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Essays in Applied Macroeconomics

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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.

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of 35200 words.

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Abstract

This thesis is composed of three chapters. The first chapter studies the role of unemployment risk on business formation. It develops and estimates a partial-equilibrium search model with risky transitions to entrepreneurship. The decomposition of rising unemployment risk for wage workers into the fall of the job finding rate and the rise of the job separation rate highlights the role of the former in driving falling entry to self-employment from paid workers. The quantitative analysis also shows that higher aggregate unemployment risk can explain most of the 16% decrease in the self-employment rate after the Great Recession and predicts a significant worsening of the entrepreneurial pool. Empirically, the chapter exploits annual variation in industry unemployment rates to show that salaried workers are deterred from entering self-employment in sectors experiencing higher unemployment increases. The second chapter investigates the impact of unemployment benefits extensions during the Great Recession on self-employment. At the micro-level, it shows that longer UI duration was, on average, not associated with lower entry to self-employment. However, these findings hide heterogeneity among the newly self-employed: Those who work less than 20 hours per week on their business were 30% less likely to enter following eligibility to extended benefits, consistent with entry by necessity when jobs are hard to find. While there was a large variation in the number of UI weeks available at the macro-level, this chapter finds that changes in benefits duration did not affect state-level self-employment rates. The third chapter studies the role of changes in households' balance sheets on new firm creation through changes in local

home values. It documents that new start-up founders were disproportionately more likely to have been turned down credit during the Great Recession. To study the impact of house price changes on start-up creation, it proposes a new instrumental variable strategy for house prices that exploits cross-sectional variation in mortgage debt-to-income ratios as a proxy for households' borrowing constraints. This chapter finds that a 1% annual increase in house prices increases the start-up rate by 0.02 percentage points.

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Chapter 1

Self-employment dynamics and unemployment risk

1.1 Introduction

Helping people create their businesses has long been recognised as critical to improving macroeconomic performance and reducing unemployment. Recent evidence suggests that small and young firms have a disproportionate role in job creation (Haltiwanger et al. [2013], Neumark et al. [2011]). However, there is heterogeneity among the self-employed. One way to disentangle this heterogeneity is to distinguish between entrepreneurs by looking at their previous labour market status, which can be informative about the objective of the business and the motivations behind business formation: Individuals who come from unemployment are more likely to be self-employed by necessity[1]. On the other hand, individuals who leave their jobs are

[1] There has recently been a focus in helping unemployed individuals create their own jobs and reduce unemployment, given the decline in the standard employment relationship (Katz and Krueger [2019], Boeri et al. [2020]). Nevertheless, evidence suggests that businesses created by previously unemployed individuals are less sustainable and less likely to hire (Galindo da Fonseca [2021]). This evidence is consistent with unemployed individuals pushed to self-employment without any other

more likely to be "opportunistic entrepreneurs" and enter to exploit new business opportunities and contribute to growth. Any change in this entrepreneurial pool's size or composition can have profound and long-lasting aggregate implications on the economy.

This paper studies the role of unemployment risk in the decision to start a business, knowing that engaging in entrepreneurial activity is a risky task. Theoretically, it develops and quantifies a partial-equilibrium search model that features both risky transitions to entrepreneurship and endogenous exit from self-employment to paid work. I decompose the rising unemployment risk for wage workers into two components: the fall of the job finding rate and the increase of the job separation rate. My first result highlights that the fall in hiring during the Great Recession drives the decline of entry into self-employment from paid work. It also quantitatively matters more than the displacement-induced entry traditionally emphasised in the literature. Second, my quantitative results show that higher aggregate unemployment risk can explain three-quarters of the 16% decrease in the self-employment rate during and after the crisis. Third, my model also predicts that it leads to a significant worsening of the entrepreneurial pool because individuals who chose to enter self-employment by choice (from paid work, opportunistic entrepreneurs) have progressively been replaced by individuals who enter from unemployment out of necessity. These findings hint at a potential role for unemployment insurance, which could foster business creation by lowering the costs associated with entrepreneurial failure. From an empirical perspective, this paper exploits annual variation in industry unemployment rates to show that salaried workers are deterred from entering self-employment in sectors experiencing higher unemployment increases. I am estimating the marginal effect of a 1% increase in the unemployment rate at the industry level and show that it is

alternatives.

associated with a 1.3 to 3 % lower entry from paid work to self-employment. This effect is also 30 % stronger for college graduates, who are more likely to start thriving businesses. This complements my time series analysis of entry into self-employment by previous labour market status, which shows that entry into self-employment from paid work falls during recessions.

The theory highlights the importance of the risk of failure in the decision to enter self-employment and how it interacts with the opportunity cost of being salaried. An unemployed or salaried individual receives business ideas/opportunities and compares future profits from pursuing the idea to her current situation. However, only some ideas will be successful, and any worker who follows an idea that fails to materialise ends up unemployed. When unemployment rises because it is harder to find a job, the model features an *unemployment risk effect* that deters salaried workers from starting a business because of the possibility of failure leading to a long spell of unemployment, now a less desirable state. Higher unemployment risk will disproportionately affect the entry decision of the employed because they are the ones who have the most to lose from failure by searching for a new job. When unemployment rises through higher job separations, this *unemployment risk effect* that dampens entry remains present but interacts with a *surplus effect* that facilitates entry because the risk of being displaced lowers the opportunity cost of entrepreneurship. It does not mean that the risk of displacement does not exist in certain sectors (Babina [2019]), but my quantitative results show that the possibility of being displaced matters less quantitatively in the aggregate for currently employed workers. On the other hand, the fall in the job finding rate quantitatively accounts for the entire fall in the aggregate entry from salaried employment during the Great Recession.

The view that the risk of failure associated with starting a business is a key determinant of entry into entrepreneurship has notably been absent from the literature that studies entrepreneurship and unemployment. This literature focused on the role of displacement in fostering business creation and reducing unemployment, motivated from a theoretical perspective by the Schumpeterian idea that displacement encourages growth and job creation (Aghion and Howitt [1994], Engbom [2020]). However, most entry into entrepreneurship/self-employment does not come from the unemployed but from previously employed workers (Sohail [2021]). Moreover, individuals who leave their jobs to become self-employed and start a business are more likely to engage in an entrepreneurial activity that creates jobs and contributes to growth, unlike the unemployed, who are more likely to enter out of necessity. This is surprising because small-scale surveys on "nascent entrepreneurship"[2] determined that, in Western countries, just over a third of all individuals actively trying to set up a business succeed. The failure risk is also likely to be a stronger deterrent for employed workers than the unemployed because they will end up in a relatively worse position if they do not achieve operation. This also implies that higher unemployment risk can cause long-term damage to the economy. The model's decomposition of the evolution of the self-employment rate shows that rising unemployment risk during the recession led to a 23% decrease in the number of opportunistic entrepreneurs (coming from paid work) and a 47% increase in the number of self-employed by necessity (from unemployment). By preventing entry from salaried workers with the highest potential to create successful and fast-growing businesses[3], higher unemployment can thus slow down output and employment growth and drag on the economic recovery

[2] "Nascent entrepreneurs" are different from the self-employed to the extent that the latter are operating a business, while the former are trying to achieve operation.

[3] The decision to start entrepreneurship/self-employment can also be seen as a process of experimentation (Kerr et al. [2014]), because of the uncertainty associated with the success of a business idea. This could explain why the likelihood of incorporation increases with experience of self-employment spells (Dillon and Stanton [2017]) and why, while most self-employed start as own account workers, their likelihood to become an employer firm is much higher than for salaried or unemployed individuals (Boeri et al. [2020]).

post-recession.

Related literature. My paper contributes to three important branches of the entrepreneurship literature.

First, I contribute to the recent literature examining the relationship between labour market outcomes and entrepreneurial choice. In the search literature, Engbom [2019] is the first to look at the opportunity cost of wage employment on entrepreneurial choice. He studies the role of an ageing labour force in explaining the slowdown in business dynamism and job-to-job mobility. Older workers are more likely to be well-matched with firms and at the top of the job ladder, with a higher opportunity cost of leaving their job to do anything else. By a composition effect, a lower share of younger workers, with a lower opportunity cost of leaving their jobs and more likely to be hired by young firms, will lower firm entry and job reallocation, further lowering business entry. Related to that, recent contributions to the occupational choice literature such as Salgado [2020] and Jiang and Sohail [2021] investigate the role of skill-biased technical change in explaining the stronger decrease in self-employment among college-educated workers. As skill-biased technical change increases the relative value of being a wage worker, the opportunity cost of starting a business for those workers increases.

Compared to those papers, I study the role of the opportunity cost of wage employment and unemployment along the business cycle and propose a simple search model with entrepreneurship that will feature two important components. First, I will model the decision to start a business as risky because few ideas end up being successful, and many tentative entrepreneurs fail in achieving operation. This choice is consistent with research using the PSED[4] that shows that only a third of

[4]The Panel Study of Entrepreneurial Dynamics is a nationally representative survey initiated to

nascent entrepreneurs would have succeeded in achieving business operation after 12 months[5], in line with earlier small-scale studies (Carter et al. [1996], Gelderen et al. [2006]). Second, I will incorporate the possibility of a self-employed business owner leaving her job and returning to paid work. Dillon and Stanton [2017] show that not accounting for the option value of returning to salaried employment underestimates the lifetime value of entrepreneurship and that the option to exit helps explain why individuals persist in trying self-employment despite median salaried earnings being higher than entrepreneurial income (Hamilton [2000]). I will also be able to study the role of unemployment risk on exit from self-employment to paid work during the downturn. My paper is related to Garcia-Trujillo [2021], who develops an occupational choice model to study the role of labour market frictions on startups and the self-employed along the business cycle, and also finds a role for the job finding rate in lowering entrepreneurial quality. While my analysis also studies the evolution of the stock of self-employed, I make two distinct contributions relative to this paper. First, I quantify the role of rising unemployment risk and the relative importance of its different drivers (job finding and separation rates) in explaining the observed changes in entry and exit during the Great Recession[6]. Second, I explicitly consider the risk of displacement while he abstracts from the role of separation shocks.

Second, I also contribute to the literature that looks at career risk and the provision of downside insurance in the decision to enter self-employment. Gottlieb et al. [2021] study the importance of career risk in inhibiting potential entrepreneurs by

understand the business formation process better. It explicitly distinguishes between self-employed individuals and "nascent entrepreneurs" who are in the process of creating a business.

[5]Even after five years, less than half of nascent entrepreneurs achieve operation (Cassar [2010]).

[6]I will also be able to explain the decline in the self-employment rate between 2007 and 2011, in part because of rising exits out of self-employment, which is not captured well by his analysis. Job separation shocks also remain important to explain entry from unemployment. Section 1.4.2 shows that looking at the fall in the job finding rate alone predicts a decline in exits from self-employment, at odds with empirical evidence. He also abstracts from on-the-job search, while it has been documented that half of new hires come from existing firms (Hall and Krueger [2012]).

leveraging a Canadian natural experiment that extended job-protected leave to 12 months after giving birth. They do not only find that entry into self-employment among Canadian women increased but also that there are positive long-run effects to the extent that these businesses are still operating five years later. Similarly, a study from Hombert et al. [2020] leverages a French reform that offered downside insurance to unemployed workers starting a business[7]. They find that registration of new firms increased after the reform and that those new firms created by unemployed workers are of no worse quality than other new businesses. Compared to these micro studies, I try to embed the notion of career risk in a simple macroeconomic model of a frictional labour market to study the aggregate consequences of unemployment risk on the decision to start a business. My results hint at a role for the extension of the provision of unemployment insurance to foster business creation.

Finally, this paper also contributes to the literature that studies the effect of displacement on entrepreneurship. Hacamo and Kleiner [2021] leverage a large dataset containing the employment histories of college graduates in the United States to show that graduating in a distressed labour market increases the probability of starting a business after graduation and leads to forced entrepreneurship. Similarly, Babina [2019] combines US matched employer-employee data with public firms' financial information to show that financially distressed companies are more likely to experience an exodus of workers starting their own company and links it to former employees exploiting opportunities that were no longer possible with their previous employer. Galindo da Fonseca [2021] studies the Canadian labour market using matched employer-employee data and finds a positive effect of displacement, measured there as firm closures, on former employees' likelihood to start a business. Finally, Yuen [2021]

[7]The PARE, or *Plan d'aide au retour à l'emploi*, was introduced by the French government in 2001. It compensated unemployed workers who decide to start a business for the difference between UI and entrepreneurial earnings.

uses months 4 and 8 of the CPS (Outgoing Rotation Groups) and focuses on the impact of the job separation rate on entry during the Great Recession[8]. Compared to this literature that often focused on unemployed workers' entrepreneurial choice using micro-level studies, I look at wage workers, who represent most new entrepreneurs, and quantify the aggregate implications of unemployment risk on self-employment entry. I find that while separation-induced entry exists in theory, it matters quantitatively less to the fall in hiring and the job finding rate, which lowers the value of being unemployed and increases the risk of engaging in business creation.

Section 1.2 motivates the theoretical analysis, describes the data and presents the decomposition of entry into self-employment by previous labour market status. Section 1.3 details the model used for the quantitative analysis and presents a comparative statics exercise that highlights the role of unemployment risk on a wage worker's entrepreneurial choice. Section 1.4 quantifies the model and presents the main quantitative results. Section 1.5 presents further evidence at the industry-level. Section 1.6 concludes.

1.2 Data

1.2.1 Data and definitions

The main data source for my analysis comes from the monthly files of the US Current Population Survey (CPS) between 1994[9] and 2021, harmonized by IPUMS.

[8]However, his ORG subsample depicts a different picture than the entire CPS data, and my framework also allows for endogenous exit and on-the-job search, which are important determinants of self-employment dynamics. Dillon and Stanton [2017] show that overlooking the option to return to paid jobs would understate the value of being self-employed, and Hall and Krueger [2012] document that almost half of new hires come from other firms, two elements absent from his analysis.

[9]I start the analysis in 1994 because of the CPS survey redesign that year. See Appendix 1.A.3 for details.

I define a self-employed business owner as an employed individual who considers herself self-employed in her main job and works more than 20 hours per week[10]. I focus on civilian households and exclude individuals working in agricultural/extracting occupations and sectors and those outside the labour force, younger than 25 years old or older than 64 years old. I describe in Appendix 1.A.4 the construction of industry and occupation classifications.

The second data source comes from the Annual Social and Economic Supplement of the CPS (ASEC), the "March Supplement", used to obtain information on workers' past wage or business income, expressed in constant 1999 US dollars. I also leverage ASEC data in section 1.5 and exploit the fact that industries are exposed to different shocks every year, affecting labour market prospects for workers in that sector.

1.2.2 Transitions along the business cycle

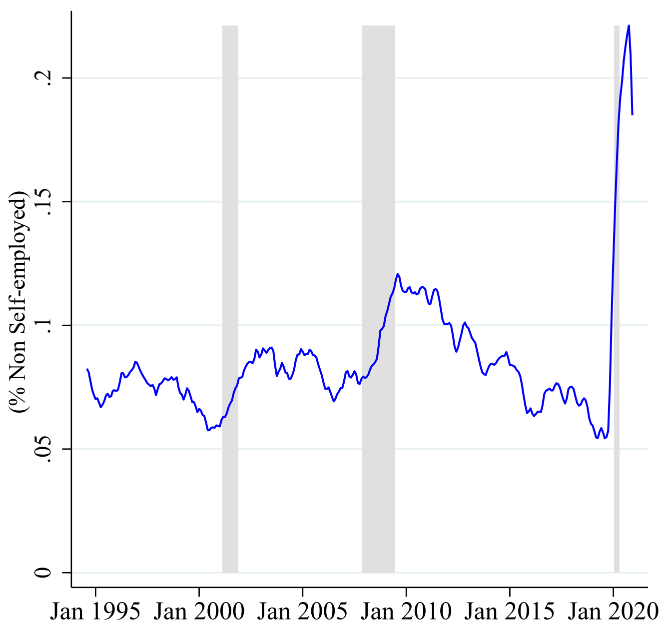
Using monthly CPS data, this section exploits time series variation along the business cycle to see whether higher unemployment risk is associated with lower entry. Distinguishing between entry to self-employment by previous labour market status (Fairlie and Fossen [2019]) is useful because it can be informative about the objective of the business venture and the motivations behind the transition to self-employment. Figure 1.1 uses the basic monthly files of the CPS to show that entry from unemployment unexpectedly increases during recessions. It went up by more than 50 % during the Great Recession and only dropped down to its pre-recession level in 2014.

Conversely, figure 1.2 shows that entry from paid work went down during the last two recessions[11], by 20% during the Great Recession and the COVID-19 recession. Exit barely increased during the Great Recession, while it slightly fell during the

[10] I focus on those who choose to commit to their business and thus only consider self-employed working more than 50% of full-time hours and exclude involuntary part-time workers.

[11] The 2001 recession had a short-lived impact on unemployment.

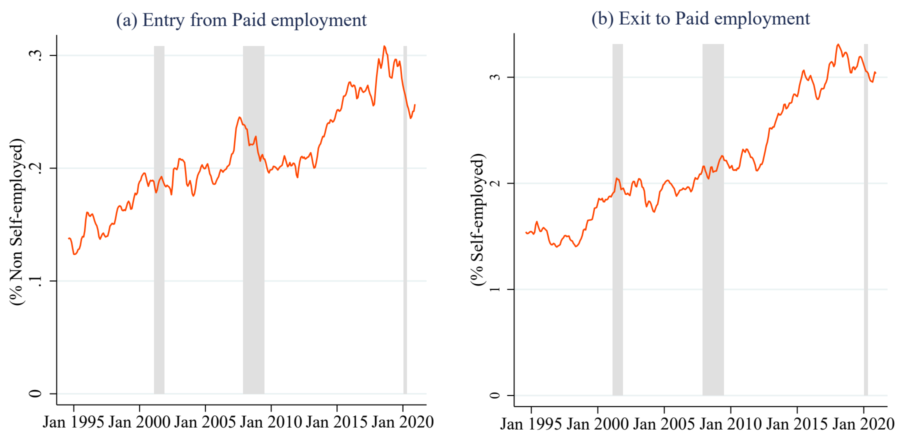
Figure 1.1: Entry from unemployment to self-employment: 1994-2020



12-month centered MA to remove seasonality. Entrant at time t: Self-employed individual who was a paid worker or unemployed in the previous month $(t-1)$. Exit at t: Self-employed individual who was previously self-employed. The sample of 25-64 year-olds excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. See Appendix 1.A.2 for additional measurement details. Source: CPS Basic Monthly Files.

COVID-19 recession. To rationalise this, I propose a theory explaining how higher unemployment risk deters employed workers from engaging in an entrepreneurial activity because of the risk associated with business creation.

Figure 1.2: Transitions between self-employment and paid work: 1994-2020



12-month centered MA to remove seasonality. Entrant at time t: Self-employed individual who was a paid worker or unemployed in the previous month $(t-1)$. Exit at t: Self-employed individual who was previously self-employed. The sample of 25-64 year-olds excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. See Appendix 1.A.2 for additional measurement details. Source: CPS Basic Monthly Files.

1.3 Theory

This section introduces a simple partial equilibrium search model with self-employment and builds on frameworks introduced by Bradley [2016][12], and Engbom [2019], which I extend to allow for risky transitions to entrepreneurship and exit from self-employment to paid work.

1.3.1 Model

Setup. Time is continuous and infinite, and workers discount the future at the rate r. Firms' decisions are not explicitly modelled, and I assume that workers receive job offers from an exogenous distribution $\mathcal{F}$ and business ideas/opportunities from an exogenous distribution $\mathcal{H}$.

I do so for two reasons: First, an exogenous wage distribution is useful to model wage heterogeneity without entering the debate about the sources of wage determination[13]. Second, I focus on workers' transitions into/out of self-employment. Introducing firms leads to complications that are unrelated to the focus of this paper[14].

Workers. There is a unit mass of ex-ante homogeneous workers, who are, at any point in time, either unemployed, self-employed or working for a firm (paid-employed).

Unemployed workers receive a flow payment of b that comprises unemployment

[12] Bradley [2016] extends the canonical wage posting model with a job ladder (Burdett and Mortensen [1998]) by introducing a decision to become a self-employed business owner.

[13] Hall and Krueger [2012] find that wage posting and bargaining co-exist as important modes of wage determination, with the former being more prevalent at lower levels of education and among women and ethnic minorities.

[14] Coles and Mortensen [2016] extend the seminal work of Burdett and Mortensen [1998] to analyse out of steady-state dynamics with an endogenous costly hiring decision but require knife-edge conditions on hiring costs to guarantee equilibrium existence.

benefits, the value of leisure/home production, and the disutility from being unemployed. They receive job offers at the rate λ_{uw} as well as business ideas at the rate λ_s.

The *Hamilton-Jacobi-Bellman* (HJB) equation for the value of being unemployed, U writes as:

$$rU = b + \lambda_{uw} \int \max\left[W(w) - U, 0\right] d\mathcal{F}(w) + \lambda_s \int \max\left[V(z') - U, 0\right] d\mathcal{H}(z') \quad (1.1)$$

$W(w)$ accounts for the value of being a salaried worker with wage $w \in [\underline{w}, \overline{w}]$, while $V(z)$ represents the expected value of being a self-employed business owner with idea $z \in [\underline{z}, \overline{z}]$.

When salaried at a firm paying a flow wage w, a paid worker receives other job opportunities at the rate λ_{ww} as well as business ideas at the same rate as unemployed workers, λ_s. She can also lose her job at the rate δ_w and subsequently become unemployed.

The HJB equation for a paid worker in a firm paying w writes as:

$$\begin{aligned} rW(w) = & w + \lambda_s \int \max\left[V(z') - W(w), 0\right] d\mathcal{H}(z') + \delta_w \left[U - W(w)\right] \\ & + \lambda_{ww} \int \max\left[W(w') - W(w), 0\right] d\mathcal{F}(w') \end{aligned} \quad (1.2)$$

Risky self-employment. Less than half of individuals in the process of starting a business achieve operation. Thus, I choose choose to model the decision to become a self-employed business owner as a risky one. Paid and unemployed workers decide to pursue a business idea z whenever they are made better off compared to their current employment status. Conditional on pursuing this idea, they will be successful with probability p and become self-employed. With a probability of $1-p$, they will fail and go into unemployment. Therefore, the expected value of being self-employed writes:

$$V(z) = pS_e(z) + (1-p)U \tag{1.3}$$

A self-employed worker receives the flow profits z of her business idea. She can also go bankrupt at the rate δ_{se} and become unemployed, and receives paid work opportunities at the rate λ_{sw}. Thus, the HJB for a self-employed worker with an idea z writes:

$$rS_e(z) = z + \delta_{se}[U - S_e(z)] + \lambda_{sw} \int \max[W(w') - S_e(z), 0]\, d\mathcal{F}(w') \tag{1.4}$$

Endogenous thresholds characterise entry into self-employment and exit back into paid work. I assume for simplicity and without loss of generality that parameter values are such that an unemployed worker will always pursue a new business opportunity that allows her to become self-employed, i.e. $z_u^* \leq \underline{z}$. A paid employee with wage w decides to go into self-employment whenever she receives an idea better than $z^*(w)$. This cutoff equates the expected surplus from being a paid worker to the expected surplus of being self-employed. That is, $z^*(w)$ solves:

$$C_1(z^*(w)) = pS_e(z^*(w)) + (1-p)U - W(w) = p[S_e(z^*(w)) - U] - [W(w) - U] = 0 \tag{1.5}$$

An increase in the probability of a successful business venture will facilitate entry into self-employment. Similarly, the model predicts, consistent with empirical evidence, that salaried workers with higher wages are less likely to transition into self-employment.

A self-employed business owner with an idea worth z will take a salaried job whenever the wage offer is above the cutoff $\tilde{w}(z)$, which satisfies:

$$C_2(\tilde{w}(z)) = W(\tilde{w}(z)) - S_e(z) = 0 \tag{1.6}$$

More successful self-employed businesses are less likely to leave for paid work. These exit cutoffs $z^*(w)$ and $\tilde{w}(z)$ are important because they determine, for a given earnings level, the individual decision to enter and leave self-employment. I will use them below to determine how worker dynamics along the business cycle and unemployment risk affects aggregate entry and exit.

Laws of Motion. The distribution of workers over paid employment $g(w)$ is characterized by the following *Kolmogorov forward equation* (KFE):

$$\begin{aligned}\dot{g}(w)(1-u-s_e) = &-\left[\delta_w + \lambda_{ww}\bar{\mathcal{F}}(w) + \lambda_s\bar{\mathcal{H}}(z^*)\right](1-u-s_e)\,g(w) \\ &+f(w)\left[\lambda_{uw}u + \lambda_{ww}(1-u-s_e)\,\mathcal{G}(w) + \lambda_{sw}s_e\mathcal{S}\left(\tilde{z}^{-1}\right)\right]\end{aligned} \tag{1.7}$$

Paid workers with income w will leave their jobs because the match gets exogenously destroyed, they get a better salaried job offer, or they move to self-employment. Unemployed workers and paid employees with wage $w' < w$ who receive an offer w will accept that offer, as well as self-employed workers with an idea worth $\tilde{z}^{-1}$ [15] or less.

The distribution of agents over self-employment $s(z)$ is described by the following

[15] Self-employed with an idea worth $\tilde{z}^{-1}$ will leave whenever they receive a salaried offer worth $\tilde{w}\left(\tilde{z}^{-1}\right) = w$ or more.

KFE[16] and writes :

$$\dot{s}(z)\, s_e = -s_e \left[\delta_{se} + \lambda_{sw} \bar{\mathcal{F}}(\tilde{w})\right] s(z) + p\lambda_s h_s(z) \left[u + (1-u-s_e)\,\mathcal{G}\left(w^{*-1}\right)\right] \quad (1.8)$$

Self-employed business owners quit because their businesses are no longer profitable (exogenous destruction) or because they receive a sufficiently attractive salaried offer. Entrants into self-employment are the unemployed, who take on any opportunity they receive, as well as salaried workers with a wage below w^{*-1} [17]. Using these two equations, I can solve for the evolution of unemployment u as:

$$\dot{u} = -u\left(\lambda_{uw} + p\lambda_s\right) + (1-u-s_e)\,\delta_w + \delta_{se} s_e + \lambda_s (1-u-s_e)(1-p) \int \left[1 - \mathcal{H}\left(z^*(x)\right)\right] d\mathcal{G}(x) \quad (1.9)$$

The novelty here comes from the risk, with a probability of $1-p$, for a salaried worker to fail her transition to self-employment and become inactive, in addition to exogenous match separations and business closures. People otherwise leave unemployment when they receive a job offer or a business opportunity.

Equilibrium. I assume throughout the analysis that parameter values are such that unemployed workers always accept to try a business idea, i.e. $z_u^* \leq \underline{z}$.

A *stationary equilibrium* in this economy is a set of value functions $\{U, W(w), S_e(z)\}$, workers' decision rules $\{z_u^*, \zeta, z^*(w), \tilde{w}(z)\}$, distributions of workers over paid employment and self-employment $\{g(w), s(z)\}$ as well as the self-employment rate s and the unemployment rate u such that :

[16] s_e denotes the self-employment rate.

[17] Salaried workers paid w^{*-1} will pursue an entrepreneurial idea whenever it is worth more than $z^*\left(w^{*-1}\right) = z$.

- The value function U is given by equation 1.1, every unemployed pursue self-employment $z_u^* \leq \underline{z}$ and the reservation wage ζ satisfies:

$$\zeta = b + (\lambda_{uw} - \lambda_{ww}) \int \max\left[W(w) - U, 0\right] d\mathcal{F}(w) \tag{1.10}$$

- The value function $W(w)$ is given by equation 1.2. $\forall w \in [\underline{w}, \overline{w}]$, salaried workers paid w will choose to enter self-employment whenever they receive an idea worth $z \geq z^*(w)$ where $z^*(w)$ is defined in equation 1.5.

- The value function $S_e(z)$ is given by equation 1.4. $\forall z \in [\underline{z}, \overline{z}]$, self-employed workers earning z will choose to leave self-employment whenever they receive a job offer $w \geq \tilde{w}(z)$ where $\tilde{w}(z)$ is defined in equation 1.6.

- The distributions of individuals over paid employment $g(w)$, self-employment $s(z)$ and unemployment u are respectively defined in equations 1.7 to 1.9 . Furthermore, $\forall w \in [\underline{w}, \overline{w}], \forall z \in [\underline{z}, \overline{z}]$ they satisfy $\dot{u} = \dot{g}(w) = \dot{s}(z) = 0$.

