Startups, Labor Market Frictions, and Business Cycles *

Gonzalo García-Trujillo†

May 13, 2021

[Link to the latest version]

Abstract

This paper studies how the labor market conditions affect the formation and growth potential of new businesses over the business cycle. I develop an occupational choice model with labor market frictions and joint firm and worker dynamics, in which heterogeneous individuals choose between being employed/unemployed workers, subsistence self-employed, or risky entrepreneurs with potential to grow. Using U.S. individual- and firm-level data, I provide support for the following mechanisms. First, unemployment makes people more willing to start businesses because of the lower outside option. Second, a lower job finding rate reduces the value of the fallback option when the business fails (harder to find a job), deterring entry from employment, especially for high-skill workers for whom the wage loss would be larger. Third, high-skill workers are more likely to start high-growth startups. With the calibrated model, I study the dynamic response of the economy to a negative aggregate productivity shock. Consistent with the empirical regularities, the higher entry from unemployment is mainly done through subsistence self-employment while the decline in the entry from employment leads to a missing generation of entrepreneurial startups. Moreover, the entrepreneurial entry composition shifts toward fewer high-skill workers, making new cohorts of businesses to have fewer high-growth startups. Both the lower entry and the lower growth potential of startups hinder the job creation recovery, keeping the job finding probability low, which in turn makes the entrepreneurial business formation to remain depressed longer.

JEL classification: E24, E32, J24, J62, J64, L25, L26

*I am deeply grateful to my advisors Borağan Aruoba, John Haltiwanger, Felipe Saffie, and Sergio Urzúa and my graduate director, John Shea, for their guidance and support. I am also thankful to David Kohn for an excellent discussion. For helpful comments, I also thank Sina Ates, Joonkyu Choi, Thomas Drechsel, Joaquin García-Cabo, Rodrigo Fuentes, Rodrigo Heresi, Gaston Navarro, Luminita Stevens, the participants at the University of Maryland Macroeconomic Workshop, Federal Reserve Board Pre-Job Market Conference 2020, Central Bank of Chile Seminars 2020, Productivity Workshop I: Understanding Productivity 2019 (Chile), and LACEA-LAMES 2018 and 2019 Annual Meetings. This paper was partially written at the Central Bank of Chile. I am specially grateful for their hospitality. This paper supersedes the earlier version "The Growth Potential of Startups, Labor Market Frictions, and Business Cycles."

†PhD Candidate, Department of Economics, University of Maryland. Email: ggarciat@umd.edu.

1 Introduction

It is a well known fact that the entry rate of employer businesses in the U.S. falls during economic downturns. Moreover, an increasing number of recent studies have documented that employer businesses born during recessions start on average smaller and grow less over their entire life-cycle.[1] Since the entry and growth of young businesses drive aggregate employment creation in the U.S., these two facts shape the recovery of the labor market in the aftermath of recessions.[2] Despite this key role, relatively little is known regarding the forces driving the entry and growth potential of startups over the cycle. From a firm-level perspective, recent studies have proposed the fall in the aggregate demand and tighter financial constraints as mechanisms to explain the decline in the entry and the shift of startups toward businesses with lower growth potential that we observed in recessions.[3] However, from an individual-level perspective, whether this kind of startup dynamics can also emerge from changes in the characteristics of the business founders over the business cycle still remains an open question.

In this paper, I study how the labor market dynamics over the business cycle affect the decisions to start businesses at the individual-level and, by shifting the entry composition of business founders, the growth potential of startups. I develop a framework in which unemployment rate and job finding probability drive the decision of heterogeneous individuals to start businesses, giving rise to a selection mechanism with respect to their previous labor force status and educational attainment. Then, by shifting the composition of business founders toward more previously unemployed and fewer highly educated individuals in downturns, labor market dynamics induce startups to have a lower potential to grow. First, I provide empirical support for three key mechanisms in the model: (i) unemployed workers are more likely to start a business due to their lower outside option; (ii) a lower job finding probability discourages (encourage) employed (unemployed) workers from starting businesses, especially highly educated workers; (iii) employed and highly educated workers are more likely to start high-growth startups. Then, I use a calibrated model to study how the labor market dynamics shape the entry and composition of startups during and after a period like the Great Recession, and quantify the effects of these dynamics on the recovery of the aggregate job creation in the aftermath of the recession.

