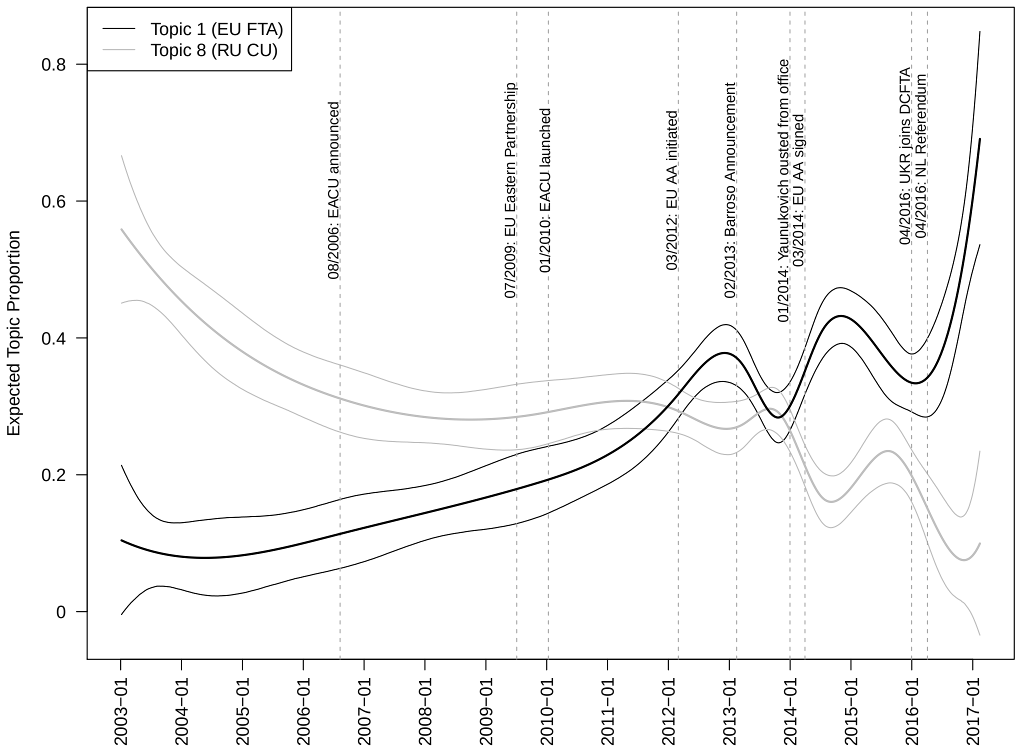


Figure 5.3 Mean Topic Proportions of EU FTA and RU CU Topic, 2003-2017. This graph depicts the prevalence of the EU FTA topic and the RU CU topic from 2003-2017. Both topics are fitted with spline for month. The figure shows how the mean topic proportions (in bold, with 95 percent confidence intervals) vary intuitively with actual changes in Ukraine-EU and Ukraine-Russia relations. Note that estimation uncertainty and variation in means is higher at the beginning and the end of the time period because less articles/data are available.

The Orange Revolution in 2004 resulted in a pro-EU government, and the WTO accession in 2008 further paved the way to negotiation of a free trade agreement with EU (Shepotylo and Vakhitov, 2015). In May 2009, the EU started the Eastern Partnership with the six ENP countries[25] in order to "[...] create the necessary conditions to accelerate political association and further economic integration between the European Union and interested partner countries" (CoEU, 2009). In addition to free trade, the European Union offered a broader Association Agreements (AA) which included political cooperation, but without the promise of future EU accession (Aslund, 2013). However, in 2010, Victor Yanukovich won the presidential elections promising to strengthen economic ties with Russia while still following a two-tier trade strategy: "From his re-election in 2010 onward, President Yanukovych had purportedly cultivated ambiguity on the geopolitical orientation of his country...neither by originally indicating his readiness to sign the AA nor by eventually rejecting it" (Cadier, 2014). His government continued negotiations on a deep and comprehensive free trade agreement with the EU (DC FTA) which was supposed to lower tariffs and Non-Tariff Barriers (NTBs) between Ukraine and the EU.

Moscow vehemently opposed both the DC FTA and the AA, because Russia viewed them as a threat to their customs union. Before the 2013 Eastern Partnership summit in Vilnius where the DC FTA was scheduled to be signed, Russia imposed import bans on major Ukrainian exports to Russia and threatened to withdraw from an existing bilateral FTA with

[25] In 2003, the EU had launched the European Neighborhood Policy (ENP), which supported structural reforms in exchange for improved market access and liberalization of visa regimes(Cadier, 2014). ENP governs the EU's relations with 16 of the EU's closest Eastern and Southern Neighbors. To the South: Algeria, Egypt, Israel, Jordan, Lebanon, Libya, Morocco, Palestine, Syria and Tunisia and to the East: Armenia, Azerbaijan, Belarus, Georgia, Moldova and Ukraine. Russia takes part in Cross-Border Cooperation activities under the ENP and is not a part of the ENP as such. Source: https://ec.europa.eu/neighbourhood-enlargement/neighbourhood/overview_en

Ukraine. Russia also promised to lower energy prices, and to provide financial assistance worth of 15 billion dollars if Yanukovich did not sign the DC FTA. On 21 November 2013, Yanukovich finally refused to sign the EU DC FTA, which triggered a civil unrest that eventually overthrew the Yanukovich regime in February 2014. Since then, a newly elected Ukrainian government has strongly committed to the path of European integration. The AA was signed in June 2014 and has only been provisionally applied since November 2014. The EU-Ukraine FTA has been provisionally applied since January 2016.

5.4.2 Trade Policy Uncertainty, Imports and Tariff Protection

Our theoretical model predicts that trade of products which are protected by higher MFN tariffs should benefit more from the reduction in trade policy uncertainty than those with lower MFN tariffs. This prediction allows us to identify the TPU effects using both variation *across time and products*. We test the prediction by interacting our TPU measures with product-specific and time-varying MFN tariffs.

	Export					Import				
	Base	+Empl	+TFP	+Ind	+Ind.Trend	Base	+Empl	+TFP	+Ind	+Ind.Trend
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$p^{EU} \times \ln(1+\tau_{MFN})$	5.124**	4.036*	4.037*	4.553*	1.155					
	(1.788)	(1.789)	(1.801)	(1.803)	(1.863)					
$\ln(1+\tau_{MFN})$	-.158	-.199	-.456	-.579	4.538**					
	(1.259)	(1.264)	(1.264)	(1.265)	(1.370)					
$p^{EU} \times \ln(1+\tau_{UKR})$						2.989**	3.460**	3.341**	3.384**	3.070**
						(.572)	(.570)	(.575)	(.575)	(.581)
$p^{CU} \times \ln((1+\tau_{CU})/$						-1.067**	-1.535**	-1.575**	-1.538**	-.206
$(1+\tau_{UKR}))$						(.243)	(.243)	(.246)	(.246)	(.252)
$\ln(1+\tau_{UKR})$						-1.788**	-2.027**	-1.678**	-1.675**	-.379
						(.229)	(.227)	(.230)	(.230)	(.247)
p^{EU}	-.158**	-.0722	-.161**	-.192**	-.826**	.0803**	.0692**	-.00118	-.0149	-.618**
	(.054)	(.054)	(.055)	(.056)	(.083)	(.026)	(.026)	(.026)	(.026)	(.041)
p^{CU}	-.176**	-.244**	-.209**	-.200**	.442**	.0706**	.0783**	.137**	.145**	.402**
	(.031)	(.031)	(.032)	(.032)	(.056)	(.020)	(.020)	(.021)	(.021)	(.031)
ln(Employment)		.357**	.369**	.374**	.374**		.401**	.422**	.431**	.345**
		(.016)	(.017)	(.017)	(.017)		(.008)	(.008)	(.008)	(.008)
TFP			.129**	.186**	.150**			.130**	.172**	.146**
			(.010)	(.013)	(.013)			(.005)	(.006)	(.006)
Quarter	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry				✓	✓				✓	✓
Year					✓					✓
Region				✓	✓				✓	✓
Observations	129502	128909	125696	125696	125696	807509	804767	786701	786701	786701
R^2	.875	.876	.876	.876	.880	.811	.813	.812	.813	.815

Table 5.4 Ukraine-EU Trade, Tariff Protection, and Trade Policy Uncertainty. The table shows the impact of uncertainty on intermediate and capital goods with different levels of tariff protection. The dependent variable is the log of firm i's exports/imports of product k to/from EU country j in quarter t, using only intermediate and capital goods. p^{EU} captures the likelihood of Ukraine signing the EU FTA. p^{CU} capture the likelihood of Ukraine joining the CU with Russia. $\ln(1+\tau_{MFN})$, $\ln(1+\tau_{UKR})$, and $\ln(1+\tau_{CU})$ are the current EU MFN tariffs vis-a-vis Ukrainian exports, current Ukrainian MFN tariffs, and tariffs under the Russian Customs Union, respectively. All models include firm-destination-HS4 product fixed effects. *Notes*: + p<0.1 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

In the following linear regressions, we focus on the interaction terms $p_{EU} \times \ln(1+\tau^{EU}_{MFN})$ for exports of Ukrainian firms to EU member states, and $p_{EU} \times \ln(1+\tau^{UKR}_{MFN})$ and $p_{CU} \times \ln[(1+\tau^{CU}_{MFN})/(1+\tau^{UKR}_{MFN})]$ for imports of Ukrainian manufacturers from the EU.[26] We expect positive coefficients for the first two cross terms and a negative coefficient for the last cross term. Products with higher tariff protection should expand more if the likelihood of signing the EU-Ukrainian FTA increases, resulting in an increased probability of tariff rates being reduced to zero. However, if the likelihood of joining CU with Russia increases, this would raise expectations that Ukraine would switch from its own tariff schedule to the CU schedule, which would result in lower imports from EU countries for products with higher CU protection, relative to Ukrainian tariffs. Table 5.4 shows the results from this test using Ukrainian exports to the EU (columns 1-5) and Ukrainian imports from EU (columns 6-10) as dependent variables. We consider only trade of intermediate and capital goods (BEC Rev. 4 classification) of Ukrainian firms with EU. All regressions include firm-country-product fixed effects.

For Ukrainian exports to the EU, we find that $p_{EU} \times \ln(1+\tau^{EU}_{MFN})$ has a significantly positive effect, which means that export of products with higher MFN tariffs expand more when probability of signing EU FTA goes up. Column (1) provides the baseline result. We control for employment (column 2), productivity (column 3), industry and region (column 4) in further specifications. The effect becomes non-significant when we add industry specific trends (column (5)), but it remains positive. Also, the effect of MFN tariff for this case turns positive, which may indicate a problem of multicollinearity in trade policy variables. According to column (4), which is our preferred model specification, elimination of TPU would increase

[26]The export equation has only one interaction term because joining the customs union does not change tariffs faced by Ukrainian exporters that export to EU countries.

exports to EU by 8.3 percent, while elimination of tariffs would increase exports to EU by 1.3 percent.

For imports, we observe a robust positive effect of $p_{EU} \times \ln(1 + \tau^{UKR}_{MFN})$, indicating that imports of products with high levels of tariff protection in Ukraine expand more when the likelihood of signing the EU FTA is high. Moreover, EU imports of goods that are more protected under the CU, relative to the Ukrainian tariffs, decrease more when p_{CU} is larger, as indicated by the negative and significant coefficient on $p_{CU} \times \ln[(1 + \tau^{CU}_{MFN})/(1 + \tau^{UKR}_{MFN})]$. Our results are robust to the inclusion of industry and regional dummies (column 9) and to accounting for industry-time trend (column 10). The magnitude of the effect is large. Based on the estimates from column (9), signing the EU FTA and completely removing TPU would increase imports from the EU by 10.1 percent. The effect of lower tariffs, on the other hand, would increase imports by only 6 percent. To the extent that imported manufacturing inputs are used to increase productivity, this could hint at potential productivity-reducing effects of trade policy uncertainty.

5.4.3 Trade Policy Uncertainty and Intermediate and Capital Goods versus Consumer Goods

Our theoretical results indicate that uncertainty matters more for goods with higher sunk costs (equations 5.2 and 5.7). Thus, intermediate and capital goods used by firms in the production process should be responsive to swings in uncertainty, while consumer goods should be less sensitive to changes in TPU. We test this prediction by estimating the same model as before, and compare the effects on all goods, capital goods, intermediate goods, and consumer goods (BEC Ver. 4 classification). We present the results in Table 5.5 for exports (columns 1-4) and imports (columns 5-8).

The results confirm our theoretical expectations. The coefficients on the interaction terms consistently vary across different types of traded goods. Capital goods with higher tariff protection are the most sensitive to changes in policy uncertainty. Intermediate goods still have significant interaction terms coefficients, but the effects are lower in magnitude. Finally, consumer goods do not respond to the TPU changes and often have the opposite sign of the coefficients on the interaction terms. These results confirm our theoretical expectations that capital and intermediate goods should react more strongly to changes in TPU.

	Export				Import			
	All	Capital	Intermediate	Consumer	All	Capital	Intermediate	Consumer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p^{EU} \times \ln(1+\tau_{MFN})$	1.460^{+}	35.35**	4.242*	-.680				
	(.876)	(12.881)	(1.822)	(1.345)				
$\ln(1+\tau_{MFN})$	-.0620	-70.66**	-.413	18.48^{+}				
	(1.236)	(27.151)	(1.256)	(10.448)				
$p^{EU} \times \ln(1+\tau_{UKR})$					2.447**	7.767**	2.668**	-1.294
					(.519)	(2.139)	(.591)	(1.553)
$p^{CU} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$					-1.606**	-5.310**	-.828**	-2.178**
					(.228)	(.769)	(.260)	(.633)
$\ln(1+\tau_{UKR})$					-1.582**	-1.712^{+}	-1.414**	-1.452**
					(.213)	(.920)	(.236)	(.553)
Quarter	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓
Observations	176651	16463	109233	50955	880486	143757	642944	93785
R^2	.868	.867	.877	.842	.812	.776	.819	.802

Table 5.5 Ukraine-EU Trade Trade Policy Uncertainty: Intermediate, Capital, and Comsumer Goods. The table shows the impact of uncertainty on intermediate and capital goods with different levels of tariff protection for intermediate, capital, and consumption goods. The dependent variable is the log of firm i's exports/imports of product k to/from EU country j in quarter t, using only intermediate and capital goods. p^{EU} captures the likelihood of Ukraine signing the EU FTA. p^{CU} capture the likelihood of Ukraine joining the CU with Russia. $\ln(1+\tau_{MFN})$, $\ln(1+\tau_{UKR})$, and $\ln(1+\tau_{CU})$ are the current EU MFN tariffs vis-a-vis Ukrainian exports, current Ukrainian MFN tariffs, and tariffs under the Russian Customs Union, respectively. We control for the probability of joining the EU FTA, the RU CU, as well as firm employment and productivity. All models include firm-destination-HS4 product fixed effects. *Notes*: + p<0.1 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

We perform a number of robustness checks, all of which are described in more detail in the appendix. One important question is whether our measure of TPU outperforms existing measures and simpler measures based on relative word frequencies. In appendix A10 and A11, we re-estimate the main results in Table 5.4 using the Economic Policy Uncertainty Index by Baker, Bloom and Davis (2016), and simple measures based on relative word frequencies, none of which changes sign or significance of our main explanatory variable based on topic models. We also re-estimate the results in Table 5.5 using alternative topics from our topic model, such as a topic about natural gas or quotas, none of which have the same effect as our TPU measure. We also employ another battery of simpler measures, such as logged word counts, relative word frequencies for both EU and CU topics, and overall number of articles, none of which changes the main results presented in the last two sections.

5.4.4 Trade Policy Uncertainty during the 2014 Transition

In this last empirical section, we show that our results also hold in shorter time frames with large changes in TPU, between 2013 and end of 2014. In January 2014, after the Euro-Maidan demonstrations, the Yanukovich regime was ended and a EU-friendly government took office. As a result, the CU with Russia became politically unfeasible and the EU FTA much more likely. The large swings in uncertainty are also very much visible in our TPU measure in Figure 5.3 above. Shortly after Yanukovich had been ousted from office, the uptick in EU FTA visualizes the actual increased likelihood of an FTA with the European Union. Therefore, we run two additional model specifications, concentrating on the 2013 and 2014 time frame that was marked by increased volatility in TPU. For this purpose, we aggregate the firm-level trade data by firm, month and HS4-product, and restrict the sample to EU-Ukraine trade as in Table 5.4 above.