- The aggregate self-employment rate s_e satisfies:

$$0 = \dot{s}_e = p\lambda_s \left[u + (1 - u - s_e) \int \bar{\mathcal{H}}\left[z^*(w)\right] d\mathcal{G}(w)\right] - s_e \left[\delta_{se} + \lambda_{sw} \int \bar{\mathcal{F}}\left[\tilde{w}(z)\right] d\mathcal{S}(z)\right] \tag{1.11}$$

1.3.2 Comparative statics

This section investigates the role of unemployment risk for paid workers in the transition to self-employment through the lens of my model. I present here, for simplicity, results without on-the-job search and endogenous exit, that is when $\lambda_{ww} = \lambda_{sw} = 0$[18].

[18] I derive comparative statics of the full model in Appendix 1.B.2. Results are similar, and I present the simplest case for ease of exposition.

Unemployment risk can go up during recessions for two reasons:

First, unemployment risk increases because hiring falls during recessions, as firms post fewer vacancies. The job finding rate decreases, making it more difficult for unemployed workers to find a job. Intuitively, insofar as transitioning to self-employment is risky, a fall in the job finding rate, because it lowers the value of being unemployed, will deter salaried workers from pursuing entrepreneurial ideas. Second, unemployment risk can also increase because workers are more likely to be fired during downturns. Matches between firms and workers get destroyed. Any previously stable job is less secure, which intuitively brings down the value of being salaried and can thus increase self-employment. I decompose the rise of unemployment risk into two components: the fall in the job finding rate and the increase in the job separation rate.

The impact of a change in the job finding rate on the decision for a salaried worker with wage w to enter self-employment can be written as:

$$\frac{dz^*(w)}{d\lambda_{uw}} \propto \underbrace{\frac{-(1-p)\, rU'(\lambda_{uw})}{r+\delta_{se}}}_{\textbf{Unemployment Risk, } <0} + \overbrace{\frac{r(\delta_w-\delta_{se})\, U'(\lambda_{uw})}{(r+\delta_{se})(r+\delta_w)}}^{\textbf{Differential Separation, } \lesseqgtr 0} \lesseqgtr 0 \tag{1.12}$$

There are two different and potentially offsetting effects. The first term represents the *unemployment risk* effect. Starting up a business is risky, so an increase in the job finding rate will lower the entry cutoff. In booms, failing the transition matters less because a previously salaried worker who is now inactive will find a new job more easily, as $U'(\lambda_{uw}) > 0$. Similarly, downturns will make a worker less likely to leave her job because of the probability of failing and becoming unemployed, which is now more costly, and more so when p is low, as the change in z^* is proportional to the probability of failure $1-p$. The second effect is a *differential separation* effect that will depend on which employment status is relatively more shielded from unemployment. The intuition is the following: If self-employment shields workers less than salaried work, i.e. when $\delta_w < \delta_{se}$, an increase in the job finding rate λ_{uw} will make self-employment more desirable because unemployed workers now receive more, and potentially better, job offers. This strengthens the *unemployment risk* effect. Similarly, in recessions, as self-employment is seen *ceteris paribus* as less secure, a fall in the job finding rate will deter transitions to self-employment. The overall effect is theoretically ambiguous and will depend on the relative strength of each effect. That said, the two separation rates are close to each other, and I expect the *unemployment risk* effect to dominate and therefore lower entry in recessions, especially when $p << 1$.

The change to the entry cutoff following a change in the job separation rate writes as:

$$\frac{dz^*(w)}{d\delta_w} \propto \underbrace{\frac{-(1-p)\,rU'(\delta_w)}{r+\delta_{se}}}_{\textbf{Unemployment Risk, } >0} + \overbrace{\frac{r(\delta_w-\delta_{se})\,U'(\delta_w)}{(r+\delta_{se})(r+\delta_w)}}^{\textbf{Differential Separation, } \lesseqgtr 0} - \underbrace{\frac{W(w)-U}{r+\delta_w}}_{\textbf{Decreasing Surplus, } <0} \lesseqgtr 0 \tag{1.13}$$

I can decompose the impact of an increase in the job separation rate into three components. First, there is also an *unemployment risk* effect: As the job separation rate δ_w increases, it lowers the value of being unemployed because any future job will now be shorter-lived, $U'(\delta_w) < 0$. This raises the entry cutoff. The *differential separation effect* is also present. If $\delta_w < \delta_{se}$, it will deter entry as self-employment is seen as relatively less safe when job separations go up. Finally, there is a third effect, absent in the job finding rate's comparative statics, which I call a *surplus effect*: An increase in δ_w will lower the value of being salaried by more than it reduces the value of being unemployed. The intuition is clear: A higher likelihood of being fired affects a paid worker directly, while the effect for unemployed workers only appears through shorter-lived employment spells. So, this effect will facilitate entry into self-employment as it lowers the surplus of being salaried over being unemployed. Abstracting from the differential separation effect as δ_w and δ_{se} are close to each other, the effect of a higher separation rate on the entry cutoff $z^*(w)$ is ambiguous and depends on the relative strengths of the *surplus* and *unemployment risk* effects.

Table 1.1 below summarises the comparative statics results and stresses the importance of business/career risk. When $p \longrightarrow 1$ and assuming $\delta_w = \delta_{se}$, leaving her current job does not affect a salaried worker as she will always succeed in business creation. In this case, the job finding rate does not affect entry. In addition, the probability of failure will dampen the impact of firing and separations because it also lowers the value of being unemployed. It remains a quantitative question to measure the effect of a change in these two rates on transitions to self-employment, which is my next exercise.

Table 1.1: Model-predicted impact on the entry cutoff $z^*(w)$

	Fall in λ_{uw}	**Rise in δ_w**
Impact on entry cutoff : $z^*(w)$		
Total effect	?	?
No Business risk ($p = 1$)	$\text{sign}(\delta_s - \delta_w)$	?
$\delta_w = \delta_s = \delta$	+	?
No Business risk ($p = 1$) and $\delta_w = \delta_s = \delta$	0	-

1.4 Quantitative analysis

This section quantifies the model by Generalised Method of Moments. It presents a transition dynamics exercise highlighting the importance of the job finding rate for entry into self-employment and the business shutdown rate for the aggregate self-employment rate.

1.4.1 Calibration and model fit

I calibrate the model to fit the US economy in 2007, before the Great Recession. The frequency of the model is monthly, and the discount factor r is calibrated to match an annual interest rate of 5 %. The self-employed separation rate or business shutdown rate δ_{se} is chosen to match monthly transitions between self-employment and unemployment. All the other parameters are jointly determined using moments from the CPS monthly files.

As my model is agnostic about the source of wage determination in the economy, I parametrise the distribution of wage offers and business opportunities to be Log-Normal:

$$\mathcal{F} \sim \text{Log-}\mathcal{N}\left(\mu_f, \sigma_f\right) \quad \mathcal{H} \sim \text{Log-}\mathcal{N}\left(\mu_h, \sigma_h\right) \tag{1.14}$$

There are, in total, 11 parameters to be jointly determined:

$$\theta = \{\lambda_{uw}, \lambda_{ww}, \lambda_{sw}, \delta_w, p, \lambda_s, \mu_f, \sigma_f, \mu_h, \sigma_h, b\} \tag{1.15}$$

Twelve empirical moments are used to calibrate these parameters. The log-normal distribution parameters for wage offers and business ideas are informed by the earnings median and standard deviation for salaried and self-employed individuals. Estimation of λ_{ww} will be determined by the paid job to paid job transition rate, while λ_{sw} will be closely related to the endogenous exit rate from self-employment to salaried work. Monthly transitions from paid work to unemployment and the unemployment rate are informed by δ_w and p, the probability of a successful entry. λ_s, the arrival rate of ideas, informs the self-employment rate and transitions into self-employment (from unemployment and paid work). Finally, the job finding rate λ_{uw} is chosen to match monthly transitions between unemployment and paid work. All the moments related to labour market transitions and employment statuses are constructed using monthly CPS data, while the median and standard deviation of earnings come from ASEC data.

I choose θ to minimise the following GMM objective, where squared percentage deviation between empirical moments and their theoretical counterparts are equally weighted:

$$\mathcal{Y} = \min \sum_{i=1}^{12} \left(\frac{\text{model}_i \left(\boldsymbol{\theta} \right) - \text{data}_i}{\text{data}_i} \right)^2 \tag{1.16}$$

Table 1.2 shows that the model can fit the data well. In most cases, percentage deviations between empirical moments and their theoretical counterparts are less than 10%. The model also works well for untargeted moments, such as average earnings by employment category. For instance, salaried workers earn roughly 37000 \$, and the model predicts 39000 \$. Similarly, the model predicts average self-employed earnings of 46000 \$, compared to slightly less than 45000 \$ in the data.

Table 1.2: Model fit - Pre-recession steady-state

	Parameter θ^*	Value	Target	Data	Model
	Worker Dynamics				
λ_{uw}	Job Finding Rate : Unemployed	0.2761	UE Rate	0.2865	0.2413
λ_{ww}	Job Offer Rate: Salaried	0.3154	Job-to-job Transitions : EE Rate	0.0154	0.0161
δ_w	Job Separation Rate	0.0069	EU Rate	0.0094	0.0101
	Self-employment Dynamics				
λ_s	Ideas Arrival Rate	0.0519	Entry from Unemployment	0.0232	0.0225
p	Probability Successful Idea	0.4382	Entry from Paid Work	0.0025	0.0026
λ_{sw}	Job Offer Rate: Self-employed	0.5575	Exit to Paid Work	0.0209	0.0211
			Self-employment rate	0.1026	0.1023
	Earnings				
b	Flow value of Unemployment	0.0880*	Unemployment rate	0.0358	0.0320
μ_f	Parameter : Offer Distribution $\sim \mathcal{F}$	-0.2430	Median Wages	28944	30358
σ_f	Parameter : Offer Distribution $\sim \mathcal{F}$	1.1433	Std. of Wages	34170	32621
μ_h	Parameter : Business Idea Distribution $\sim \mathcal{H}$	-0.3562	Median Self-employed income	28140	27506
σ_h	Parameter : Business Idea Distribution $\sim \mathcal{H}$	1.4793	Std. Of Self-employed income	54205	55451
	Externally Calibrated				
r	Interest rate	0.0040	Annual Interest Rate of 5%		
δ_s	Business Separation Rate	0.0074	Self-employment to Unemployment Rate (CPS)		

* b as a percentage of average earnings, i.e. $\frac{b}{\mathbf{E}_G(w)}$. Earnings in constant 1999 US Dollars. The sample of 25-64 y.o excludes members of the armed forces . and individuals working in agricultural/mining occupations and industries. Source: CPS ASEC for 2007. Moments: Monthly averages for H2 2007. Source: CPS Basic Monthly files.

1.4.2 Results - Transition dynamics of entry and exit

I now turn to study the quantitative importance of rising unemployment risk during the Great Recession on self-employment dynamics. I will proceed in two steps: I first look at the role of increasing unemployment risk for workers and then investigate the importance of rising unemployment risk for the self-employed.

To analyse the impact of unemployment risk for paid workers on aggregate self-employment dynamics, I first decompose it into two components: the fall in the job finding rate and the increase in the job separation rate. I will follow Engbom [2021] and solve a perfect foresight transition experiment, where changes in the job finding rate λ_{uw} and the job separation rate δ_w mimic the evolution of the UE and EU rates, starting from the 2007, pre-Great Recession steady state until December 2011. The UE and EU rates represent the job finding and separation probabilities: The fraction of unemployed (salaried) workers in the previous month who found paid work (became unemployed)[19].

I then perform the transition dynamics exercise, looking at the rising unemployment risk for entrepreneurs. Business exits also went up during the Great Recession. The SU rate, the fraction of self-employed workers who go into unemployment, increased during that period[20]. I also solve a perfect foresight transition experiment where changes in δ_{se} mimic the evolution of the SU rate from December 2007 to December 2011[21].

[19] This definition is slightly different from the standard UE rate that commonly includes transitions between unemployment and self-employment. A similar comment applies to the EU rate. I describe how I compute a path for $\lambda_{uw,t}$ and $\delta_{w,t}$ in Appendix 1.C.2

[20] See Appendix 1.A.1.

[21] I also describe how I compute a path for $\delta_{se,t}$ in Appendix 1.C.2.

1.4.2.1 The Great Recession - A decomposition of rising unemployment risk

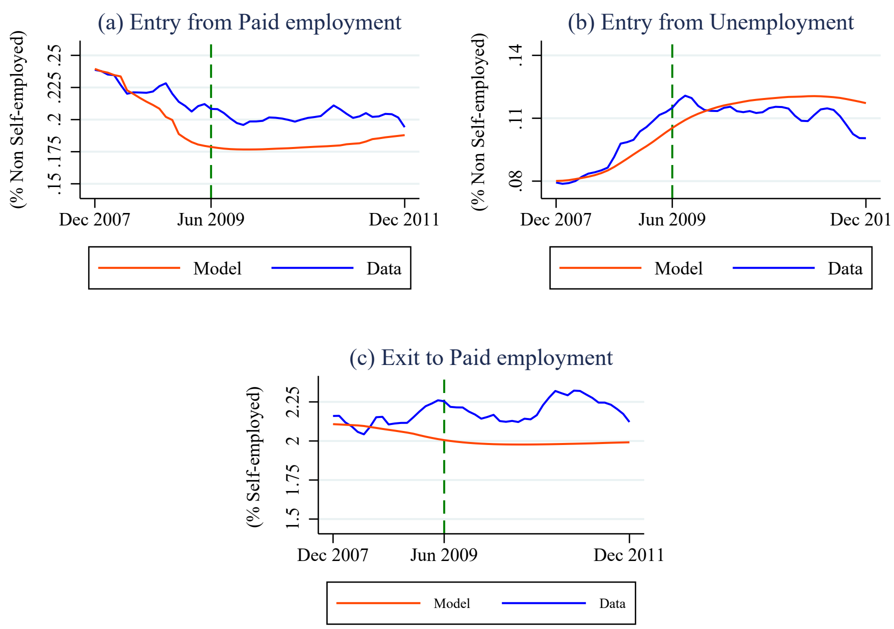
The Great Recession was characterised by a large and persistent fall in the fraction of unemployed workers finding a paid job the next month (the job finding probability), which went down by 40 % and took a decade to recover. While the job separation probability started to decline immediately after the end of the recession, the job finding probability only started to rise again in 2012 to reach its pre-recession level in 2018[22]. When looking at figures 1.3 to 1.7, it is important to note that agents expect, from the beginning of the recession, that the job finding and separation rates will follow the paths for $\lambda_{uw,t}$, $\delta_{w,t}$ and $\delta_{se,t}$ so that their starting point is not necessarily exactly at (but close to) the pre-recession steady-state.

Job finding rate λ_{uw}. I show in figure 1.3 the impact of the fall in λ_{uw}, all else equal. Entry from paid work goes down by 25% in the model, slightly higher than the observed 20 % fall during the Great Recession. Moreover, the entry pattern in the model closely resembles what is observed in the data. Entry from unemployment also goes up, as in the data. However, the model also predicts a 6% decline in the exit rate, inconsistent with the data that shows a slight upward trend.

Job separation rate δ_w. I perform the same exercise for the increase in the separation rate δ_w during and after the Great Recession. In contrast with the fall in the job finding rate, figure 1.4 shows that an increase in the job separation rate will lead to an increase in entry from salaried work by 7%, inconsistent with the empirical evidence during that period. Entry from unemployment also goes up, as in the data.

[22] See Appendix 1.A.1.

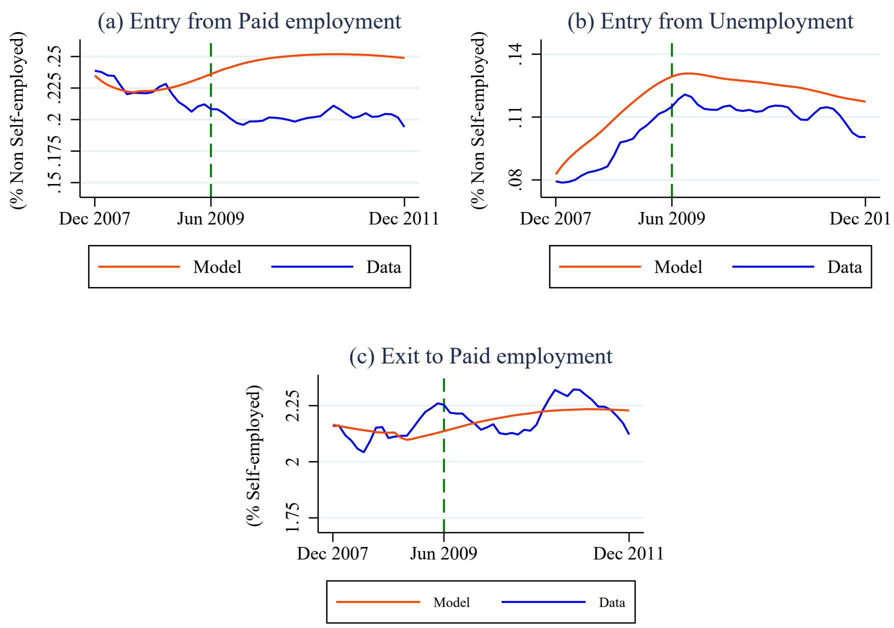
Figure 1.3: Transition dynamics of a fall in λ_{uw}



Appendix 1.C.2 explains how I construct the path for $\lambda_{uw,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

Exit increases slightly, as in the data that shows a slight upward trend.

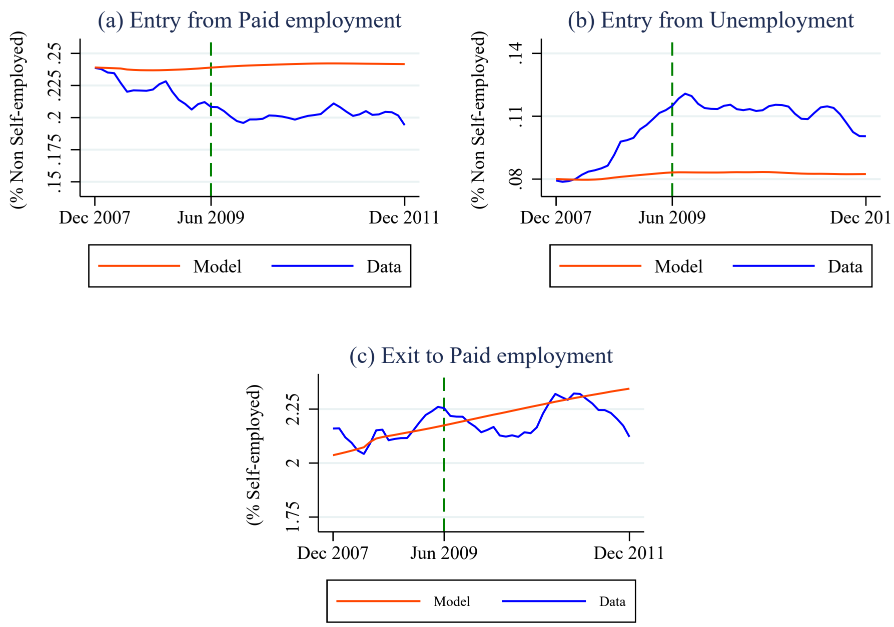
Figure 1.4: Transition dynamics of a rise in δ_w



Appendix 1.C.2 explains how I construct the path for $\delta_{w,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

Business shutdown rate δ_{se}. I finally look at the role of a higher separation rate for the self-employed because it lowers the relative value of being an entrepreneur relative to being a paid worker and can thus deter entry. However, figure 1.5 shows that in contrast with the job finding rate λ_{uw}, a higher separation rate for the self-employed has essentially no impact on entry from paid work or entry from unemployment. Higher separations to unemployment δ_{se} nonetheless lead to a 15% increase in exit from self-employment to paid work, consistent with (but larger than) the data, unlike dynamics induced by λ_{uw} that predicted a fall in exit to salaried work.

Figure 1.5: Transition dynamics of a rise in δ_{se}



Appendix 1.C.2 explains how I construct the paths for $\delta_{se,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

1.4.2.2 The overall impact of unemployment risk

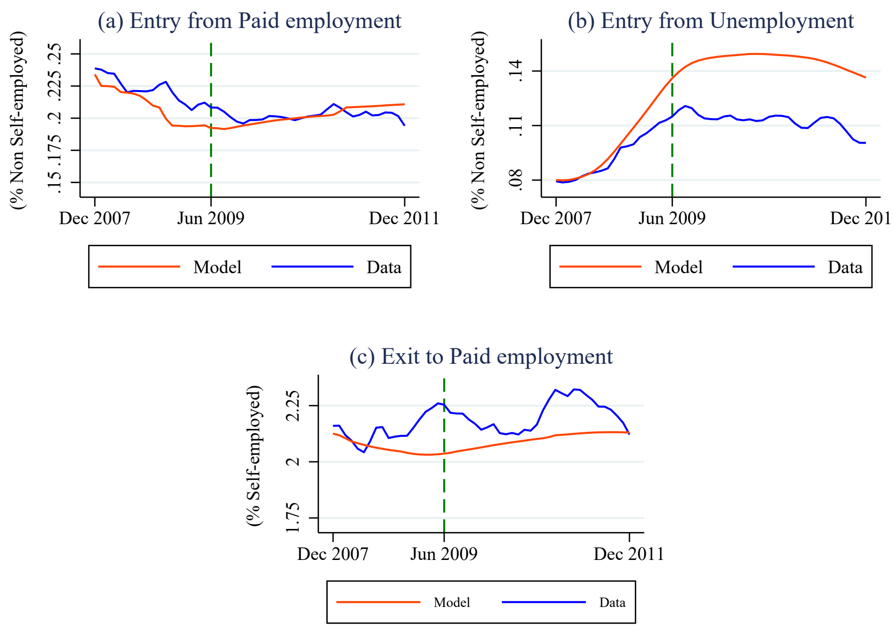
Overall, the three exercises above confirm the importance of the job finding rate in explaining entry to self-employment, especially compared to the separation rates δ_w and δ_{se}. These findings give more credence to my hypothesis relative to the displacement hypothesis. The risky business creation hypothesis and career risk deter salaried workers from starting an entrepreneurial activity in distressed times. On the other hand, a higher self-employment separation rate δ_{se} matters more for transitions back to paid work. I consider two additional exercises to evaluate the relative importance of each of these forces. First, I will look at the role of unemployment risk for workers and abstract from rising unemployment risk for entrepreneurs by studying the transition dynamics of a joint fall in the job finding rate λ_{uw} and a rise in the job separation δ_w. I do so to compare the importance of the job finding rate λ_{uw} with the job separation rate δ_w. I then look at the overall impact of higher unemployment risk for workers and entrepreneurs on entry and exit by looking at the joint changes in λ_{uw}, δ_w and δ_{se} together[23].

Joint fall in λ_{uw} and rise in δ_w. I look at the transition dynamics of a fall in λ_{uw} and a rise in δ_w together, to evaluate the importance of rising unemployment risk on the worker side. Figure 1.6 shows that the fall of the job finding rate remains the driving force of entry from salaried work, which is predicted to fall by 20%, as in the first exercise in figure 1.3 and the data. Moreover, the entry pattern in the model co-moves relatively well with the data. Entry from unemployment also increases, this time by 80 %, a greater rise (but in line with) than observed in the data. However,

[23] In Appendix 1.D.3.1, I provide additional evidence on the importance of a lower job finding rate on entry to self-employment, and of a higher business shutdown rate on exit, by looking at transition dynamics induced by: A joint change in δ_w and δ_{se} and a joint change in λ_{uw} and δ_{se}.

exit is also predicted to go down, while the data shows a slightly increasing trend.

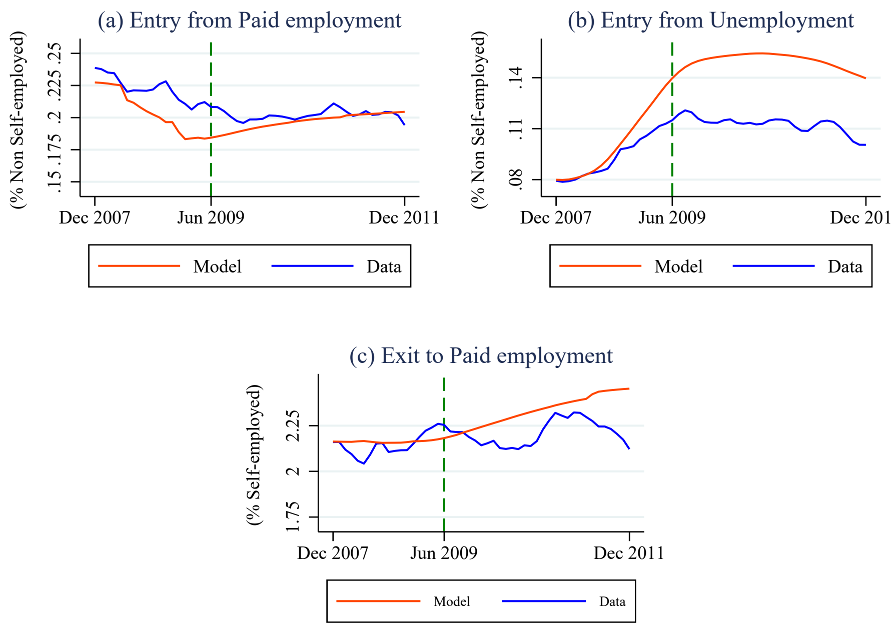
Figure 1.6: Transition dynamics of a joint fall in λ_{uw} and rise in δ_w



Appendix 1.C.2 explains how I construct the paths for $\lambda_{uw,t}$ and $\delta_{w,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

Joint fall in λ_{uw} and rise in δ_w and δ_{se}. I finally look in figure 1.7 at the overall impact of rising unemployment risk for paid workers and entrepreneurs. The difference with the previous exercise is that I consider the increase in self-employment separations (business shutdowns). The transition exercise confirms that the fall in the job finding rate remains the main driver of entry from paid work, which falls by 20% as in figure 1.6. Nevertheless, comparing figure 1.7 (c) to figure 1.6 (c) shows that rising separations to unemployment δ_{se} should be taken into account to better explain exits to paid-work and generate an increasing exit pattern that is closer to the data during the recession and until 2010.

Figure 1.7: Transition dynamics of a fall in λ_{uw} and a rise in δ_w and δ_{se}



Appendix 1.C.2 explains how I construct the paths for $\lambda_{uw,t}$, $\delta_{w,t}$ $\delta_{se,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

To summarise, there are two takeaways from these additional exercises. First, the changing dynamics of entry to self-employment from paid work and unemployment are driven by what happened to the workers' side and especially the fact that it is now harder to find a job when unemployed. It deters entry from salaried workers because starting an entrepreneurial spell is risky. The risk of displacement is quantitatively less important for paid workers. Second, considering what has happened to the self-employed[24] and the fact that business exits have gone up during the recession can help better explain why more entrepreneurs decided to leave self-employment in favour of paid work during the downturn.

The results of this section come with a caveat: The individual's decision to try self-employment will depend on the job-finding rate at the arrival of the idea. The introduction of a probability of success that depends on the time spent developing a business idea would be a promising extension that will allow for a richer analysis by making the individual's decision-making depend on the job-finding and separation rates at the end of the trial period.

Moreover, the quantitative analysis above focused on the impact of shocks to the opportunity cost of wage work on entry and exit in and out of self-employment. Another alternative approach could extend the model to introduce aggregate productivity or demand shocks. While these shocks could also lead to a rise in unemployment, their impact on transitions between salaried work and self-employment is likely to depend on the relative effect of a fall in demand or productivity during recessions on self-employed businesses versus larger firms (and the value of wage work in those firms).

[24]I provide additional reduced form evidence in Appendix 1.D.1 and show that earnings for the self-employed have gone down by more than for paid workers.

1.4.3 Unemployment risk and the self-employment rate

After studying the role of higher unemployment risk on the flows of entry and exit, I look at its impact on the aggregate stock of self-employed. I show in figure 1.8 the evolution of the self-employment rate induced by: A fall in the job finding rate λ_{uw}, a rise in the job separation rate for workers δ_w, a rise in separations for the self-employed δ_{se} as well as the evolution induced by the joint change in these three parameters, and I compare it with the 16% fall observed between 2007 and 2011.