The contribution of this paper to the literature is twofold. First, this paper is the first to

[1] For the United States, this fact has been documented by Sedláček & Sterk (2017), Moreira (2016), and Smirnyagin (2020) using firm-level data from the Longitudinal Business Database (LBD).

[2] Haltiwanger, Jarmin & Miranda (2013), and Decker, Haltiwanger, Jarmin & Miranda (2014) provide empirical evidence on the importance of young firms in aggregate job creation.

[3] Sedláček & Sterk (2017) argue that a fall in the aggregate demand reduces the return to the expenditure in advertisement needed to accumulate customer base, making entrants choose to start businesses with lower growth potential. Smirnyagin (2020) argues that financial frictions slow the rate at which firms reach their target size, making larger projects less profitable for entrepreneurs when financial conditions deteriorate.

relate the decline in the growth potential of startups during downturns to the characteristics of founders. Empirically, I do this by using both individual level-data (CPS, SIPP) and firm-level data (SBO) to document the change in the composition of business founders over the cycle and link this with the ex-post performance of startups. Theoretically, I develop a tractable model that features a selection at entry mechanism with respect to the previous labor force status and educational attainment of business founders, giving rise to an endogenous composition of founders. Second, I study labor market dynamics as a driver for the entry and growth potential of startups over the business cycle, adding to the previous literature that has proposed aggregate demand and financial constraints channels as possible explanations.

To formalize the analysis, I build a dynamic occupational choice model with labor market frictions and joint firm and worker dynamics, in which heterogeneous individuals choose between being employed/unemployed workers or risky businesses owners, either as subsistence self-employed or as entrepreneurs with potential to grow. This occupational structure implies that (i) individuals must sacrifice valuable jobs to start a business when employed, and (ii) business owners can find another job if the business fails.[4] The existence of this fallback option reduces the cost of a business failure, but how fast individuals can find another job depends on the job finding probability. Therefore, the unemployment rate and job finding probability become drivers of the entry and composition of business founders.

In this environment, labor market downturns affect the entry and composition of business founders through two channels. First, more people solve the occupational problem from unemployment with a lower opportunity cost, increasing the business entry, but mostly as a stopgap activity while they keep searching for a job. Second, a lower job finding probability reinforces the entry from unemployment, but it discourages employed workers from quitting their jobs to start businesses because they know that if the business fails, it will be harder to find another wage job. In other words, it reduces the value of the fallback option. I will refer to this mechanism as the "fear to fail" effect. This effect is stronger for high-skill workers because they face a larger wage loss if they have to search for a job longer. Because these are individuals with a high outside option, who decide to start businesses only with good entrepreneurial ideas, the cohorts of businesses born in downturns will contain disproportionately fewer potentially high-growth entrepreneurs. In addition to these two channels operating through the labor market, lower aggregate demand during recessions directly discourages business entry for unemployed and employed workers, so only individuals with the most promising ideas start businesses. I refer to these channels as the "labor force composition" channel, the "labor market tightness"

[4]Similar to Hombert, Schoar, Sraer & Thesmar (2020) and Choi (2017), the uncertainty whether the business will survive makes not only the current but also the expected future value of the outside option a determinant of the occupational problem.

channel, and the “profitability” channel, respectively.

I start the analysis by presenting some key features of the aggregate firm and labor market dynamics. First, using U.S. firm-level data from the Business Dynamics Statistics (BDS), I document the procyclical entry of employer businesses, the procyclical and persistent initial average size of startups, and the lower growth potential of cohorts of businesses started in downturns. Then, using U.S. individual-level data from the Current Population Survey (CPS), I show how the entry and composition of business founders changes over the cycle. I show that the total entry into self-employment increases in recessions, while the share of businesses started by individuals previously in employment (unemployment) decreases (increases) during recessions. I also show that entry rates by previously employed individuals declines across all educational levels, but it is more pronounced for highly educated workers.