In the first model, we interact the TPU measure with HS4-product MFN tariffs. We control for firm-level factors and use firm-product-destination fixed effects, as well fixed effects for month, industry, region, and time trends. The results are show in Table 5.6 below. Consistent with our prior findings, the interaction term $p_{EU} \times \ln(1 + \tau^{UKR}_{MFN})$ is positive and significantly different from zero. As TPU with regards to the EU FTA is reduced (p_{EU} increases), imports of products that are more protected under current Ukrainian MFN tariffs expand, since those products would benefit the most from the FTA with the EU. Conversely, the coefficient on $p_{CU} \times \ln[(1 + \tau^{CU}_{MFN})/(1 + \tau^{UKR}_{MFN})]$ is significant and negative. For higher values of p_{CU}, imports of products that would be more protected under a potential customs union relative to the status quo Ukrainian MFN tariffs decrease substantively. In line with our prior results, this holds for Ukrainian imports only: exports to the EU are not affected by the interaction $p_{EU} \times \ln(1 + \tau^{EU}_{MFN})$.

One concern could be that we are merely picking up the beginning of the civil war in Eastern Ukraine since March 2014. Shortly after the 2014 transition occurred, a fully-fledged war broke out in Donbass (including Donetsk and Luhansk) from March 2014, severely reducing the data from those regions. Then, Crimea was annexed by Russia in March 2014 and firms from Crimea stopped reporting to the Ukrainian statistical services. Therefore, model 4 and 8 in Table 5.6 exclude firms based in Crimea, Donetsk, and Luhansk. Our results remain under this alteration and various other model specifications.

In the second model, we take a difference-in-difference approach, leveraging the 2014 political transition as a shock to trade policy uncertainty with regards to Ukrainian relationships with Russia and the EU. The logic is the following: the 2014 transition led to the formation of a new, EU-friendly government in Kiev. Hence, the *transition reduced uncertainty* with regards to the EU FTA for Ukrainian firms. Firms that trade products which are more protected under Ukrainian MFN tariffs or the potential CU with Russia should react more strongly to this reduction in uncertainty. We thus run the same model as before, but instead of using our TPU measure, we include a dummy variable *Post* that equals 1 for all months following the February 2014 transition, and zero otherwise. We interact this Post-dummy with the same measures of Ukrainian MFN tariffs ($Post \times \ln(1+\tau^{UKR}_{MFN})$), EU MFN tariffs ($Post \times \ln(1+\tau^{EU}_{MFN})$), and the ratio of CU tariffs to Ukrainian MFN tariffs ($Post \times \ln[(1+\tau^{CU}_{MFN})/(1+\tau^{UKR}_{MFN})]$) as before. Since the *Post*-dummy implies a reduction in TPU with regards to the EU FTA (or equivalently, an increase in p_{EU}), we expect all three interaction terms to be positive.[27] We show the results in Table 5.7 below. In line with our expectations, within firm-products-EU destinations with higher Ukrainian MFN tariffs and products with larger tariffs under the CU expand significantly more in the period following the 2014 transition. Consistent with our prior models, we find these effects for imports from but not for exports to the EU. These results hold controlling for a host of fixed effects, firm-level covariates, and a time trend. Again, the results also hold up excluding Crimea, Donetsk, and Luhansk, suggesting that we are not picking up the beginning of the conflict in Eastern Ukraine.

[27]Note that this approach is very similar to Facchini et al. (2019).

	Base	+Ind&Reg	+Trend	-C/D/L	Base	+Ind&Reg	+Trend	-C/D/L
	(1) Exports	(2) Exports	(3) Exports	(4) Exports	(5) Imports	(6) Imports	(7) Imports	(8) Imports
$ln(1+\tau_{EU})$	.097	.097	.097	.097				
	(.19)	(.19)	(.19)	(.22)				
$ln(1+\tau_{EU}) \times p^{EU}$	.016	.016	.016	.008				
	(.04)	(.04)	(.04)	(.05)				
$ln(1+\tau_{UKR})$					.113	.115	.115	.117
					(.18)	(.18)	(.18)	(.18)
$ln(1+\tau_{UKR}) \times p^{EU}$					.116**	.116**	.116**	.133**
					(.04)	(.04)	(.04)	(.04)
$\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					.049	.050	.050	.064
					(.09)	(.09)	(.09)	(.09)
$\ln((1+\tau_{CU})/(1+\tau_{UKR})) \times p^{CU}$					-.146**	-.142**	-.142**	-.156**
					(.05)	(.05)	(.05)	(.06)
p^{CU}	-.707**	-.716**	-.716**	-.716**	-2.111**	-2.099**	-2.099**	-2.215**
	(.18)	(.18)	(.18)	(.19)	(.24)	(.24)	(.24)	(.25)
p^{EU}	.886**	.892**	.892**	.928**	1.822**	1.812**	1.812**	1.863**
	(.24)	(.24)	(.24)	(.24)	(.27)	(.27)	(.27)	(.28)
TFP	.129*	.136*	.136*	.134*	.409**	.451**	.451**	.440**
	(.06)	(.06)	(.06)	(.06)	(.08)	(.09)	(.09)	(.09)
$ln(empl)$	.159	.105	.105	.166	.592**	.533**	.533**	.501**
	(.13)	(.13)	(.13)	(.15)	(.16)	(.17)	(.17)	(.19)
Month FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs		✓	✓	✓		✓	✓	✓
Region FEs		✓	✓	✓		✓	✓	✓
Trend			✓	✓			✓	✓
Observations	324599	324599	324599	301726	320566	320566	320566	297653
R^2	.923	.923	.923	.919	.894	.894	.894	.890

Table 5.6 Ukraine-EU Trade and Trade Policy Uncertainty, 2013-2014. The table shows the impact of uncertainty on intermediate and capital goods with different levels of tariff protection, between 2013 and 2014. The dependent variable is the log of firm i's exports/imports of product k to/from EU country j in month t, using only intermediate and capital goods. p^{EU} captures the likelihood of Ukraine signing the EU FTA. p^{CU} capture the likelihood of Ukraine joining the CU with Russia. $\ln(1+\tau_{MFN})$, $\ln(1+\tau_{UKR})$, and $\ln(1+\tau_{CU})$ are the current EU MFN tariffs vis-a-vis Ukrainian exports, current Ukrainian MFN tariffs, and tariffs under the Russian Customs Union, respectively. All models include firm-destination-HS4 product fixed effects. The models 2 and 6 add industry- and region fixed effects and models 3 and 7 add a time trend. The models 4 and 8 exclude Crimea, Donetsk, and Luhansk. *Notes*: + p<0.10 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

	Base	+Ind&Reg	+Trend	-C/D/L	Base	+Ind&Reg	+Trend	-C/D/L
	(1) Exports	(2) Exports	(3) Exports	(4) Exports	(5) Imports	(6) Imports	(7) Imports	(8) Imports
$ln(1+\tau_{EU})$	.103	.104	.104	.102				
	(.19)	(.19)	(.19)	(.22)				
Post× $ln(1+\tau_{EU})$	-.006	-.007	-.007	-.010				
	(.02)	(.02)	(.02)	(.02)				
$ln(1+\tau_{UKR})$					.152	.154	.154	.159
					(.19)	(.19)	(.19)	(.19)
Post × $ln(1+\tau_{UKR})$					.124**	.125**	.125**	.126**
					(.03)	(.03)	(.03)	(.03)
$\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					.010	.012	.012	.018
					(.09)	(.09)	(.09)	(.09)
Post× $\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					.112**	.111**	.111**	.114**
					(.02)	(.02)	(.02)	(.02)
Post	.215**	.218**	.218**	.225**	.311**	.308**	.308**	.330**
	(.05)	(.05)	(.05)	(.05)	(.07)	(.07)	(.07)	(.07)
TFP	.129*	.136*	.136*	.134*	.402**	.444**	.444**	.433**
	(.06)	(.06)	(.06)	(.06)	(.09)	(.09)	(.09)	(.09)
$ln(empl)$	.159	.105	.105	.165	.590**	.533**	.533**	.502**
	(.13)	(.13)	(.13)	(.15)	(.16)	(.17)	(.17)	(.19)
Month FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs		✓	✓	✓		✓	✓	✓
Region FEs		✓	✓	✓		✓	✓	✓
Trend			✓	✓			✓	✓
Observations	324599	324599	324599	301726	320566	320566	320566	297653
R^2	.923	.923	.923	.919	.894	.894	.894	.890

Table 5.7 Ukraine-EU Trade and Post-February-2014 Transition. The table shows the impact of the 2014 political transition on goods with different levels of tariff protection, between 2013 and 2014. The dependent variable is the log of firm i's exports/imports of product k to/from EU country j in month t, using only intermediate and capital goods. *Post* is a dummy variable that equals 1 for all the month-years after February 2014 and 0 otherwise. Post × $ln(1+\tau_{EU})$ captures the effect of the political transition to an *EU-friendly government* on exports to the EU in goods that are more protected by EU MFN tariffs. Post × $ln(1+\tau_{UKR})$ captures the effect of the political transition on imports from the EU that are more protected by Ukrainian MFN tariffs. Post× $\ln((1+\tau_{CU})/(1+\tau_{UKR}))$ captures the effect of the political transition on imports of goods from the EU that would be more protected under a customs union with Russia. All models include firm-destination-HS4 product fixed effects. The models 2 and 6 add industry- and region fixed effects and models 3 and 7 add a time trend. The models 4 and 8 exclude Crimea, Donetsk, and Luhansk. *Notes*: + p<0.10 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

The results above lend credibility to our main finding: a reduction in TPU leads to an increase in imports of intermediate and capital goods, and this relationship is conditional on the current level of tariff protection, as shown in our theoretical model.[28] Firm-level imports increase more for goods that are more protected under the status quo, because firms face an increase in the probability that duties might be reduced in the future. As demonstrated in this section, these results are not only an artifact of a long-run trend towards further integration of Ukraine with the EU, they also hold in the context of high policy volatility between 2013 and end of 2014, and the expected impact of the political transition itself.[29]

5.5 Discussion of Limitations

Some limitations with regards to the findings of this paper remain, which can be summarized along the issues of measurement and external validity. First, we assume that the relative salience of the EU FTA and RU CU topics approximate the likelihood of the respective policy being enacted. Our measure seems to vary intuitively along real political developments in Ukraine as shown in Figure 5.3, and structural topic models are appealing

[28] For completeness, we run the same models with weekly data and show the results in Table C.9, Table C.10 (using a HP-filtered version of our TPU measure), and C.7 in the appendix. While the results in Table C.9 are not significant, the coefficients are all signed as expected. All other alternative models show significant results, consistent with the findings from the main text. The weekly tables should be interpreted with caution, though. First, the weekly firm-level trade data is incredibly noisy, as is our measure of TPU, shown in Figure C.5. Second, most firms will make their decisions to import or exports well in advance. It seems unlikely that firms to react to swings in TPU on a weekly basis, and adjust imports of intermediates.

[29] In Table C.8 in the appendix, we show a *placebo test* for the difference-in-difference regression, using 2012/2013 data and February 2013 instead of the actual transition in February 2014. The coefficient on the ratio $(Post \times \ln[(1+\tau^{CU}_{MFN})/(1+\tau^{UKR}_{MFN})]$ becomes insignificant, as we would expect in the absence of a shock to the TPU with regards to economic integration with either EU or Russia. The coefficient on $(Post \times \ln(1+\tau^{UKR}_{MFN}))$ stays significant but becomes, negative, indicating an opposite trend of expectations. This is also shown in Figure 5.3: at the beginning of 2013, Yanukovich declined to sign the already negotiated DC FTA.

because they require less choices of specific key words by the researcher. Despite these advantages of our approach, there are some caveats to it. On the one hand, while a measure of relative topic salience works well in our application due to the non-compatibility of the EU trade agreement and the customs union with Russia, it might not work so well in other cases were policies are not strictly mutually exclusive. In these instances, researchers might want a measure that is based on volatility of different options, rather than salience. On the other hand, even more saturated topic models using more document-level covariates might not produce desired topics, or too general topics which do not speak to the policies under investigation. Therefore, I will explore different alternative measurement techniques in the future, based on pre-defined dictionaries and external texts as training sets for classification of news documents. These bear the risk of introducing more researcher bias (King, Lam and Roberts, 2017), but could serve as alternative measures in addition to topic models. In any case, their performance could be compared against each other. Which one of these is more adequate will depend on the case and the policy alternatives under investigation.

Second, one could criticize that the case of Ukraine does not allow for much generalization of the finding that firm's imports of intermediates do react to swings in uncertainty between trade policies, before those are resolved by one policy being locked in. Indeed, Ukraine faced particularly high and volatile policy uncertainty linked to the 10-year long political transition phase following the orange revolution. However, the findings are highly complementary to existing work on the positive impact of the orange revolution on productivity of politically connected firms (Earle and Gehlbach, 2015). Like this related work, we highlight the stark distributional consequences of economic integration decisions across firms within the same sectors, which depend on firm-level characteristics such as the products these firms trade. Moreover, while Ukraine can be regarded as a most-likely (George and Bennett, 2005) or theory-informing case (Odell, 2001), the implications from our theoretical and empirical findings could in principle be extended to other cases. For example, after the fall of the Iron Curtain, many countries of the former Soviet Union could have chosen economic integration with either the Russian Federation or the European Community, which consequently pushed for the inclusion of former Soviet states via a combination of economic incentives and strict conditionality (Schimmelfennig and Sedelmeier, 2005). Another current case is the United Kingdom's decision about its future relationship with the European Union, following the 2016 referendum on leaving the EU. I will discuss how future work could leverage these cases and apply alternative measurement techniques in the concluding chapter of this dissertation.

5.6 Conclusion

Despite the ubiquity of uncertainty and intermediate inputs in IPE and Economics, it remains unclear how firm's decisions to source intermediate and capital goods are affected by uncertainty between alternative trade policies. Leveraging firm-product-destination-level data from Ukraine, and applying machine learning techniques to over 2000 Ukrainian business news briefs, we find that a reduction in TPU has a strong and positive impact on imports of intermediate and capital goods, We estimate that a full reduction of TPU increases imports of intermediate and capital goods by 10.1 percent.

Moreover, we find that goods which are more protected under status quo tariffs are more responsive to a reduction in TPU.

The results of this paper have implications for the study of uncertainty in international trade. First, our results show a need to reconsider some core assumptions of theoretical work on trade and uncertainty in IPE. While some studies assume that private interests will tend to be in favor of stable (and open) trade policies (Mansfield and Reinhardt, 2008*a*), others assume that political leaders will tie their hands by signing PTAs, because of their welfare-increasing effects (Hollyer and Rosendorff, 2012). In contrast, we show that theses premises could be too over-simplifying, as swings in uncertainty between trade policies affect firms differently depending on the type of good they import, as well as the trading partner. As Mansfield and Reinhardt (2008*a*, p.642) argued over ten years ago, if trade institutions help to stabilize the expectations of private actors, then "it would be useful to analyze this micro-causal mechanism more directly in a study cast at the level of individual firms' responses to trade agreement formation". We follow this line of work, and additionally show that firms rationally adjust their import behavior already during the negotiation phase of PTAs, even the agreement has not been realized yet (Handley, 2014; Handley and Limao, 2015). Thus, we provide evidence of the effect of large swings of uncertainty on firm's expectations before uncertainty-reducing trade agreements are enacted. We also show, using tariff schedules, that the design of the respective agreements is key for understanding the distributional consequences of PTAs. Therefore, it might be beneficial for scholars of IPE to pay more attention to the political process, including exogenous shocks to expectations about future outcomes, and their impact on corporate political activity (You, 2016).

Second, the paper shows how quantitative text analysis tools other than dictionary approaches can be applied to the study of trade and political uncertainty.[30] There are many interesting potential cases which could be analyzed using the same or a similar measurement techniques, like the current discussion about different, clearly-named alternatives for the exit of the United Kingdom from the European Union, or the types of membership the EU is likely to grant to accession countries. LDA and structural topic models could also be used to measure other types of policy uncertainty when countries face multiple, mutually exclusive policy options. Examples of those include the joining of military alliances, or joining international organizations that exclude the membership in others for technical or political reasons. New advances in text-as-data research and machine learning thus hold promise for future research on policy uncertainty.

Finally, the paper adds to our understanding of how uncertainty can be a barrier to economic growth in developing and emerging economies. Our model shows that uncertainty affects productivity of firms if there is a hold-up of investment necessary for the import of intermediate and capital goods, which in turn affects the intensive margin of exports. This is particularly consequential given the importance of technological upgrading and learning by exporting for long-term sustainable economic and productivity growth in developing countries.

[30]So far, machine learning techniques are only applied in econometrics for model and variable selection, for instance in the context of regressions using instrumental variables (Belloni, Chernozhukov and Hansen, 2014).