Figure 1.8 (a) shows that the fall in the job finding rate λ_{uw} can explain part of the decline in the number of self-employed. However, it is mainly the rise in δ_{se}, the rate at which the self-employed go into unemployment, that drives the fall of the self-employment rate, as can be seen in figure 1.8 (c) and (d). This happens because lower entry from paid work has been offset by higher entry from unemployment during the downturn.

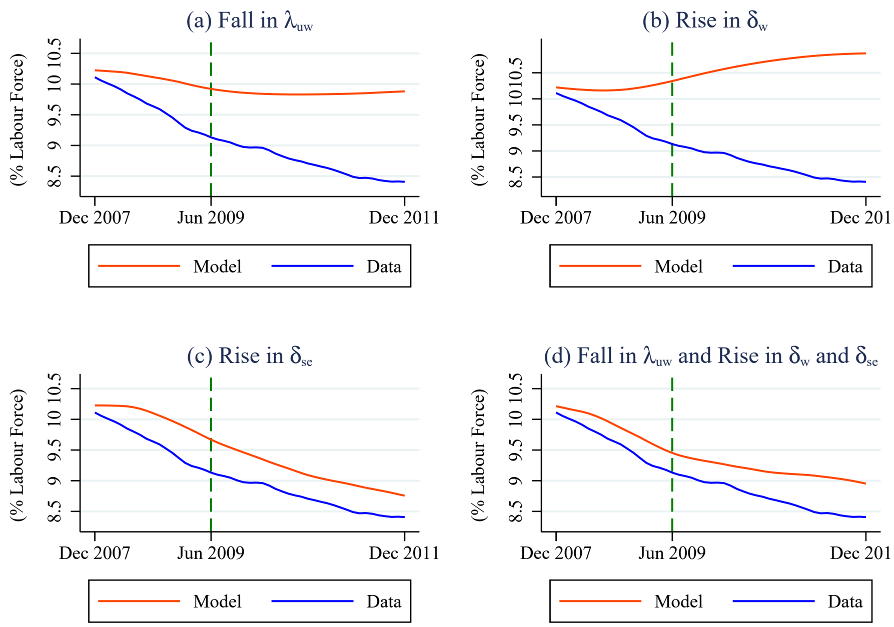
Overall, higher aggregate unemployment risk can explain well the decline of entrepreneurial activity during that period. Figure 1.8 (d) shows the model-implied evolution of the self-employment rate resulting from higher unemployment: It falls by slightly more than 12% in the model between 2007 and 2011 and closely tracks the evolution observed in the data, explaining 75% of the decline[25].

1.4.3.1 Opportunity entrepreneurs and necessity self-employed

I now use the model to decompose the decline of the entrepreneurship rate and predict the evolution of opportunistic entrepreneurs (entrepreneurs who started from paid work) and necessity self-employed (who started from unemployment) during and after

[25] See Appendix 1.D.3.2 for further evidence on the importance of δ_{se} and λ_{uw} on the self-employment rate.

Figure 1.8: Self-employment rate: Model vs data



Appendix 1.C.2 explains how I construct the paths for $\lambda_{uw,t}$, $\delta_{w,t}$ and $\delta_{se,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

the Great Recession. While I do not observe the evolution of the stock of each type of self-employed in the CPS (primarily because an individual can be self-employed during the first interview without any information about her prior employment status), the theory allows me to discipline data on flows between employment statuses to track the evolution of entrepreneurs by type[26].

That is, I use the transition dynamics exercise and study the impact of higher aggregate unemployment risk on the evolution of the number of opportunistic entrepreneurs and necessity self-employed between the pre-recession steady-state in 2007 and the end of 2011.

Figure 1.9 shows that higher unemployment risk leads to a 23% decline in the stock of opportunistic entrepreneurs and a 47% increase in the stock of necessity self-employed. In addition to the fall in the number of entrepreneurs, the quality of the entrepreneurial pool has also worsened.

A closer look at the evolution of the stock of entrepreneurs by type predicted by my model reveals the importance of a lower job finding rate in worsening the average quality of entrepreneurs. I separate in table 1.3 the three sources of unemployment risk and show the model-induced evolution of the stock of opportunistic entrepreneurs and necessity self-employed induced by the fall in the job finding rate λ_{uw}, the rise in the job separation rate δ_w and the rise in the separation rate for entrepreneurs (business exits) δ_{se}.

This decomposition shows that while both the self-employed separation rate δ_{se} and the job finding rate λ_{uw} play an important role in the decline of opportunistic entrepreneurship in the aftermath of the crisis (-16 % and -10 % respectively), it is the fall in hiring through a lower λ_{uw} which drives the decline in entrepreneurial

[26]Model derivations with two entrepreneurial types are presented in Appendix 1.D.2.

Figure 1.9: Evolution of entrepreneurship by type

This figure displays the evolution of each type of self-employed induced by a joint fall in the job finding rate λ_{uw} and a rise in the separation rates δ_w and δ_{se} for paid workers and the self-employed. Appendix 1.C.2 explains how I construct the paths for $\lambda_{uw,t}$, $\delta_{w,t}$ and $\delta_{se,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

Table 1.3: Model-implied evolution of entrepreneurship by previous labour market status

	Pre Recession - 2007	Post Recession - 2011	% Change
Self-employment rate (%) - Data			
Overall	10.11	8.41	**-16.85**
Self-employment rate (%) - Model			
Overall	10.21	8.95	**-12.35**
λ_{uw} *only*	10.22	9.88	-3.35
δ_w *only*	10.22	10.87	6.38
δ_s *only*	10.23	8.76	-14.38
Opportunistic Entrepreneurs (%) - Model			
Overall	8.65	6.65	**-23.11**
λ_{uw} *only*	8.66	7.78	-10.11
δ_w *only*	8.65	8.69	0.47
δ_s *only*	8.66	7.26	-16.17
Necessity Self-employed (%) - Model			
Overall	1.57	2.3	**47.02**
λ_{uw} *only*	1.57	2.1	33.92
δ_w *only*	1.57	2.18	39.01
δ_s *only*	1.57	1.5	-4.48

"λ_{uw} only": Evolution implied by the fall in the job finding rate λ_{uw}, all other parameters kept constant. Similar comments apply to "δ_w only" and "δ_{se} only" tables. Appendix 1.C.2 explains how I construct the paths for $\lambda_{uw,t}$, $\delta_{w,t}$ and $\delta_{se,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. **Pre Recession - 2007**: December 2007, the beginning of my transition dynamics exercise. **Post Recession - 2011**: December 2011, the end of my transition dynamics exercise.

quality. Higher business exits drive both opportunistic and necessity entrepreneurs to unemployment and discourage entry from unemployment, while longer job spells encourage it and deter entry from paid work.

The model predicts that higher unemployment risk during the Great Recession led to a 12.2% fall in the percentage of self-employed coming from paid employment, from 84.7 % (8.65/10.21) to 71.4 % (6.65/8.95). The fall of the job finding rate alone led to a 7.1%[27] fall in the percentage of self-employed coming from salaried work, more than half the overall decline implied by my model.

These findings could also help explain why the US economy suffered from a slow recovery after the financial crisis, because opportunistic entrepreneurs are more likely to contribute to productivity growth than the necessity self-employed. The compositional change would lead to a decline in aggregate productivity. Recent literature stressed the long-term implications of lower firm entry in recessions (Moreira [2016], and Sedláček and Sterk [2017]) on output and employment growth. In line with this work, I find that the decline in the number of entrepreneurs is disproportionately driven by the fall in the number of opportunistic entrepreneurs.

[27] From 84.7 % (8.66/10.22) to 78.7 % (7.78/9.88).

1.5 Further evidence at the industry-level

My quantitative analysis highlighted how higher aggregate unemployment risk deterred entry from paid work and led to a small increase in exit back to paid employment. This section exploits yearly variation in local unemployment rates across industries to see whether higher future unemployment in the sector a paid employee is working in has an impact on her decision to enter self-employment. I hypothesise that a worker who expects unemployment to be higher in the future in her sector is less likely to leave her job to try self-employment, as she will no longer easily find a new job if the entrepreneurial idea is unsuccessful.

I estimate the relationship between unemployment risk and transitions into/out of self-employment using the following specification:

$$P_{iojst} = \beta_u \Delta u_{js,t} + \Gamma X_{it} + \tau_s + \tau_t + \tau_o + \tau_j + \epsilon_{iojst} \tag{1.17}$$

P_{iojst} is an indicator equal to 1 if the individual has made a transition between time $t-1$ and time t. The sample for entry comprises individuals who are paid workers at time $t-1$, while only individuals who are self-employed at time $t-1$ are included in the exit sample. Unemployment is measured at the 2-digit industry level in each state. Controls X_i include a quadratic in age, marital status, race and earnings in the individual's previous occupation[28].

I also control for the worker's past education status[29] and add a different time trend for each education group, in line with the literature on the skill-biased en-

[28]Earnings at $t-1$ are added because of their importance in determining transitions into/out of self-employment. It is standard for search or occupational choice models where paid workers are presented with an outside option to feature less mobility at the top of the earnings distribution.

[29]College graduate, high school graduate, high school dropout.

trepreneurial decline (Salgado [2020], Jiang and Sohail [2021]), which documented a decline of self-employment in the United States over the last forty years that has been driven by college graduates. State, year, industry and occupation fixed effects are accounted for, respectively, by τ_s, τ_t, τ_j and τ_o. The relevant industries and occupations for the decision to move between paid work and self-employment are those before the transition, i.e. at time $t-1$. I finally control for the local economic environment and demand using state-level estimates of annual GDP growth between 1998 and 2020 from the Bureau of Economic Analysis (BEA).

Table 1.4: Unemployment rate changes and transitions between paid work and self-employment across industries

	Entry		Exit		Entry: College		Entry: Non-College	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\Delta u_{j,s,t}$: **Unemployment Rate Change**	**-0.0178*****	**-0.0079****	**0.0019**	**0.0022**	**-0.0242****	**-0.0122**	**-0.0132*****	**-0.0052**
	(0.0048)	***(0.0036)***	***(0.0065)***	***(0.0057)***	***(0.0105)***	***(0.0083)***	***(0.0049)***	***(0.0032)***
Year, State, Industry, Occupation FE : $\tau_t, \tau_s, \tau_j, \tau_o$	YES	YES	YES	YES	YES	YES	YES	YES
Control for past income : $w_{i,t-1}, z_{i,t-1}$ and GDP growth $\Delta y_{s,t}$	YES	YES	YES	YES	YES	YES	YES	YES
N	135800	245797	15023	24835	56287	99256	79513	146541
Pseudo R2	0.3074	0.2981	0.2249	0.2282	0.2512	0.2460	0.3663	0.3462
Marginal Effect : $\Delta u = +1$ **(%)**	**-2.9231**	**-1.3366**	**0.1867**	**0.2164**	**-4.1482**	**-2.1468**	**-2.0475**	**-0.8381**

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Analysis restricted to state x industries with more than 100 observations to compute unemployment rates. The sample of 25-64 year-olds excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Columns (1): Household-level analysis - Household heads. Columns (2): All individuals. Entry: Self-employed who was a salaried worker the previous year $(t-1)$. Exit: Salaried worker who was self-employed the previous year $(t-1)$. Controls X_{it} include dummies for gender, race, a quadratic in age, and dummies for individuals with high school and college degrees. Education dummies interacted with a linear time trend. Past income: $w_{i,t-1}$ wage for paid-workers at $t-1$, $z_{i,t-1}$ for self-employed at $t-1$. Earnings are in constant 1999 US dollars. State-level GDP growth from BEA regional economic accounts. Source: CPS ASEC March supplement.

Table 1.4 displays the results. Higher future unemployment at the sectoral level is associated with lower entry from paid work, especially for household heads. Stronger results for householders are expected to the extent that the risk of failing to start up a business after leaving their relatively more secure salaried job is a stronger deterrent for individuals who are traditionally the main income earners in the household. The marginal effect of a future increase in the sectoral unemployment rate by 1% is associated with a 1.3 to 3 % lower probability of entry. The last two columns also show that this negative correlation between entry and future unemployment changes is stronger for college graduates, where a 1% future increase in the unemployment rate is associated with a 4.1% lower probability of entry. On the other hand, exit to paid work and unemployment changes are unrelated.

The interpretation of these findings is not causal. The analysis in this section highlights the cross-sectional correlation between higher future unemployment changes and lower transitions from wage work to self-employment, which is predicted by the model. Unemployment rate changes may as well be endogenous to transitions between wage work and self-employment. For instance, future unemployment changes might be correlated with past decisions of previous prospective entrepreneurs not to enter, which affects job creation and future unemployment changes. Overall, these findings confirm and strengthen my quantitative results on the negative relationship between unemployment and entry from salaried workers to self-employment.

1.6 Conclusion

In this paper, I studied the effect of labour market outcomes and unemployment risk on self-employment dynamics. The industry-level analysis helped me show that employees are less likely to leave their job and start self-employment in sectors with higher unemployment increases if they expect that it will be harder for them to find a job after failure. I developed a simple model of a frictional labour market that featured risky transitions to self-employment, in line with evidence that most "nascent entrepreneurs" fail to achieve business operation. My quantitative exercise shows that the possibility of failing to start a business acts as a powerful deterrent to entry into self-employment as unemployment rises. Salaried workers are less likely to leave their job when they think it will be harder to find a new one if their business idea does not work out. It highlights the role of the job finding rate, not the separation rate, as a driver of entry into entrepreneurship. My quantitative analysis also showed that higher aggregate unemployment risk for wage workers and entrepreneurs could explain the evolution of the self-employment rate during and after the Great Recession.

Two avenues seem fruitful for future research: First, my model currently only allows for heterogeneity across jobs/businesses, but it can be extended to allow for heterogeneity between sectors or workers as well. Different workers are exposed to different shocks across the job ladder, depending on their skills, experience and industry. For instance, my empirical results suggested that college-educated workers are more likely to be affected by unemployment risk. Second, there is little work on the design and the desirability of optimal policies to support self-employment. My results highlight that workers are deterred from leaving their jobs because failure to materialise the entrepreneurial idea will leave them jobless. The extension of UI to the self-employed, because it lowers the costs associated with failure, could potentially foster business creation. It also hints at the importance of a leave of absence policy to help workers experiment with entrepreneurship. It seems promising to incorporate a duration dimension to my model and analyse the role of leave of absence policies.

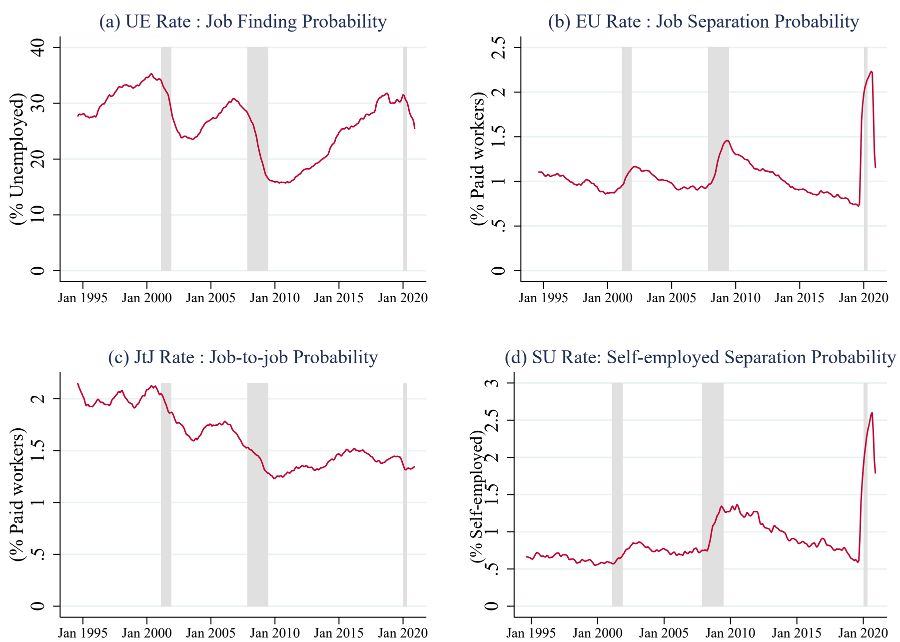
Appendix

1.A Appendix A

1.A.1 CPS - Additional data on flows

I present in figure 1.A1 additional data on flows between employment statuses that I use in my quantitative analysis. The UE rate, the fraction of unemployed workers last month who found a job, went down by 40% during the 2008-9 recession and recovered its 2007 level ten years later. On the other hand, the EU rate, the fraction of salaried workers last month who became unemployed, went up by 50% during the Great Recession and started to go down by the end of 2009 to recover its pre-crisis level in 2014. The JtJ rate represents the fraction of salaried workers who found a salaried job with another employer. It is pro-cyclical like the UE rate and fell by 20% during the Great Recession. Finally, the SU rate represents the rate of business shutdowns, the fraction of self-employed business owners who go into unemployment. It went up by 80% during the financial crisis, but unlike the EU rate, it did not immediately decline afterwards and remained persistently high until 2012.

Figure 1.A1: UE, EU, JtJ and SU rates (1994-2020)



12-month centered MA to remove seasonality. The sample of 25-64 year-olds excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Same across two months: The same individual answers the household survey over two months. Source: CPS Basic Monthly Files.

1.A.2 Measurement

In section 1.2.2, I presented transitions between paid work and self-employment using the sample of individuals whose responses were provided by the same person across two months (”Same across two months”, 75 to 80% of survey respondents). I do so because a change in the Current Population Survey’s interviewing protocol documented by Fujita et al. [2021] might have affected measures of transitions across employment statuses. They document an increase in missing answers to a question related to employer-to-employer transitions since 2007 and relate it to the Respondent Identification Policy (RIP). This procedure was introduced in January 2008 to protect the confidentiality of within-household responses: They show that the RIP has affected the measurement of employer-to-employer (EE) transitions, as information about the previous employer can no longer be used. The policy allows respondents to refuse to share answers about their employment status in a month with other household members. This invalidates dependent interviewing questions, which must be asked again.

Besides, answers on respondents’ occupation activities and class-of worker are also affected by the Respondent Identification Policy since they rely on dependent interviewing[30]. Fujita et al. [2021] note that answers the same respondent provides over two months are less likely to be affected by the policy because dependent interviewing still applies, and previous answers to employment status questions are being brought forward.

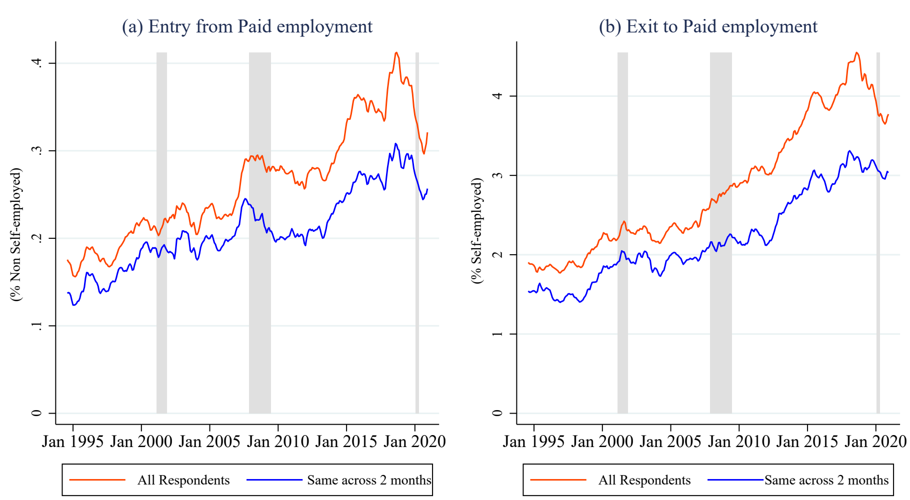
It is why I look in figure 1.2 (a) at entry into self-employment from paid work for respondents whose identity does not change across two consecutive months[31], which

[30] See Bureau [2006], 6-5. Answers to the class-of-worker question define whether an individual is self-employed or salaried.

[31] ”Self-Self” respondents and ”Proxy-Proxy” respondents, the vast majority of respondents in the CPS.

is likely to be a better measure because it is not subject to the RIP. I compare it with the entire sample (All Respondents) in figure 1.A2. While entry from paid employment goes down in similar proportions in both time series between the end of 2007 and 2011, they started to diverge during the Great Recession, when the RIP was introduced. Entry goes down by 20% in the "Same across two months sample" vs 15% in the entire sample between the end of 2007 and 2011. However, the former series exhibits a stronger co-movement with the business cycle. Both time series of entry also exhibit a similar decline during the 2020 recession. Exit from self-employment to paid work does not seem to be particularly cyclical.

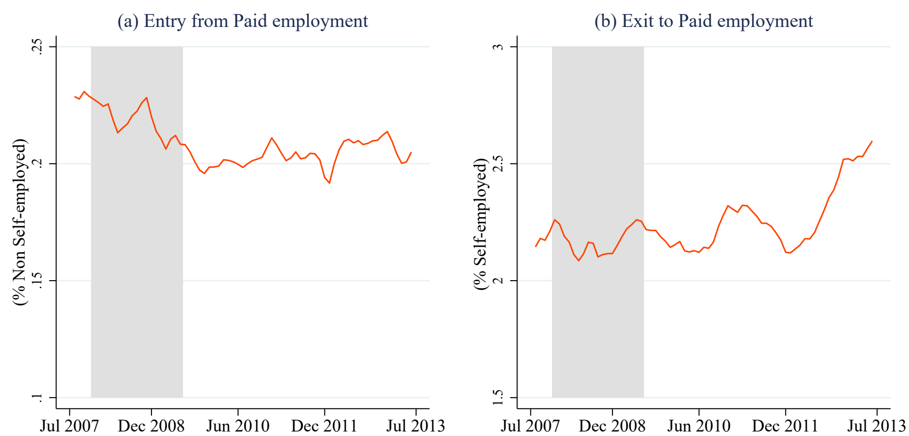
Figure 1.A2: Transitions between self-employment and paid work - By survey respondent identity



12-month centered MA to remove seasonality. Entrant at time t: Self-employed individual who was a paid worker or unemployed in the previous month $(t-1)$. Exit at t: Self-employed individual who was previously self-employed. The sample of 25-64 year-olds excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Same across two months: The same individual answers the household survey over two months. Source: CPS Basic Monthly Files.

While "Self-Self" and "Proxy-Proxy" respondents are not affected by the RIP introduced in 2008, the increase in missing answers to the question related to employer-to-employer transitions started in early 2007. To see whether this change could affect the observed entry and exit flows during the Great Recession, I show in figure 1.A3 flows for individuals who entered the survey after January 2007, for whom answers are provided by the same individual across two months ("Same across two months" sample), excluding those who entered before. Figure 1.A3 displays entry and exit flows that are similar to figure 1.A2 and do not affect my findings: Entry falls by similar proportions (slightly more than 15 %) while exits are not cyclical.

Figure 1.A3: Transitions between self-employment and paid work: Post-2007 survey respondents

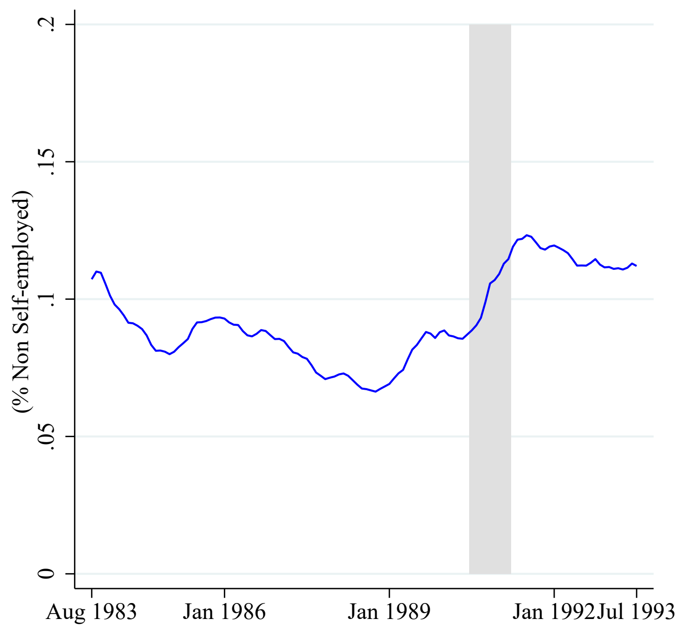


12-month centered MA to remove seasonality. Entrant at time t: Self-employed individual who was a paid worker or unemployed in the previous month $(t-1)$. Exit at t: Self-employed individual who was previously self-employed. The sample of 25-64 year-olds excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Source: CPS Basic Monthly Files.

1.A.3 Before 1994

The introduction of dependent interviewing in January 1994 led to a discontinuity in the measurement of transitions across employment statuses (for instance, between paid work and self-employment). It makes the comparison between pre- and post-survey redesign data impossible. I present here time series of transitions between self-employment and paid work and unemployment between 1983 and 1993. Pre-1983 data cannot be used as it does not include the incorporated self-employed, classified as wage workers. Figures 1.A4 and 1.A5 (a) and below show how entry from unemployment and from paid-work varied during that period.

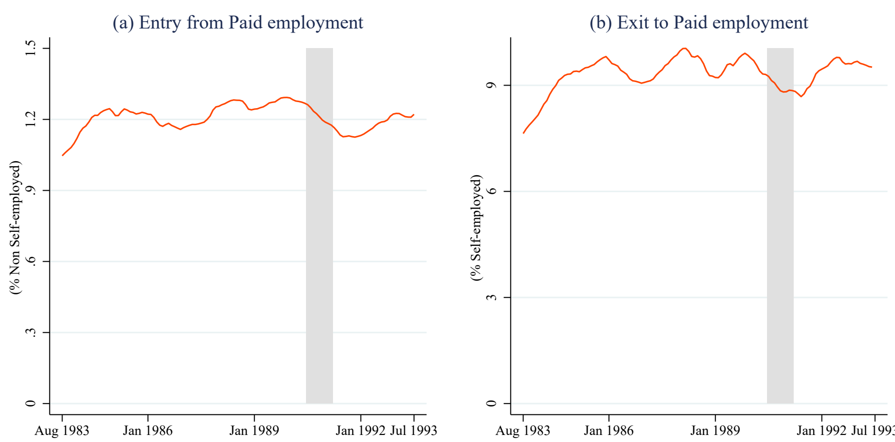
Figure 1.A4: Entry from unemployment to self-employment: 1983-1993



12-month centered MA to remove seasonality. Entrant at time t: Self-employed individual who was a paid worker or unemployed in the previous month $(t-1)$. Exit at t: Self-employed individual who was previously self-employed. The sample of 25-64 year-olds excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Source: CPS Basic Monthly Files.

Entry from Unemployment went up by 40% during the 1990 recession, while entry from salaried work went down by roughly 10%: This pattern is similar to the 2008 and 2020 recessions. Figure 1.A5 (b) shows the time-series of exit from self-employment to paid work during that period. Exit went down by slightly less than 10% during the 1990 recession. Transition levels are not directly comparable to the post-1994 period because of the CPS redesign, which notably led to the introduction of dependent interviewing. Dependent interviewing could eliminate many spurious transitions by bringing forward past answers to employment status questions for non-unemployed workers.

Figure 1.A5: Transitions between self-employment and paid work: 1983-1993



12-month centered MA to remove seasonality. Entrant at time t: Self-employed individual who was a paid worker or unemployed in the previous month $(t-1)$. Exit at t: Self-employed individual who was previously self-employed. The sample of 25-64 year-olds excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Source: CPS Basic Monthly Files.

1.A.4 Data - industry and occupation classifications

Throughout my analysis, I rely on broad industry and occupation classifications constructed by IPUMS and based on variables *ind1990* and *occ1990* that are comparable across time. I focus on civilians and therefore exclude individuals working in the armed forces. I exclude individuals working in jobs with industry codes between 940 and 960 and occupation codes 905, which correspond to the military forces.

I exclude individuals working in agricultural and mining industries and occupations for two reasons. The literature on entrepreneurship usually looks at the non-agricultural sector, and I, therefore, exclude individuals working in industries 010 to 032 and occupations 473 to 498, corresponding to the Agriculture, Farming, Forestry and Fishing industries and occupations. I also exclude mining for sample size reasons. Few individuals are working in the mining industry in the CPS. As a result, I exclude from the analysis industries 040 to 050 and occupations 614 to 617. All the other industries and occupations are aggregated into the ten broad industry and fourteen broad occupation categories of *ind1990* and *occ1990*.

1.B Appendix B

1.B.1 Additional derivations - Model

I present here additional derivations that will help with the comparative statics. I first solve for the value of being unemployed U as a function of parameters because I chose to write my comparative statics results as a function of U. The value of being salaried or self-employed will enter the value of U, so I first need to write those value functions as functions of U and parameters.