I then present the model, which has five key ingredients. First, the occupational structure allows the decisions of entry, exit, and quits of individuals to be endogenous outcomes. Second, heterogeneity in labor skills gives rise to a distribution of outside options for business founders, generating a selection at entry mechanism with respect to the previous labor force status and educational attainment of the founders. Third, labor market frictions are the key ingredient that generates variations in the entry and composition of business founders through two equilibrium objects, the unemployment rate and the job finding probability. Fourth, the availability of two technologies to start a business allows to capture the different motivations behind this decision. Entrepreneurship offers a better technology while the subsistence alternative allows to search for a job with better efficiency and without paying the fixed operational cost. Fifth, convex hiring costs help to discipline the firm dynamics over age. In this environment, individuals choose their occupations conditional on their current labor force status (matched or unmatched), labor skills, entrepreneurial ability, and aggregate productivity. The model generates endogenous entry/exit of entrepreneurs, endogenous quits to start businesses, endogenous job finding probability, and exogenous separations.

The quantitative analysis is divided into two parts. In the first part, I give empirical support to the three mechanisms that drive the channels in the model. To test the predictions related to the “labor force composition” and “labor market tightness” channels, I use data from the Survey of Income and Participation Program (SIPP). To take the model to the data, similar to Levine and Rubinstein (2018), I proxy the subsistence technology with unincorporated self-employment and entrepreneurship with incorporated businesses with owners spending more than 35 hours per week in this activity. First, I estimate the transition probabilities from employment and unemployment into both types of self-employment. The results support *prediction 1*: unemployed workers are more prone to start businesses because of their lower outside option. Then, I estimate the effect of the job finding rate on the previous four transition probabilities. The results support *prediction 2*: a fall in the job finding probability discourages employed workers from starting businesses, with a stronger decline for high-skilled workers. Finally, using data from the Survey of Business Owners (SBO), I provide empirical support for *prediction 3*: high-skill employed workers are more likely to start high-growth businesses.

In the second part of the quantitative analysis, I calibrate the model to reproduce a set of selected labor market and firm dynamics features of the U.S. pre-Great Recession period. To discipline the labor market dynamics, the model is calibrated to match the masses and flows between labor market states. The model also matches the educational distribution of business owners and relative wages from the data, which pin down the entry rate by educational level. To discipline the firm dynamics, the model matches a set of moments capturing the relative size of startups, relative size of businesses by the education level of the owners, survival probabilities, growth, and employment shares. While not directly targeted, the model captures well the entry by type of businesses, with most of the business being started in the form of subsistence self-employment. The model also captures well the entry composition by previous labor force status, with subsistence self-employment having a larger entry from unemployment than the entrepreneurial alternative. It also fits well the entry composition by the founders' education, with entrepreneurs being relatively more educated than subsistence self-employed. These are important features in the model since they shape the entry and growth potential of startups.

Then, with the calibrated model, I solve two perfect foresight transition dynamics exercises to better understand the mechanisms driving the entry and compositional dynamics during downturns. First, I feed the model with an exogenous aggregate productivity path that triggers an unemployment rate dynamic that mimics the one exhibited by the U.S. during and after the Great Recession. The model reproduces well the labor market dynamics and the persistent decline in the entry of employer businesses, mostly driven by the decline in transitions from employment into entrepreneurship. The entry composition of employer businesses shifts toward more previously unemployed and fewer high-skill business founders. The disproportionately decline in the entry of highly educated workers makes startups start at a smaller average size and contain fewer potentially high-growth businesses. Both features hinder job creation recovery, keeping the labor market depressed longer, and the entry into entrepreneurship persistently low. I also perform a decomposition analysis to quantify the relative importance of the entry and composition margins in the persistent decline of aggregate job creation. At the time of the recession, most of the fall in job creation is accounted for by the decreasing labor demand of existing firms and the missing generation of new employer businesses, with a minimal effect from the compositional change. However, as the economy starts recovering, the compositional shift becomes more important, preventing job creation from a faster recovery. In particular, the educational composition change seems to account for most of the slower job creation while the "labor force composition" channel just explains a small fraction of the difference. Still, the "labor force composition channel plays a key role in driving the entry from unemployment, which is mostly done as a stopgap activity in the form of subsistence self-employment.