Appendix C

Theory, Data, and Robustness Checks

C.1 Theoretical Appendix

C.1.1 Exporting under Uncertainty without Intermediates

If the future is uncertain, with the source of uncertainty generated by the state of the trade policy, the firm has two decisions to make. First, it decides on whether to export or not. We assume that the firm is risk neutral, so it cares only about expected profits.[1] We also assume that the transition probability matrix (5.6) is common knowledge, shared by all firms. Second, the firm decides on the optimal timing to start exporting. As shown by Handley and Limao (2015), the relationship between cutoffs under uncertainty is given by

$$\tilde{c}^{EU}_{EX,MFN} = \left[\frac{1-\beta(1-p_{CU})}{1-\beta(1-\frac{a_{CU}}{a_{MFN}}p_{CU})} \right]^{\frac{1}{1-\sigma}} \times c^{EU}_{EX,MFN} \tag{C.1}$$

There is no effect of uncertainty on extensive margins of exports to EU if $p_{CU} = 0$. An increase in the probability of switching from MFN to the CU, which is the only probability that matters in this case, lowers the marginal cost cutoff, making it tougher to enter the EU markets. The effect is stronger the smaller the ratio $a_{CU}/a_{MFN} = (\tau^{EU}_{EX,CU}/\tau^{EU}_{EX,MFN})^{-\sigma}$ is. On the other hand, if $\tau^{EU}_{EX,CU} = \tau^{EU}_{EX,MFN}$, there is no effect of uncertainty on exports to EU for any level of p_{CU}.

To sum up, a reduction in the probability of joining the RU CU would increase exports to the EU if firms perceive that joining the Customs Union increases EU tariffs applied against Ukrainian exports, and would have have no effect if firms perceive EU policy to remain unchanged.

[1]It might be an interesting extension to consider a risk averse firm, which imposes different modifications of the objective function, and the firm faces a trade off of lower expected return in order to reduce the risk of an adverse outcome.

If the future is uncertain, with the source of uncertainty generated by the state of the trade policy, the firm has two decisions to make. First, it decides on whether to export or not. We assume that the firm is risk neutral, so it cares only about expected value. [2] We also assume that the transition probability matrix (5.6) is a common knowledge, shared by all firms. Second, the firm decides on the optimal timing to start exporting. If it starts exporting today, its expected present value of profits is given by

$$\Pi_e(a_s, c) = \pi(a_s, c) + E_s \sum_{t=1}^{\infty} \beta^t \pi(a_s^{'}, c) \tag{C.2}$$

Alternatively, it may delay the decision, solving the following stopping problem

$$\Pi(a_s, c) = \max \left\{ \Pi_e - I_{EX}, \beta E_s \Pi(a_s', c) \right\} \tag{C.3}$$

where the first element in brackets is the expected benefits of investing today and the second element is the expected benefit of delaying the decision for one period. The value of the option of investing into exporting is given by

$$V_s \equiv \Pi(a_s, c) - \Pi_e(a_{s,}c) + I_{EX} \tag{C.4}$$

and the optimal stopping problem can be re-formulated as

$$V_s = max \left\{ 0, \beta E_s V_{s'} - \pi(a_s, c) + I_{EX}(1 - \beta) \right\} \tag{C.5}$$

where exporting decision is taken when $V_s = 0$.

[2] It might be an interesting extension to consider a risk averse firm, which imposes different modifications of the objective function, and the firm faces a trade off of lower expected return in order to reduce the risk of an adverse outcome.

Consider a firm evaluating the decision to start exporting to the EU. Observing (C.5) and given assumptions about the TPU process, the option value V_s is decreasing with $\pi(a_s, c)$, therefore decreasing in a and increasing in c. When a increases (trade policy switches from MFN to FTA state), the probability that it will stay in the FTA state goes up (in fact we assume that it is 1), while probability that a takes lower values (switches to MFN or CU) diminishes, in other word Λ_{FTA} stochastically dominates Λ_{MFN}, which in turn stochastically dominates Λ_{CU}. This leads to $E_s V_{s'} = \quad V_{s'} d\Phi(a_{s'}|a_s)$ is increasing in c. According to Dixit and Pindyck (1994), this leads to a unique cutoff c_s^U such that all firms with $c \leq c_s^U$ export to EU and firms with $c > c_s^U$ do not export to EU. Moreover, given our Markov process the cutoff is given by

$$c_{EX,MFN}^{U,EU} = \quad \frac{1 - \beta(1 - p_{CU})}{1 - \beta(1 - \frac{a_{CU}}{a_{MFN}} p_{CU})}^{\frac{1}{1-\sigma}} \times c_{EX,MFN}^{D,EU} \tag{C.6}$$

C.1.2 Importing Intermediate Goods under Uncertainty

We consider the case of import tariff uncertainty only. A firm decides on the optimal timing to start importing intermediate inputs. In order to optimally chose mix of inputs, a firm solves the following stopping problem

$$\Pi_s^{IM} = \max \quad \Delta\Pi_s^e - \widetilde{I}_{IM}, \beta E_s \Pi_{s'}^{IM}$$

where $\Delta\Pi_s^e = \pi(a^j, \mu_s \times c) - \pi(a^j, c) + E_s \sum \beta^t [\pi(a^j, \mu_{s'} c) - \pi(a^j, c)] = \Delta\pi(a^j, \mu_s \times c) + E_s \sum \beta^t \Delta\pi(a^j, \mu_{s'} c)$.

The value of the option of investing into importing is given by

$$V_s^{IM} \equiv \Pi_s^{IM} - \Delta\Pi_e(a_s, c) + \widetilde{I}_{IM} \tag{C.7}$$

and the optimal stopping problem can be re-formulated as

$$V_s^{IM} = max \quad 0, \beta E_s V_{s'}^{IM} - \Delta\pi(a^j, \mu_s \times c) + \widetilde{I}_{IM}(1-\beta) \tag{C.8}$$

where importing decision is taken when $V_s^{IM} \leq 0$.

The option value V_s^{IM} is decreasing with $\Delta\pi(a^j, \mu_s \times c)$, therefore increasing in μ and c. When μ decreases (trade policy switches from MFN to FTA state), the probability that it will stay in the FTA state goes up (in fact we assume that it is 1), while probability that μ takes higher values (switches to MFN or CU) diminishes. This leads to $E_s {V^{IM}}_{s'} = \quad V_{s'}^{IM} d\Phi(\mu_{s'}|\mu_s)$ is increasing in $\mu \times c$. According to Dixit and Pindyck (1994), this leads to a unique cutoff c_s^U such that all firms with $c \leq c_s^U$ import from EU and firms with $c > c_s^U$ do not. Moreover, given our Markov process the cutoff is given by

$$\tilde{c}_{IM,MFN}^{EU} = \left(\frac{1-\beta(1-p_{CU})}{1-\beta(1- \quad \frac{\mu_{CU}^{1-\sigma}-1}{\mu_{MFN}^{1-\sigma}-1} \quad \times p_{CU})} \right)^{\frac{1}{1-\sigma}} \times c_{IM,MFN}^{EU} \tag{C.9}$$

C.2 Quantitative Text Appendix

C.2.1 Text Data and Pre-Processing

We first download all news briefs from Nexis that are somehow related to either the EU FTA or the Russian CU using very broad Boolean search terms. Too large corpora (collections of texts) result in very general topics. Some pre-selection is necessary in order to find narrower topics related to TPU. The selection is no very restrictive, though, since we only pre-select all articles that note either EU FTA or RU CU *anywhere in the text*.[3] Figure C.1 below shows a typical article from Ukraine Business Weekly, downloaded from Nexis in .txt format. We split the articles using the "### of ### Documents" line and retrieve the publication date using regular expressions. We also extracted the title for each article, and then retain only the text body of each article for further processing. We remove all meta-data prior to applying the topic models. We find 2201 articles between 2003 and 2016, amounting to about 15 articles per month on average. Duplicate articles and non-business news are excluded from the search. Figure C.2 shows the total number of UBW articles per month retrieved from Nexis and provides a description of the raw data.

The raw articles contain meta information, such as copyright information, title, length, and publication date. From the raw articles, we retrieve title and publication date. We then erase all the meta information using *regular expressions* until we are left with only the text body of the articles. Most

[3] The following Boolean search term was used: "HLEAD(russian federation OR russia* OR eu OR european union*) AND HLEAD(ukrain*) AND Body(trade agreement* OR free trade OR customs union OR trade deal OR free trade agreement OR eurasian customs union OR eacu OR eurasian economic union OR eeu OR association agreement OR dcfta OR aa)". Including more terms did only increase the number of documents marginally and hence, we are confident that the sample of news releases is not biased towards Ukraine-EU or Ukraine-Russian relations.

quantitative text analysis techniques like the models we are using make the *bag-of-words* assumption, ignoring the order of words in a document. The only textual property that matters for the analysis of the texts is the relative frequency with which words occur within a given document in our collection of texts. However, we treat bigrams like "vladimir putin" and compound terms like "customs union" as single terms in the analysis, as they convey meaning in conjunction.

Finally, we remove common English stopwords that do not convey meaning. We also stem the endings of words, leaving only the word "roots" for further analysis and remove words occurring in less than one or two documents.[4] After these preparatory steps, the articles are translated into a "document-term" matrix (dtm) which can be further analyzed. The *dtm* is a matrix of the form $d \times w$, where rows d represent single documents (here individual news releases) and the columns w represent terms and how frequently they occur in each document, resulting matrix in a large and sparse 2201×5968 matrix which can be further analyzed.

Figure C.2 below shows the number of articles per month downloaded from Nexis. One can clearly see the overall increase in discussion of any sort of trade agreement, with either Russia or the European Union over time, peaking in 2014 around the final conclusion of the EU FTA and the peak of the trade tensions between the EU and Russia. There are also two low points in the number of articles, one at the end of 2006, and another around the beginning of 2011. These represent structural breaks in the textual data available in Nexis. During these time frames only a limited number of articles is available online. In 2006, all single articles are joined

[4] All of the steps in this paragraph are standard in quantitative text analysis. For a good review and explanation of "stopwords", "stemming", and "bigrams" and pre-processing of documents see Grimmer and Stewart (2013).

1 of 219 DOCUMENTS

Ukraine Business Weekly

December 26, 2012

ECONOMIC POLICY

LENGTH: 215 words

DATELINE: Kyiv December 20

BROK: EU-UKRAINE ASSOCIATION AGREEMENT SHOULD BE SIGNED IN NOVEMBER 2013

The EU-Ukraine Association Agreement should be signed in November 2013 at a summit in Vilnius, Chairman of the European Parliament's Foreign Affairs Committee Elmar Brok has said.

"The association agreement, including a free trade agreement, should be signed at a summit in Vilnius in November 2013," he said at a press conference in Kyiv on Thursday.

Brok recalled that in order to sign the agreement, Ukraine must fulfill the conditions outlined in European Parliament resolution, in particular, hold elections in line with European standards, create an Electoral Code, taking into account the opinion of the Venice Commission, reform the law enforcement system, and reduce the powers of the Higher Council of Justice.

He also stressed the need to remove selective justice. He said that it was necessary to resolve issues on the cases of former Prime Minister Yulia Tymoshenko and former Interior Minister Yuriy Lutsenko.

"The cases of Tymoshenko and Lutsenko should be resolved from the very beginning. If they are resolved, it will be much easier to fight for the European prospects of Ukraine," he said.

Brok noted that Germany's proposal on Tymoshenko's treatment in Charité Clinic (Germany) "still remains in force."

LOAD-DATE: January 9, 2013

LANGUAGE: ENGLISH

DOCUMENT-TYPE: Emerging Markets

PUBLICATION-TYPE: Newsletter

Figure C.1 Example Ukraine Business Weekly Article. The figure shows a screen shot of a typical article of Ukraine Business Weekly, as retrieved from Nexis.

in one document for one month.In 2011, there is one month without any recordings from Ukraine Business weekly. However, this does not affect our TPU measure.

Many single words in the UBW press releases naturally occur together forming so-called bigrams, as described above. We do not want to treat these as individual words, as they clearly appear and convey meaning together. Table C.1 below shows the most commonly occurring bigrams, ranked by *G2* (a log-likelihood statistic.). Some of the most commonly occurring bigrams are “association agreement” or “free trade”. These are further cleaned by removing bigrams with stopwords[5] which leaves about 360 bigrams.

[5]Stopwords are terms which do not convey meaning, like “the”, “also”, or “have”.

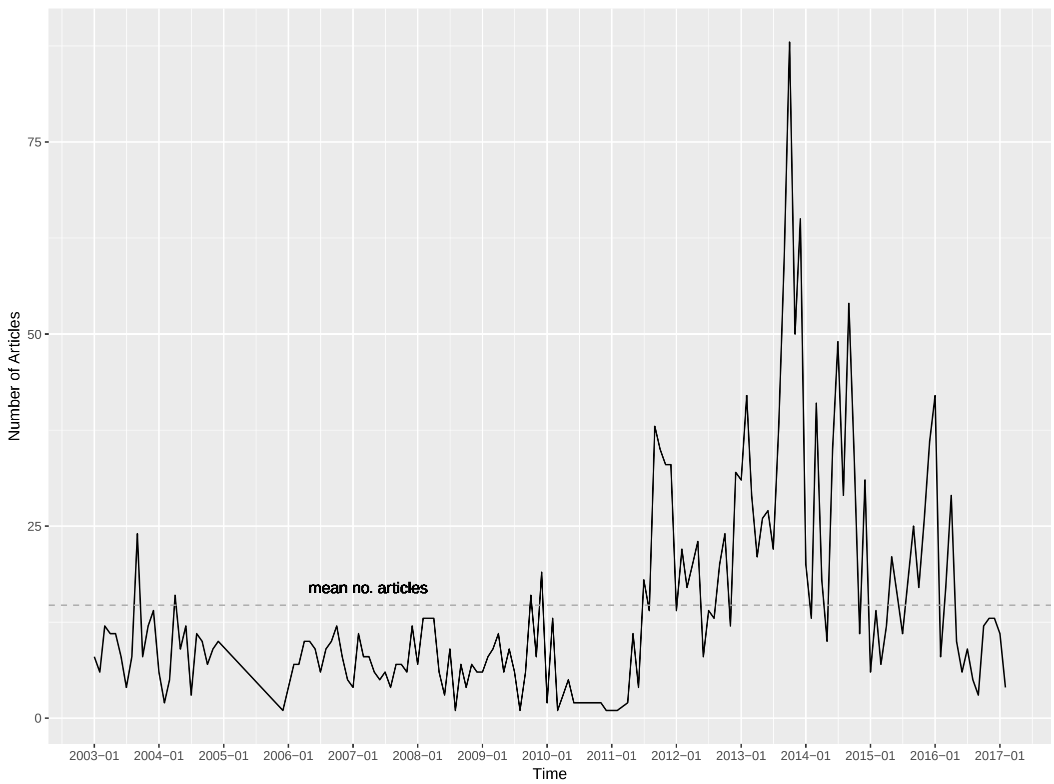


Figure C.2 Number of Articles retrieved from Nexis over Time. The figure shows the number of Ukraine Business Weekly articles about international trade retrieved from Nexis between 2003 and 2017. It shows that the overall salience of trade policy is quite low before 2012, and then increases as negotiations between Ukraine and the EU progress, and conflict with Russian intensifies.

Word 1	Word 2	Frequency	G2
association	agreement	1954	19681.70
free	trade	1667	18213.69
european	union	1777	16020.75
company	news	1325	14984.43
economic	policy	1127	10636.42
prime	minister	816	10253.63
customs	union	890	8929.12
press	service	784	8387.41
trade	area	762	7700.77
million	tonnes	837	7488.57
told	interfax	610	7313.53
viktor	yanukovych	472	6398.05
trade	zone	582	6328.04
web	site	372	6271.47
verkhovna	rada	338	5733.27
press	conference	505	5688.02
president	viktor	478	5285.12
cubic	meters	324	4804.68
mykola	azarov	310	4748.70
ukrainian	president	699	4627.77
press	release	368	4177.94
net	profit	275	3591.02
eastern	partnership	245	3402.39
euro	2012	233	3259.51
european	commission	420	3133.11
naftogaz	ukrainy	206	3048.06
january	1	320	3027.47
minister	mykola	272	3006.65
member	states	253	2978.60
square	meters	216	2933.53

Table C.1 30 Most Common Bigrams. The table shows the most common bigrams in the Ukraine Business Weekly articles used for generating the TPU measure. Especially politicians, different EU agreements, and EU institutions appear frequently.