I first see how the value of being salaried or self-employed varies with the worker's wage or business's productivity. Differentiating equations 1.2 and 1.4 give:

$$W^{'}(w) = \frac{1}{r + \delta_w + \lambda_{ww}\overline{\mathcal{F}}(w) + \lambda_s \overline{\mathcal{H}}(z^*(w))} \tag{1.18}$$

$$S_e^{'}(z) = \frac{1}{r + \delta_{se} + \lambda_{sw}\overline{\mathcal{F}}(\tilde{w}(z))} \tag{1.19}$$

Using integration by parts, I can write the value functions for the unemployed, the paid workers, and the self-employed just as a function of parameters and U:

$$W(w) = \frac{1}{r + \delta_w}\left[w + \delta_w U + \lambda_{ww}\int_w^{\overline{w}} W^{'}(s)\,\overline{\mathcal{F}}(s)\,ds + p\lambda_s \int_{z^*(w)}^{\overline{z}} S_e^{'}(t)\,\overline{\mathcal{H}}(t)\,dt\right] \tag{1.20}$$

$$S_e(z) = \frac{1}{r + \delta_{se}}\left[z + \delta_{se} U + \lambda_{sw}\int_{\tilde{w}(z)}^{\overline{w}} W^{'}(s)\,\overline{\mathcal{F}}(s)\,ds\right] \tag{1.21}$$

$$U = \frac{1}{r}\left[b + \lambda_{uw}\int_{\zeta}^{\overline{w}} W^{'}(s)\,\overline{\mathcal{F}}(s)\,ds + p\lambda_s \int_{\underline{z}}^{\overline{z}} S_e^{'}(t)\,\overline{\mathcal{H}}(t)\,dt\right] \tag{1.22}$$

I write the comparative statics as a function of U, and I need to differentiate U with respect to λ_{uw} and δ_w. The derivative of the value of unemployment U with respect to the job finding rate λ_{uw} writes as:

$$rU^{'}\left(\lambda_{uw}\right)=\int_{\zeta}^{\overline{w}}W^{'}\left(s\right)\overline{\mathcal{F}}\left(s\right)ds-\lambda_{uw}W^{'}\left(\zeta\right)\overline{\mathcal{F}}\left(\zeta\right)\frac{d\zeta}{d\lambda_{uw}} \tag{1.23}$$

ζ denotes the reservation wage defined in section 1.3 of the paper. Differentiating ζ with respect to λ_{uw} gives:

$$\frac{d\zeta}{d\lambda_{uw}}=\frac{r+\delta_w+\lambda_s+\lambda_{ww}\overline{\mathcal{F}}\left(\zeta\right)}{r+\delta_w+\lambda_s+\lambda_{uw}\overline{\mathcal{F}}\left(\zeta\right)}\times\int_{\zeta}^{\overline{w}}W^{'}\left(s\right)\overline{\mathcal{F}}\left(s\right)ds>0 \tag{1.24}$$

Therefore:

$$rU^{'}\left(\lambda_{uw}\right)=\left(\int_{\zeta}^{\overline{w}}W^{'}\left(s\right)\overline{\mathcal{F}}\left(s\right)ds\right)\times\left[1-\frac{\lambda_{uw}\overline{\mathcal{F}}\left(\zeta\right)}{r+\delta_w+\lambda_s+\lambda_{uw}\overline{\mathcal{F}}\left(\zeta\right)}\right]>0 \tag{1.25}$$

Similarly, the derivative of the value of Unemployment U with respect to the job separation rate δ_w writes:

$$rU^{'}\left(\delta_w\right)=-\lambda_{uw}\int_{\zeta}^{\overline{w}}W^{'}\left(s\right)^2\overline{\mathcal{F}}\left(s\right)ds-\lambda_{uw}W^{'}\left(\zeta\right)\overline{\mathcal{F}}\left(\zeta\right)\frac{d\zeta}{d\delta_w} \tag{1.26}$$

Differentiating the reservation wage ζ with respect to δ_w gives:

$$\frac{d\zeta}{d\delta_w}=-\frac{r+\delta_w+\lambda_s+\lambda_{ww}\overline{\mathcal{F}}\left(\zeta\right)}{r+\delta_w+\lambda_s+\lambda_{uw}\overline{\mathcal{F}}\left(\zeta\right)}\times\left(\lambda_{uw}-\lambda_{ww}\right)\times\int_{\zeta}^{\overline{w}}W^{'}\left(s\right)^2\overline{\mathcal{F}}\left(s\right)ds\lesseqgtr 0 \tag{1.27}$$

Therefore:

$$rU^{'}\left(\delta_w\right)=-\lambda_{uw}\int_{\zeta}^{\overline{w}}W^{'}\left(s\right)^2\overline{\mathcal{F}}\left(s\right)ds\times\left[1-\frac{\left(\lambda_{uw}-\lambda_{ww}\right)\overline{\mathcal{F}}\left(\zeta\right)}{r+\delta_w+\lambda_s+\lambda_{uw}\overline{\mathcal{F}}\left(\zeta\right)}\right]<0 \tag{1.28}$$

The value of unemployment increases with the job finding rate, as better job offers arrive at a higher frequency and allow a worker to leave for better jobs, $U^{'}\left(\lambda_{uw}\right)>0$. Similarly, as the job separation rate increases, the value of unemployment goes down because future job spells (which are more valuable than being unemployed) are now shorter, $U^{'}(\delta_w) < 0$. I will use these two derivatives to see how entry varies with unemployment risk in the subsection below.

1.B.2 Comparative statics - Proofs of section 1.3.2

1.B.2.1 Simplest case: $\lambda_{sw} = \lambda_{ww} = 0$

I first look at the simplest case, where there is no entry and on-the-job search, i.e. when $\lambda_{sw} = \lambda_{ww} = 0$. I derive comparative statics of entry from paid work with respect to changes in the job finding and job separation rates, λ_{uw} and δ_w.

Equation 1.5 implicitly defines the entry cutoff $z^*(w)$ such that a salaried worker paid w will accept any offer $z > z^*(w)$. I totally differentiate that equation after plugging in equations 1.20 to 1.22 to see how the entry cutoff varies with the job finding rate. Rearranging gives:

$$\begin{aligned}\frac{dz^*(w)}{d\lambda_{uw}} &= -\left[\frac{\partial C_1}{\partial z^*(w)}\right]^{-1} \times \left[\frac{-prU^{'}(\lambda_{uw})}{r+\delta_{se}} + \frac{rU^{'}(\lambda_{uw})}{r+\delta_w}\right] \\ &\propto \frac{-(1-p)\,U^{'}(\lambda_{uw})}{r+\delta_{se}} + \frac{r(\delta_w-\delta_{se})\,U^{'}(\lambda_{uw})}{(r+\delta_{se})(r+\delta_w)} \lesseqgtr 0\end{aligned} \tag{1.29}$$

The denominator is always positive. Indeed:

$$\frac{\partial C_1}{\partial z^*(w)} = pS_e^{'}(z^*(w))\,\frac{r+\delta_w+\lambda_s\overline{\mathcal{H}}(z^*(w))}{r+\delta_w} > 0 \tag{1.30}$$

As discussed in section 1.3.2, two effects are potentially offsetting each other: an *unemployment risk* effect that lowers transitions into self-employment in recessions and a *differential separation* effect that can facilitate transitions from paid work to self-employment in downturns if self-employment is relatively more shielded from separation shocks than salaried work. Similarly, I use total differentiation and rearrange to show that the change in the entry cutoff with respect to the job separation rate δ_w can be written as:

$$\begin{aligned} \frac{dz^*(w)}{d\delta_w} =& -\left[\frac{\partial C_1}{\partial z^*(w)}\right]^{-1} \times \left[-\frac{prU'(\delta_w)}{r+\delta_{se}} + \frac{rU'(\delta_w)}{r+\delta_w} - \frac{U-W(w)}{r+\delta_w}\right] \\ &\propto \frac{-(1-p)U'(\delta_w)}{r+\delta_{se}} + \frac{r(\delta_w-\delta_{se})U'(\delta_w)}{(r+\delta_{se})(r+\delta_w)} - \frac{W(w)-U}{r+\delta_w} \lesseqgtr 0 \end{aligned} \tag{1.31}$$

As discussed earlier, there is now an additional effect, a *decreasing surplus* effect that increases entry into self-employment in recessions.

1.B.2.2 Full comparative statics with entry and exit - General case

I present full comparative statics of the model with entry and exit, and on-the-job search, $\lambda_{ww} \neq 0$, $\lambda_{sw} \neq 0$. I am interested in how entry and exit cutoffs change with unemployment risk and how it varies depending on whether higher unemployment is driven by an increase in the job separation rate δ_w compared to a fall in the job finding rate λ_{uw}. The main difference with the previous section is that the entry and exit cutoffs now interact. Therefore, how the entry cutoff changes with the job finding rate will affect how the exit cutoff changes with the job finding rate. Using equation 1.5 as well as solutions for the value functions U, $W(w)$ and $S_e(z)$, I obtain:

$$\frac{dz^*(w)}{d\lambda_{uw}} = -\left[\frac{\partial C_1}{\partial z^*(w)}\right]^{-1} \times$$
$$\left[\frac{-prU'(\lambda_{uw})}{r+\delta_{se}} + \frac{rU'(\lambda_{uw})}{r+\delta_w} - \frac{p\lambda_{sw}}{r+\delta_{se}} W'(\tilde{w}(z^*))\overline{\mathcal{F}}(\tilde{w}(z^*))\frac{d\tilde{w}(z^*)}{d\lambda_{uw}}\right]$$
$$\propto \frac{-(1-p)rU'(\lambda_{uw})}{r+\delta_{se}} + \frac{r(\delta_w - \delta_{se})U'(\lambda_{uw})}{(r+\delta_{se})(r+\delta_w)}$$
$$+\frac{\mathbf{p}\lambda_{\mathbf{sw}}}{\mathbf{r}+\delta_{\mathbf{se}}}\mathbf{W}'(\tilde{\mathbf{w}}(\mathbf{z}^*(\mathbf{w})))\overline{\mathcal{F}}(\tilde{\mathbf{w}}(\mathbf{z}^*(\mathbf{w})))\frac{\mathbf{d}\tilde{\mathbf{w}}(\mathbf{z}^*)}{\mathbf{d}\lambda_{\mathbf{uw}}} \tag{1.32}$$

Results are similar to the simplest case without exit and job-to-job transitions, except that the change in the exit cutoff will impact entry, what I call a *feedback effect*. For instance, if $\frac{d\tilde{w}(z^*)}{d\lambda_{uw}} < 0$, i.e. the self-employed are less likely to exit in recessions, a fall in the job finding rate will further deter a paid worker to enter self-employment as exit will be harder. I now turn to the impact of higher separations on entry:

$$\frac{dz^*(w)}{d\delta_w} = -\left[\frac{\partial C_1}{\partial z^*(w)}\right]^{-1} \times$$
$$\Bigg(-\frac{prU'(\delta_w)}{r+\delta_{se}} + \frac{rU'(\delta_w)}{r+\delta_w} - \frac{U-W(w)}{r+\delta_w} - \frac{p\lambda_{sw}}{r+\delta_{se}}W'(\tilde{w}(z^*))\overline{\mathcal{F}}(\tilde{w}(z^*))\frac{d\tilde{w}(z^*)}{d\delta_w}...$$
$$-\left[\frac{p\lambda_{sw}}{r+\delta_{se}}\int_{\tilde{w}(z^*(w))}^{\overline{w}} W'(s)^2\overline{\mathcal{F}}(s)\,ds - \frac{\lambda_{ww}}{r+\delta_w}\int_{w}^{\overline{w}} W'(s)^2\overline{\mathcal{F}}(s)\,ds\right]\Bigg)$$
$$\propto \frac{-(1-p)rU'(\delta_w)}{r+\delta_{se}} + \frac{r(\delta_w-\delta_{se})U'(\delta_w)}{(r+\delta_{se})(r+\delta_w)} - \frac{W(w)-U}{r+\delta_w}$$
$$+\left[\frac{\mathbf{p}\lambda_{\mathbf{sw}}}{\mathbf{r}+\delta_{\mathbf{se}}}\int_{\tilde{\mathbf{w}}(\mathbf{z}^*(\mathbf{w}))}^{\overline{\mathbf{w}}} \mathbf{W}'(\mathbf{s})^{\mathbf{2}}\overline{\mathcal{F}}(\mathbf{s})\,\mathbf{ds} - \frac{\lambda_{\mathbf{ww}}}{\mathbf{r}+\delta_{\mathbf{w}}}\int_{\mathbf{w}}^{\overline{\mathbf{w}}} \mathbf{W}'(\mathbf{s})^{\mathbf{2}}\overline{\mathcal{F}}(\mathbf{s})\,\mathbf{ds}\right]$$
$$+\frac{\mathbf{p}\lambda_{\mathbf{sw}}}{\mathbf{r}+\delta_{\mathbf{se}}}\mathbf{W}'(\tilde{\mathbf{w}}(\mathbf{z}^*))\overline{\mathcal{F}}(\tilde{\mathbf{w}}(\mathbf{z}^*))\frac{\mathbf{d}\tilde{\mathbf{w}}(\mathbf{z}^*)}{\mathbf{d}\delta_{\mathbf{w}}} \tag{1.33}$$

There are two additional effects compared to the baseline example of section 1.3.2. The first effect, also described above for the job finding rate, is a *feedback effect* of exit on entry. The second effect is a *duration effect*. An increase in the job separation rate δ_w will lower the length of any future job spell a worker transitions to through on-the-job search, which increases entry. However, at the same time, all the future job spells of the self-employed after exit will also be shorter, and this decreases entry. The overall direction of the *duration* effect is ambiguous as the duration effect affects both the value of being salaried (through on-the-job search) and self-employed (through endogenous exit to paid work).

I can also analyze the job finding and separation rates' effects on exit. I also use equation 1.7 as well as solutions for the value functions U, $W(w)$ and $S_e(z)$ to derive the change in the exit cutoff with respect to the job finding rate. It writes as:

$$\begin{aligned}\frac{d\tilde{w}(z)}{d\lambda_{uw}} &= -\left[\frac{\partial C_2}{\partial \tilde{w}(z)}\right]^{-1}\left[\frac{\delta_w - \delta_{se}}{(r+\delta_w)(r+\delta_{se})} rU'(\lambda_{uw}) - p\lambda_s \frac{S_e'(z^*(\tilde{w}))\overline{\mathcal{H}}(z^*(\tilde{w}))}{r+\delta_w}\frac{dz^*(\tilde{w})}{d\lambda_{uw}}\right] \\ &\propto \frac{\delta_{se} - \delta_w}{(r+\delta_w)(r+\delta_{se})} rU'(\lambda_{uw}) + p\lambda_s \frac{S_e'(z^*(\tilde{w}(z)))\overline{\mathcal{H}}(z^*(\tilde{w}(z)))}{r+\delta_w}\frac{dz^*(\tilde{w}(z))}{d\lambda_{uw}}\end{aligned} \tag{1.34}$$

There are two terms to consider: The first is a *differential separation effect* that depends on whether the self-employed or paid workers are better protected from separation shocks. If $\delta_{se} > \delta_w$, i.e. if the salaried are less likely to be separated to unemployment than the self-employed, an increase in the job-finding rate will lower exit to paid work (by increasing the cutoff), as paid workers are less likely to go to unemployment, which is now more desirable. The second corresponds to the impact of a change in the entry cutoff, a *feedback effect*. For instance, if $\frac{dz^*(\tilde{w})}{d\lambda_{uw}} < 0$, i.e. entry increases in booms, an increase in the job finding rate will further increase exit to paid work as re-entry to self-employment will always be possible. The denominator of the above expression is always positive. Indeed:

$$\frac{\partial C_2}{\partial \tilde{w}(z)} = W^{'}(\tilde{w}(z)) \times \left[1 + \frac{\lambda_{sw}\overline{\mathcal{F}}(\tilde{w}(z))}{r+\delta_{se}}\right] > 0 \tag{1.35}$$

I can finally also look at the impact of separations on the exit cutoff:

$$\begin{aligned}
\frac{d\tilde{w}(z)}{d\delta_w} &= -\left[\frac{\partial C_2}{\partial \tilde{w}(z)}\right]^{-1}\left(\frac{U - W(\tilde{w}(z))}{r+\delta_w} + \frac{(\delta_{se}-\delta_w)}{(r+\delta_w)(r+\delta_{se})} rU^{'}(\delta_w)\ldots\right. \\
&\quad \left. - \frac{p\lambda_s}{r+\delta_w} S_e^{'}(z^*(\tilde{w}(z)))\overline{\mathcal{H}}(z^*(\tilde{w}(z)))\frac{dz^*(\tilde{w}(z))}{d\delta_w} - \left(\frac{\lambda_{ww}}{r+\delta_w} - \frac{\lambda_{sw}}{r+\delta_{se}}\right)\int_{\tilde{w}(z)}^{\overline{w}} W^{'}(s)^2\,\overline{\mathcal{F}}(s)\,ds\right) \\
&\propto \frac{W(\tilde{w}(z)) - U}{r+\delta_w} - \frac{(\delta_{se}-\delta_w)}{(r+\delta_w)(r+\delta_{se})} rU^{'}(\delta_w) + \left(\frac{\lambda_{ww}}{r+\delta_w} - \frac{\lambda_{sw}}{r+\delta_{se}}\right)\int_{\tilde{w}(z)}^{\overline{w}} W^{'}(s)^2\,\overline{\mathcal{F}}(s)\,ds \\
&\quad + \frac{p\lambda_s}{r+\delta_w} S_e^{'}(z^*(\tilde{w}(z)))\overline{\mathcal{H}}(z^*(\tilde{w}(z)))\frac{dz^*(\tilde{w}(z))}{d\delta_w}
\end{aligned} \tag{1.36}$$

There are also *feedback* and *duration effects*, in addition to a *decreasing surplus effect*. For instance, if $\frac{dz^*(\tilde{w}(z))}{d\delta_w} < 0$, an increase in the job separation rate δ_w will lower the exit cutoff, because re-entry will be easier. As for entry, the *duration effect* features two components that offset each other, as both values of being self-employed and salaried go down. The *surplus effect* tends to lower exit because the rise of the job separation rate δ_w lowers the value of being salaried more than it lowers the value of being unemployed, as paid workers are directly affected by separation shocks.

1.C Appendix C

1.C.1 Calibration details

There are 11 parameters to calibrate jointly. To find the vector of parameters θ^* that best matches the data, I solve this high-dimensional problem by proceeding in two steps:

- I first generate a high number of possible solutions θ_k, $k = 1...N_1$. For each candidate vector, I solve the model according to the solution method described in the following subsection and compute the 12×1 vector of model-implied theoretical moments, $\mathbf{model}\left(\theta_k\right)$. I then calculate the GMM objective of equation 1.16 and rank θ_k accordingly, from the lowest distance to the highest.

- I then take a subsample of the $N_2 < N_1$ best candidates and run a local solver using an interior-point method with each selected θ as a starting point.

The N_1 vectors $\theta \in \mathcal{K} \subset \mathbf{R}^{11}$ are drawn from a (quasi-random) "Sobol" sequence to populate the parameter space as efficiently as possible. $N_1 = 1000000$ and $N_2 = 10000$.

1.C.2 Algorithm

The solution algorithm works as follows: Given a grid of N possible earnings $\mathbf{x} = [\underline{x}, \bar{x}]$, I make an initial guess for the value functions $\mathbf{U^0}$, $\mathbf{W^0}\left(\mathbf{x}\right)$, $\mathbf{S_e^0}\left(\mathbf{x}\right)$:

- I obtain thresholds for self-employment entry and exit: $\mathbf{z}^*\left(\mathbf{x}\right)$ and $\tilde{\mathbf{w}}\left(\mathbf{x}\right)$.

- Given these thresholds, I update the value functions to get $\mathbf{U^1}$, $\mathbf{W^1}\left(\mathbf{x}\right)$, $\mathbf{S_e^1}\left(\mathbf{x}\right)$ using an implicit method as in Achdou et al. [2021]. I iterate until convergence.

- I then obtain Kolmogorov Forward Equations (KFE) and distributions by inverting the HJB transition matrix.

- I compute the model-implied theoretical moments.

More specifically, I define $\mathbf{v} = [U, W(\mathbf{x}), S_e(\mathbf{x})]$ a $2 \times N + 1$ vector. I can write the system of Hamilton Jacobi Bellman equations as:

$$r\mathbf{v} = \mathbf{u} + \mathbf{A}(\mathbf{v})\,\mathbf{v} \tag{1.37}$$

I take $\mathbf{v}_0$ as my initial guess. For each iteration $j = 1, 2...$, I obtain optimal entry and exit rules $\mathbf{z}_j^*$ and $\tilde{\mathbf{w}}_j^*$ that solve equations 1.5 and 1.6 as well the reservation wage ζ_j. This allows me to construct the optimal transition matrix $\mathbf{A}_j = \mathbf{A}(\mathbf{v}_j)$:

$$\mathbf{v}_{j+1} = \left[\mathbf{I}_{2N+1}\left(r + \frac{1}{\Delta}\right) - \mathbf{A}_j\right]^{-1} \times \left[\mathbf{u} + \frac{\mathbf{v}_j}{\Delta}\right] \tag{1.38}$$

The step-size Δ is chosen to be equal to 1000. I iterate until $\|\mathbf{v}_{j+1} - \mathbf{v}_j\| < \epsilon$ for some small tolerance level ϵ. Once I obtain $\mathbf{v}^*$ and $\mathbf{A}^*$ that solve the HJB problem, it remains to solve for the KFE and distributions. I just need to solve for the vector $\mathbf{g}^*$ that solves $\mathbf{A}^T\mathbf{g} = 0$.

Once normalized, the first entry of that vector will give the mass of unemployed u, the sum of the second to $N^{th} + 1$ entries the mass of salaried workers and the last N entries (from $N + 2$ to $2N + 1$) the mass of self-employed workers s_e. I can then obtain the distributions $g(w)$ and $s(z)$. $N = 250$.

1.C.2.1 Time-dependent value functions: Transition dynamics

I explain in this subsection how I compute the transition dynamics. At time $t = 0$, the agent forecasts a change in the path of parameter value, $\lambda_{uw,t}$, $\delta_{w,t}$ or $\delta_{se,t}$ until time T. I follow Achdou et al. (2021): I first solve for the value function at the end of the transition at time T (December 2011, 4 years after the start of the recession) and then iterate it backwards in time, in a similar way to section 1.C.2, except that Δ can be interpreted as a time step. This gives me entry and exit cutoffs at each $t = 0...T$, as well as a transition matrix $\mathbf{A}_t$. I use them to solve for the distribution vector $\mathbf{g}_t$ forward in time, starting from the pre-recession steady-state distribution vector $\mathbf{g}_0$. I am thus able to obtain transitions across labour market statuses as well as employment states implied by the model between time 0 and time T.

1.C.2.2 Paths for λ_{uw}, δ_w and δ_{se}

While parameters are jointly determined in my estimation procedure, some parameters will be particularly informative about certain moments. For instance, λ_{uw} will inform the "UE rate", defined as the share of unemployed workers at $t-1$ who found a paid job at month t. Similarly, δ_w will inform the "EU rate", i.e. the share of salaried workers at $t-1$ who end up unemployed at t. δ_{se} is estimated separately using CPS data: It is equal to the continuous-time counterpart of the "SU rate", the share of self-employed at $t-1$ who end up unemployed at t. Starting from the pre-recession steady-state, I will construct a path for $\lambda_{uw,t}$ that mimics the evolution of the UE rate over that period, that is:

$$\lambda_{uw,t+1} = \lambda_{uw,t} \times (1 + \Delta \text{UE Rate}_{t+1,t}) \tag{1.39}$$

ΔUE Rate$_{t+1,t}$ denotes the percentage change in the UE rate between t and $t+1$. I construct an analogous path for the job separation rate $\delta_{w,t}$:

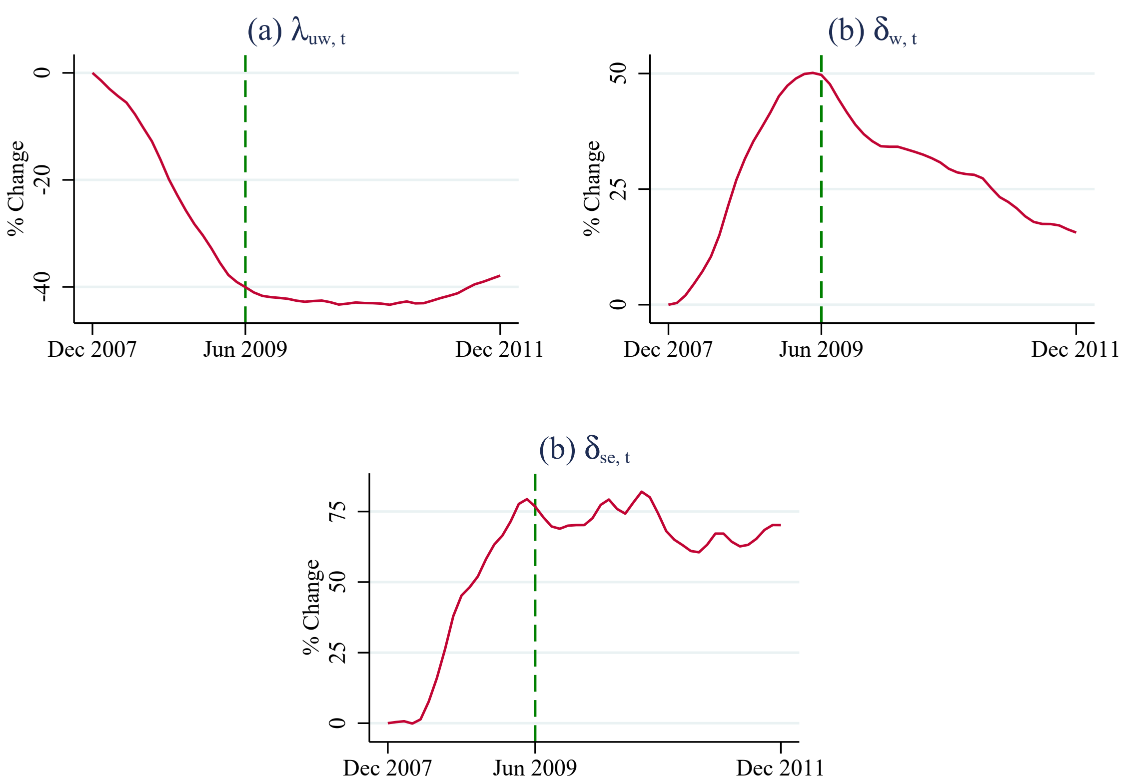
$$\delta_{w,t+1} = \delta_{w,t} \times (1 + \Delta \text{EU Rate}_{t+1,t}) \tag{1.40}$$

I also construct a path for the business exit rate $\delta_{se,t}$:

$$\delta_{se,t+1} = \delta_{se,t} \times (1 + \Delta \text{SU Rate}_{t+1,t}) \tag{1.41}$$

The constructed paths for $\lambda_{uw,t}$, $\delta_{w,t}$ and $\delta_{se,t}$ and allow the model to generate paths for UE Rate$_t$, EU Rate$_t$ and SU Rate$_t$ that closely resemble their empirical counterparts. They are represented in figure 1.C1 below.

Figure 1.C1: Paths for $\lambda_{uw,t}$, $\delta_{w,t}$ and $\delta_{se,t}$



1.D Appendix D

1.D.1 Reduced-form evidence on earnings

To complement the analysis of section 1.4.2, table 1.D1 shows the evolution of earnings across employment statuses between 2007 and 2011. Median earnings fell by more than 18% for the self-employed, whereas they only went down by less than 3% for salaried workers. A worsening of the entrepreneurial pool cannot be the only driver of this decline through higher entry from unemployment. Entrepreneurial earnings at the top of the income distribution have also dropped by more than paid workers. For instance, the last column of table 1.D1 shows that paid employees at the top of the income distribution have experienced an increase in their wages, while self-employed earnings in the last decile went down by 8%. Self-employment has overall become less desirable.