Second, to isolate the effects associated with the "labor market tightness" channel from the "profitability" channel, I compute the impulse response functions for a one-time unexpected negative shock to aggregate productivity, and I perform a counterfactual analysis making the individuals believe that the job finding probability holds constant throughout the entire transition. The results show an amplification effect arising from the former channel. When I mute the decline of the job finding probability in the occupational problem, entry into entrepreneurship falls by less, and it is not disproportionately larger for highly educated individuals anymore. This means that the growth potential of startups also falls less, and aggregate job creation recovers faster. The results show that the "labor market tightness" channel accounts for a 33% of the decline in the entrepreneurship rate, and a 30% of the increase in the unemployment rate at the peak of the recession period. Therefore, firm and worker dynamics interact in equilibrium to amplify the effects and persistence of an aggregate productivity/demand shock: a lower job creation of startups declines further the job finding probability, deterring, even more, and more persistently, the entry of startups, especially high-growth businesses. This mechanism generates a slower recovery in the entry of employer businesses and aggregate job creation, consistent with the labor market dynamics in the aftermath of the Great Recession in the U.S.[5]

The remaining structure of this document is as follows. Section 2 summarizes the related literature and contributions. Section 3 presents evidence about the aggregate dynamics of business formation, business founders' composition, and the relation between ex-post firm performance and business owners' characteristics. Section 4 develops the model and provides intuition for the model mechanisms in a partial equilibrium analysis. Section 5 presents the empirical analysis and the results from the calibrated structural model. Section 6 concludes.

2 Related Literature and Contributions

My work contributes to four main strands in the literature. First, my work relates to the literature on firm dynamics studying business cycles as a source of variation in the entry and growth potential of startups. Recently, Sedláček & Sterk (2017) and Moreira (2016) argue that the worsening demand conditions at the time of birth lead to a selection at entry mechanisms that

[5] The labor market tightness in the U.S. returned to its pre-recession level just in October 2014, much slower than the recovery of aggregate demand.

makes firms to start smaller in recessions and grow less over their entire life-cycle. Similarly, Smirnyagin (2020) and Vardishvili (2020) argue that financial frictions and the potential entrants' ability to delay entry prevent large projects from being started in recessions. In related work, Ates & Saffie (2020) argue that the credit shortages associated with recessions lead to "Fewer but Better" firms. In their framework, financial intermediaries assign scarce funds to the most promising ideas, decreasing the number of entrants but increasing their average productivity. These works are consistent with the results from Pugsley, Sedláček & Sterk (2020) who, using Census microdata, find that most of the differences in growth speed among startups are determined by ex-ante heterogeneity rather than persistent ex-post shocks. However, these works assume that potential entrants are ex-ante identical, with businesses heterogeneity only arising from the different types of businesses that entrants decide to start. I contribute to these works in two dimensions. First, I argue two business founders' characteristics as a new source of ex-ante business heterogeneity: the previous labor force status and educational attainment. Second, I study labor market dynamics rather than aggregate demand or financial constraints mechanisms as the driver for the decision to start businesses and their future performance.

In a similar line, Sedláček (2020) and Siemer (2014) study the effects of the deficit of startups during the Great Recession on the U.S. aggregate employment dynamics in the medium- to long-run. They find that even when the immediate impact of a drop in the firm entry on aggregate employment is small, in the later years, the negative effect of the missing generation of firms strengthens because of the lack of older firms growing large in the future. My model also generates this pattern, but the shift of composition toward fewer high-skill founders leads to a deficit of high-growth startups, which slows down, even more, the labor market recovery. This feature in the model increases the persistence of the decline in the entry of employer businesses after the recessions.