C.2.2 Structural Topic Model and Text Diagnostics

For measuring TPU from the documents, we use so-called "topic models", developed by computer scientists for the analysis and organization of large-scale text corpora. Topic models analyze relative word occurrences in un-labeled documents in order to discover "themes" that run through the documents.[6] Topic models belong to the family of unsupervised classification methods because they infer the content of topics from the texts rather than assuming them. It is therefore crucial to understand that topics *are not defined ex ante* by the researcher, like in hand-coding of documents based on pre-defined dictionaries.[7]

The simplest topic model is the *Latent Dirichlet Allocation* (LDA)[8], a generative probabilistic model for discrete data (Blei, Ng and Jordan, 2003). Topics are defined here as a distribution over a vocabulary of words which represent interpretable themes. The LDA is a mixed membership Bayesian model, in which documents are represented as a mixture of topics. Thus, each document can be conceived as a vector of proportions, indicating the fraction of words belonging to a latent topic. Generative probabilistic models treat documents as if they had been generated according to a particular process involving observed and latent variables. The joint probability distribution of that process can be used in order to compute the conditional distribution, i.e. the the posterior distribution, of the hidden variables,

[6]These models have been successfully applied in both Political Science (Grimmer, 2010; Roberts et al., 2014) and Economics (Mueller and Rauh, 2018), and many more fields such as Genetics or Information Science (Blei, 2012).

[7]For a good description of the basics of dictionary-based text analysis see Neuendorf (2002, CH6). A well-known application of dictionary-based methods keywords representing left-right ideology in order to estimate scores of party positions using their election manifestos (Laver and Garry, 2000).

[8]Note that this section provides only a short and non-technical introduction into topic models, oriented at Roberts et al. (2014). The interested reader is referred to Blei, Ng and Jordan (2003) for the LDA topic model, and to Roberts and Stewart (2015) for more technical details on the Structural Topic Model (STM).

given the observed variables. The observed variables are the document-level words, and the unobserved variables refer to the topic structure.

A topic K is defined as a distribution over a fixed vocabulary V. The data generating process is as follows: the LDA assumes that documents (press releases) are created by K topics. Across documents, we first randomly choose a distribution over topics β_k. Each document is modeled as a distribution over K topics, θ_d. Within each document, words are generated by a two step process. First, for each word $z_{d,n}$, one draws a topic for that word from a multinomial distribution $z_{d,n} \sim Mult(\theta_d)$ (with $z_{d,n}$ indexing the topic assignment for the n-th word in document d). Second, an actual word $w_{d,n}$ is drawn from a distribution over the vocabulary $w_{d,n} \sim Mult(\beta_{z_{d,n}})$ where $\beta_{k,v}$ is the probability of drawing the v-th word in the vocabulary for topic k. The likelihood of a word for a given topic is then the probability of a topic within a given document times the probability of a term in the overall word distribution, $p(z_{d,n}) \cdot p(w_{d,n})$. This joint distribution of the latent and observed parameters (Blei, Ng and Jordan, 2012) is formally given by

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \quad \prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \quad .$$

Finally, the LDA assumes a Dirichlet prior for the topic proportions over documents d, so that $\theta_d \sim Dirichlet(\alpha)$ (Blei, Ng and Jordan, 2003). This joint probability distribution of words documents and topics over a vocabulary can be used in order to calculate the probability of topics for each word, and the topic posterior probabilities θ_d for each document. Higher posterior likelihoods of a topic means that a high proportion of terms in document is related to that topic. The intuition behind LDA is that *documents* in a collection of documents (also called text *corpus*) contain multiple *topics* or themes. All documents in the collection are composed of the same topics, but they exhibit these topics in different proportions, and each word contributes to individual topics to a certain degree. Bigrams like "Association Agreement" or "Eastern Partnership" are related to the topic "EU-Ukraine FTA" , while terms like "customs union" or "EACU" would be related to the topic "Russia-Ukraine Customs Union". Topic models do not require any prior information about the texts. Only the number of topics K needs to be determined ex ante by the researcher.

Structural topic models (STMs) allow the introduction of document-level covariates (e.g. date, publication type, outlet, author) similar to covariates in regression models, in order to increase model fit and allow for topics to vary by covariates (Roberts et al., 2014).[9] The document-level covariates can affect either topical prevalence, topical content, or both. *Topical prevalence* is the frequency with which a topic is discussed and *topical content* the variation in words used to discuss a topic (Roberts et al., 2014, p.4).[10] We make use of the weekly publication date of UBW articles in order to provide better estimates of topical prevalence over time. We concentrate on topical prevalence because we are interested in the change in salience of trade policies over time rather than the change in words used to describe them.[11]

We use the STM algorithm with $K = 10$ topics[12], and include the publication week as a flexible b-spline in order to adjust topic estimation for

[9] A well known application in Political Science are party manifestos, which contain information about the election year, the type of election (federal, subnational), and the author (the party). See Volkens et al. (2015).

[10] Moreover, in STMS, topics can be correlated with each other and both the prior distribution over topics and the word use within topics can vary by covariates.

[11] See Appendix 3 for discussion and analysis of difference in tone or evaluative word use over time.

[12] We use a combination of automated methods and qualitative judgment in order to arrive at the number of topics. See Appendix 2 for a thorough discussion of of how we chose K.

variation over time. Adjusting for general trends over time is key in order to retrieve relative changes in topic salience and correct for seasonality and absolute growth of the topics over time. The resulting topical prevalences for an EU FTA and a CU with Russia are described in the following section.

Most of the quantitative text analysis has been conducted in R using the *Quanteda* package (Benoit and Nulty, 2017) and the *STM* package (Roberts et al., 2014). In order to determine the number of topics, we use a combination of automated cross-validation methods and qualitative judgment of the semantic content of the topics. This is a standard procedure recommended both for simple LDA topic models (Blei, Ng and Jordan, 2012) and structural topic models Roberts et al. (2014, p.1068-1070). First, we estimate the model for many different values of K, between 5 and 150 topics. The *searchK*-function in the *stm package (Roberts, Stewart and Tingley, 2015)* includes a few tests for choosing among these different numbers of topics (Wallach et al., 2009). Figure C.3 in the appendix plots the results of these analyses. The most important indicator here is the held-out log-likelihood, a cross-validation measure, and the model residuals, both in the upper panel of the figure. The held-out likelihood is the probability of words appearing within a document when these words have been removed. This measure is similar to cross-validation, when some proportion of the data is held out for estimation and then used for validation later on. In this case, we set the share of held-out words to 0.5. As one can see from the figure, the held-out likelihood gets larger (the predictive performance of the model increases) with more topics, indicating a better model fit as the model becomes more flexible. Similarly, the model residuals are reduced with a higher number of topics. Note also that the model fit in terms of the held-out likelihood does not improve anymore for $K > 50$. In fact, residuals get larger for more than

50 topics, and the model fit gets worse, too. This illustrates the bias-variance trade-off, and that we are over-fitting the model with $K > 50$ Lantz (2015). Hence, this first test shows that we need a number of topics smaller or equal to 50.

Second, we inspect the topics for different K and check whether they capture the CU with Russia and the EU FTA. The number of topics that seems to best capture both CU and FTA exclusively is a K of 10. According to the diagnostic values reported in the appendix, this model with 10 topics does not have a perfect fit to the data. However, it captures well the substantive measure we are interested in. This is a typical trade-off using topic models: not always does the model with the best technical fit also provide the most intuitive and/or interpretable topics (Lucas et al., 2015). Using K larger or equal to 25 provides a very good model fit, but slices up topics unnecessarily. For instance, a high number of topics like 30, 40, or 50 finds single topics for European Parliament discussions of the FTA and meetings between the Commission and Ukrainian officials.[13]

However, we want these to be represented by a more general EU-Ukrainian trade topic. We show in the main text that high values in our EU-FTA and RU CU topic proportions correspond to both the actual development of general trade relations between Ukraine and the EU/Russia and that the press releases which score high on these topics are indeed about the EU FTA and the CU, respectively.

[13]We also calculate the STM for a K of 20, which has a significantly better model fit. The monthly topic proportions are very similar to the ones we report below. The correlations between the chosen topics from a topic model with 10 and 20 topics are 0.83 and 0.74 for the EU FTA and the CU, respectively.

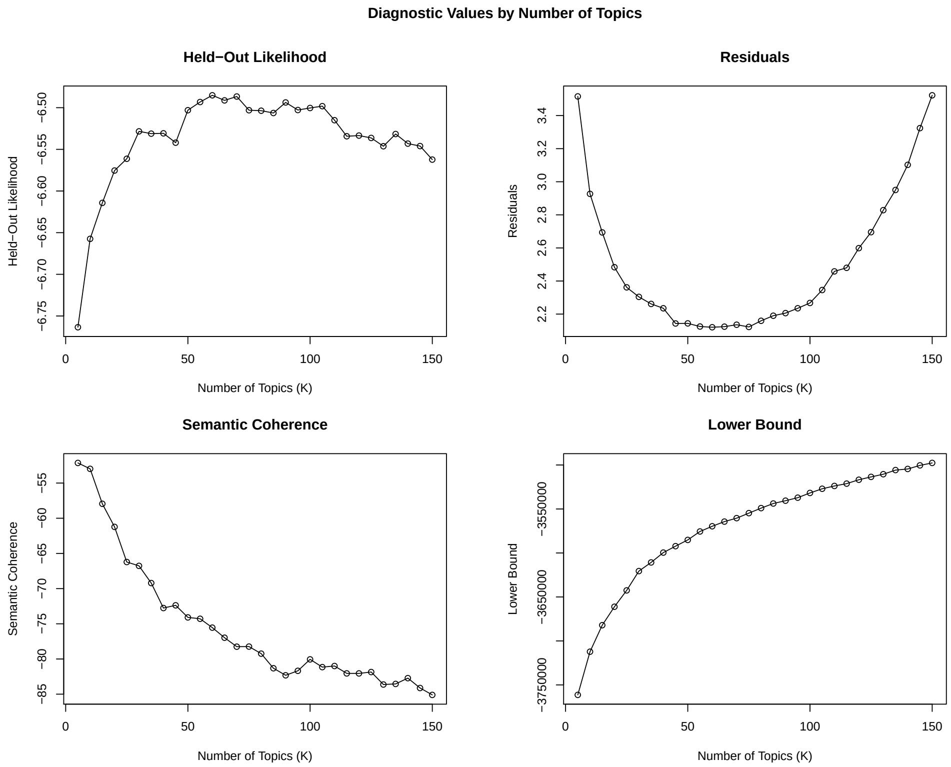


Figure C.3 Cross-Validation for the Structural Topic Model. The figure depicts different cross-validation tests generated from the structural topic model across different numbers of topics, *K*, with the most important one being the Held-Out-Likelihood in the upper left corner of the plot.

We show the *mean topic prevalence per month* in Figure C.4. Although being very volatile, the topic proportions approximate the development of the Ukrainian trade policy over the last 15 years: while in 2003, the topic of forming a customs union with Russia dominated the economic news, relative to the EU FTA topic. The prevalence of CU topic gradually declined before it almost completely disappeared from the policy discussion in 2014 when the FTA with the EU was signed. We also see the two time periods when only few or no articles where available in Nexis, in 2006, and in 2011. As the estimated topics represent the relative prevalence over time, this is not an issue for the estimation process, though. In 2011, both topics are equally affected by missing data, and the low number of articles in 2005-2006 still leads to the topics being estimated correctly relative to each other. Figure C.5 below shows the raw data with weekly frequency.

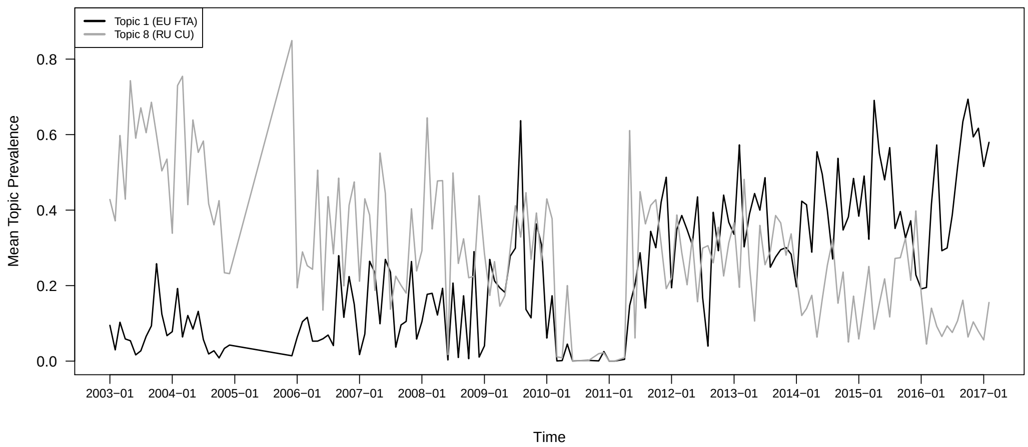


Figure C.4 Mean Topic Prevalence per Month for EU FTA and the RU CU topic, 2003-2017. The plot shows the average prevalence (salience) of the EU FTA topic and the RU CU topic over time. While the CU topi is more prevalent in the beginning of the investigation period, it declines in salience and is take over between 2012 and 2014 by the EU FTA topic, reflecting the higher likelihood of the prospective agreement.

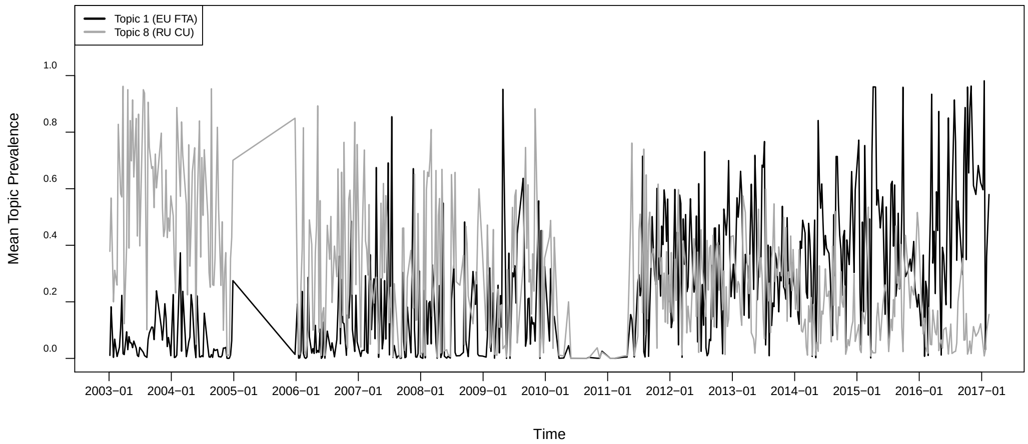


Figure C.5 Mean Topic Prevalence per Week. The same as Figure C.4 above aggregated by weeks instead of months.

C.2.3 Stationarity of Trade Policy Uncertainty Measure

We also test for non-stationarity of our TPU measures and reject it in both cases, regardless of whether we include a trend or not. However, both series have strong autocorrelation patterns. For the monthly data, Table C.2 presents estimations for AR(3) processes and also VAR model where we look how the two topics are influencing each other. Lags beyond the third one are not significant. We also fitted ARIMA models and found no evidence of moving average components in both cases.

C.2.4 Validity of Trade Policy Uncertainty Measure

A way to validate the topic model chosen here is to look at press releases which exhibit high proportions of the respective topics. Do these documents refer to the EU FTA and the RU CU, respectively? Figure C.6 below shows two snippets from example articles with high topic proportions on EU FTA and Russian CU topics. One can see that press releases with high proportions of the topics estimated above do indeed discuss the EU FTA

	(1)	(2)	(3)	(4)
Dependent variable	p^{EU}	p^{CU}	p^{EU}	p^{CU}
Model	AR(3)	AR(3)	VAR	VAR
L.p^{EU}	.285**		.241**	-.053
	(.07)		(.08)	(.08)
L2.p^{EU}	.261**		.220**	.025
	(.08)		(.08)	(.08)
L3.p^{EU}	.294**		.261**	-.017
	(.08)		(.08)	(.08)
L. p^{CU}		.070	-.012	.150
		(.06)	(.08)	(.08)
L2. p^{CU}		.411**	-.009	.387**
		(.08)	(.07)	(.07)
L3. p^{CU}		.353**	-.147*	.306**
		(.07)	(.07)	(.07)
ADF	-5.994	-7.350		
p-value	.000	.000		
N	146	146	133	133

Notes: * $p<0.05$, ** $p<0.01$. Standard errors in parentheses.