Table 1.D1: Earnings across employment categories: 2007-2011

Earnings	*10th Percentile*	*Lower Quartile*	*Median*	*Upper Quartile*	*90th Percentile*
Paid employed (N=95258)					
2007	8844	17559	28944	45024	68340
2011	8003	16302	28158	44460	70395
Change (%)	**-9,51**	**-7,16**	**-2,72**	**-1,25**	**3,01**
Self-employed (N=10841)					
2007	5628	13668	28140	52260	100500
2011	4446	11115	22971	48165	92625
Change (%)	**-21,00**	**-18,68**	**-18,37**	**-7,84**	**-7,84**

Earnings in constant 1999 US dollars. The sample of 25-64 year-olds includes paid-workers and self-employed with positive income and excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Source: CPS March Supplement (ASEC).

1.D.2 Model solution - Opportunity vs necessity entrepreneurs

To determine the evolution of each type of self-employed, I extend the model to allow for two unemployment states instead of one. An individual can enter self-employment from unemployment (s_{eu}) or from paid-work (s_{ep}). The HJB equations are modified as follows:

$$rU = b + \lambda_{uw} \int \max\left[W(w) - U, 0\right] d\mathcal{F}(w) + p\lambda_s \int \max\left[\left(S_{eu}(z') - U\right), 0\right] d\mathcal{H}(z') \tag{1.42}$$

$$\begin{aligned} rW(w) =& w + \lambda_s \int \max\left[pS_{ep}(z') + (1-p)U - W(w), 0\right] d\mathcal{H}(z') + \delta_w \left[U - W(w)\right] \\ &+ \lambda_{ww} \int \max\left[W(w') - W(w), 0\right] d\mathcal{F}(w') \end{aligned} \tag{1.43}$$

$$rS_{ej}(z) = z + \delta_{se}\left[U - S_{ej}(z)\right] + \lambda_{sw} \int \max\left[W(w') - S_{ej}(z), 0\right] d\mathcal{F}(w') \quad \forall j = \{u, p\} \tag{1.44}$$

Conditional on the idea z, there are no *ex-ante* differences in my model between the value of an opportunistic entrepreneur and a self-employed by necessity. In equilibrium, choice entrepreneurs earn much more because their opportunity cost of leaving salaried work is higher than for the unemployed, so they only pursue better ideas. The laws of motion evolve as follows:

$$\dot{g}(w)(1-u-s_{eu}-s_{ep}) = -\left[\delta_w + \lambda_{ww}\bar{\mathcal{F}}(w) + \lambda_s\bar{\mathcal{H}}(z^*)\right](1-u-s_{eu}-s_{ep})\,g(w)$$
$$+f(w)\left[\lambda_{uw}u + \lambda_{ww}(1-u-s_{eu}-s_{ep})\,\mathcal{G}(w)\right]$$
$$+\lambda_{sw}f(w)\left[\left(s_{eu}\mathcal{S}_u\left(\tilde{z}^{-1}\right) + s_{ep}\mathcal{S}_p\left(\tilde{z}^{-1}\right)\right)\right] \tag{1.45}$$

$$\dot{s}_u(z)\,s_{eu} = -s_{eu}\left[\delta_{se} + \lambda_{sw}\bar{\mathcal{F}}(\tilde{w})\right]s_u(z) + p\lambda_s h_s(z)\,u \tag{1.46}$$

$$\dot{s}_p(z)\,s_{ep} = -s_{ep}\left[\delta_{se} + \lambda_{sw}\bar{\mathcal{F}}(\tilde{w})\right]s_p(z) + p\lambda_s h_s(z)(1-u-s_{eu}-s_{ep})\,\mathcal{G}\left(w^{*-1}\right) \tag{1.47}$$

$$\dot{u} = -u(\lambda_{uw} + p\lambda_s) + (1-u-s_{eu}-s_{ep})\,\delta_w + \delta_{se}(s_{eu}+s_{ep})$$
$$+\lambda_s(1-u-s_{ep})(1-p)\int\left[1-\mathcal{H}(z^*(x))\right]d\mathcal{G}(x) \tag{1.48}$$

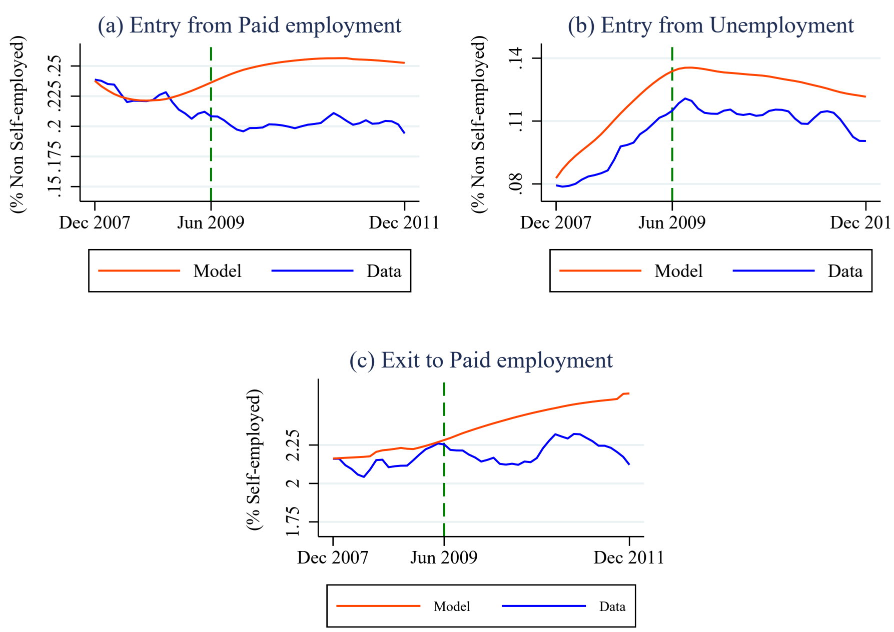
Solving the model numerically follows the same procedure described in Appendix 1.C.2. I define $\mathbf{v} = [U, W(\mathbf{x}), S_{eu}(\mathbf{x}), S_{ep}(\mathbf{x})]$ a $3\times N+1$ vector as there are now two different self-employment states, the opportunistic entrepreneurs and the necessity self-employed. Once I solve for $\mathbf{v}^*$ and $\mathbf{A}^*$ in the HJB problem, and find and normalize the vector $\mathbf{g}^*$ solving $\mathbf{A}^T\mathbf{g} = 0$, I can also find the number of workers in each sector. The first entry will again give the number of unemployed, the second to $N^{th}+1$ entry the number of salaried workers, and the last 2N entries the number of self-employed. In particular, the total number of workers in entries N+2 to 2N+1 corresponds to the mass of necessity self-employed, while the total number of workers from entry 2N+2 to the last entry will represent the number of opportunistic entrepreneurs.

1.D.3 Further evidence - Transition dynamics

1.D.3.1 Further evidence on the evolution of entry and exit

I present in this section additional evidence to support my results from section 1.4.2. I first show transition dynamics of entry and exit driven by increases in δ_{se} and δ_w, keeping the job finding rate constant. Compared to figure 1.7 in the main body of the paper, figure 1.D1 also isolates the impact of the job finding rate λ_{uw} on transition dynamics:

Figure 1.D1: Transition dynamics of an increase in δ_w and δ_{se}

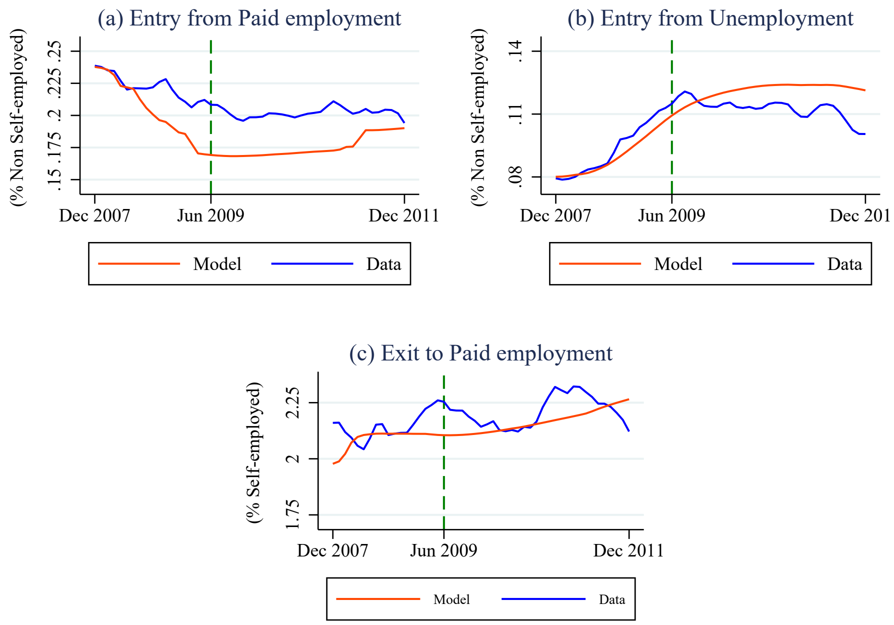


Appendix 1.C.2 explains how I construct the paths for $\delta_{w,t}$ and $\delta_{se,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

This figure complements the results of figures 1.3 and 1.5 that showed that the job finding rate was the driver of self-employment entry dynamics. Entry from paid work is predicted to increase by 8%, at odds with the data.

Similarly, figure 1.D2 looks at the transition dynamics induced by a fall in λ_{uw} and a rise in δ_{se}. The top left graph is almost identical to figure 1.7 (a), which strengthens my results about the relatively less important role of the risk of displacement on entry from paid work.

Figure 1.D2: Transition dynamics of a fall in λ_{uw} and a rise in δ_{se}



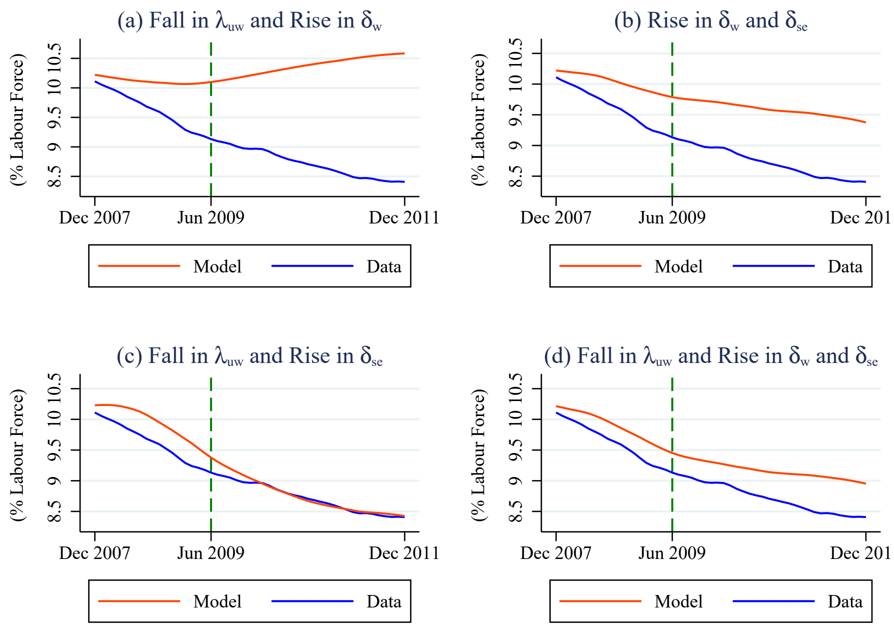
Appendix 1.C.2 explains how I construct the paths for $\lambda_{uw,t}$ and $\delta_{se,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

1.D.3.2 Further evidence on the evolution of the stock of self-employed

Figure 1.D3 strengthens the results from section 1.4.3. In that section, I showed that higher unemployment risk could explain almost the entire decrease in the self-employment rate. I highlighted the role of the self-employed separation rate (business exits δ_{se}). Figure 1.D3 (a) confirms that the rising unemployment risk for workers alone is not sufficient to explain the decrease in the number of entrepreneurs because endogenous exit to paid work is also predicted to fall during the 2008-9 recession (figure 1.6), unlike what happened in the data where it was slightly increasing. Figure

1.D3 (b) also shows that the job finding rate λ_{uw} remains more important than the job separation rate δ_w in explaining self-employment dynamics because the former leads to a large decline in the entry from paid work. In contrast, the latter leads to increased entry from paid work.

Figure 1.D3: Transition dynamics - Evolution of the self-employment rate



Appendix 1.C.2 explains how I construct the paths for $\lambda_{uw,t}$ and $\delta_{se,t}$. All other parameters fixed to their pre-recession parameter values of section 1.4.1. The dashed green line marks the end of the Great Recession, according to the NBER.

Chapter 2

Unemployment insurance and self-employment during the Great Recession

2.1 Introduction

It took more than five years after the start of the Great Depression for the United States to adopt a public unemployment insurance system. Since then, the state-administered unemployment insurance (UI) system has helped unemployed workers who lost a job through no fault of their own. A long line of research has studied unemployment benefits' micro and macroeconomic impacts. Recent evidence has particularly emphasized the advantages of a more generous UI system in terms of macroeconomic stabilization (McKay and Reis [2016]), supporting aggregate demand (Kekre [2021]) and improving match quality and productivity (Nekoei and Weber [2017], Farooq et al. [2020]). Compared with the 1929 crisis, the policy response to the effects of the Great Recession on labour markets has been quick. Between

June 2008 and December 2013, through a series of legislation amendments, federal funding for state programs, and newly introduced emergency benefits, the duration of unemployment benefits more than tripled, increasing from 26 weeks before the financial crisis to up to 99 weeks, with notable differences across states and over time.

This paper studies the role of this large extension to the provision of unemployment insurance on self-employment activity in the aftermath of the Great Recession. At the state level, I find a small and statistically insignificant effect of longer unemployment benefits on aggregate self-employment dynamics. Analysis of individual-level data confirms this result: Eligibility to additional weeks of benefits does not, on average, change the likelihood of unemployed workers leaving unemployment for self-employment. However, there is substantial heterogeneity among the newly self-employed: I find that the provision of extended benefits is associated with a 30% lower probability of entry for the lowest type of entrants from unemployment[1]. Moreover, I show that there is a role for unemployed workers' expectations of future benefits duration changes: A 10-week increase in the duration of unemployment benefits is, on average, associated with a 12% lower likelihood of entry for those who are about to exhaust their eligibility to UI. This effect is 50% more powerful for entrants who work less when self-employed.

The view that extended benefits could affect transitions into self-employment has been absent from the literature that studies the aggregate implications of longer UI duration. It traditionally focused on its impact on aggregate employment and labour force attachment. This is surprising because starting a self-employment spell has long been recognised as a way out of unemployment (Evans and Leighton [1989]) when jobs are harder to find, and entry into self-employment from unemployment has gone up during the last recessions (Fairlie and Fossen [2019]). However, workers who enter by

[1] Those working less than 20 hours in their new self-employment spell.

necessity after losing their job are less likely to create thriving businesses (Galindo da Fonseca [2021]). Therefore, being eligible for UI for longer could allow unemployed workers to search for jobs that are better suited to them instead of creating subsistence businesses that will possibly shut down. It could reduce mismatch and improve aggregate productivity in the long run.

Related Literature. This chapter contributes to two branches of the downside insurance literature for jobless workers.

First, this chapter contributes to the literature that studies the role of unemployment insurance on labour market outcomes during the Great Recession. There is no consensus about the impact of the large increase in the duration of unemployment benefits between 2008 and 2013 on unemployment. Rothstein [2011], Farber and Valletta [2015] and Farber et al. [2015] use individual-level data from the CPS and find that benefits extension had a negligible impact on exits to employment but were associated with a significantly lower probability of exiting the labour force. Chodorow-Reich et al. [2018] attempt to address the endogeneity of benefits duration to local economic conditions by exploiting the difference between the contemporaneously measured state unemployment rate, on which benefits extensions are based, and the revised unemployment rate, which better reflects local economic conditions then. They conclude that duration increases had a limited impact on the unemployment rate. Similarly, Boone et al. [2021] find little effects of UI duration on aggregate employment. They rely on a border county pair strategy that leverages benefits duration differences between pairs of contiguous counties across state borders and also use an event-study approach that instruments state-level changes to the duration of unemployment benefits using nationwide changes. On the other hand, Hagedorn et al. [2013] emphasize the role of expectations and their impact on job creation: Using a similar border county pair strategy, they propose an estimator that takes the effect of job creators' expectations of future benefit duration into account. Their results suggest that unemployment benefits extensions during the recession have played an essential role in keeping the unemployment rate elevated and slowing down the recovery. Likewise, Johnston and Mas [2018] study the impact of an unanticipated UI duration cut in Missouri in April 2011 and show that this led to a significant increase in the vacancy-to-unemployment ratio as workers who became eligible for a shorter period of benefits increased their search effort.

Compared to this literature, my contribution is to analyse the potential impact of unemployment benefits extensions during the Great Recession on entrepreneurial activity, which has not been studied much before. The state-level analysis exploits the same IV strategy as in Boone et al. [2021], who use nationwide changes to UI duration to address the classical problem of endogeneity of unemployment benefits to local economic conditions. My results indicate that longer UI duration had a limited macroeconomic effect on self-employment activity taken as a whole, consistent with their findings on aggregate employment[2]. Using individual-level data, I also find that longer unemployment benefits were not associated with lower entry to self-employment, except for the lowest type of new self-employed who work less than 20 hours per week. My results are consistent with earlier evidence that suggests a limited role for extended UI on exits from unemployment to employment (Rothstein [2011], Farber and Valletta [2015], Farber et al. [2015]). However, I find that future changes to UI duration deter entry to self-employment for eligible workers about to lose their benefits.

Second, this chapter also contributes to a literature that addresses the role of downside insurance on entrepreneurial activity. Hombert et al. [2020] studies the

[2]Their use of QCEW data excludes the self-employed.

implementation of a 2002 French reform that guaranteed unemployed workers an income at least equivalent to the value of their unemployment benefits if they started a business. The PARE[3] reform led to an increase in the number of firms, and the authors find that entrepreneurial quality, measured by value added per worker, did not decrease following the policy. Similarly, Gottlieb et al. [2021] find that a policy increasing the duration of job-protected leave following maternity increased the number of self-employment spells. There are key differences with those papers: I look at the provision of better downside insurance following a nationwide increase in the duration of unemployment benefits that was not targeted towards the self-employed or prospective entrepreneurs, and that took place during a downturn.

Two papers related to this research are Gaillard and Kankanamge [2021] and Xu [2022], who study the effects of UI generosity on transitions from unemployment to self-employment. They find that increased generosity has been associated with lower entry to self-employment. In comparison, I find that unemployment benefits extensions during the Great Recession did not disincentivize entry to self-employment, except for the lowest type of self-employed who were more representative of necessity entrants. My work differs in that I exploit individual-level information on current unemployment duration to measure eligibility, while they rely on state-level differences in total UI generosity[4].

Section 2.2 describes changes to the unemployment insurance system during the recession and presents the data. Section 2.3 presents summary statistics for states with different increases in unemployment benefits and investigates the relationship between entrepreneurial activity and UI duration at the state level. Section 2.4 stud-

[3] *Plan d'aide au retour à l'emploi.*

[4] My analysis of the impact of unemployment benefits extensions will identify the effects of longer UI duration only on the sample of individuals who have exhausted their eligibility to regular benefits: This is a more relevant sample to look at because most unemployment spells end quickly in the United States.

ies the role of the extension of UI duration on transitions to self-employment using individual-level data. Section 2.5 concludes.

2.2 Context and data

2.2.1 Background on UI duration during the Great Recession

The role of unemployment insurance on aggregate employment as an automatic stabilizer has been studied extensively in the literature, even though, as emphasized earlier, it did not reach a definitive conclusion about its effect on aggregate employment. Before the Great Recession, eligible unemployed workers could claim up to 26 weeks of UI benefits while searching for a job, with slight variation across states[5].

In addition, job-seekers have been able to claim up to 20 additional weeks of unemployment insurance benefits during downturns since the introduction of the Extended Benefits (EB) program in 1970[6]. The EB program is on a cost-sharing basis between the federal and state governments. It has introduced a set of unemployment rate "triggers" states could choose from to activate the provision of additional benefits. During the Great Recession, it became a 100% federally funded program, which led to much wider adoption and availability across states.

Moreover, the significant impact of the Great Recession on the labour market also led to the introduction of a large nationwide extension of UI benefits, the Emergency Unemployment Compensation Program (EUC). Between July 2008 and December

[5]To be eligible, a claimant must have worked for a minimum period before being laid off and have earned a minimum amount of wages varying across states. In addition, the claimant must be actively searching for a new job. In two states, Massachusetts and Montana, claimants could receive up to 30 and 28 weeks of benefits, respectively.

[6]The Extended Unemployment Compensation Act of 1970 required states to provide up to 13 weeks of additional unemployment benefits when the state-level unemployment rate reaches a predetermined level. Besides, states could also opt to provide up to 7 additional weeks of benefits at a very high unemployment rate.

2013, several laws allowed UI claimants to be eligible for up to 53 additional weeks of benefits while unemployed. In particular, the Unemployment Compensation Extension Act (UECA) of November 2008 introduced state-level variation in the duration of federally-funded benefits because job seekers in states with a higher unemployment rate were eligible for more additional weeks[7]. Federal funding of unemployment benefits extensions ended on January 1, 2014. In total, unemployed workers could receive up to 99 weeks of unemployment benefits in the aftermath of the Great Recession. On average, between 2007 and 2010, figure 2.1 shows that workers were eligible for an average of 52 additional weeks of unemployment benefits. There is variation, however, as, in some states and months, workers could only claim regular benefits, while in others, they were eligible for up to 73 extra weeks.

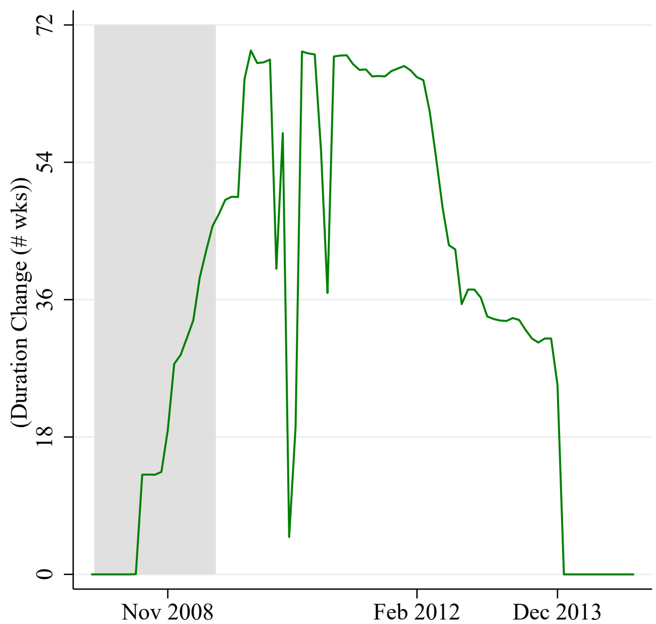
2.2.2 Data

The primary data source for my analysis comes from monthly data from the IPUMS version of the US Current Population Survey (CPS) between 2005 and 2014. A self-employed business owner is defined as someone who is employed and declares being self-employed in her primary job. I exclude armed forces members and restrict my analysis to civilian households in the labour force aged between 25 and 64 years old, not working in agricultural/extracting occupations and sectors.

The other data source comes from state-level data on the duration of unemployment benefits. Information about regular unemployment benefits workers were eligible for between 2005 and 2014 is obtained from the *Significant Provisions of State Unemployment Insurance Laws* from the Department of Labor's Employment and

[7]Between June and November 2008, the EUC program provided 13 additional weeks to all eligible unemployed. In November 2009, the Worker, Homeownership and Business Assistance Act (WHBA) expanded the EUC program by creating several tiers that provide additional weeks of benefits in states with a very high unemployment rate. From 2012 onward, the number of extra weeks available decreased as benefits were rolled back.

Figure 2.1: UI Duration changes : Nov 2007 - Dec 2014



Duration change: Average across states of EB and EUC weeks available in a given month. Source: *Significant Provisions of State Unemployment Insurance Laws*, *Extended Benefit Trigger Notice Reports*, *Emergency Unemployment Compensation Trigger Notice Reports* and author's calculations.

Training Administration (ETA), which contains bi-annual information on the duration of benefits. I also use the *Extended Benefit Trigger Notice Reports* between 2005 and 2014 and the *Emergency Unemployment Compensation Trigger Notice Reports* between 2008 and 2013 from the DOL's ETA to obtain weekly information on the number of weeks unemployed workers were eligible for under the extended state-level (EB) and federal benefits (EUC) programs introduced during the Great Recession.[8]

2.2.3 Mechanism

At first glance, the relationship between unemployment benefits duration and self-employment is unclear. While salaried workers would not be affected by the extension of unemployment benefits as they would not be eligible for UI if they failed[9], an increase in the duration of benefits can impact prospective entrepreneurs in two ways:

On the one hand, as entry into self-employment in downturns is driven by the unemployed who transition to self-employment in the absence of suitable paid jobs, a longer duration can *reduce* transitions to self-employment because workers can afford to continue looking for a better job after the exhaustion of regular benefits. If those additional benefits had not been available, many more unemployed workers would have started self-employment by necessity.

On the other hand, an extension to the duration of benefits might also give more time to prospective entrepreneurs among the unemployed to develop a business idea and enter self-employment successfully. This would instead *increase* the number of self-employment spells, consistent with Gottlieb et al. [2021], where the federal exten-

[8] I follow Isaacs [2012], Isaacs [2013] and Whittaker and Isaacs [2013] to construct state-level EUC duration and also rely on LAUS data from the Bureau of Labor Statistics to compute the number of regular weeks available in each state and month in states that, after 2012, make it contingent on the state unemployment rate.

[9] Payroll taxes fund UI. As a result, the unincorporated self-employed cannot have access to it, while the incorporated self-employed only can if they pay themselves wages and contribute to payroll taxes, subject to minimum work history requirements.

sion of maternity leave in Canada increased entrepreneurial activity among eligible women and with Hombert et al. [2020] in France. The micro-level evidence in section 2.4 tries to assess the relative importance of these two mechanisms.

2.3 Descriptive statistics and state-level analysis

2.3.1 Descriptive statistics

In the United States, the increase in the duration of benefits varied considerably across states and over time as the EUC program was suspended several times. In addition, from 2011 onward, several states started to reduce the duration of regular unemployment benefits[10], which automatically reduced the number of EUC weeks workers were eligible for.

To compare states with different increases in the duration of benefits during the Great Recession, I classify them into two categories: Those with a higher than the median increase in benefits duration between 2007 and early 2010 and those with a lower than median increase[11]. Table 2.1 shows that states with a below-median increase in benefits duration have a lower unemployment rate and a slightly higher self-employment rate ex-ante but do not otherwise differ in terms of industrial structure. This is important because the self-employment rate varies across industries due to different incentives to start self-employment in certain sectors, which could affect the evolution of the self-employment rate as both unemployment and the duration of benefits go up[12] during the recession. Among the hardest hit industries during

[10]These states are Arkansas, Missouri, South Carolina, Florida, Illinois (in 2012 only), Michigan, Georgia, North Carolina and Kansas.

[11]I choose to compare benefits duration between December 2007 and March 2010 as this latter date coincides with the maximum average benefits duration in the United States, before the several suspensions of the EUC program later that year.

[12]Hombert et al. [2020] rely on heterogeneity across industries in the propensity to become a sole

the 2008-09 downturn were manufacturing and construction (Goodman and Mance [2011]): However, the two groups of states are similar regarding employment shares in each sector before the recession. Similar comments apply to industries with a high self-employment rate, such as the entertainment, business and personal services industries, or with a low self-employment rate, such as the transportation, trade and utilities sectors: The industry employment share was similar across the two groups, and my results are unlikely to be driven by different industrial structures[13].

Table 2.1: Economic and industry characteristics across states

Economic and Industry Characteristics	All States	Higher Duration Increase	Lower Duration Increase
Average Duration Increase (wks)	67.39	73	57.64
	(9.15)	*(0)*	*(8.89)*
Pre-Recession Self-employment Rate	10.8	10.53	11.28
	(2.05)	*(2.13)*	*(1.81)*
Pre-Recession Unemployment Rate	4.78	5.05	4.3
	(1.03)	*(0.92)*	*(1.04)*
Pre-Recession % Emp: Construction	8.54	8.12	9.26
	(1.55)	*(1.45)*	*(1.46)*
Pre-Recession % Emp: Manufacturing	13.21	14.24	11.42
	(4.32)	*(4.03)*	*(4.22)*
Pre-Recession % Emp: Entertainment, Business and Personal Services*	11.75	11.67	11.89
	(2.45)	*(2.7)*	*(1.92)*
Pre-Recession % Transportation, Trade and Utilities**	25.29	25.14	25.54
	(1.9)	*(1.53)*	*(2.38)*
N	51	26	25

Pre-recession data: 2005:1-2007:10 averages. Higher (lower) duration increase: Difference in UI duration between 2007:11-2010:3 above (below) median. Self-employment and employment share: The sample of 25-64 y.o excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Industry Groups: Based on Census Bureau 1990 Industrial Classification System. Unemployment rate: Sample of 16+ civilians in the labour force. * Addition of Entertainment and Recreation Services, Business and Repair Services and Personal Services Industry Groups. ** Addition of Retail Trade, Wholesale Trade and Transportation, Communications and other Utilities Industry Groups. Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

2.3.2 State-level analysis

The previous section showed no real differences across the groups of states with different changes in benefits duration. I now investigate the relationship between higher

proprietor to evaluate the effects of the PARE reform.