Second, my work also contributes to the literature studying entrepreneurship as an occupational choice in the labor market. The studies addressing the decline in U.S. business dynamism have proposed the increasing value of the outside option of entrepreneurs to explain the downward trend in the U.S. entrepreneurship rate in the last three decades. Engbom (2019) argues that the aging of the workforce has increased the opportunity cost of potential entrants because older people have usually found better jobs. Salgado (2020), and Kozeniauskas (2018) find that the decline in the entrepreneurship rates has been relatively larger for highly educated individuals, a fact they explain by the increasing returns to high skill labor due mostly to skill-biased technological change. I also argue the outside option as a driver for entry decisions, but I focus the analysis on the business cycle, and I propose the dynamics of the job finding probability as a determinant for the entry of highly educated individuals in downturns.

Regarding the role of labor market frictions on the decision to become an entrepreneur. Galindo Da Fonseca (2019) argues the difference in the outside option to self-employment between employed and unemployed workers as a key driver for differences in the entry decisions and firm size. Using Canadian administrative tax data, he finds that differences in outside options cause unemployed workers to be more likely to become self-employed than wage workers, but to create smaller firms that are more likely to exit. Similarly, Poschke (2019) argues that labor market frictions generate a positive relationship between unemployment and self-employment rates. He develops a cross-country analysis for a stationary equilibrium using a Diamond-Mortensen-Pissarides model extended with an occupational choice structure and firm heterogeneity.

Related to the "fear to fail" mechanism, Hombert et al. (2020) empirically study how the extension of the unemployment insurance to self-employment implemented in France in 2002 affected the decision to start businesses. They find a sharp increase in the entry rate, which they attribute to the smaller "fear to fail" effect. Gaillard & Kankanamge (2019) address this fact using a structural model with risky entrepreneurship and search frictions. They show that by allowing entrepreneurs, upon a business failure, to go to unemployment and claim UI benefits, the entry rate increases because the cost of a business failure decreases. Choi (2017) proposes outside options of business founders as a key source of heterogeneity in the early growth trajectory of young firms. He shows that entrepreneurs with higher outside options as paid workers tend to take larger business risks, and thus exhibit a more up-or-out type of firm dynamics. My work contributes to this line of research in three dimensions. First, I perform a business cycle analysis rather than a steady state comparison, which allows me to study the dynamic effects of a countercyclical "fear to fail" on entry decisions. Second, my framework explicitly captures the dissimilar characteristics and motivations between subsistence self-employed and entrepreneurs, and their opposite entry dynamics. Third, the firm dynamics feature in the model allows the study of the persistent effects from the change in the entry and composition of business founders on the aggregate job creation.

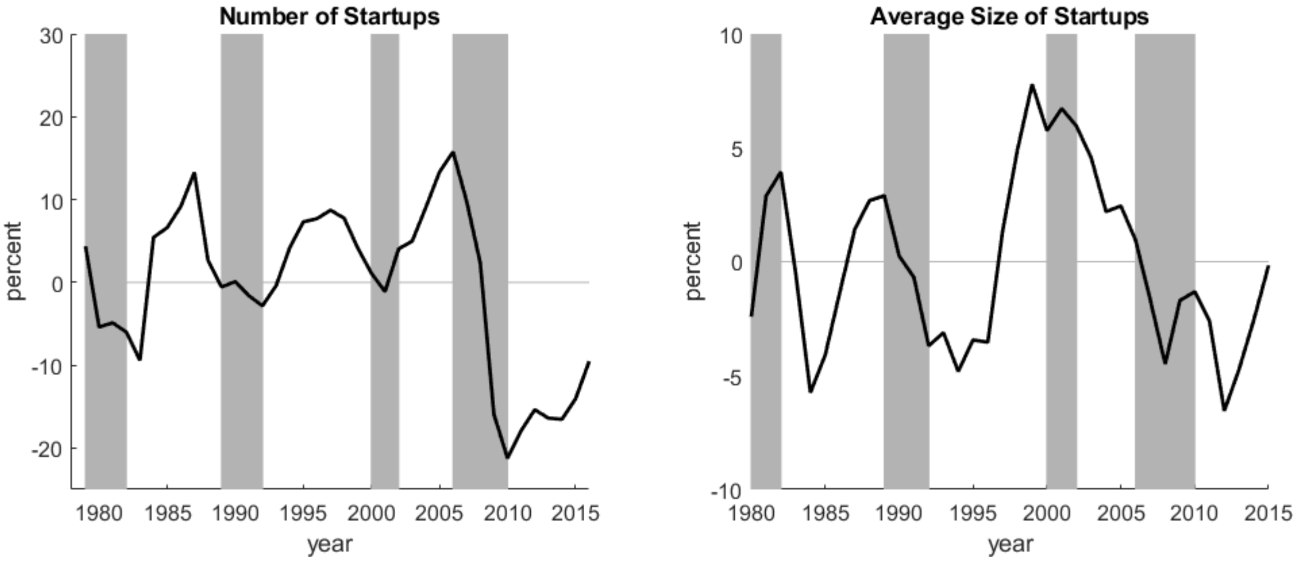
Few empirical works have studied how the characteristics of entrepreneurs vary over the business cycle. Levine & Rubinstein (2018) distinguish between entrepreneurs and other self-employment and, using data from NLSY79, show that entrepreneurship is procyclical, while self-employment is countercyclical. Fairlie & Fossen (2019) and Fossen (2020), using CPS data, show that entry into self-employment increases during recessions in the U.S., mostly due to the larger inflows from unemployment. The results in my paper are consistent with their findings. Also, to the best of my knowledge, my paper is the first to develop a structural model to study the drivers of the changes in entry and composition over the cycle in terms of previous labor force status and educational attainment of business founders.