Table C.2 Test of Stationarity of Topics. Columns (1) and (2) report point estimates of AR(3) models for corresponding series. Columns (3) and (4) present point estimates of a VAR model. ADF is the value of the Dickey Fuller test statistics without trend or drift with the corresponding p-value below. The null hypothesis is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process.

and the RU CU, respectively. The press releases identified as belonging to the EU FTA topic are about EU institutions and the progress of the Association Agreement with Ukraine, whereas the press releases belonging to the CU topic are about the customs union and the common economic space between Russia, Ukraine, Belarus, and Kazakhstan. This does not mean that the respective press releases are only about the EU FTA or the CU with Russia as documents can consist of a mixture of topics.[14]

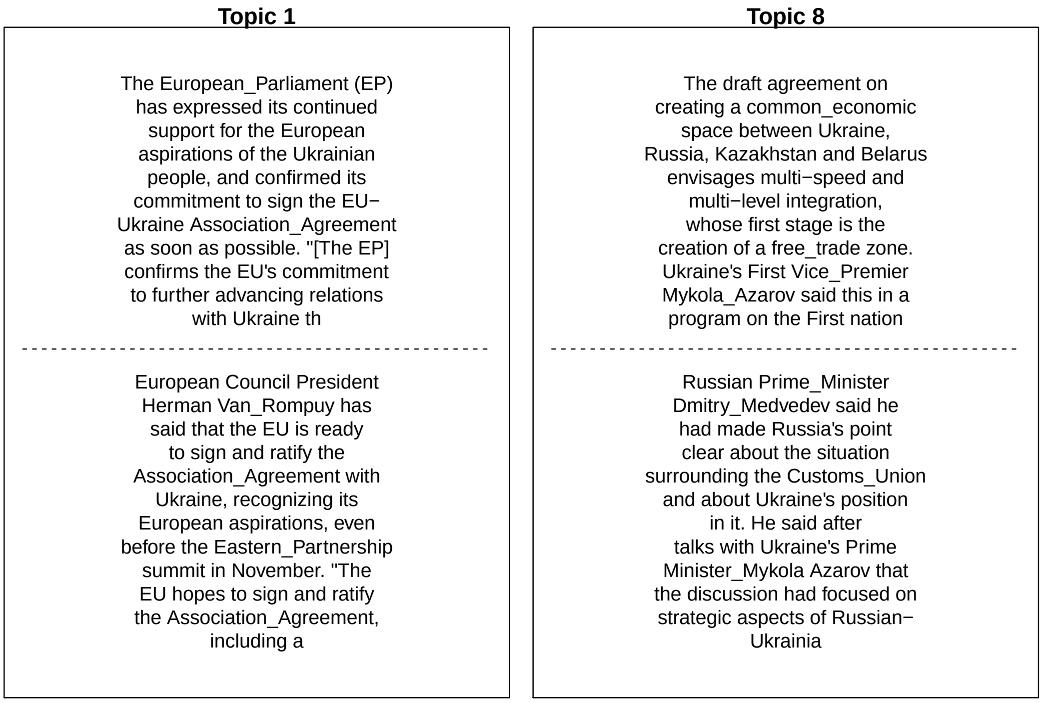


Figure C.6 Example Articles for EU FTA and RU CU Topic. The figure shows articles from Ukraine Business Weekly with high topic proportions for the EU FTA (left, Topic 1) and the RU CU topic (right, Topic 8), showing that articles related to these topics are indeed about the FTA and the CU, respectively.

Below in Figure C.7 we also provide wordclouds for the two topics, with EU FTA in black and RU CU in gray. The clouds show words that occur with a high probability, and the size of the words relates to the probability of a word to occur in the text collection, given the respective topic.

[14] In Appendix 1.3, we also plot word clouds of these two topics.

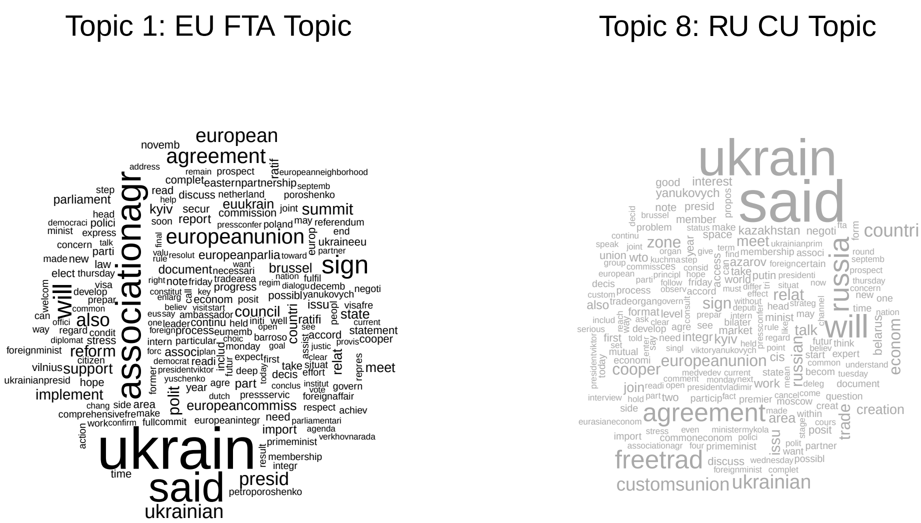
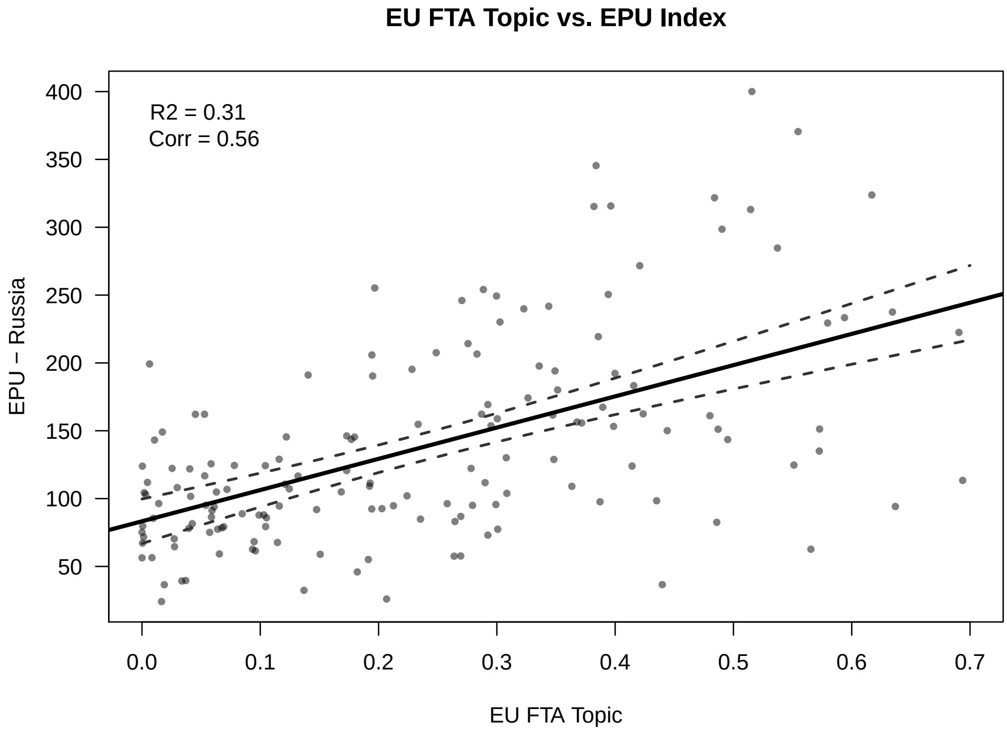


Figure C.7 Word Clouds for EU FTA and RU CU Topics. The size of the words refers to the probability of a word in the corpus given the respective topic.

Given that there are other measures of policy uncertainty like the one developed by Baker, Bloom and Davis (2016), why are we using a new measure? First, while both measures rely on news coverage, we do not use a pre-defined dictionary of terms related to uncertainty like the Economic Policy Uncertainty (EPU) index. The STM does only require us to specify the number of topics, but no pre-defined keywords or dictionaries. Second, we do not measure general economic uncertainty, but *trade policy uncertainty* for *specific* and substantively important *trade policy event*s between *specific trade partners*. The decision between a CU and the EU FTA is not captured by broad economic policy uncertainty. The EPU index picks up any kind of uncertainty and does not differentiate between global events (financial crisis), domestic uncertainty-inducing events (policy reforms), or specific events in relation to particular partners (e.g. Russian stop of gas exports, or threats thereof). In contrast, our measure picks up likelihood of changes in a specific trade policies with respect to particular countries/entities (Russia vs. EU). The interpretation of topic probabilities as uncertainty is derived from the fact that the two events (FTA vs. CU) are theoretically incompatible with each other and (even if compatible to a certain extent) not politically feasible at the same time. In a nutshell, our measure enables us to test predictions about uncertainty with respect to a specific policy vis-a-vis specific partners of Ukraine in the realm of trade - all three of which cannot be achieved by using the EPU index.

Despite these conceptual and empirical differences between ours and the Baker, Bloom and Davis 2016 measure, the reader might still want to compare the two measures. Ideally, we would compare our CU and FTA topics over time with a Ukraine-specific economic policy uncertainty index. However, Baker et al. have not developed the economic policy uncertainty index for Ukraine yet. In the absence of EPU for Ukraine, we plot our measures of EU FTA and RU CU probability against the EPU for Russia, shown in Figure C.8 below. From a Russian perspective, a higher EU FTA probability should mean higher economic policy uncertainty (challenging Russian regional foreign policy), and a higher CU probability should be associated with lower uncertainty (strengthening Russian regional foreign policy). The EU FTA measure correlates positively with the Russian economic uncertainty measure, indicating higher uncertainty when an EU FTA with Ukraine becomes more likely. The CU topic is inversely correlated with Russian economic uncertainty, but only weakly so. This makes sense if EU-Ukrainian trade relations are indicative of EU-Russian relations, and that this relationship is one determinant of the economic policy index for Russia. Russian economic policy uncertainty can only be a proxy for a potential Ukrainian economic policy uncertainty, but signs and the strength of the relationships are in line with our expectations, and add some face validity to our measure.



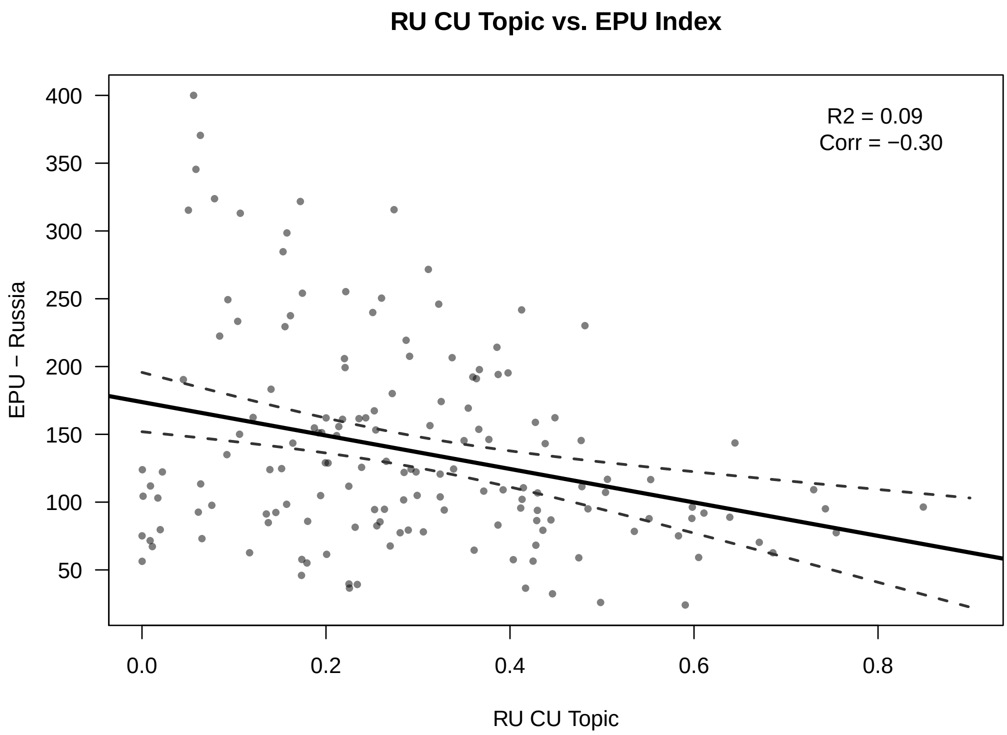


Figure C.8 Trade Policy Uncertainty (TPU) vs. Economic Policy Uncertainty (EPU) Index Baker, Bloom and Davis (2016). The figure shows the bivariate relationship between the Economic Policy Uncertainty Index developed by Baker, Bloom and Davis (2016), and the EU FTA and RU CU topics from the STM. It shows that intuitively, the EU FTA topic is positively related to higher Russian EPU, while the RU CU topic is negatively correlated with economic policy uncertainty.

C.2.5 Trade Policy Uncertainty and Sentiment

It could be a concern that UBW reports generally more negatively about the EU FTA than about the RU CU. Political Economy research has shown that newspapers can have considerable political bias, often driven by the demand factors like political ideology of readers (Gentzkow and Shapiro, 2010). In our case, we would be worried if our measure would only reflect change in sentiment or tone in the news releases over time. This concern is mitigated to a certain extent because are using an economic news release service, rather than daily newspapers. Compared to news papers articles, standard in press release services like Reuters concentrate on the content of news, strip away evaluative language By conducting a so-called *sentiment analysis* of the news releases, we show that the tone of UBW releases is always more positive than negative, but is constant across time and topics. Sentiment analyses describe the emotional state or mood of written text (Gonçalves et al., 2013). Here, we use a very simple, lexical-based approach applying pre-defined dictionaries of positive and negative terms. A number of different dictionaries for the English language exist, including commercially available dictionaries like the Linguistic and Word Count (LIWC) program. We use a freely available dictionary developed by Theresa Wilson, Janyce Wiebe, and Paul Hoffmann at the University of Pittsburgh (Wilson, Wiebe and Hoffman, 2005). The results are shown below.

The principle of this sentiment analysis is straightforward. We first take our collection of UBW press releases between 2003 and 2017, and apply two dictionaries to it: one dictionary with about 3900 negative English words and one with about 2200 positive words. Positive and negative connotations of words were developed by linguists and are described in depth in (Wilson, Wiebe and Hoffman, 2005). Then, we calculate the relative frequencies with which positive and/or negative terms occur in each single press release. Below in Figure C.9, we plot the result of this exercise, where the X-axis indicates the respective month of publication and the Y-axis indicates the word frequencies of positive and negative terms (i.e., positive or negative terms divided by the sum of positive and negative terms) per month. The plot shows two results. First, regardless of the time period, there are always more positive than negative terms used in the press releases used in our further analysis. Second, the use of positive relative to negative terms is quite constant over time. While there is less variability in the relative frequencies (because there are more articles later on), there is no huge decline or increase of either positive or negative sentiment over time. This shows that the use of evaluative terms is stable over time: if there is a bias in terms of negative or positive reporting, it does not change dramatically over time.