[13]In table 2.A1, I show that the two groups of states are also similar in terms of workforce characteristics.

unemployment duration and the self-employment rate at the state level. My objective is to see how entrepreneurial activity evolves when the duration of UI benefits changes. To do so, I rely on two strategies: In my first specification, I exploit the full-time series dimension between 2007 and 2014 and control for economic conditions. My second strategy follows Boone et al. [2021]. It focuses on the impact of the extension and the termination of the Emergency Unemployment Compensation (EUC) program, which, as a nationwide policy change introduced in 2008 and terminated in 2013, provides variation across states in the duration of benefits exogenous to local economic conditions.

The nationwide expansion of the EUC program in November 2008 gave workers 13.7 extra weeks on average[14], while its termination in December 2013 led to an average decrease of 30.7 weeks, ranging from 14 to 47 weeks[15]. Addressing the endogeneity of benefits to local economic conditions is important because workers could have become eligible for additional benefits as a result of a rapid worsening of local economic conditions during the recession, which could affect the identification of the impact of benefits extensions on self-employment.

I estimate the following model:

$$S_{e\ s,t} = D_{s,t} + \gamma_s + \lambda_t + u_{s,t} + \epsilon_{st} \tag{2.1}$$

I control for state-invariant characteristics and time (year-month) fixed effects. My

[14] In states with a low unemployment rate, workers would benefit from 7 additional weeks. In states with an unemployment rate above 6%, workers could claim 20 extra weeks upon expiration of their regular benefits.

[15] North Carolina is excluded from the analysis as the federal government terminated its EUC program agreement with the state in July 2013. North Carolina refused to be bound by the non-reduction clauses of the Unemployment Extension Act of July 2010 that stipulates reductions in the number of EUC weeks available when a state reduces the number of regular weeks unemployed workers are eligible for.

first specification leverages the entire sample and tries to overcome the endogeneity problem of unemployment benefits duration by controlling for local economic conditions using a cubic polynomial of the state-level unemployment rate to control for automatic increases in the duration of UI as unemployment increases, as in Rothstein [2011]. Therefore, changes in $D_{s,t}$ capture the impact of the federal expansion, suspensions and termination of the EUC program, as well as state differences in EB triggers.

In my second strategy to address the endogeneity issue, I follow Boone et al. [2021] and implement their IV approach in a one-year window before and after nationwide policy changes: It instruments total changes in state-level benefits duration with variation induced by the introduction of additional weeks of unemployment benefits at the federal level in November 2008 (UECA) and the end of the program in December 2013. More precisely, the instrument will be equal to the duration of the state-level benefits one month before the policy change for all observations before the change and equal to the new duration induced by the expansion/termination of the EUC program alone for all observations after the change.

I report results in table 2.2. Looking at the first specification, column (1) shows that not accounting for the business cycle with year fixed effects leads me to overstate the negative impact of UI duration extensions on self-employment. Using the entire sample between November 2007 and December 2014, column (2) shows that a 10-week increase in benefits duration is associated with a less than 0.02 percentage point decline in self-employment, and coefficient estimates are not statistically different from zero. In other words, the coefficient estimate suggests that increasing the duration of UI by 73[16] weeks, the maximum observed during the recession, leads to a 0.12

[16] $D_{s,t}$ is scaled by ten so that it represents the impact of a 10-week increase in the duration of

Table 2.2: OLS/IV estimates: Effect of unemployment benefits duration on state-level self-employment rates

	Specification 1 : 2007:11-2014:12		Specification 2: IV - EUC	
	(1)	(2)	(1) - 2007:11-2009:10	(2) - 2013:1-2014:12
10 week Duration $D_{s,t}$	-0.0454**	-0.0172	-0.026	-0.0115
	(0.0151)	*(0.0402)*	*(0.189)*	*(0.139)*
First-stage F-statistic	/	/	52.198	573.77
State, Time FE	NO	YES	YES	YES
N	4386	4386	1224	1200

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Self-employment rate: The sample of 25-64 y.o excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Specification 2: One-year window before and after the EUC expansion of 2008:11 and termination of 2013:12. Column (2): North Carolina was excluded from the sample.

percentage point decrease in the self-employment rate, compared to a 1.4 percentage decrease in the self-employment rate between 2007 and 2014.

Turning to the event study approach, columns (1) and (2) respectively look at the impact of the extension of the EUC in November 2008 and its termination in December 2013 on entrepreneurial activity. Results are similar to the full sample analysis and suggest a limited role for unemployment benefits duration changes in explaining self-employment dynamics. All coefficients are close to zero and not statistically significant. These results suggest that the EB and EUC programs didn't markedly affect self-employment activity.

2.4 Micro-level evidence

To further support the state-level findings, I now look at monthly individual-level data to see whether the provision of extended benefits impacted the transitions of unemployed workers to self-employment. This allows me to evaluate the relative importance of the necessity entry hypothesis, according to which workers are *pushed*

benefits.

to self-employment when paid jobs are scarce, with the role of downside insurance favouring transitions to self-employment because workers have more time to develop their business idea. Compared to Rothstein [2011] and Farber and Valletta [2015] who look at the role of extended benefits on transitions out of unemployment (either to employment or out of the labour force), I also study the potential role of expectations of future benefits duration changes on the decision to start self-employment. I estimate the Probit specification below:

$$P_{i,s,t} = \beta_d \delta^e_{i,s,t} + \beta_e \Delta D_{s,t+1} + \beta_{de} \left(\delta^e_{i,s,t} \times \Delta D_{s,t+1}\right) + \alpha X_{i,s,t} + \tau_s + \tau_t + \epsilon_{ist} \qquad (2.2)$$

$\delta^e_{i,s,t}$ is an indicator equal to 1 if the unemployed worker is eligible for additional benefits, i.e. whenever she has exhausted her regular unemployment benefits, but additional benefits (EB or EUC) are available at the state level. As in the previous section, I control for local economic conditions using a cubic polynomial of the state unemployment rate. Variation in eligibility will thus come from the extension, suspensions and termination of the EUC program and across-state differences in EB triggers.

$\Delta D_{s,t+1}$ represents the change in the number of weeks available at the state level between time t and the following month $t+1$[17]. The interaction term between $\Delta D_{s,t+1}$ and $\delta^e_{i,s,t}$ accounts for the possibility that an unemployed worker continues searching for a paid job instead of entering self-employment if she expects UI duration to increase, which is a potentially important driver of entry for a worker who has almost exhausted all the benefits she was eligible for. The specification accounts for state and time (year-month) fixed effects, with τ_s and τ_t respectively. Controls $X_{i,s,t}$ include a

[17] It is, as in the previous section, scaled by 10.

quadratic in age, dummy variables for education, race and gender, and a cubic polynomial for the unemployment rate. In addition, I follow Farber and Valletta [2015] and account for individuals' unemployment spell length with indicator variables to control for the effect of regular benefits[18].

2.4.1 Baseline specification

I show results in table 2.3. Consistent with the state-level evidence, longer unemployment benefits are not associated with a change in entry to self-employment. Coefficient estimates for β_d are negative but not statistically different from zero, a result that is consistent across all specifications. Controlling for local economic conditions with the unemployment rate does not alter the results, nor does accounting for future increases in unemployment benefits duration.

Table 2.3: UI duration extension and transitions to self-employment

	(1)	(2)	(3)	(4)	(5)	(6)
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	-0.0353	-0.0346	-0.0393	-0.0387		
	0.0328	*0.0326*	*0.0332*	*0.0330*		
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible			0.0033	0.0030		
			(0.0189)	*(0.0190)*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					-0.0413	-0.0412
					(0.0913)	*(0.0915)*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					-0.0390	-0.0384
					(0.0351)	*(0.0349)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, Last Month					-0.0754***	-0.0770***
					(0.0269)	*(0.0272)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					0.0075	0.0073
					(0.0194)	*(0.0195)*
$\Delta D_{s,t+1}$: Future Benefits Change			0.0207	0.0222	0.0209	0.0225
			(0.0221)	*(0.0225)*	*(0.0220)*	*(0.0224)*
Marginal Effect : Eligibility $\delta^e_{i,s,t} = 1$ (%)	**-8.2293**	**-8.0811**	**-9.1257**	**-8.9875**	**-9.5781/-9.0636**	**-9.5570/-8.9183**
Marginal Effect : 10-wk future increase $\Delta D_{s,t+1}$ (%)			**6.0308**	**6.3572**	**-12.6254/7.1861**	**-12.6237/7.5241**
Unemployment Controls	NO	YES	NO	YES	NO	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	168020	168020	166877	166877	166877	166877

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. **Columns (5) and (6) : (a)/(b) for marginal effects apply to those in their last month of UI eligibility (a) and those in another month (b)**. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report having been laid off as cause of unemployment. Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

[18] I use monthly indicator variables for individuals' unemployment duration up to 6 months and then use an indicator variable for individuals' unemployment duration for $]6,9]$, $]9,12]$, and $]12,28]$ months.

In columns (3) and (4), I also look at the effect of expectations of future UI duration changes. I do so to see whether unemployed workers who planned to enter self-employment by necessity became more reluctant to do so if they believed they would be eligible for unemployment benefits for longer. Coefficient estimates for β_{de} are close to zero and not statistically significant, suggesting that future benefits changes do not matter in the decision to leave unemployment for self-employment. In columns (5) to (6), I distinguish between eligible workers depending on whether they will exhaust their eligibility for UI in the following month. I find that while coefficient estimates for eligibility β_d do not change, there are now anticipation effects, but only for workers who are about to lose eligibility for unemployment benefits. For those workers, a 10-week future increase in the duration of unemployment benefits is associated with a 12.6% lower probability of entering self-employment (columns (5)-a and (6)-a).

2.4.2 Heterogeneity among entrants

The relationship between the provision of downside insurance and the decision to start a business could also depend on the objective of the self-employment spell. To distinguish between the necessity entry and the risk motives, I separate new entrants to self-employment into two groups: Those who report working at least 20 hours per week when self-employed and those who report working less than 20 hours. I expect the provision of downside insurance to act as a stronger deterrent for the second group, which is more representative of the necessity self-employed than the first group.

Tables 2.4 and 2.5 report the results, respectively, for the new self-employed working more than 20 hours and the self-employed working less than 20 hours. Table 2.4 shows coefficient estimates for β_d that remain statistically not different from zero.

These results are consistent with the idea that unemployment benefits extensions will not change these individuals' decision to start self-employment because they are more committed to creating a business. Besides, providing downside insurance for that subgroup could even help to start self-employment as it allows more time to start a business. On the other hand, table 2.5 shows that being eligible for extended UI during the recession is associated with a significantly lower exit from unemployment to self-employment, as expected for entrants by necessity. The marginal effect of eligibility for extended benefits for this group working less than 20 hours per week shows that it is associated with a 30% lower probability of starting self-employment on average (columns (1) to (4), (5)-b, (6)-b)[19].

Table 2.4: UI duration extension and transitions to self-employment (work more than 20 hours per week)

	(1)	(2)	(3)	(4)	(5)	(6)
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	0.0245	0.0257	0.0212	0.0223		
	(0.0443)	*(0.0446)*	*(0.0439)*	*(0.0443)*		
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible			0.0095	0.0095		
			(0.0200)	*(0.0201)*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					0.0649	0.0651
					(0.1131)	*(0.1135)*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					0.0187	0.0198
					(0.0470)	*(0.0473)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, Last Month					-0.0463*	-0.0476*
					(0.0252)	*(0.0254)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					0.0126	0.0125
					(0.0203)	*(0.0203)*
$\Delta D_{s,t+1}$: Future Benefits Change			-0.0037	-0.0025	-0.0035	-0.0022
			(0.0274)	*(0.0279)*	*(0.0272)*	*(0.0277)*
Marginal Effect : Eligibility $\delta^e_{i,s,t} = 1$ (%)	**6.3826**	**6.6981**	**5.5043**	**5.7906**	**17.6398/4.8226**	**17.7112/5.1245**
Marginal Effect : 10-wk future increase $\Delta D_{s,t+1}$ (%)			**1.4714**	**1.7708**	**-11.6914/2.3172**	**-11.6945/2.6285**
Unemployment Controls	NO	YES	NO	YES	NO	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	168020	168020	166877	166877	166877	166877

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. **Columns (5) and (6) : (a)/(b) for marginal effects apply to those in their last month of UI eligibility (a) and those in another month (b)**. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report having been laid off as cause of unemployment. Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

The anticipation effects of a change in the duration of future benefits $\Delta D_{s,t+1}$ remain present for individuals who are about to lose their eligibility in the following

[19]Regarding the marginal effect of eligibility on those in their last month, it is large (-53%) but imprecisely estimated as β_d is not statistically significant.

Table 2.5: UI duration extension and transitions to self-employment (work less than 20 hours per week)

	(1)	(2)	(3)	(4)	(5)	(6)
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	-0.1318*	-0.1318*	-0.1354*	-0.1352*		
	(0.0711)	*(0.0710)*	*(0.0720)*	*(0.0719)*		
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible			-0.0106	-0.0110		
			(0.0278)	*(0.0278)*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					-0.2597	-0.2596
					(0.1871)	*(0.1873)*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					-0.1298*	-0.1296*
					(0.0689)	*(0.0688)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, Last Month					-0.1304**	-0.1316**
					(0.0559)	*(0.0560)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					-0.0051	-0.0055
					(0.0291)	*(0.0291)*
$\Delta D_{s,t+1}$: Future Benefits Change			0.0665*	0.0677*	0.0666*	0.0679*
			(0.0370)	*(0.0370)*	*(0.0369)*	*(0.0368)*
Marginal Effect : Eligibility $\delta^e_{i,s,t} = 1$ (%)	**-31.271**	**-31.2691**	**-31.9575**	**-31.9302**	**-53.1675/-30.8542**	**-53.1509/-30.8246**
Marginal Effect : 10-wk future increase $\Delta D_{s,t+1}$ (%)			**17.3752**	**17.6695**	**-17.689/19.2407**	**-17.6616/19.5503**
Unemployment Controls	NO	YES	NO	YES	NO	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	168020	168020	166877	166877	166877	166877

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. **Columns (5) and (6) : (a)/(b) for marginal effects apply to those in their last month of UI eligibility (a) and those in another month (b)**. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report having been laid off as cause of unemployment. Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

month, for both subgroups of newly self-employed. Moreover, these anticipation effects are more powerful for those starting self-employment and working less than 20 hours per week, which is consistent with entry by necessity: Table 2.5 shows that a 10-week future increase in UI duration is associated in with a 17.7% lower probability of entry for this group (columns (5)-a and (6)-a) compared to an 11.7% lower probability of entry for those who work more than 20 hours in their self-employment activity (table 2.4 columns (5)-a and (6)-a).

However, there is a possibility that individuals continue claiming UI benefits while self-employed, potentially leading to an underestimation of transitions out of unemployment and affecting my results. While unobservable, it is more likely to matter for claimants entering self-employment by necessity and less likely to be an issue for most individuals entering self-employment and working more than 20 hours/week, who are more committed.

In summary, eligibility for extended benefits during the Great Recession was not associated with lower entry to self-employment, except for low-type entrants who are more likely to start subsistence businesses. The deterrent effect was absent for those who committed more to their self-employment spell. These results strengthen the aggregate analysis from the previous section and show that extending unemployment insurance did not notably affect entry to self-employment, except for future benefit exhaustees.

2.4.3 Heterogeneity along the business cycle

I now investigate heterogeneous effects along the business cycle. If unemployed individuals enter self-employment by necessity, the impact of providing downside insurance could vary depending on the scarcity of salaried jobs.

I re-estimate equation 2.2 by splitting the sample into two periods: 2007:11-2011:12 and 2012:1-2014:12. The second period corresponds to the (slow) recovery of the US economy as the unemployment rate goes down and the number of weeks available through the EB and EUC programs falls progressively. The provision of UI may have a stronger impact on entry to self-employment during downturns when paid jobs are scarcer. Table 2.6 shows results for the two sub-samples. There are no differences between the two sub-periods: Coefficient estimates for β_d are similar across the two sub-periods, close to estimates of table 2.3 and not statistically different from zero.

2.4.4 UI-ineligible unemployed

I re-estimate equation 2.2 for the sample of workers who reported another reason than layoff as the cause of unemployment, i.e. they voluntarily left their job or just entered the labour force. Rothstein [2011] and Farber and Valletta [2015] use the sample of

Table 2.6: UI duration extension and transitions to self-employment along the business cycle

	(1)		(2)		(3)	
	2007:11-2011:12	2012:1-2014:12	2007:11-2011:12	2012:1-2014:12	2007:11-2011:12	2012:1-2014:12
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	-0.0489	-0.0277	-0.0480	-0.0242		
	(0.0544)	*(0.0610)*	*(0.0542)*	*(0.0655)*		
$\Delta D_{s,t} \times \delta^e_{i,s,t}$: For Eligible			0.0009	0.0559		
			(0.0204)	*(0.0535)*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					-0.2684	0.1540
					(0.2072)	*(0.1803)*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					-0.0391	-0.0457
					(0.0530)	*(0.0660)*
$\Delta D_{s,t} \times \delta^e_{i,s,t}$: For Eligible, Last Month					-0.0453	-0.0191
					(0.0333)	*(0.0842)*
$\Delta D_{s,t} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					(0.0043)	(0.0927)
					0.0206	*0.0758*
$\Delta D_{s,t}$: Future Benefits Change			0.0335	-0.0182	0.0332	-0.0209
			(0.0281)	*(0.0562)*	*(0.0280)*	*(0.0568)*
Unemployment Controls	YES	YES	YES	YES	YES	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	110596	57424	110596	56281	110596	56281

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report having been laid off as cause of unemployment. Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

UI-ineligible workers as a test to control for economic conditions: This sample is not entitled to unemployment benefits, so duration changes should not affect their decision to leave unemployment for self-employment. This is what table 2.7 below shows. Coefficient estimates for β_d remain statistically insignificant. Interestingly, columns (5) and (6) show estimates for β_{de} that are also indistinguishable from zero. Therefore, a change in the future duration of unemployment benefits in the following month does not affect the decision of UI-ineligible unemployed workers to enter self-employment, unlike UI-eligible workers about to lose their eligibility for unemployment benefits.

This is not surprising because this group was not eligible for unemployment benefits. In Appendix 2.B, table 2.B4 also shows that the effect of extended UI on the newly self-employed working less than 20 hours per week is indistinguishable from zero if they were not eligible for UI, in contrast with table 2.5 of section 2.4.2 where UI-eligible workers were 30% less likely to transition to self-employment.

Table 2.7: UI duration extension and transitions to self-employment - UI-ineligible unemployed

	(1)	(2)	(3)	(4)	(5)	(6)
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	0.0204	0.0210	0.0342	0.0347		
	(0.0370)	*(0.0366)*	*(0.0369)*	*(0.0365)*		
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible			-0.0002	-0.0003		
			(0.0192)	*(0.0192)*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					-0.1063	-0.1067
					(0.1530)	*(0.1533)*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					0.0410	0.0416
					(0.0370)	*(0.0366)*
$\Delta D_{s,t} \times \delta^e_{i,s,t}$: For Eligible, Last Month					0.0829	0.0825
					(0.0551)	*(0.0553)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					-0.0028	-0.0029
					(0.0199)	*(0.0199)*
$\Delta D_{s,t+1}$: Future Benefits Change			0.0298	0.0304	0.0299	0.0305
			(0.0327)	*(0.0334)*	*(0.0328)*	*(0.0335)*
Unemployment Controls	NO	YES	NO	YES	NO	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	125327	125327	124176	124176	124176	124176

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report not having been laid off as cause of unemployment. Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

2.5 Conclusion

In this chapter, I studied the consequences of changes to the duration of unemployment benefits during and after the Great Recession on self-employment activity. At the state level, heterogeneity in UI duration was not associated with different self-employment dynamics between 2007 and 2014. At the individual level, I found that eligibility for extended unemployment benefits was, on average, not associated with a different probability of entering self-employment. However, I uncovered anticipation effects: workers who would lose their unemployment benefits in the following month were less likely to enter self-employment if they expected a future increase in benefits duration that would enable them to remain eligible. Besides, a closer distinction between the newly self-employed according to the effort they put into their business strengthens the necessity entry hypothesis. The provision of extended benefits was associated with a 30% reduction in the probability of entering self-employment for those who commit less than 20 hours to their self-employment spell.

Two avenues seem fruitful for future research: First, monthly data from the CPS allows tracking individuals for only up to 16 months following their first interview. While there is evidence that businesses created by the unemployed tend to perform worse, it would be interesting to follow the performance of companies created by unemployed workers who benefited from extended benefits during recessions. Looking at their performance in terms of value-added, jobs created, and labour productivity would help evaluate the persistence of the effects of UI extensions in the medium term. Second, it would be interesting to study further the aggregate and welfare implications of a more generous UI system for the self-employed.

Appendix

2.A Appendix A

2.A.1 Additional information on workforce characteristics across the two groups of states

Table 2.A1: Workforce characteristics across states

Workforce Characteristics	All States	Higher Duration Increase	Lower Duration Increase
% White	69.23	69.44	68.86
	(14.37)	*(13.69)*	*(15.48)*
% College Graduates	33.55	33.62	33.43
	(5.01)	*(4.59)*	*(5.67)*
% Homeowners	72.38	71.31	74.24
	(6.52)	*(7.51)*	*(3.62)*
Annual Income : 2005-2007	37655	38021	37020
	(4253.42)	*(4447.65)*	*(3814.29)*
N	51	26	25

Pre-recession data: 2005:1-2007:10 averages. Higher (lower) duration increase: Difference in UI duration between 2007:11-2010:3 above (below) median. Self-employment and employment share: The sample of 25-64 y.o excludes members of the armed forces and individuals working in agricultural or mining sectors/occupations. Earnings in constant 1999 US Dollars. Source: CPS Basic Monthly Files, CPS ASEC, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

Table 2.A1 presents additional information on labour force characteristics across the two groups of states with different changes in unemployment benefits duration. It complements table 2.1 and shows no differences in worker characteristics across the two groups of states.

2.B Appendix B

2.B.1 Additional evidence along the business cycle

Tables 2.B1 and 2.B2 investigate the potential heterogeneous effects of longer UI duration along the business cycle on two groups of entrants: Those who report working more than 20 hours per week on their business, and those who report less. Table 2.B1 confirms the results of table 2.4: Eligibility to extended UI was not associated with a different probability to enter for those who commit at least twenty hours per week, regardless of the period considered.

On the other hand, table 2.B2 shows that longer UI is associated with less entry for workers who commit less than 20 hours per week as self-employed only during the recession period when jobs were harder to find. Coefficient estimates β_d for the 2012-2014 period are weaker and no longer statistically significant.

Table 2.B1: UI duration extension and transitions to self-employment along the business cycle (work more than 20 hours per week)

	(1)		(2)		(3)	
	2007:11-2011:12	2012:1-2014:12	2007:11-2011:12	2012:1-2014:12	2007:11-2011:12	2012:1-2014:12
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	0.0156	0.0039	0.0164	0.0145		
	(0.0544)	*(0.1055)*	*(0.0542)*	*(0.1092)*		
$\Delta D_{s,t+1}$: Future Benefits Change			0.0046	0.0882		
			(0.0210)	*(0.0775)*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					-0.1782	0.2950
					(0.1793)	*(0.2075)*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					0.0246	-0.0245
					(0.0553)	*(0.1036)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, Last Month					-0.0449*	0.1087
					(0.0254)	*(0.0889)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					0.0080	0.0927
					(0.0211)	*(0.0901)*
$\Delta D_{s,t+1}$: Future Benefits Change			0.0144	-0.0591	0.0142	-0.0592
			(0.0345)	*(0.0671)*	*(0.0344)*	*(0.0666)*
Unemployment Controls	YES	YES	YES	YES	YES	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	110596	57424	110596	56281	110596	56281

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report having been laid off as cause of unemployment. Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

Table 2.B2: UI duration extension and transitions to self-employment along the business cycle (work less than 20 hours per week)

	(1)		(2)		(3)	
	2007:11-2011:12	2012:1-2014:12	2007:11-2011:12	2012:1-2014:12	2007:11-2011:12	2012:1-2014:12
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	-0.1407*	-0.0878	-0.1396*	-0.0970		
	0.0769	*0.1010*	*0.0770*	*0.1046*		
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible			-0.0072	-0.0230		
			0.0303	*0.0793*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					-0.3723	-0.2427
					0.2888	*0.3116*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					-0.1314*	-0.0845
					0.0747	*0.1042*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, Last Month					-0.0395	-0.2366**
					0.0612	*0.1113*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					-0.0046	0.0572
					0.0309	*0.1106*
$\Delta D_{s,t+1}$: Future Benefits Change			0.0622	0.1036	0.0618	0.0969
			0.0392	*0.0815*	*0.0391*	*0.0804*
Unemployment Controls	YES	YES	YES	YES	YES	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	110596	56217	110596	55100	110596	55100

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report having been laid off as cause of unemployment. Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

2.B.2 Additional evidence among the UI-ineligible group

In tables 2.B3 and 2.B4, I re-estimate equation 2.2 for UI-ineligible workers and look at the two groups of entrants, depending on the number of hours they put in their self-employment spell. Table 2.B3 confirms my findings in table 2.7 for entrants working more than 20 hours per week, i.e. no effect of eligibility to extended UI and no effect of future duration increases. Table 2.B4 shows that when looking at UI-ineligible workers, the results of table 2.5 disappear. Coefficient estimates for β_d and β_{de} are no longer statistically significant. Eligibility to extended benefits and anticipation effects of future duration changes no longer matter in their decision to enter self-employment, which was expected because they were not eligible for unemployment benefits.

Table 2.B3: UI duration extension and transitions to self-employment (work more than 20 hours per week) - UI-ineligible unemployed

	(1)	(2)	(3)	(4)	(5)	(6)
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	0.0092	0.0106	0.0153	0.0168		
	(0.0417)	*(0.0416)*	*(0.0437)*	*(0.0437)*		
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible			-0.0216	-0.0217		
			(0.0243)	*(0.0244)*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					-0.4214*	-0.4232*
					(0.2371)	*(0.2371)*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					0.0320	0.0336
					(0.0444)	*(0.0443)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, Last Month					-0.0021	-0.0021
					(0.0216)	*(0.0217)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					-0.0209	-0.0209
					(0.0246)	*(0.0247)*
$\Delta D_{s,t+1}$: Future Benefits Change			0.0247	0.0251	0.0247	0.0251
			(0.0352)	*(0.0360)*	*(0.0354)*	*(0.0363)*
Unemployment Controls	NO	YES	NO	YES	NO	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	125327	125327	124176	124176	124176	124176

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report not having been laid off as cause of unemployment. Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

Table 2.B4: UI duration extension and transitions to self-employment (work less than 20 hours per week) - UI-ineligible unemployed

	(1)	(2)	(3)	(4)	(5)	(6)
$\delta^e_{i,s,t}$: Eligible to Longer Benefits	0.0304	0.0291	0.0496	0.0482		
	(0.0555)	*(0.0557)*	*(0.0548)*	*(0.0550)*		
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible			0.0376	0.0376		
			(0.0285)	*(0.0284)*		
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, Last Month					0.1105	0.1130
					(0.1670)	*(0.1674)*
$\delta^e_{i,s,t}$: Eligible to Longer Benefits, $\neq$ Last Month					0.0435	0.0418
					(0.0589)	*(0.0592)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, Last Month					0.1011	0.1000
					(0.0651)	*(0.0649)*
$\Delta D_{s,t+1} \times \delta^e_{i,s,t}$: For Eligible, $\neq$ Last Month					0.0316	0.0316
					(0.0286)	*(0.0285)*
$\Delta D_{s,t+1}$: Future Benefits Change			0.0306	0.0319	0.0305	0.0319
			(0.0380)	*(0.0381)*	*(0.0379)*	*(0.0380)*
Unemployment Controls	NO	YES	NO	YES	NO	YES
Individual Characteristics Controls	YES	YES	YES	YES	YES	YES
State, Time (Year-Month) FE	YES	YES	YES	YES	YES	YES
N	125327	125327	124176	124176	124176	124176

Clustered by state standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample of 25-64 year unemployed civilians not working/worked in agricultural and mining sectors/occupations, and who report not having been laid off as cause of unemployment.Individual controls include a quadratic in age, education, race and gender dummies, and indicator variables for unemployment duration. Unemployment controls: Cubic polynomial in the state unemployment rate (3-months trailing MA). Source: CPS Basic Monthly Files, DOL ETA (EB and EUC Trigger Reports, State Insurance Laws) and author's calculations.