Another concern in relation to word use is that word choice *within topics* could be varying over time. For mitigating some of these concerns, we also do the sentiment analysis from above for articles with high topic proportions of both of EU FTA topic and the RU CU topic. Below, we plot the same graph as above, but restrict the sample of documents to those with topic proportions higher than the 75th percentile of the overall distribution of the respective topic. This reduces the sample of articles from UBW to 569 for both topics, but still leaves enough variation over time. One can see that the picture does not change from looking at the whole sample. Over time, positively and negatively connotated terms are quite constant, both in the whole sample of articles and in articles which are very highly related to either the EU FTA or the RU CU. This result holds for other thresholds such as median or mean topic proportions. This supports or assertion that

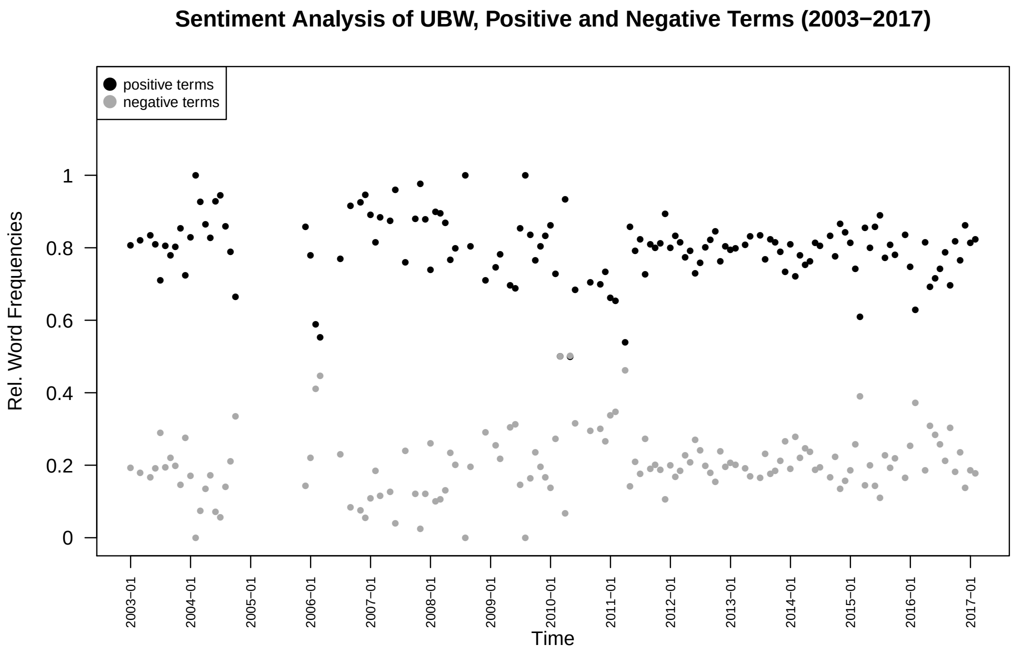
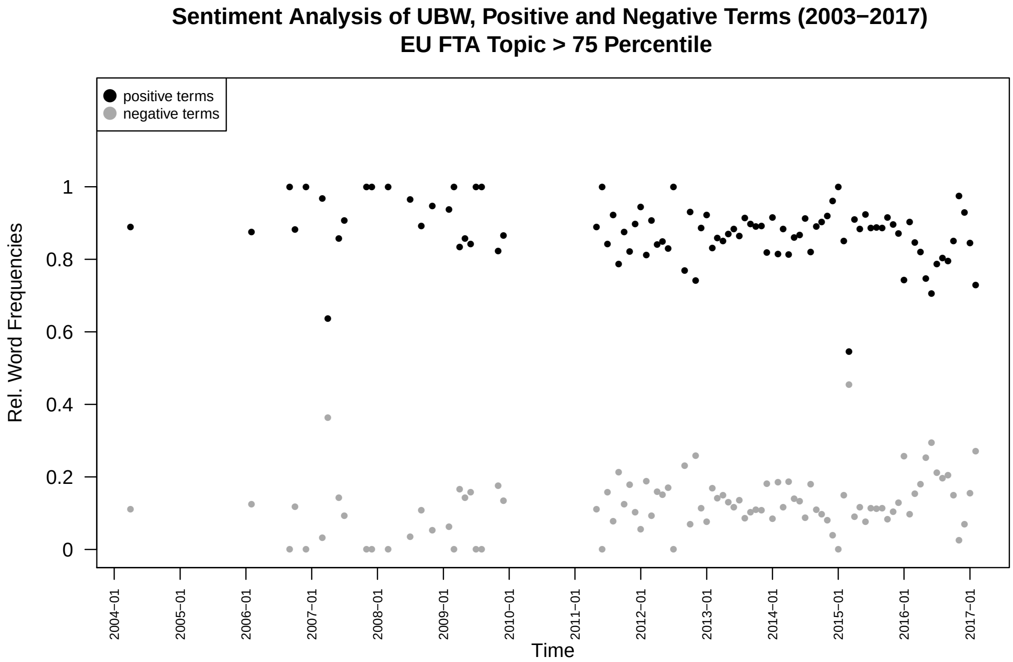


Figure C.9 Positive and Negative Sentiment in Ukraine Business Weekly Articles. One possible objection to our measure is that we are only picking up biased, negative or positive reporting on the EU FTA or the CU. The figure depicts positive and negative sentiment in the language used in the Ukraine Business Weekly briefs used in the topic model, showing that positive words are used more than negative words, on average, but that this positive bias is constant over time.

the news releases from Ukraine Business Weekly do not change tone or sentiment substantively over the time period of investigation.[15] Moreover, it is not the case that articles discussing the EU FTA are generally more positive in tone than articles discussing the RU CU.

[15]Note that this could look quite different if our news source would be daily newspapers. Since the reporting in press releases is rather technical, it is not surprising that there is no change in positive or negative tone over time.



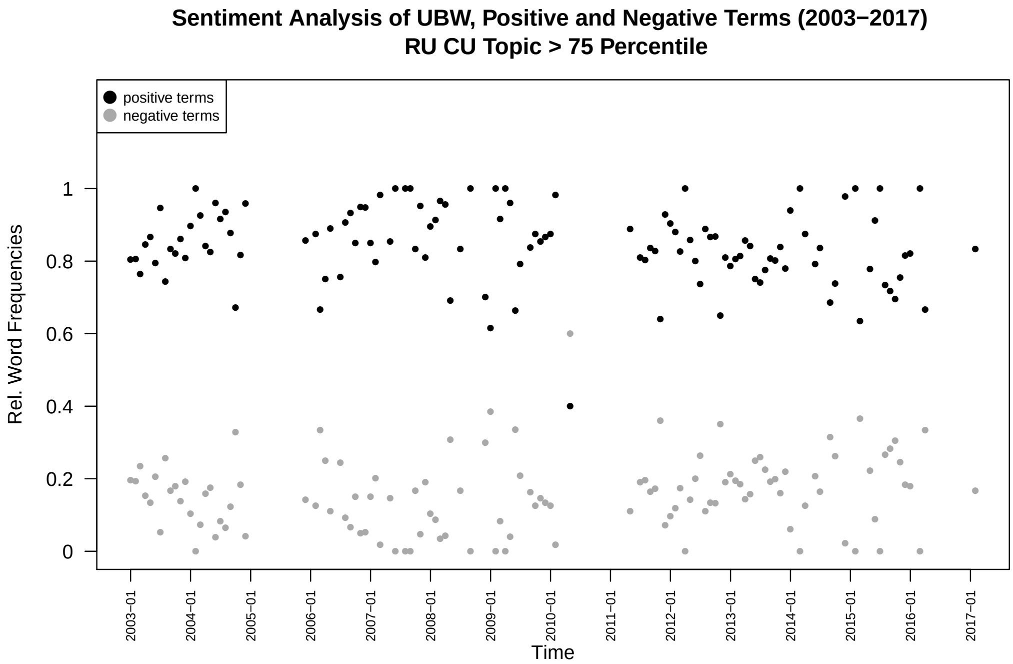


Figure C.10 Positive and Negative Sentiment in Ukraine Business Weekly Articles. Here we show the results of a sentiment analysis using only articles with high topic proportions for EU FTA (left) and RU CU topic (right). The figures show that while positive sentiment is larger than negative sentiment, this positive bias is constant over time, and most importantly, not different between articles that talk mostly about the EU FTA and articles that talk mostly about the RU CU.

C.3 Empirical Analysis Appendix

C.3.1 Tariffs in Ukraine and Customs Union, 2003 - 2013

Table C.3 presents the evolution of the applied MFN rates of Ukraine and CU between 2003-2013, average difference in those rates, number of lines at HS4 digit level where the Ukrainian MFN rates are higher then the CU rates, and the number of lines where the Ukrainian MFN rates are lower.

Tariff Year	**Mean**			**Number of Lines with**	
	Ukraine MFN τ_{UKR}	CU MFN τ_{CU}	Difference $\tau_{CU} - \tau_{UKR}$	higher tariffs $\tau_{UKR} > \tau_{CU}$	lower tariffs $\tau_{UKR} \leq \tau_{CU}$
2003	6.94	11.92	4.93	196	949
2004	6.34	11.61	5.14	158	987
2005	5.75	11.34	5.50	130	1015
2006	5.17	10.78	5.55	164	1036
2007	5.13	10.58	5.38	175	1029
2008	5.18	10.53	5.32	179	1028
2009	4.70	10.66	5.94	151	1057
2010	4.81	9.70	4.89	185	1028
2011	4.67	9.86	5.20	187	1032
2012	4.67	11.18	6.50	92	1129
2013	4.77	10.12	5.35	128	1093
All	5.29	10.78	5.43	159	1035

Table C.3 Differences in Applied MFN tariffs between Ukraine and CU, 2003-2013. The table depicts the average Ukrainian MFN tariffs across time and contrasts them with Russian the Customs Union tariffs. On average, MFN tariffs are over 5 percentage points lower than CU tariffs, and only few MFN tariff lines were higher than the CU tariffs.

C.3.2 Summary Statistics

	Obs.	**Mean**	**St. Dev.**	**Min.**	**Max.**
		A. Exporters to EU			
ln(Export)	129502	9.888	2.621	-4.286	19.561
$p^{EU} \times \ln(1+\tau_{MFN})$	129502	0.004	0.005	0.000	0.071
p^{EU}	129502	0.174	0.124	0.000	0.411
p^{CU}	129502	0.319	0.155	0.000	0.849
$\ln(1+\tau_{MFN})$	129502	0.022	0.021	0.000	0.176
TFP	125696	1.647	1.344	-8.312	10.356
ln(Employment)	128909	5.501	2.135	0.000	11.264
		B. Importers from EU			
ln(Import)	807509	8.282	2.628	-2.301	20.718
$p^{EU} \times \ln(1+\tau_{UKR})$	807509	0.006	0.007	0.000	0.167
$p^{CU} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$	807509	0.018	0.019	-0.200	0.449
$p^{EU}_{alt} \times \ln(1+\tau_{UKR})$	807509	0.048	0.046	0.000	1.048
$p^{CU}_{alt} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$	807509	0.064	0.063	-0.666	1.338
$p^{EU}_{alt1} \times \ln(1+\tau_{UKR})$	807509	0.009	0.009	0.000	0.178
$p^{CU}_{alt1} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$	807509	0.010	0.011	-0.112	0.240
p^{EU}	807509	0.171	0.123	0.000	0.411
p^{CU}	807509	0.326	0.160	0.000	0.849
$\ln(1+\tau_{UKR})$	807509	0.036	0.031	0.000	0.405
Quota topic	807509	0.097	0.068	0.001	0.310
Natural gas topic	807509	0.062	0.042	0.000	0.179
EU FTA relative word freq.	807509	0.246	0.117	0.000	0.440
RU CU relative word freq.	807509	0.189	0.082	0.024	0.350
ln(EU FTA) word count	807509	3.667	1.346	0.000	6.129
ln(RU CU) word count	807509	3.389	0.944	0.693	5.576
ln(Number of articles)	807509	3.196	1.071	0.000	5.313
TFP	786701	2.157	1.206	-14.755	11.228
ln(Employment)	804767	5.553	1.746	0.000	11.264

Table C.4 Summary Statistics. The table reports summary statistics for the key variables interest for two different samples: exporting firms and importing firms. The data is quarterly between 2003 and 2013 at the level of firm, product, destination or origin country.

C.3.3 Robustness: Other Uncertainty Measures

An important question is whether the novel measure of trade policy uncertainty is better than existing ones. Also, it might be the case our measure capture overall economic uncertainty rather than specific trade policy concerns which would put in question the validity of our main results presented above. Below, we use two simpler measure of uncertainty to demonstrate the robustness of our results. First, we consider the Economic Policy Uncertainty (EPU) index developed by Baker, Bloom and Davis (2016), which capture the level of policy-related economic uncertainty. The EPU also allows us to separate overall uncertainty from the trade policy uncertainty. We use the EPU index for EU and Russia for the same period as our original results and include them in our regression analysis alongside to our TPU measures, respectively.[16] Second, we also use simple relative frequency of words related to the EU FTA and the RU CU in the news briefs as alternative measures, to counter the argument that our measure might just pick up overall salience of trade policy.

We estimate a model using the natural log of intermediate and capital goods imports to the EU as the dependent variable and include firm-country-product fixed effects. The results using the EPU index are presented in columns (1) - (4) of Table C.5. First, the significance and size of the coefficients with the TPU measures remain virtually unchanged, while the coefficients with the EPU measures are not significant in most cases. This indicates that the TPU measure captures trade related uncertainty better than the general ones. The results with the relative frequency measures are presented in columns (5)-(8) of Table C.5. The results show that the relative word frequency of EU FTA does not capture TPU better than our measure.

[16]Note that we use the EPU indices for the EU and Russia because there is no readily available measure for Ukraine.

The coefficient of the interaction term $p_{EU} \times \ln(1+\tau_{UKR})$ remains virtually unchanged, positive and significant. At the same time the simple frequency measure of RU CU performs well. One reason for this could be that the CU topic model measure does not include some news relevant to developments around the CU. However, the overall conclusion from these result is that our measures outperform the overall measure of economic policy uncertainty and add more information than just simple word count measures. Most importantly, our main results using our EU FTA topic model measure hold including alternative measures of uncertainty and simple word counts.

	EPU measure				EU&CU relative frequency			
	Base	+Empl	+TFP	+Ind&Region	Base	+Empl	+TFP	+Ind&Region
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$p^{EU} \times \ln(1+\tau_{UKR})$	3.370**	3.595**	3.512**	3.546**	3.551**	4.547**	3.957**	4.003**
	(.588)	(.586)	(.592)	(.591)	(.755)	(.752)	(.759)	(.759)
$p^{CU} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$	-1.081**	-1.515**	-1.462**	-1.395**	.938**	.559*	.393	.399
	(.262)	(.261)	(.264)	(.264)	(.258)	(.258)	(.261)	(.261)
$p^{EU}_{alt} \times \ln(1+\tau_{UKR})$	-.274**	-.106	-.163	-.167+	-.501	-1.064*	-.550	-.556
	(.100)	(.100)	(.101)	(.101)	(.531)	(.528)	(.535)	(.535)
$p^{CU}_{alt} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$	.0113	-.0157	-.0909	-.115	-7.192**	-7.541**	-7.101**	-7.003**
	(.069)	(.069)	(.070)	(.070)	(.348)	(.347)	(.350)	(.351)
$\ln(1+\tau_{UKR})$	-1.490**	-1.924**	-1.555**	-1.561**	-2.202**	-2.387**	-2.102**	-2.096**
	(.258)	(.256)	(.260)	(.260)	(.242)	(.241)	(.244)	(.244)
Quarter	✓	✓	✓	✓	✓	✓	✓	✓
Industry				✓				✓
Region				✓				✓
Observations	807509	804767	786701	786701	807509	804767	786701	786701
R^2	.811	.813	.812	.813	.812	.813	.813	.813

Table C.5 EU Imports and Trade Policy Uncertainty: Alternative Uncertainty Measures. The dependent variable is the log of the value of HS 4 digit product k import of firm i from an EU country j within quarter-year t. We consider only intermdeiate and capital good imports, according to BEC Ver. 4 classification. Alternative measures of uncertainty are EPUs for EU and Russia in columns (1)-(4) and frequency of words EU and CU in columns (5)-(8) The cross term $p^{EU} \times \ln(1+\tau_{UKR})$ captures the effect of the likelihood of the EU FTA on imports of goods with different levels of tariff protection. The cross term $p^{CU} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$ captures the effect of the likelihood of joining the RU CU on imports of goods with different levels of tariff protection. We control for probability of joining EU FTA and RU CU, employment, productivity. All models are estimated with firm-country-product fixed effects. *Notes*: + p<0.1 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

C.3.4 Robustness: Other Topics and Salience of Trade

Another concern could be that we are just picking up changes in other trade topics or other types of uncertainty related to the Ukraine-EU and Ukraine-Russian relations. We provides further robustness checks in Table C.6 using the same model specification for EU imports of intermediate and capital goods as before. In column (1) we include frequency of topic 3 from our text analysis above, which is related to quantitative trade restrictions, using the words "quota", "steel", and "milk". More frequent mentioning of this topic is negatively associated with imports from EU, but it does not effect our measures of TPU effect on trade. In column (2) we include topic 10 from our text analysis, which includes specific words "gas" – referring to the natural gas disputes, a different type of uncertainty frequently featuring in the Ukraine-Russia relationships which could also affect firm performance. Again, this topic negatively influence trade, but the effect is not significant at the 5 percent level. When we control for the overall level of debate on the EU FTA and the RU CU, including the natural logs of word counts for these topics in column (3), we observe significant signs of the coefficients but our main measures of TPU still remain significant, albeit slightly smaller in magnitude. We observe similar results when we include relative frequencies instead of logs of word counts in column (4). In column (5) we control for the overall number of articles on trade topics capturing importance of all trade related topics which has positive and significant coefficient, indicating that trade is more discussed when imports from the EU are at higher levels. In column (6) we include all additional controls, which does not impact significance of our measure $p_{EU} \times \ln(1 + \tau_{UKR})$, but the CU related measure loses significance. This is not surprising, since the impact of relationships with CU on trade with EU is of the second order of magnitude,while the direct measure remains positive and significant in all model specification. Finally, we also report results with lagged values of TPU measures in column (7), which gives expected and significant signs for the variable of interest. These results lend further credibility to our results and our measure of TPU. Using absolute and relative word frequency measures, alternative uncertainty-inducing topics other than the EU FTA or the RU CU, and simple measures of overall salience of trade policy does not change the main results of this paper.