Chapter 3

Housing wealth and business creation

3.1 Introduction

Providing access to finance to small and young businesses has been a constant pre-occupation of policymakers in developed and developing countries. This has been motivated by young firms' reliance on their owners' net worth (Robb and Robinson [2012]), but also by empirical evidence stressing the positive impact of better access to finance on growth (Rajan and Zingales [1998]). The housing boom and bust episode in the United States in the early 2000s has led to unprecedented changes in households' balance sheets: Between 2001 and 2007, home equity extraction quadrupled (Aladangady and O'Flaherty [2020]), fuelling an increase in consumer spending and employment. Similarly, it has been argued that the severity and long-lasting impact of the Great Recession could be attributed to household deleveraging following the house price crash (Mian et al. [2013]), hampering the recovery in aggregate demand and employment.

This paper studies the impact of changes in housing wealth on new firm creation between 2002 and 2014. It proposes a new instrumental variable strategy for house price growth that exploits cross-sectional variation in mortgage debt-to-income ratios (DTI)[1] as a proxy for households' borrowing constraints. While metropolitan areas with a high DTI were similar in industrial structure and economic conditions to other cities, the city-level share of households with a high DTI mortgage before the housing boom is a strong predictor of subsequent house price changes. I find that more startups are created in cities experiencing faster home appreciation, although the effect is modest. My IV estimates suggest that a 1% annual increase in house prices at the city level leads to a 0.02 percentage points increase in the startup rate. I also find quantitatively similar estimates using another instrument, proposed by Guren et al. [2020] and which exploits cities' different sensitivities to regional house price cycles[2]. Furthermore, investing the relationship between house price changes and startup formation at the city-industry level allows me to disentangle the impact of house prices on new firm creation resulting from two different channels: (i) changes in households' collateral constraints and (ii) housing wealth effects increasing consumer demand. While the impact of house price growth is stronger in the construction and non-tradeable sectors, estimates from tradeable industries show that higher collateral values tend to matter more than wealth effects: Roughly $\frac{2}{3}$ of the effect of house price growth on new firm formation can be attributed to the collateral channel.

Relation to the literature. This paper is related to an extensive literature that studies the role of housing wealth and access to credit on entrepreneurial activity. Hurst and Lusardi [2004] leveraged survey-level data from the Panel Study of Income

[1]Debt-to-income is also known as payment-to-income. DTI corresponds to the ratio between monthly payment obligations and total income.

[2]Their paper studies variation in the housing wealth elasticity over time.

Dynamics (PSID) to show that household wealth was not related to the propensity to start a business, except at the top end of the distribution, hinting at a limited role for credit constraints. This result contrasts with recent findings from Herkenhoff et al. [2021], who combine administrative and credit agency data to document that employer firm ownership and self-employment activity increase with credit limits and show that entry to entrepreneurship increases following bankruptcy flag removals. Similarly, Siemer [2019] exploits industry-level variation in external financial dependence and shows that financial constraints reduced employment growth in small and young firms relative to large firms during the Great Recession. As housing accounts for a large percentage of the total wealth of households in the United States, the effects of house price changes on firms' decisions have also been studied. Adelino et al. [2015] look at the role of the collateral lending channel and show that increased access to home equity between 2002 and 2007 led to higher employment growth in small establishments compared to large establishments. Davis and Haltiwanger [2021] find that house price changes and local banks' supply shocks can explain a large share of the variation of young firms' employment, and Mehrotra and Sergeyev [2021] show that the impact of falling house prices during the Great Recession on job creation and destruction was more substantial for young firms. Regarding investment, Chaney et al. [2012] show that increases in the value of real estate owned by US public firms between 1993 and 2007 led to higher corporate investment[3].

Compared to this existing work that looked at the intensive margin of firms' decisions, I focus on the extensive margin and try to evaluate the role of house prices and collateral wealth on new firm[4] formation between 2002 and 2014. I also compare

[3]Bahaj et al. [2020] in the UK find similar results when looking at the housing wealth of firms' directors.

[4]The distinction between firms and establishments is important because existing firms create up to 40% of new establishments.

my findings with the impact of house price changes on existing firms' decisions to expand their activity through new establishments to evaluate the importance of the collateral channel[5].

Second, this paper is also related to a literature that looks at the importance of weakening credit standards in explaining the surge and subsequent collapse of real estate prices of the early 2000s. Mian and Sufi [2009] and Mian and Sufi [2021] argue that the mortgage default crisis in 2007-9 was fuelled by a credit supply shift targeting previously underserved segments of the population, low-income subprime borrowers, and that housing markets which were more exposed to the private label mortgage market saw a larger variation in mortgage origination and home values during the boom-bust episodes. Consistent with this idea, Justiniano et al. [2022] document a surge in private-label mortgages securitization, a decoupling of mortgage rates compared to Treasury yields that is interpreted as an easing of credit conditions after 2003, as well as an increase in the number of mortgage brokers despite the end of the refinancing boom in 2003. Cox and Ludvigson [2021] confirm that mortgage lending standards are an important driver of house price changes, using survey responses from households and loan officers. Moreover, Greenwald [2018] emphasized that loosening debt-to-income ratio standards were critical for understanding the housing boom and bust episodes: As DTI limits eased at the turn of the millennium, borrowing limits were relaxed because additional housing collateral could be used, increasing the demand for housing and house prices. In comparison, I exploit geographic variation in debt-to-income ratios among originated mortgages as a proxy for households' borrowing constraints and use the CBSA-level share of high DTI mortgages before the surge

[5]My paper is related to Schmalz et al. [2017] who also find, in France, that higher regional house price growth in the 1990s acts as an incentive for homeowners to start an entrepreneurial activity, and to Fairlie and Krashinsky [2012] who find a large effect of housing appreciation on transitions to self-employment between 1994 and 2004 in the United States. By contrast, I focus on employer firms during the housing boom and bust.

in real estate prices as an instrument for house price changes. High DTI cities experienced disproportionately higher house price growth and a much more substantial decline in house prices after the housing market's collapse.

Section 3.2 presents the data and motivates the analysis. Section 3.3 details the instrumental variable's construction and shows its relationship with house price changes. Section 3.4 presents estimates of the impact of house price growth on new firm creation. Section 3.5 concludes.

3.2 Data and motivation

3.2.1 Data

In this paper, I exploit city-level variation in house price growth to study its impact on new firm formation. I use the Office of Management and Budget's (OMB) 2013 delineation of Core Based Statistical Areas (CBSA) as my definition of cities[6]. This leaves me with 381 metropolitan CBSAs. The primary data source for my analysis comes from the Business Dynamics Statistics (BDS) database of the US Census Bureau. The BDS is an annual dataset that provides information about the creation and destruction of firms, establishments and jobs. My variable of interest is the startup rate, which represents the number of new firms (age 0) created in a given area in year t normalized by the total number of firms in that area.

The second important data source for the analysis comes from origination files of the Single Family Loan Performance Data and the Single Family Loan-Level Dataset files from Fannie Mae and Freddie Mac, respectively. These files have contained, since 1999, borrower and loan-level financial information about the universe of originated

[6] I use the terms city, CBSA and metropolitan area interchangeably. I also choose the 2013 delineation of cities because the Census Bureau uses it in the BDS dataset.

mortgages that the two Government-sponsored Enterprises securitized. In particular, I use individual-level information about debt-to-income ratios in section 3.3 to construct a CBSA-level measure of borrowing constraints.

I augment these two datasets with other sources. Annual house prices data at the city level comes from the Federal Housing Finance Agency (FHFA), which I rely on to construct real house prices using the GDP Implicit Price Deflator from the Bureau of Economic Analysis (BEA). I also leverage information from the Survey of Consumer Finances (SCF), a triennial survey of US households with detailed information about their balance sheets. I use the SCF below to document a relatively more important deterioration of credit constraints for entrepreneurs relative to the rest of the population during the housing bust. Finally, annual data on local economic controls comes from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS) for the unemployment rate, the BEA Regional Economic Accounts for real GDP per capita and population growth, and the Quarterly Census of Employment and Wages (QCEW) for city-level industry employment shares.

3.2.2 Startups and credit conditions along the business cycle

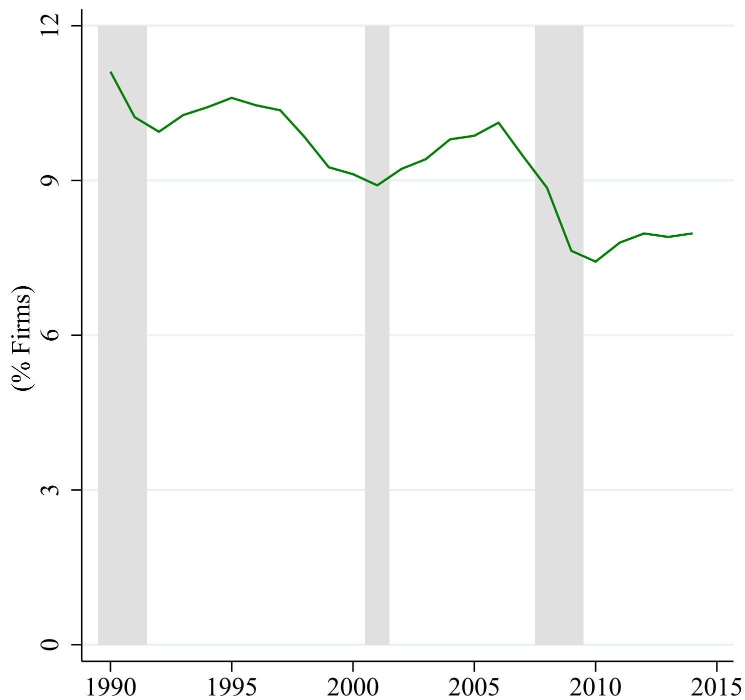
My objective in this paper is to quantify the impact of changes to housing wealth during the housing boom and bust on the creation of new firms. Figure 3.1 shows the evolution of the startup rate between 1990 and 2014, which has been trending down throughout the period[7].

While the startup rate has fallen by 30% since the early 1990s, it falls by more during downturns: It went down by 15% between 2007 and 2010 and also fell during the 1990 recession[8]. The startup rate also increased during the early 2000s as property

[7]The secular decline in business dynamism of the US economy during several decades has long been documented, see Haltiwanger et al. [2012], Decker et al. [2014].

[8]Similar comments apply to another measure of business creation, the establishment entry rate.

Figure 3.1: Firm entry - Startup rate in the BDS (1990-2014)



Startup rate: Ratio between the number of age 0 firms (entrants) and the total number of firms. Source: Business Dynamics Statistics and author's calculations.

prices rose.

I also present descriptive evidence from the Survey of Consumer Finances about borrowing constraints that entrepreneurs face and document a relatively stronger tightening of credit conditions for them relative to the rest of the population during the recession. In the SCF, my sample of entrepreneurs comprises household heads who declare being self-employed business owners and managing their business[9]. The survey gives information about respondents' past applications for credit. In particular, it asks them whether they have applied for credit and been denied or obtained less than requested in the past five years or if they did not apply for credit because they thought they would be turned down. I use positive answers to any of those questions to measure credit constraints.

Figure 3.2 shows the time series of the share of credit-constrained households using this measure. Individuals who started their business less than five years ago ("Young Entrepreneurs" in figure 3.2) were generally more likely to experience credit constraints in the preceding five years than other households and other entrepreneurs[10]. The share of entrepreneurs or "young entrepreneurs" reporting being credit constrained went up by almost 40% between 2007 and 2010, hinting at a disproportionate impact of the financial crisis for this group, while it was trending down in the early 2000s. A potential explanation comes from young firm owners' reliance on their wealth to fund and develop their businesses. In addition, a significant share of households' wealth resides in their housing[11], so the housing cycle of the early 2000s could explain the evolution of credit conditions for young firm owners in figure 3.2.

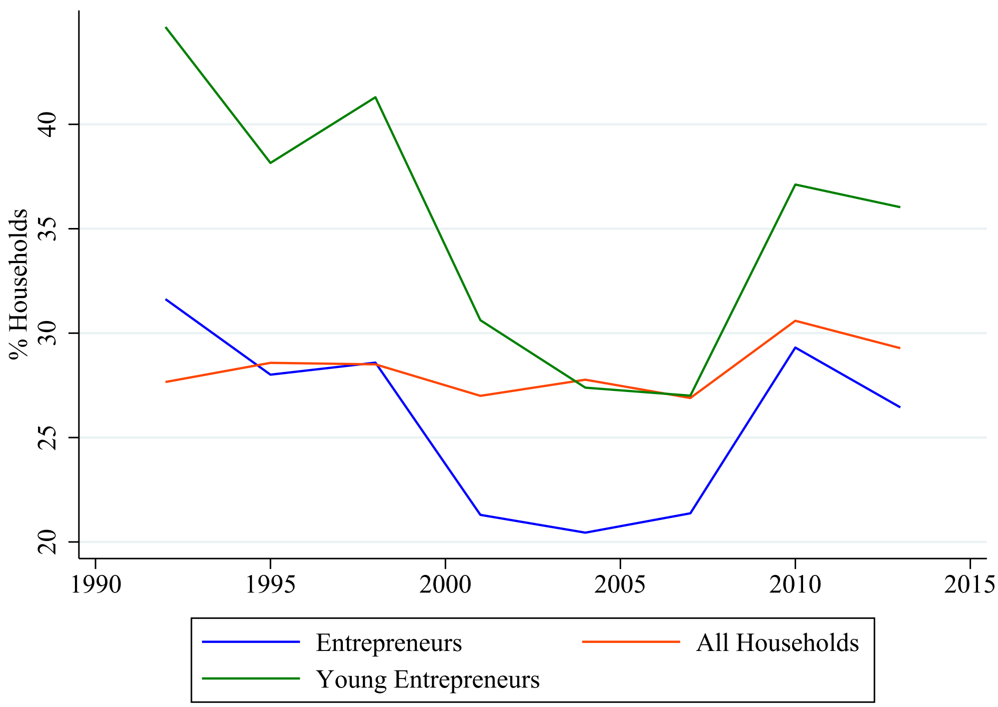
See Appendix 3.A.1

[9] I follow De Nardi et al. [2007] who define entrepreneurs as self-employed business owners managing their businesses.

[10] Entrepreneurs, including those who started a business recently, tend to earn more than other households. See Appendix 3.A.2

[11] *ibid.*

Figure 3.2: Credit-constrained households in the Survey of Consumer Finances (1992-2013)



Credit-constrained: Respondent answered yes to a question asking about being denied credit or not obtaining as much as requested (X407), or not applying because of fear of being turned down (X409) during the last five years. Source: Survey of Consumer Finances.

3.3 Debt-to-income ratios, borrowing constraints and house prices

I now evaluate this possibility and construct an instrument for house prices that relies on city-level exposure to the surge and collapse of real estate prices during the 2000s and early 2010s by exploiting cross-sectional variation in the debt-to-income ratio (DTI) for originated mortgages.

3.3.1 Instrument mechanism

The DTI has been used in the literature as a measure of borrowing constraints: Johnson and Li [2010] document that households with a high DTI are up to 50% more likely[12] to report having been turned down for credit and that their consumption is much more sensitive to lagged income than other households. Likewise, Cooper [2013] shows that high DTI households with low liquid wealth display consumption patterns that are more sensitive to their housing wealth, consistent with its use as collateral. Besides, to further support the use of high debt-to-income ratios as a measure of credit constraints, I also use data from the Home Mortgage Disclosure Act (HMDA), which contains information about all mortgage applications in the United States, whether approved or not. Table 3.1 shows that the high debt-to-income ratio is the second most reported reason for mortgage denial, with 15% of mortgage applicants denied credit because of it.

For all those reasons, the instrument for house prices I use is based on the pre-existing share, at the city level for all 381 metropolitan CBSAs in the years 1999-2001, of home purchase mortgages originated with a high debt-to-income ratio. I interpret it

[12] 27% of households with a high DTI compared to 19% for all other households.

Table 3.1: Most common reasons for denial of mortgage applications (1999-2014)

Reason	% Denied Mortgage Applications
Debt-to-Income Ratio	18.08
	(3.97)
Credit History	29.75
	(7.85)
Collateral	11.68
	(3.87)
Other*	40.48
	(7.90)
N	14223712

Table 1 reports the three most commonly named reasons for denial: DTI, credit history and insufficient collateral.
*: Other named reasons are: insufficient cash, employment history, unverifiable information, incomplete application, mortgage insurance denial, and other unnamed reasons. Summary statistics based on yearly information from "National Aggregate Table 8-2: Reasons for Denial of Applications for Conventional Home Purchase Loans". Source: Home Mortgage Disclosure Act and author's calculations.

as the share of borrowing-constrained households. I use the datasets from Fannie Mae and Freddie Mac which contain information about the DTI at origination, to construct it. I define a high debt-to-income ratio to be above 43%, which corresponds to the "ability to repay" criterion of the Dodd-Frank reform[13]. 1999 to 2001 correspond to the first three years where mortgage-level data from Fannie and Freddie Mac are available[14]. I also choose the city-level average of high DTI mortgages during this period because it corresponds to a period just before the housing boom[15], hence the interpretation as a pre-existing share before the change in credit conditions.

The idea behind using the CBSA-level share of borrowing-constrained households before the boom-bust episode resides in that the credit standards' relaxation nation-wide (and subsequent tightening) will disproportionately affect those areas. A high

[13] I also experimented with alternative values of 36 and 40 % with similar results.

[14] Fannie Mae loan-level data is only available from 2000.

[15] It has also been documented that the turn of the millenium was the period after which DTI limits were liberalized, with most mortgages above the 36% threshold and many mortgages with a DTI at origination above 50% (Greenwald [2018]). Demyanyk and Van Hemert [2009] also show a progressive deterioration of loan performance and a worsening of lending standards between 2001 and 2007, with a rising fraction of mortgages with low documentation.

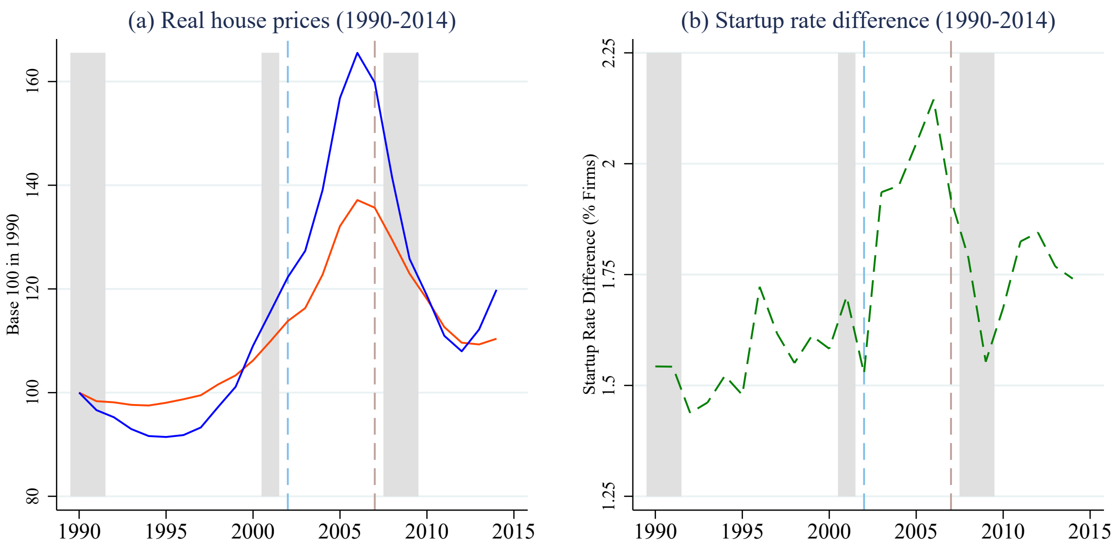
debt-to-income ratio being one of the main reasons behind a mortgage denial, it will become relatively easier to access credit in high DTI cities following the credit supply shift. Real estate prices will increase more in high DTI cities during the boom and fall harder after the housing market crash because households are more likely to be overleveraged. For my instrument to be valid, it is important that conditional on observable controls, there are no other factors, for instance a local credit demand shock, differentially impacting startup formation in high DTI cities at the same time as credit conditions change.

3.3.2 Descriptive evidence - High and low DTI cities

To highlight this, I separate metropolitan areas into two groups: Cities with a pre-existing percentage of borrowing-constrained households above the median and cities below the median. Figure 3.3 panel (a) shows that house prices moved together in high and low DTI cities in the 1990s before diverging in the early 2000s. Prices increased more in high DTI areas between 2002 and 2007 before going down faster after the subprime mortgage crisis in 2007. This evolution is consistent with a weakening of lending standards affecting more high DTI cities.

Figure 3.3 panel (b) shows the evolution of the startup rate difference between high and low debt-to-income ratio CBSAs between 1990 and 2014. While highly exposed cities had a generally higher startup rate between 1990 and 2014, their evolution followed the same trend across the two groups before the housing bubble of the early 2000s. After 2001, when house price growth accelerated, the startup rate increased more in areas with a high share of borrowing-constrained households, and it did so until 2006 when property prices peaked. That difference narrowed after the housing bubble burst: High DTI cities saw a relatively larger fall in the startup rate compared

Figure 3.3: House prices and firm entry in high and low DTI cities (1990-2014)



Blue dashed bar: 2002. Pink dashed bar: 2007. **Real house prices:** Constructed using nominal house price indices from FHFA and GDP deflator from BEA. **Startup rate difference:** Constructed by subtracting the average startup rate in low DTI cities from its average in high DTI cities. Source: BDS, FHA, BEA, Fannie Mae Single Family Loan Performance Data, Freddie Mac Single Family Loan-Level Dataset and author's calculations.

to low DTI cities, with the difference dropping below its year 2000 level. Nevertheless, there was no differential pre-trend in the evolution of startup rate during the 1990s for highly exposed cities.

Table 3.2 provides additional information about economic and industry characteristics of high and low DTI cities. The startup rate was, on average higher in highly exposed cities, although it evolved similarly over time, as shown in figure 3.3. High and low-exposed CBSAs had a similar unemployment rate in the 1990s and experienced relatively similar house price growth. It was slightly higher in high DTI areas during the 1990s, but the difference is not comparable to the one observed during the 2000s boom and bust episodes, as highlighted by figure 3.3. Besides, I also examine differences in industry composition as a driver of subsequent differences in the startup rate. House price changes were more likely to affect non-tradeable industries such as construction or leisure & hospitality through wealth effects on consumption than tradeable sectors like manufacturing. Nevertheless, table 3.2 shows that industry shares for these three sectors were close to each other across the two groups. Real income was, on average, slightly higher in high DTI cities in 2000 but comparable. Demographic characteristics are comparable, with a similar percentage of homeowners and college-educated workers. The only difference in demographic characteristics comes from higher population growth in high DTI cities, but this was not specific to the 1990s. Regardless, high and low DTI shared similar characteristics overall.

3.3.3 Instrumental variable strategy

I now describe how I use the share of borrowing-constrained households to construct an instrument for house price changes. My strategy is to interact the pre-existing percentage of high DTI households with a shift that captures nationwide changes

Table 3.2: Characteristics of high and low DTI cities before the real estate boom and bust (1990-2001)

	All Metropolitan Areas	Higher Debt-to-Income	Lower Debt-to-Income
% High DTI Mortgages (1999 - 2001)	20.87	22.41	17.32
	(3.27)	*(2.51)*	*(1.65)*
Economic and Industry Characteristics			
Annual growth - House prices (%)	3.55	3.75	3.09
	(3.94)	*(4.44)*	*(2.44)*
Annual growth - Real house prices (%)	1.33	1.53	0.88
	(4.01)	*(4.50)*	*(2.53)*
Unemployment rate (%)	5.40	5.52	5.16
	(2.26)	*(2.29)*	*(2.19)*
Startup rate (%)	9.49	9.97	8.42
	(1.74)	*(1.68)*	*(1.34)*
% Employment - Construction	5.99	5.88	6.25
	(1.84)	*(1.72)*	*(2.06)*
% Employment - Manufacturing	17.93	17.24	19.5
	(7.26)	*(6.76)*	*(8.05)*
% Employment - Leisure and Hospitality	11.20	11.42	10.71
	(3.85)	*(4.34)*	*(2.32)*
Real Income**	34285	35109	32072
	(5237)	*(4948)*	*(5375)*
Demographic Characteristics			
College-educated** (%)	24.2	24.59	23.14
	(5.87)	*(5.46)*	*(6.76)*
Homeowner** (%)	68.70	67.13	72.91
	(6.97)	*(7.20)*	*(4.00)*
Annual Population Growth (%)	1.32	1.53	0.83
	(1.13)	*(1.16)*	*(0.86)*
N	381	190	191

**: Estimates from 2000 American Community Survey. Real house prices are constructed using nominal house price indices from FHFA and GDP deflator from BEA. Source: BDS, FHFA, BLS, Fannie Mae, Freddie Mac, QCEW, 2000 ACS and author's calculations.

in credit conditions. To do so, I consider two alternatives: One is based on the nationwide growth of employment among mortgage and non-mortgage loan brokers. The second one is based on the change of the interest rate premium associated with a mortgage with a high debt-to-income ratio, above 43%.

In the first case, I rely on data on the nationwide number of loan brokers from the BLS Current Employment Statistics Survey (CES) and use the annual percentage growth in the number of brokers, denoted as $\Delta\mu_t$ as a measure of a nationwide change in credit conditions[16]. The first city-level instrument for house price changes becomes:

$$Z_{1,i,t} = \theta_{DTI,i} \times \Delta\mu_t \tag{3.1}$$

Figure 3.B1 panel (a) in Appendix 3.B shows the time-series of employment for loan brokers between 1990 and 2014. Their number went up after 2000 and collapsed during the financial crisis, consistent with easing mortgage conditions, especially after 2003, and tightening once the housing bubble burst. Therefore, I expect $Z_{1,i,t}$ to correlate positively with house price growth.

In the second case, I compute the premium associated with a high DTI mortgage by estimating the following equation using the Fannie Mae and Freddie Mac datasets:

$$r_{i,j,t} = \phi_{k,t} \cdot K_{i,t} + \gamma_j + \gamma_t + \nu_{i,j,t} \quad k = \{FICO, LTV, DTI\} \tag{3.2}$$

$K_{i,t}$ is an indicator variable equal to 1 when the originated mortgage has a risky characteristic k. I take into account three characteristics[17]: Low FICO credit score

[16] Justiniano et al. [2022] show that after 2003, the number of loan brokers did not go down despite the end of the 2001 refinancing wave, and note that this suggests that loan brokers started to target underserved households, like subprime borrowers.

[17] I choose these two other characteristics because credit score and LTV are, besides DTI, the two other main reasons behind mortgage denial. The cutoff of 660 for the FICO credit score often corresponds to the distinction between prime and subprime mortgages (e.g. Mian and Sufi [2009]), and the 80% threshold for LTV is chosen because lenders may require private mortgage insurance

(below 660), high loan-to-value ratio (above 80%) and high debt-to-income ratio (above 43%). γ_j and γ_t are time (year-quarter) and city fixed effects. $\phi_{k,t}$ is the time-varying mortgage premium associated with a mortgage that has risky characteristic k at time t: $\phi_{DTI,t}$ therefore represents the relative premium associated with a mortgage that has a high debt-to-income ratio at time t. Using $\hat{\phi}_{DTI,t}$ as a proxy for credit conditions, the second city-level instrument for house price changes becomes:

$$Z_{2,i,t} = \theta_{DTI,i} \times \tilde{\Delta}\hat{\phi}_{DTI,t} \tag{3.3}$$

$\tilde{\Delta}\hat{\phi}_{DTI,t}$ represents the annual change in the premium associated with high DTI mortgages. One potential concern with constructing the instrument this way is that mortgage rate premia could vary across CBSAs because of local shocks. However, Hurst et al. [2016] show that mortgage pricing for GSE-securitized mortgages does not vary across regions with different default risks. Figure 3.B1 panel (b) in Appendix 3.B shows the estimated mortgage premium for high DTI mortgages between 2000 and 2014. While the mortgage premium in basis points is low, it drops during the housing boom and increases after the financial crisis, consistent with changes in credit conditions. $Z_{2,i,t}$ should be negatively correlated with house price growth.

3.3.4 First-stage results

In section 3.4, I will investigate the role of housing wealth shocks on firm entry by exploiting variation across cities in house price changes: I will regress the startup rate on annual house price growth. In this section, I run the first-stage equation to show the instruments' predictive power for house price changes:

(PMI) for mortgages with collateral less than 20% of the value of the house because they are seen as riskier. See Appendix 3.B for summary statistics of mortgage characteristics.

$$\Delta HP_{i,t} = \alpha Z_{k,i,t} + \tilde{\Gamma} X_{i,t} + \tilde{\delta}_i + \tilde{\delta}_t + \tilde{\epsilon}_{i,t} \qquad k = \{1, 2\} \tag{3.4}$$

$\Delta HP_{i,t}$ represents the annual percentage change in real house prices in city i. $\tilde{\delta}_i$ and $\tilde{\delta}_t$ are respectively city and year fixed effects. $X_{i,t}$ is a set of controls at the city level to account for the possibility that local economic conditions could drive both house prices and business creation: It includes CBSA-level changes in the unemployment rate and real GDP per capita. I also add local population growth as a control to X_{it} because it could drive both house price and startup creation. I also follow Davis and Haltiwanger [2021] and use information from the Quarterly Census of Employment and Wages (QCEW) to create a control for local demand. It is constructed as the sum over high-level industries of lagged city-level employment shares interacted with nationwide industry employment growth. It is added to capture the effect of house price growth on new startup formation that is independent of local demand shocks and different industrial structures across cities. I focus on the housing boom and bust years between 2002 and 2014.

Table 3.3 shows the first-stage results. Columns (1) to (6) show that the two instruments based on the pre-existing share of high DTI mortgages perform well, with a robust first-stage F-statistic higher than or around 100 in both cases, well above the standard threshold for weak instruments of 10. Besides, the relationship between the instruments and house price changes is also robust to adding city-level business cycle variables and local demand shocks: Coefficient estimates for $Z_{k,i,t}$ do not change much. Therefore, the relationship between house price growth and the share of high DTI mortgages is unlikely to be driven by local demand shocks that differentially affect high DTI cities as credit conditions change, which would violate

Table 3.3: First-stage - House price growth response

	IV Strategy 1			IV Strategy 2		
	(1)	(2)	(3)	(1)	(2)	(3)
$Z_{i,t}$	0.0187***	0.0158***	0.0153***	-0.113***	-0.0951***	-0.0926***
	(0.002)	*(0.002)*	*(0.002)*	*(0.010)*	*(0.009)*	*(0.009)*
N	4,953	4,953	4,894	4,953	4,953	4,894
Bus Cycle Controls	NO	YES	YES	NO	YES	YES
Pop Growth & Local Demand	NO	NO	YES	NO	NO	YES
First-stage F	99.59	90.73	95.19	118.20	107.29	101.92

Standard errors clustered at the CBSA-level. *** p<0.01 ** p<0.05 * p<0.1. All specifications include year and CBSA fixed effects. **IV strategy 1**: Shift based on loan brokers' employment changes. **IV Strategy 2**: Shift based on high DTI mortgage premium changes. **Bus Cycle Controls** : CBSA-level unemployment rate changes and % changes in real GDP per capita. **Pop Growth & Local Demand**: % changes in CBSA population and demand shifter. Demand shifter: Sum over QCEW supersectors of lagged CBSA employment share interacted with nationwide employment growth. Source: BLS, BEA, FHFA, Fannie Mae, Freddie Mac, QCEW and author's calculations.

the exclusion restriction.

3.4 House prices and firm creation

To study the impact of house price changes on firm entry at the CBSA level, I estimate the following regression equation:

$$s_{i,t} = \beta \Delta HP_{i,t} + \Gamma X_{i,t} + \delta_i + \delta_t + \epsilon_{i,t} \tag{3.5}$$

$s_{i,t}$ is the city-level startup rate, the number of new firms created divided by the total number of firms at time t. My coefficient of interest is β. δ_i and δ_t are respectively city and year fixed effects, and $X_{i,t}$ includes the same set of controls as in the first stage equation 3.4.

3.4.1 Baseline specification

Table 3.4: Startup rate response to house price growth

	OLS			IV Strategy 1			IV Strategy 2		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta HP_{i,t-1,t}$	0.0390***	0.0398***	0.0304***	0.0271***	0.0262***	0.0178*	0.0281***	0.0273***	0.0207**
	(0.004)	*(0.004)*	*(0.004)*	*(0.008)*	*(0.010)*	*(0.010)*	*(0.009)*	*(0.010)*	*(0.010)*
Observations	4,953	4,953	4,894	4,953	4,953	4,894	4,953	4,953	4,894
Bus Cycle Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES
Pop Growth & Local Demand	NO	NO	YES	NO	NO	YES	NO	NO	YES

Standard errors clustered at the CBSA-level. *** p<0.01 ** p<0.05 * p<0.1. All specifications include year and CBSA fixed effects. **IV strategy 1**: Shift based on loan brokers' employment changes. **IV Strategy 2**: Shift based on high DTI mortgage premium changes. **Bus Cycle Controls** : CBSA-level unemployment rate changes and % changes in real GDP per capita. **Pop Growth & Local Demand**: % changes in CBSA population and demand shifter. Demand shifter: Sum over QCEW supersectors of CBSA lagged employment share interacted with nationwide employment growth. Source: BDS, BLS, BEA, FHFA, Fannie Mae, Freddie Mac, QCEW and author's calculations.

Table 3.4 shows the main results of this paper. IV estimates are slightly lower but close to OLS, which hints at measurement error being a relatively less important issue. The inclusion of the local demand shifter and control for population growth in columns (3), (6) and (9) lowers estimates of the effect of house price growth on startup creation by roughly 30% in both the OLS and IV cases. Cities where home values appreciated more were also, all else equal, cities which experienced a favourable economic environment and saw an influx of new residents attracted by local economic conditions. Regardless, coefficient estimates for β remain statistically significant and close to each other across the two IV strategies. The coefficient estimate in column (6) suggests that a one percentage point increase in real house price growth is associated with the startup rate going up by roughly 0.02 percentage points. In other words, a 10% annual increase in real house prices in a city compared to other cities will raise the startup rate by only 0.2 percentage points. This suggests that the effect of house prices on new firm formation is modest, given a startup rate on average around 8% during the period and large differences across cities[18]. In Appendix 3.C.2, I use the

[18] See figure 3.1 and Appendix 3.C.1

sensitivity instrument proposed by Guren et al. [2020]: My estimates for β with this IV are almost identical to table 3.4, which reinforces my findings.

3.4.2 Intensive margin - Existing firms

The majority of new establishments created in any year are new firms, but between a third and 40% of new establishments are created by existing firms. If the main effect of home appreciation on business formation operates through increased collateral values relaxing liquidity constraints, I expect house price growth to have a lower impact on existing firms' incentives to expand their activity through new establishments than on new firms. To evaluate the importance of house prices on prospective entrepreneurs' borrowing constraints, I re-estimate equation 3.5 with a different dependent variable, the number of new establishments created by existing firms at time t normalized by the total number of establishments. This *existing establishment entry rate* captures the intensive margin of business creation. Table 3.5 presents my results:

Table 3.5: Impact of house price growth on existing firms' establishment creation

	OLS			IV Strategy 1			IV Strategy 2		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta HP_{i,t-1,t}$	-0.0018	-0.0042***	-0.0044***	0.0064	0.0037	0.0044	-0.0000	-0.0042	-0.0038
	(0.001)	*(0.001)*	*(0.001)*	*(0.005)*	*(0.007)*	*(0.007)*	*(0.005)*	*(0.006)*	*(0.006)*
Observations	4,952	4,952	4,893	4,952	4,952	4,893	4,952	4,952	4,893
Bus Cycle Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES
Pop Growth & Local Demand	NO	NO	YES	NO	NO	YES	NO	NO	YES

Standard errors clustered at the CBSA-level. *** p<0.01 ** p<0.05 * p<0.1. All specifications include year and CBSA fixed effects. **IV strategy 1**: Shift based on loan brokers' employment changes. **IV Strategy 2**: Shift based on high DTI mortgage premium changes. **Bus Cycle Controls** : CBSA-level unemployment rate changes and % changes in real GDP per capita. **Pop Growth & Local Demand**: % changes in CBSA population and demand shifter. Demand shifter: Sum over QCEW supersectors of CBSA lagged employment shares interacted with nationwide employment growth. Source: BDS, BLS, BEA, FHFA, Fannie Mae, Freddie Mac, QCEW and author's calculations.

Columns (4) to (9) show that IV estimates of the business creation elasticity β are no longer statistically different from zero when looking at existing firms' establishment creation. OLS estimates are negative, but their magnitude remains 7 to 10 times lower than comparable estimates for the effect of house price growth on new firm formation in table 3.4. These results imply that house price growth does not affect existing firms' decisions to expand, which is not surprising because new and young firms are more likely to rely on the owner's wealth than more mature firms. I draw similar conclusions using the sensitivity IV in Appendix 3.C.2 and find no role for housing wealth shocks on existing firms.

3.4.3 Industry-level analysis - The housing wealth effect and collateral channels

I further investigate the relationship between house price changes and business creation in each city at the industry level. Looking at the industry by city data helps me compare the importance of the collateral channel with housing wealth effects increasing consumer demand. This also helps me look at possible industry composition effects, where cities with higher home appreciation have an industrial structure which is more sensitive to house price changes (e.g. non-tradeable sectors or industries where it is easier to start a business). I estimate an equation similar to equation 3.5, but at the industry-level:

$$s_{i,j,t} = \beta \Delta HP_{i,t} + \Gamma X_{i,t} + \delta_i + \delta_{j,t} + \epsilon_{i,j,t} \tag{3.6}$$

$\delta_{j,t}$ denotes 2-digit NAICS sector by year fixed effects to capture industry-specific shocks. I follow an approach similar to Mian and Sufi [2014] and distinguish between non-tradeable industries (retail trade, accommodation and food services and arts, entertainment and recreation) and construction versus other tradeable sectors[19]. I estimate equation 3.6 separately for non-tradeable and construction and then for all other sectors. For this latter group, housing wealth effects on consumption are likely less important because the demand for tradeables is national. Therefore, I expect the overall effect of home appreciation to be weaker: The impact of appreciation in home values on business creation should only work through the relaxation of prospective entrepreneurs' borrowing constraints. This is what table 3.6 shows:

Table 3.6: Startup rate response to house price growth across industries

	OLS			IV Strategy 1			IV Strategy 2		
	All	T	NT & C	All	T	NT & C	All	T	NT & C
$\Delta HP_{i,t-1,t}$	0.0240***	0.0203***	0.0328***	0.0278***	0.0239**	0.0366**	0.0292***	0.0253**	0.0379**
	(0.002)	*(0.003)*	*(0.005)*	*(0.008)*	*(0.010)*	*(0.016)*	*(0.009)*	*(0.010)*	*(0.017)*
Observations	63,652	44,691	18,961	63,652	44,691	18,961	63,652	44,691	18,961

Standard errors clustered at the CBSA x sector level. *** p<0.01 ** p<0.05 * p<0.1. All specifications include industry by year and CBSA fixed effects, CBSA-level unemployment rate changes, % changes in real GDP per capita and % changes in CBSA population. **IV strategy 1**: Shift based on loan brokers' employment changes. **IV Strategy 2**: Shift based on high DTI mortgage premium changes. T: Tradeable Sectors. NT & C: Non-tradeable sectors and Construction. See Appendix 3.C.1 for list of industries. Source: BDS, BLS, BEA, FHFA, Fannie Mae, Freddie Mac and author's calculations.

IV coefficient estimates in columns (4) and (7) also show that within industries, the effect of a 1% annual increase in house prices raises is not different (slightly higher) than considering all sectors in a city together (table 3.4). It tends to indicate that the impact of house price growth on new firm creation is unlikely to be explained by differences in industrial structure across CBSAs.

The coefficient associated with the non-tradeable and construction sectors in columns (6) and (9) is 50% stronger than for tradeable industries. Within non-tradeables and construction, a one percentage point increase in real house price growth raises the startup rate by roughly 0.037 percentage points, compared to 0.025 points

[19]See Appendix 3.C.1 for the list of tradeable and non-tradeable industries.

for non-tradeables in columns (5) and (8). Assuming that tradeable industries are unaffected by wealth effects on consumption from higher local home values, this 50% difference suggests that $\frac{2}{3}$ of the impact of house price growth on new firm creation comes from the relaxation of prospective entrepreneurs' borrowing constraints rather than housing wealth effects on consumption.

A caveat to this result lies in the possibility that, unlike products made by established firms, tradeable goods produced by startups are not traded, because it takes time and resources for young firms to create a network in other locations. In that case, any effect of house price changes on firm formation in the tradeable sector would only operate through wealth effects increasing consumer demand. While this does not affect my findings suggesting a limited role for house price changes overall, it hints at an even weaker role for housing wealth effects increasing consumer demand in the tradeable sector versus non-tradeable industries.

My findings are different to Adelino et al. [2015], who find no role for housing wealth effects on consumption demand in explaining a more significant impact of house prices on small establishments to larger ones between 2002 and 2007. By contrast, I find that it can explain up to $\frac{1}{3}$ of the impact of house price changes on new firm formation, vs $\frac{2}{3}$ for the collateral channel. Many firms remain small, and old-small businesses are much less sensitive to the business cycle than young-small firms in the US (Fort et al. [2013][20]). One potential explanation for our different findings comes from the role of customer base acquisition, which is more difficult for young businesses than mature firms, and *a fortiori* for newly created firms. It could also explain why the impact of house price changes also operates through housing wealth effects on consumption for new firms but not existing small businesses.

[20]Clymo and Rozsypal [2022] also confirm this finding using the universe of Danish firms: Young-small firms are the most cyclical while old-small firms are among the least sensitive to the business cycle.

3.5 Conclusion

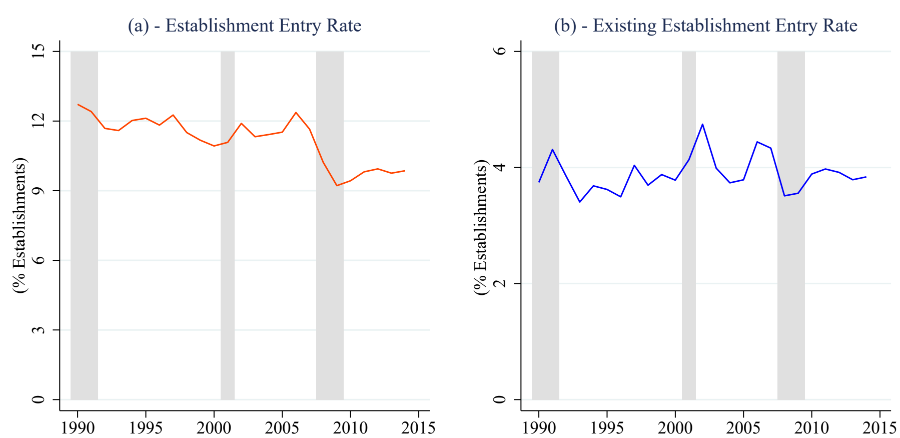
In this paper, I studied the effects of the early 2000 housing boom and bust on new firm entry. I addressed the endogeneity of house prices by proposing a new instrument that relies on geographical variation in households' debt-to-income ratios before the 2000s housing cycle as a proxy for borrowing constraints. I found a modest but statistically significant effect of house price growth on firm entry: A one percentage point increase in local real house price growth drove the startup rate by 0.02 percentage points. I find that this effect of home appreciation on business creation mostly comes through the relaxation of prospective entrepreneurs' borrowing constraints rather than housing wealth effects: It cannot be attributed to specific sectors such as non-tradeables and construction. These findings also indicate that the impact of house price growth on business creation is concentrated among new entrants, as it plays no role in existing firms' decision to expand their activity with new establishments.

Appendix

3.A Appendix A

3.A.1 Additional evidence on business entry

Figure 3.A1: Establishment entry and existing establishment entry rate (1990-2014)



Existing establishment entry rate: Ratio between the number of establishments created by existing (age>0) firms at time t and the total number of establishments. Source: Business Dynamics Statistics and author's calculations.

Figure 3.A1 panel (a) shows the evolution of another measure of business cre-

ation: The establishment entry rate, which represents the ratio between the number of new establishments created during the year and the total number of establishments between 1990 and 2014. It was trending down during the 1990s. It fell during the 1990 recession and after 2007, like the startup rate in figure 3.1. Panel (b) shows the existing establishment entry rate, which measures the creation of new establishments by existing firms. Unlike the startup rate, it is not trending down and is less cyclical.

3.A.2 Additional evidence from the SCF

I motivated my analysis by presenting figure 3.2 in section 3.2, which hinted at the presence of credit constraints for entrepreneurs, especially those who started their businesses recently (”Young Entrepreneurs”). While ”Young Entrepreneurs” report being more credit constrained than the rest of the population, they are wealthier and earn more, as shown in table 3.A1. As for other households, an important part of their wealth resides in their housing (37% vs 43% for all households). It means that the housing cycle of the 2000s could have driven the share of entrepreneurs who report being credit constrained.

Table 3.A1: Income, wealth and the housing share: 1992-2014

	All Households	**Entrepreneurs**	**Young Entrepreneurs**
Income : Median	36309	64388	55369
Wealth : Median	77531	391844	194574
Housing as % Wealth : Median	42.74	34.82	37.26
N	188388	36753	7981

Entrepreneurs: Self-employed business owners. Respond positively to questions about owning and managing a business (X3103 and X3104), and declare being self-employed (X4106). **Young Entrepreneurs:** Entrepreneurs who started their business less than five years ago. Income and wealth (medians): Rounded to the nearest integer. Housing share: Ratio between home value (gross) and total household wealth. Source: Survey of Consumer Finances.

3.B Appendix B

This section contains additional information about the construction of the instruments introduced in section 3.3.3. Table 3.B1 provides descriptive statistics for the sample of mortgages securitized by Fannie Mae and Freddie Mac and used to estimate the mortgage rate premium associated with a high DTI, a low FICO Credit Score and a high LTV (equation 3.2). Unlike the share of high DTI mortgages, the percentage of high LTV or low FICO mortgages did not increase during the housing boom. Panel (b) of figure 3.B1 shows yearly averages of the interest rate premium for a mortgage with a DTI above 43%, used to construct the second instrument $Z_{2,i,t}$. It falls by 50% between 2003 and 2006 before tripling after 2007.

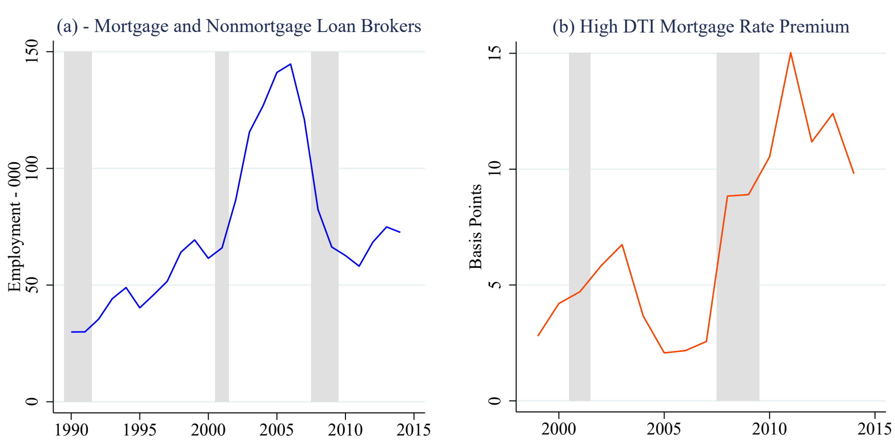
Panel (a) shows yearly averages of the number of loan brokers used to construct the first instrument $Z_{1,i,t}$.

Table 3.B1: Descriptive statistics - Mortgages securitized by Fannie Mae and Freddie Mac (1999-2014)

	All Years : 1999-2014	*1999-2001*	*2002-2007*	*2008-2014*
Interest Rate	5.53	7.33	6.01	4.46
	(1.27)	*(0.69)*	*(0.60)*	*(0.89)*
% DTI >43	20.05	19.89	24.10	16.04
	(40.04)	*(39.92)*	*(42.77)*	*(36.70)*
% FICO <660	9.64	16.50	14.32	2.69
	(29.51)	*(37.12)*	*(35.03)*	*(16.17)*
% LTV >80	16.64	27.51	15.23	14.50
	(37.25)	*(44.66)*	*(35.93)*	*(35.21)*
N	46664787	6558505	20082185	20024097

Sample of mortgages securitized by the two Government Sponsored Enterprises for all 381 metropolitan CBSAs. It excludes mortgages originated in Puerto Rico and without information about the CBSA. Source: Fannie Mae, Freddie Mac and author's calculations.

Figure 3.B1: Time series of the two IV shifts described in section 3.3.3



Source: BLS Current Employment Statistics (CES), Fannie Mae, Freddie Mac and author's calculations.

3.C Appendix C

3.C.1 Additional details - Estimation (section 3.4)

Table 3.C1 gives the list of 2-digit NAICS sectors used in the city-by-industry regression analysis of section 3.4.3. I exclude the Agriculture (NAICS 11), Mining (NAICS 21) and Utilities (NAICS 23) sectors from my analysis because of few CBSAs with a non-zero number of startups. I follow Davis and Haltiwanger [2021] and also omit the Education (NAICS 61) and Other Services (NAICS 81) as they contain a large number of non-profit businesses.

Table 3.C1: List of tradeables and non-tradeables & construction 2-digit NAICS industries

Non-tradeables & Construction	Tradeables
Accommodation and Food Services (72)	Administrative and Support and Waste Management and Remediation Services (56)
Arts, Entertainment, and Recreation (71)	Finance and Insurance (52)
Construction (23)	Health Care and Social Assistance (62)
Retail Trade (44-45)	Information (51)
	Management of Companies and Enterprises (55)
	Manufacturing (31-33)
	Professional, Scientific, and Technical Services (54)
	Real Estate and Rental and Leasing (53)
	Transportation and Warehousing (48-49)
	Wholesale Trade (41-42)

Table 3.C2 presents descriptive evidence about house price changes and the startup rate across CBSAs between 2002 and 2014. It shows a sizeable cross-sectional variation in new firm entry during the boom and the bust. During both periods, the startup rate of cities in the 9^{th} decile is 70% higher than for the bottom 10%. There is a similarly large variation in house price growth throughout both periods.

Table 3.C2: House price growth and firm entry across CBSAs - 2002-2014

	Average	Median	P10	P90
Real estate boom: 2002 - 2007				
Annual growth - House prices (%)	7.22	5.18	0.64	16.53
	(6.98)			
Annual growth - Real house prices (%)	4.57	2.69	-1.97	13.11
	(6.68)			
Startup rate (%)	9.19	9.03	6.81	11.60
	(1.89)			
Real estate bust: 2008 - 2014				
Annual growth - House prices (%)	-1.61	-1.41	-9.71	7.19
	(7.07)			
Annual growth - Real house prices (%)	-3.19	-3.01	-10.53	5.22
	(6.83)			
Startup rate (%)	7.56	7.57	5.43	9.48
	(1.63)			

Real house prices are constructed using nominal house price indices from FHFA and the GDP deflator from BEA. Source: BDS, FHFA, BEA.

3.C.2 Impact of house price changes on firm entry - Sensitivity IV

Guren et al. [2020] propose an instrument that exploits the fact that when house prices change at the regional level, some cities are more sensitive than others. Following their example, when house prices change in the Northeast region, they tend to respond more systematically in Providence than in Rochester (Guren et al. [2020]). They estimate the sensitivity of CBSAs to regional house price cycles by using the variation in city-level prices that is orthogonal to local economic conditions, and obtain a sensitivity estimate for each metropolitan CBSA, $\hat{\gamma}_i$. I use their $\hat{\gamma}_i$ estimates for each city i and follow their approach of interacting it with regional house price changes using a leave-one-out procedure that excludes CBSA i. The sensitivity IV for house prices becomes:

$$Z_{3,i,t} = \hat{\gamma}_i \times \Delta HP_{r,-i,t} \tag{3.7}$$

$HP_{r,-i,t}$ represents the regional price index in the US Census Region r constructed by excluding CBSA i. Table 3.C3 presents estimates of the impact of house price changes on new firm formation using this instrument. IV estimates are close to those of table 3.4 and also hint at a modest role for house price growth in explaining the formation of new firms, with a 1% annual increase in real house prices driving the startup rate by 0.018 percentage points versus 0.02 points in table 3.4. Table 3.C4 presents estimates of the impact of home appreciation on existing firms, which are similar to table 3.5 and show no role for house price changes in existing firms' decision to expand through new establishments.

At the city by industry level, table 3.C5 shows that the impact of house price growth on new firm formation was 50% stronger for Non-Tradeables and Construction (0.021 percentage points) than for Tradeables (0.014) percentage points. Although coefficient estimates are lower, these results are consistent with table 3.6.

Table 3.C3: Startup rate response to house price growth with sensitivity IV

	OLS			Sensitivity IV (GMNS)		
	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta HP_{i,t-1,t}$	0.0390***	0.0398***	0.0304***	0.0262***	0.0255***	0.0179***
	(0.004)	*(0.004)*	*(0.004)*	*(0.005)*	*(0.005)*	*(0.005)*
Observations	4,953	4,953	4,894	4,940	4,940	4,894
Bus Cycle Controls	NO	YES	YES	NO	YES	YES
Pop Growth & Local Demand	NO	NO	YES	NO	NO	YES

Standard errors clustered at the CBSA-level. *** p<0.01 ** p<0.05 * p<0.1. All specifications include year and CBSA fixed effects. **Bus Cycle Controls** : CBSA-level unemployment rate changes and % changes in real GDP per capita. **Pop Growth & Local Demand**: % changes in CBSA population and demand shifter. Demand shifter: Sum over QCEW supersectors of CBSA lagged employment share interacted with nationwide employment growth. Source: BDS, BLS, BEA, FHFA, QCEW and author's calculations.

Table 3.C4: Impact of house price growth on existing firms' establishment creation with sensitivity IV

	OLS			Sensitivity IV (GMNS)		
	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta HP_{i,t-1,t}$	-0.0018	-0.0042***	-0.0044***	-0.0003	-0.0030	-0.0030
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	4,952	4,952	4,893	4,939	4,939	4,893
Bus Cycle Controls	NO	YES	YES	NO	YES	YES
Pop Growth & Local Demand	NO	NO	YES	NO	NO	YES

Standard errors clustered at the CBSA-level. *** p<0.01 ** p<0.05 * p<0.1. All specifications include year and CBSA fixed effects. **Bus Cycle Controls** : CBSA-level unemployment rate changes and % changes in real GDP per capita. **Pop Growth & Local Demand**: % changes in CBSA population and demand shifter. Demand shifter: Sum over QCEW supersectors of CBSA lagged employment share interacted with nationwide employment growth. Source: BDS, BLS, BEA, FHFA, QCEW and author's calculations.

Table 3.C5: Startup rate response to house price growth across industries - sensitivity IV

	OLS			Sensitivity IV (GMNS)		
	All	T	NT & C	All	T	NT & C
$\Delta HP_{i,t-1,t}$	0.0240***	0.0203***	0.0328***	0.0157***	0.0138***	0.0206***
	(0.002)	*(0.003)*	*(0.005)*	*(0.003)*	*(0.003)*	*(0.006)*
Observations	63,652	44,691	18,961	63,490	44,580	18,910

Standard errors clustered at the CBSA x sector level. *** p<0.01 ** p<0.05 * p<0.1. All specifications include industry by year and CBSA fixed effects, CBSA-level unemployment rate changes, % changes in real GDP per capita and % changes in CBSA population. T: Tradeable Sectors. NT & C: Non-tradeable sectors and Construction. See Appendix 3.C.1 for list of industries. Source: BDS, BLS, BEA, FHFA and author's calculations.

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