	Quota	Gas	Word count	Word freq.	Num. of art.	All	Lags
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$p^{EU} \times \ln(1+\tau_{UKR})$	3.077**	3.373**	2.752**	3.012**	3.441**	2.402**	1.715**
	(.575)	(.575)	(.576)	(.576)	(.575)	(.574)	(.588)
$p^{CU} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$	-1.364**	-1.532**	-1.152**	-1.296**	-1.563**	-.388	-.535*
	(.246)	(.246)	(.245)	(.246)	(.246)	(.245)	(.239)
Quota topic	-.409**					-1.786**	
	(.028)					(.042)	
Natural gas topic		-.0802+				-.792**	
		(.046)				(.064)	
ln(EU FTA) word count			.0335**			-.0717**	
			(.003)			(.008)	
ln(RU CU) word count			-.117**			-.0989**	
			(.004)			(.008)	
EU FTA relative word freq.				-.0203		-.186**	
				(.028)		(.048)	
RU CU relative word freq.				-.628**		-1.155**	
				(.028)		(.060)	
ln(Num. of articles)					.0178**	.219**	
					(.003)	(.004)	
Quarter	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓
Observations	786701	786701	786701	786701	786701	786701	772844
R^2	.813	.813	.813	.813	.813	.814	.814

Table C.6 EU Imports and Trade Policy Uncertainty: Robustness to other Topics. The dependent variable is the log of the value of HS 4 digit product k import of firm i from an EU country j within quarter-year t. We consider only intermdeiate and capital good imports, according to BEC Ver. 4 classification. The cross term $p^{EU} \times \ln(1+\tau_{UKR})$ captures the effect of the likelihood of the EU FTA on imports of goods with different levels of tariff protection. The cross term $p^{CU} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$ captures the effect of the likelihood of joining the RU CU on imports of goods with different levels of tariff protection. We control for probability of joining EU FTA and RU CU, employment, productivity. All models are estimated with firm-country-product fixed effects. *Notes*: + p<0.1 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

C.3.5 Robustness: Weekly Data and Placebo Tests

	Base	+Ind&Reg	+Trend	-C/D/L	Base	+Ind&Reg	+Trend	-C/D/L
	(1) Exports	(2) Exports	(3) Exports	(4) Exports	(5) Imports	(6) Imports	(7) Imports	(8) Imports
$ln(1+\tau_{EU})$	-.175	-.170	-.170	-.195				
	(.22)	(.23)	(.23)	(.25)				
Post $\times$ $ln(1+\tau_{EU})$	-.011	-.011	-.011	-.013				
	(.02)	(.02)	(.02)	(.02)				
$ln(1+\tau_{UKR})$					.048	.049	.049	.072
					(.20)	(.20)	(.20)	(.21)
Post $\times$ $ln(1+\tau_{UKR})$					.120**	.120**	.120**	.123**
					(.03)	(.03)	(.03)	(.03)
$\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					-.048	-.044	-.044	-.041
					(.12)	(.12)	(.12)	(.13)
Post $\times$ $\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					.093**	.092**	.092**	.097**
					(.03)	(.03)	(.03)	(.03)
Post	.343**	.344**	.344**	.360**	-.065	-.069	-.069	-.084
	(.10)	(.10)	(.10)	(.10)	(.13)	(.13)	(.13)	(.14)
TFP	.086	.087	.087	.087	.456**	.502**	.502**	.493**
	(.06)	(.06)	(.06)	(.06)	(.13)	(.13)	(.13)	(.14)
$ln(empl)$	.175	.134	.134	.200	.703**	.649**	.649**	.641*
	(.11)	(.12)	(.12)	(.13)	(.20)	(.22)	(.22)	(.26)
Week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs		✓	✓	✓		✓	✓	✓
Region FEs		✓	✓	✓		✓	✓	✓
Trend			✓	✓			✓	✓
Observations	588602	588602	588602	552380	579120	579120	579120	542867
R^2	.909	.909	.909	.904	.863	.863	.863	.857

Table C.7 Ukraine-EU Trade and Post-February-2014 Transition: Weekly Data. The table shows the impact of the 2014 political transition on goods with different levels of tariff protection, between 2013 and 2014. The dependent variable is the log of firm i's exports/imports of product k to/from EU country j in week t, using only intermediate and capital goods. *Post* is a dummy variable that equals 1 for all the weeks after February 2014 and 0 otherwise. Post $\times$ $ln(1+\tau_{EU})$ captures the effect of the political transition to an *EU-friendly government* on exports to the EU in goods that are more protected by EU MFN tariffs. Post $\times$ $ln(1+\tau_{UKR})$ captures the effect of the political transition on imports from the EU that are more protected by Ukrainian MFN tariffs. Post$\times$ $\ln((1+\tau_{CU})/(1+\tau_{UKR}))$ captures the effect of the political transition on imports of goods from the EU that would be more protected under a customs union with Russia. All models include firm-destination-HS4 product fixed effects. The models 2 and 6 add industry- and region fixed effects and models 3 and 7 add a time trend. The models 4 and 8 exclude Crimea, Donetsk, and Luhansk. *Notes*: + p<0.10 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses

	Base	+Ind&Reg	+Trend	-C/D/L	Base	+Ind&Reg	+Trend	-C/D/L
	(1) Exports	(2) Exports	(3) Exports	(4) Exports	(5) Imports	(6) Imports	(7) Imports	(8) Imports
$ln(1+\tau_{EU})$	.270	.270	.270	.318				
	(.53)	(.53)	(.53)	(.62)				
post	-.061*	-.057*	-.057*	-.061+	.014	.012	.012	-.012
	(.03)	(.03)	(.03)	(.03)	(.05)	(.05)	(.05)	(.06)
post $\times$ $ln(1+\tau_{EU})$	.015	.014	.014	.010				
	(.02)	(.02)	(.02)	(.02)				
$ln(1+\tau_{UKR})$					-.410**	-.413**	-.413**	-.495**
					(.15)	(.15)	(.15)	(.17)
post $\times$ $ln(1+\tau_{UKR})$					-.067**	-.066*	-.066*	-.061*
					(.03)	(.03)	(.03)	(.03)
$\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					-.548**	-.552**	-.552**	-.634**
					(.14)	(.15)	(.15)	(.16)
post $\times$ $\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					-.035	-.035	-.035	-.026
					(.02)	(.02)	(.02)	(.03)
TFP	.051*	.052*	.052*	.054*	.132	.133	.133	.141
	(.03)	(.03)	(.03)	(.03)	(.10)	(.10)	(.10)	(.10)
$ln(empl)$	.122	.108	.108	.142	.246*	.252*	.252*	.238+
	(.09)	(.09)	(.09)	(.10)	(.12)	(.12)	(.12)	(.12)
Month FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs		✓	✓	✓		✓	✓	✓
Region FEs		✓	✓	✓		✓	✓	✓
Trend			✓	✓			✓	✓
Observations	342081	342081	342081	309464	343386	343386	343386	310559
R^2	.925	.925	.925	.921	.894	.894	.894	.889

Table C.8 Ukraine-EU Trade and Political Transition. Placebo Difference-in-Difference Estimation. The table shows a placebo test for the difference-in-difference estimation in Table 5.7, using February 2013 instead of February 2014 for the moment of the transition. The dependent variable is the log of firm i's exports/imports of product k to/from EU country j in month t, using only intermediate and capital goods. *Post* is a dummy variable that equals 1 for all the month-years after February 2014 and 0 otherwise. Post $\times$ $ln(1+\tau_{EU})$ captures the effect of the political transition to an *EU-friendly government* on exports to the EU in goods that are more protected by EU MFN tariffs. Post $\times$ $ln(1+\tau_{UKR})$ captures the effect of the political transition on imports from the EU that are more protected by Ukrainian MFN tariffs. Post$\times$ $\ln((1+\tau_{CU})/(1+\tau_{UKR}))$ captures the effect of the political transition on imports of goods from the EU that would be more protected under a customs union with Russia. All models include firm-destination-HS4 product fixed effects. The models 2 and 6 add industry- and region fixed effects and models 3 and 7 add a time trend. The models 4 and 8 exclude Crimea, Donetsk, and Luhansk. *Notes*: + p<0.10 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

	Base	+Ind&Reg	+Trend	-C/D/L	Base	+Ind&Reg	+Trend	-C/D/L
	(1) Exports	(2) Exports	(3) Exports	(4) Exports	(5) Imports	(6) Imports	(7) Imports	(8) Imports
$ln(1+\tau_{EU})$	-.198	-.192	-.192	-.220				
	(.23)	(.23)	(.23)	(.25)				
$ln(1+\tau_{EU}) \times p^{EU}$	-.006	-.006	-.006	-.008				
	(.02)	(.02)	(.02)	(.02)				
$ln(1+\tau_{UKR})$					.055	.055	.055	.072
					(.21)	(.21)	(.21)	(.21)
$ln(1+\tau_{UKR}) \times p^{EU}$					.026	.026	.026	.029
					(.02)	(.02)	(.02)	(.02)
$\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					-.037	-.034	-.034	-.026
					(.13)	(.13)	(.13)	(.13)
$\ln((1+\tau_{CU})/(1+\tau_{UKR})) \times p^{CU}$					-.018	-.016	-.016	-.018
					(.02)	(.02)	(.02)	(.03)
p^{CU}	-2.282**	-2.289**	-2.289**	-2.378**	-4.159**	-4.142**	-4.142**	-4.268**
	(.57)	(.57)	(.57)	(.59)	(.72)	(.72)	(.72)	(.75)
p^{EU}	-2.194**	-2.198**	-2.198**	-2.275**	-3.276**	-3.265**	-3.265**	-3.371**
	(.52)	(.52)	(.52)	(.54)	(.59)	(.59)	(.59)	(.62)
TFP	.081	.082	.082	.081	.467**	.514**	.514**	.505**
	(.06)	(.06)	(.06)	(.06)	(.13)	(.14)	(.14)	(.14)
$ln(empl)$	.180+	.138	.138	.209+	.701**	.649**	.649**	.637*
	(.11)	(.12)	(.12)	(.13)	(.20)	(.22)	(.22)	(.26)
Week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs		✓	✓	✓		✓	✓	✓
Region FEs		✓	✓	✓		✓	✓	✓
Trend			✓	✓			✓	✓
Observations	555274	555274	555274	521323	546348	546348	546348	512375
R^2	.909	.909	.909	.905	.864	.865	.865	.858

Table C.9 Ukraine-EU Trade and Trade Policy Uncertainty, 2013-2014: Weekly Data. The table shows the impact of uncertainty on intermediate and capital goods with different levels of tariff protection, between 2013 and 2014. The dependent variable is the log of firm i's exports/imports of product k to/from EU country j in week t, using only intermediate and capital goods. p^{EU} captures the likelihood of Ukraine signing the EU FTA. p^{CU} capture the likelihood of Ukraine joining the CU with Russia. $\ln(1+\tau_{MFN})$, $\ln(1+\tau_{UKR})$, and $\ln(1+\tau_{CU})$ are the current EU MFN tariffs vis-a-vis Ukrainian exports, current Ukrainian MFN tariffs, and tariffs under the Russian Customs Union, respectively. All models include firm-destination-HS4 product fixed effects. The models 2 and 6 add industry- and region fixed effects and models 3 and 7 add a time trend. The models 4 and 8 exclude Crimea, Donetsk, and Luhansk. *Notes*: + p<0.10 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

	Base	+Ind&Reg	+Trend	-C/D/L	Base	+Ind&Reg	+Trend	-C/D/L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exports	Exports	Exports	Exports	Imports	Imports	Imports	Imports
$ln(1+\tau_{EU})$	-.170	-.160	-.160	-.169				
	(.18)	(.19)	(.19)	(.20)				
$ln(1+\tau_{EU}) \times p^{EU-HP}$	-.083	-.093	-.093	-.148				
	(.36)	(.35)	(.35)	(.37)				
$ln(1+\tau_{UKR})$					-.565*	-.563*	-.563*	-.562*
					(.24)	(.24)	(.24)	(.25)
$ln(1+\tau_{UKR}) \times p^{EU-HP}$					1.819**	1.814**	1.814**	1.852**
					(.50)	(.50)	(.50)	(.52)
$\ln((1+\tau_{CU})/(1+\tau_{UKR}))$					.583**	.577**	.577**	.611**
					(.21)	(.21)	(.21)	(.22)
$\ln((1+\tau_{CU})/(1+\tau_{UKR})) \times p^{CU-HP}$					-2.755**	-2.714**	-2.714**	-2.845**
					(.71)	(.71)	(.71)	(.74)
p^{CU-HP}	.000	.000	.000	.000	.000	.000	.000	.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
p^{EU-HP}	2.859**	2.889**	2.889**	3.093**	3.417*	3.406*	3.406*	3.478*
	(1.08)	(1.08)	(1.08)	(1.12)	(1.37)	(1.37)	(1.37)	(1.42)
TFP	.081	.082	.082	.082	.458**	.505**	.505**	.496**
	(.06)	(.06)	(.06)	(.06)	(.13)	(.14)	(.14)	(.14)
$ln(empl)$	.180+	.138	.138	.208	.699**	.651**	.651**	.639*
	(.11)	(.12)	(.12)	(.13)	(.20)	(.23)	(.23)	(.26)
Week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs		✓	✓	✓		✓	✓	✓
Region FEs		✓	✓	✓		✓	✓	✓
Trend			✓	✓			✓	✓
Observations	555274	555274	555274	521323	546348	546348	546348	512375
R^2	.909	.909	.909	.905	.865	.865	.865	.858

Table C.10 Ukraine-EU Trade and Trade Policy Uncertainty (HP-Filtered), 2013-2014: Weekly Data. The table shows the impact of uncertainty on intermediate and capital goods with different levels of tariff protection, between 2013 and 2014. The dependent variable is the log of firm i's exports/imports of product k to/from EU country j in week t, using only intermediate and capital goods, using HP-filtered versions of the uncertainty measures. p^{EU} captures the likelihood of Ukraine signing the EU FTA. p^{CU} capture the likelihood of Ukraine joining the CU with Russia. $\ln(1+\tau_{MFN})$, $\ln(1+\tau_{UKR})$, and $\ln(1+\tau_{CU})$ are the current EU MFN tariffs vis-a-vis Ukrainian exports, current Ukrainian MFN tariffs, and tariffs under the Russian Customs Union, respectively. All models include firm-destination-HS4 product fixed effects. The models 2 and 6 add industry- and region fixed effects and models 3 and 7 add a time trend. The models 4 and 8 exclude Crimea, Donetsk, and Luhansk. *Notes*: + p<0.10 * p<0.05, ** p<0.01. Robust standard errors clustered by firm are in parentheses.

Chapter 6

Conclusion

Motivated by new theories and empirical evidence about the importance of firms in politics and the economy, this dissertation explored the role of firms in two key research areas in International and Comparative Political Economy: individual preference formation and the role of institutions for reducing trade policy uncertainty. The dissertation aimed to answer the following research questions:

1. Do political preferences of employees align with those of their employers?
2. Under what conditions do political preferences of employees align with those of their employers?
3. How does policy uncertainty affect firm-level trade?

I draw on micro-level data from firm and employee political donations and firm-product-level trade to examine the micro-foundations of important IPE theories and contribute to our understanding of preference formation and the role of institutions and uncertainty for international trade. Existing work on preference formation and the uncertainty-reducing role of international institutions provides a well-developed theoretical toolkit that most often takes countries or sectors as the theoretical and empirical unit of analysis. However, this is at odds with new data which highlights large productivity differences between corporations and heterogeneity in the distributional consequences of economic or policy shocks across firms (Kim and Osgood, 2019). Moreover, even though existing work on preference formation and institutions, either implicitly or explicitly, theorizes along individual's firm of employment (Owen and Johnston, 2017; Walter, 2017) or the expectations of firms with regards to trade institutions (Hollyer and Rosendorff, 2012; Kucik, 2012; Mansfield and Reinhardt, 2008*a*), the firm is usually ignored in empirical analyses following these discussions. In practice, key variables are measured at sectoral or country-level, and theoretical models assume homogeneous impacts along those levels of analyses.[1]

This happens in part because collecting original firm level data is inherently difficult, due to its large and unstructured nature. For instance, the US campaign finance data used for the first two papers of this dissertation contain over 62 million transactions between 1980 and 2018, over 4.2 million unique employer names, and over 880,000 occupation names. As described above, neither employers or occupations have unique identifiers. Therefore, I developed a script to link employers and occupations to unique IDs, implemented in the programming language python. Due to the size of the data, I ran the script on a high-performance computer cluster and matched it to firm, industry, and occupation codes. This allowed the aggregation to different levels of observation and the subsequent analysis of firm-employee political alignment. Similarly, firm-level trade data is often only provided

[1]For the few exceptions see Na-Kyung Lee and Liou (2019) and Hertel-Fernandez (2018) for individual preferences, and Handley and Limao (2015) as well as Handley (2014) for the impact of trade policy uncertainty on firm exports. Recent contributions relying on granular product-level data (but not firm-level data) on international trade are Kim, Liao and Imai (2019) and Chaudoin, Kucik and Pelc (2016).

by national governments, and data protection laws require the use of anonymous IDs and coarse geographical indicators (Bernard et al., 2018; Kim and Osgood, 2019). This means that one can usually not match firm-specific political variables or geographic variables of interest to the data, such as firm-specific political connections or constituency-level election outcomes. In the last paper of this dissertation, we circumvented this problem by combining a time-series measure of uncertainty with granular product-level tariff data to estimate the impact of uncertainty swings on the firm based on those firms' traded products.[2] As the use of large-scale administrative data becomes more and more common in the social sciences, these problems are not unique to the projects in this dissertation (Grimmer, 2015). Thus, this thesis also highlights the challenges in working with and generating data at the level of the firm.

6.1 Implications and Future Research

The remainder of this chapter discusses the main findings of this thesis and their implications for future research. The results and the original data will lay the groundwork for a new research agenda on corporations and politics which focuses on the political activities of firms *and* their employees. Within this broad agenda, I will investigate further the alignment between firms and their employees, and use new firm-level data to answer long-standing questions on the political economy of trade and money in politics. Further, this future work will address the limitations of this thesis with regards to causal identification, representativeness of country cases, and measurement of key concepts.

[2]This is similar to the approach taken by Baccini, Pinto and Weymouth (2017) or Handley and Limao (2015).

6.1.1 Firm-Employee Alignment and Business Coalitions

In the first two papers, I study when employees align politically with their company. While there is an ongoing debate on the impact of one's firm, sector, or occupation on individual preferences, there is no clear consensus with regards to which one is more important. Moreover, existing studies rely on stated preferences of employees, and usually study either firm or individual preferences in isolation. Therefore, I leverage campaign contributions data from US firms and their employees between 2003 and 2016 to compare firm and employee preferences. I find that employees in firms and sectors with more specific assets are more aligned politically, on average, but I find no impact of occupational skill specificity on alignment. Further, I show that more employee donations flow to candidates that their company PAC supports in the same electoral cycle. This hints towards a possible mechanism by which firms could signal their preferred candidates to employees, providing a link between firm and employee donations visible in the aggregate data. The findings have three broad implications for the study of preference formation, coalitions, and money in politics.

First, this has crucial implications for coalition formation and societal cleavages. Given the empirical fragmentation of partisan donations across firms, broad class-based cleavages across sectors as described by Rogowski (1989) seem unlikely in the US economy of today.[3] However, the clustering of high firm-employee alignment in some sectors of the US economy could also indicate that those firms are more likely to form ad-hoc coalitions or become politically active via umbrella associations such as the National Association

[3] Hiscox (2002*a*) already noted the modern day US would be characterized by high asset specificity, and hence, by sector-based coalitions. Hall and Soskice (2001*b*) also describe the US skill formation system as firm-centered, compared to sector-based models in coordinated market economies.

of Manufacturers or the American Chamber of Commerce (Hansen, Mitchell and Drope, 2005).

In future work, I want to build on these findings and investigate the impact of firm- and sector-level alignment on coalition formation and corporate political activities. This is especially interesting because the impact of alignment is theoretically ambiguous. On the one hand, corporations with politically homogeneous top management might be more likely to be connected in ideologically extreme associations like the American Legislative and Exchange Council (Hertel-Fernandez, 2016), and could be more likely to engage in joint lobbying with similar companies. Connections and preference alignment between CEOs could thus be an important mechanism for coalition formation between firms and for overcoming barriers to collective political action.[4] On the other hand, very homogeneous firms might actually be less likely to form coalitions because they could face more difficulties to cooperate with firms which follow a more moderate strategy and split donations equally between parties (La Raya and Schaffner, 2015). I would expect the latter to be more prominent on cross cutting policies requiring more compromise between both sides of the political aisle. In any case, I want to improve the measure of alignment so that it does not only reflect candidate donations. For example, employees might express their political views by donating to PACs of sectoral umbrella organizations such as the National Association of Manufacturers (NAM), occupational associations such as the National Association for Realtors (NAR), membership organizations such as Americans for Prosperity, or their company PAC, all of which might provide important information about employee preferences. In addition,

[4]This channels seems particularly relevant considering the important impact role of chief executive's ideology and donations for company strategy and performance documented in Management and Economics (Cohen et al., 2019; Fremeth, Richter and Schaufele, 2013; Gupta, Nadkarni and Mariam, 2019; Unsal, Hassan and Zirek, 2016).

clusters of firms or employees donating to similar committees could be identified using dynamic clustering algorithms (Kim, Liao and Imai, 2019). Hence, I could track politically alike firms over time, observing changes in cluster composition and likely coalitions. I can then add corporate lobbying data and analyze the impact of alignment and cluster composition on joint lobbying on bills or policies over time. This research would contribute to both our understanding of political cleavages within and across sectors (Hiscox, 2002*b*; Kim, 2017), as well as the development and durability of business coalitions in American Politics (Hertel-Fernandez, 2016; Martin and Swank, 2012).

6.1.2 Firms, Sectors, and Occupations as Preference Sources

Second, the finding that sectoral and firm specificity matter more for alignment than occupations suggests that where individuals work matters more for alignment than what they do. While this goes against recent IPE and CPE research which highlights occupations as a main source of political preferences (Kitschelt and Rehm, 2014; Owen and Johnston, 2017; Walter, 2017), it could hint towards important differences between stated preferences and political action. The economic drivers of individuals who have already decided to become politically active might just be different from the economic correlates of individual stated preferences on topics such as free trade, which have been studied at length (Kuo and Naoi, 2015), but shown to be unstable (Guisinger, 2009; Rho and Tomz, 2017) and susceptible to framing (Naoi and Kume, 2015). These findings also suggest that where somebody works deserves much more attention in the study of money in US politics than is currently the case. Rather than treating individual donors as mostly ideologically motivated (Ansolabehere, de Figueiredo and

Snyder, 2003; Barber, 2016; Bonica, 2016*a*), this dissertation builds on work highlighting the strategic nature of individual giving (Barber, Canes-Wrone and Thrower, 2017; Fremeth, Richter and Schaufele, 2013; Gimpel, Lee and Pearson-merkowitz, 2008), and provides motivation to further study the economic motivations for individual giving. Thus, the dataset on matched firm-employee donations provides an opportunity to study the importance of firm-, occupation, or sectoral characteristics on political preferences in the form of donations to unions, membership- and trade associations, and political candidates.

One particular interesting future project would be to link long-term structural changes in the US economy to individual and corporate campaign donations. One of the most notable changes is the rise of 'superstar' firms (Bernard et al., 2018; Mayer and Ottaviano, 2008) and the increase in economic concentration and market power (Azar, Marinescu and Steinbaum, 2017; De Loecker, Eckhout and Unger, 2018). Since the 1980s, average markups of firms have risen from 21 percent to over 60 percent above marginal cost, with large variations across different sectors of the economy. These changes might have affected the composition of political donations over time. Using the methodology of De Loecker and Eckhout (2018) to measure market power of US publicly traded companies between 1980 and today, the linked campaign finance data allows to answer whether changes in market power have equally led to increased concentration in PAC and individual donations from a few companies. In addition, the identifiers for individual occupations allow to evaluate whether an increase in concentration of employee donations would come from rank- and file employees or from top executives. While PAC contributions of firms are constrained by the strict limits on federal donations, individuals represent the largest share of candidate's contribution receipts.[5] Employee donations could thus be another important resource for firms to exert political influence, in addition to other non-monetary resources like employee votes or brand reputation (Tripathi, Ansolabehere and Snyder, 2002). If correct, this would likely have implications for how market power might translate into political power of firms. Given the importance of campaign donations for politics in the US, this might also have consequences for the unequal representation of political interests in the US (Gilens and Page, 2014; Schlozman, Verba and Brady, 2012) and beyond (Elsässer, Hense and Schäfer, 2018).

A problem with existing databases on campaign donations is that they do not sufficiently differentiate between individuals' sector and occupation of employment, or that both are lumped together, despite their key role in CPE, IPE, and Economics. In another future paper, I want to link occupation and industry codes to Congressional committees and subcommittees with jurisdiction about them. If individual donations are mostly driven by their firm, they should donate more to politicians which sit on committees regulating their sector. Conversely, if their donations are motivated by their occupation, they should donate more to committees overseeing their profession. I can then test the responsiveness of sector- or occupation-specific donations to legislators changing committee or subcommittee assignments. To strengthen causal identification, I can exploit quasi-random committee exiles of members of Congress to causally estimate the impact of sector- or occupation regulating committees on individual donations (Powell and Grimmer, 2016). Case studies of particular sectoral and occupational at the federal level could be used to illustrate the links between jobs, legislator responsibilities, and donations. This work would go beyond similar work

[5]Moreover, publicly traded companies employed almost 30 percent of US private sector employees in 2000 (Davis et al., 2006).

(Barber, Canes-Wrone and Thrower, 2017) by looking at all employees of publicly traded companies, by clearly differentiating between sectors and occupations of donors, and by analyzing both committees and subcommittees assignments of legislators. Thus, I will be able to better analyze the relative importance of industries and professions for individual political preferences (Kitschelt and Rehm, 2014; Owen and Johnston, 2017; Walter, 2017), and equally contribute to the American Politics work on individual donor preferences (Barber, 2016; Barber, Canes-Wrone and Thrower, 2017).

6.1.3 Political Economy of Trade and Uncertainty

In the last paper, I investigate the impact of trade policy uncertainty on firm-level imports of intermediate and capital goods, using fine-grained Ukrainian firm-product-destination level trade data between 2004 and 2014. While existing work on trade and uncertainty highlights the role of institutions in decreasing uncertainty for corporations, most of the research abstracts from the firm and analyzes only very broad industries (Carnegie, 2014) or the country-level (Hollyer and Rosendorff, 2012; Kucik, 2012; Mansfield and Reinhardt, 2008*a*). As a consequence, this work essentially assumes away the distributional consequences of uncertainty reduction across firms in the same industry. We leverage the firm-product-destination-level data on Ukrainian firms between 2003 and 2014 to investigate how trading firms react to swings in uncertainty. Ukraine is a particularly interesting case to study political uncertainty because Ukrainian firms faced a highly unpredictable trade policy, as the government was long undecided whether to integrate economically with Russia or the European Union. We find that reductions in uncertainty with regards to an FTA with the EU increases firm-level imports of intermediate in capital goods, but not for consumer goods. Moreover, in line with our theoretical model, imports of goods which are more protected under the status quo (and hence, would benefit most from the EU FTA), expand more.

These findings have important implications for research on firms in trade and trade politics, and the study of uncertainty in international trade. First, the lion share of the IPE work on uncertainty assumes that firms will uniformly welcome reductions in policy ambiguity (Mansfield and Reinhardt, 2008*a*), and that political leaders pursue FTAs because they are welfare-generating, on average (Hollyer and Rosendorff, 2012; Mansfield and Milner, 2012). In contrast, we show the clear distributional consequences of uncertainty reductions. Whether firms are affected by uncertainty crucially depends on the goods they trade and the trading partner, as well as the design of the prospective trade agreement (Dür, Baccini and Elsig, 2014). The use of aggregate, country-level, and un-directed trade flow data therefore provides only a partial and incomplete picture when analyzing the impact of uncertainty on trade. Moreover, non-trade issues such as intellectual property and foreign direct investment have been particularly contentious in the last years (Peel, Hornby and Sanderson, 2019; USTR, 2019). Therefore, future work could look more closely at specific uncertainty with regards to intellectual property intensive goods (Osgood and Feng, 2018; USTR, 2019), contract-intensive goods (Nunn, 2007), or trade in services (Weymouth, 2017). Further, this paper illustrates a case in which firms rationally adjust their import behavior based on the negotiation status of trade agreements, even if the agreement has not been signed yet. Hence, we provide further micro-level evidence on how political institutions serve as anchors for the expectations of private actors (Broz and Plouffe, 2010). Moreover, the paper shows that globally integrated firms sourcing investment-intensive goods from abroad are the main beneficiaries of uncertainty reduction via PTAs.[6] Thus, this research also contributes to broader work on how integration in global value chains promotes firm support for trade openness (Jensen, Quinn and Weymouth, 2015; Manger, 2009; Osgood, 2018).

I want to extend this work on trade policy uncertainty to different countries and policy cases. A particularly interesting case to study the impact of uncertainty on business activitity is the United Kingdom's 2016 decision to exit the European Union. Compared to Ukraine, even more different trade policy options, between staying a fully-fledged member in the Common Market and a free trade agreement like the EU-Canada Comprehensive Economic and Trade Agreement (CETA), are on the table, with particular political uncertainty about which can produce a majority in the British parliament. The exit from the EU is expected to have large negative effects on the British economy (Dhingra et al., 2017). Moreover, the uncertainty about the future of the UK-EU relationship has already been shown to affect overall UK growth (Born et al., 2019), as well as overall exports (Crowley, Exton and Han, 2019), and investment (Bloom, Chen and Mizen, 2019). With available high-quality firm-level data in the United Kingdom, I want to investigate the impact of trade policy uncertainty on firm-level trade and foreign direct investment in the UK. To improve on the measure of uncertainty employed in this thesis, I can imagine two alternative measurement strategies for trade policy uncertainty stemming from Brexit. First, I would add measures based on volatility of topics similar to the popular VIX index for expectations of stock market volatility (Whaley, 2009), rather than relative importance of topics. Second, I would also employ alternative dictionary approaches, incorporating synonyms

[6] This point is related to the finding by Carnegie (2014) who finds that the World Trade Organization boosts trade in contract-intensive goods and fixed capital investment.

of uncertainty as in Baker, Bloom and Davis (2015), but more tailored towards the specific policies causing uncertainty. Alternatively, one could also use training sets of articles discussing *political uncertainty* in general and *trade policy uncertainty* in particular to classify documents in order to generate the uncertainty measure (Hassan et al., 2019). These bear the risk of introducing more researcher bias (King, Lam and Roberts, 2017), but could serve as alternative measures in addition to topic models whose performance could be compared against each other. This research would contribute to our understanding of the distributional consequences of uncertainty for firms' international activities and extend the work of this dissertation to a particularly relevant case of policy uncertainty.

Finally, I also want to investigate the impact of corporate influence on newly emerging protectionist trade policies in the United States. In 2018 and 2019, the US government decided to put tariffs on imports of steel, aluminum, and many consumer products from China on the basis of security concerns. The tariffs have already negatively affected US consumers and import-dependent firms (Amiti, Redding and Weinstein, 2019), and while the tariffs have initially benefited industries in competitive districts important for the Republican party (Fajgelbaum et al., 2019), retaliatory tariffs by foreign countries have targeted the same districts, offsetting positive vote gains for the Republicans (Fetzer and Schwarz, 2019). Importers of affected products can apply to the Department of Commerce (DoC) and the US International Trade Commission (USITC) to be exempted from the tariff and import-competing companies get the opportunity to argue against these exemptions. This represents a unique opportunity to observe both import-competing firms and importing firms within the same industry to mobilize politically. Thus, I will be able to investigate the impact of between-firm differences on the likelihood of the DoC and USITC to grant protection or an exemption from protection. I expect that import-competing companies are more likely to prevent an exemption if they are located in strategically important swing districts. Moreover, I theorize that approval or denial of exemptions will further depend on prior political connections to the Republican party via campaign donations or lobbying. I will test this argument and hence, be able to determine which combination of corporate political strategies leads for protectionism to prevail over free trade and vice versa. This research contributes to the firm-level political economy of trade that looks at within-industry heterogeneity of political preferences (Kim, 2017; Osgood, 2017*b*). It also adds to the under-researched lobbying of the executive branch (Hansen and Prusa, 1997; Ludema, Mayda and Mishra, 2018; Webb Yackee and Webb Yackee, 2006) and how insulated executive agencies are from political influence (Weingast and Moran, 1983).

6.2 Summary of Future Work and Outlook

There are many reasons to keep study firms in IPE, CPE, and Political Economy more broadly. Firms are incredibly important actors in terms of donations and lobbying, and they provide the main source of an individual's livelihood. Similarly, many empirical developments seem to consolidate the importance of firms for the future, such as the trends towards market and concentration, and labor market monopsomy. However, the lack of fine-grained data about firm's political and economic activities has thus far prevented researchers to answer some of the most interesting questions related to firm's involvement in the political process.

The newly available micro-level data on corporations will enable new research agenda on the role of firms in politics. This agenda includes the role of firms in shaping trade policy, the importance of political alignment between firms for the formation of business coalitions, and how much one's workplace affects individual political attitudes. This work will have far-reaching implications for public policy, the workplace as a site of politics and preference formation, and for the role of international institutions in guiding international trade. I will be very glad to keep on contributing to this new and exciting research agenda with timely and relevant work on the role of firms in politics.

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