Fourth, my work also contributes to the growing literature introducing a frictional labor market into models with firm dynamics and business cycles. Elsby & Michaels (2013) introduces a notion of firm size using decreasing returns in a random search and matching model with endogenous job destruction and aggregate uncertainty. To overcome the challenge of setting wages by Nash bargaining in a multi-worker firm framework, they use the marginal worker in an environment without the entry of firms. Schaal (2017) builds on the block recursivity approach from Menzio & Shi (2010) to extend a model of directed search on the job to a multi-worker firm environment that allows for endogenous entry and exit. In his model, constant hiring costs are needed to obtain the property of block recursivity. Audoly (2020) extends the Rank-Preserving Equilibrium approach from Moscarini & Postel-Vinay (2013) to build an on-the-job search model with convex hiring costs that features endogenous entry and exit, but with a constant returns to scale technology.[6] In my framework, endogenous entry and convex hiring costs are needed ingredients. The endogenous entry makes the selection of business evolve over the business cycle, and convex hiring costs help to discipline young firms' dynamics.[7] My model abstracts from on-the-job search, which simplifies the wage setting procedure, but still, the decreasing returns, convex hiring cost, and labor skills heterogeneity make the wage setting procedure challenging.[8] To keep the model tractable, I assume that entrepreneurs do not directly hire workers but instead buy labor units from labor agencies that match with workers under searching frictions in a one-worker-one-firm fashion. This assumption allows me to use a standard search and matching mechanism, avoiding the complexities of a framework where multi-worker firms face search frictions in a labor market with heterogeneous labor skills. Then, I set wages following a Nash bargaining solution computed for the representative worker of each level of labor skills as in Nakajima (2012).

[6] Engbom (2019) and Audoly (2020) use a constant return to scale technology and convex hiring costs. Then, the firm size is pinned down by the convex hiring cost and the entry-exit continuous process. Every firm will eventually exit, making firms not grow infinitely.

[7] In the literature, the parameters related to the stochastic technological process are also used to discipline the firm size distribution. In my framework, they are primarily used to match the high exit rates from the individual-level data.

[8] Shimer (2006) shows that in models with on-the-job search, the requirements of a convex set of possible payoffs for a unique Nash equilibrium is not satisfied. If wages are set before quit decisions, and the contract also lasts for at least some periods in the future, then the turnover that a firm will face is affected by the agreed wages. This generates multiple Nash equilibrium, violating the uniqueness of the standard models.



Source: author's calculations with BDS data. Figures plot percentage deviations with respect to the mean over 1979 - 2016.

Figure 1: Entry and Average initial Size

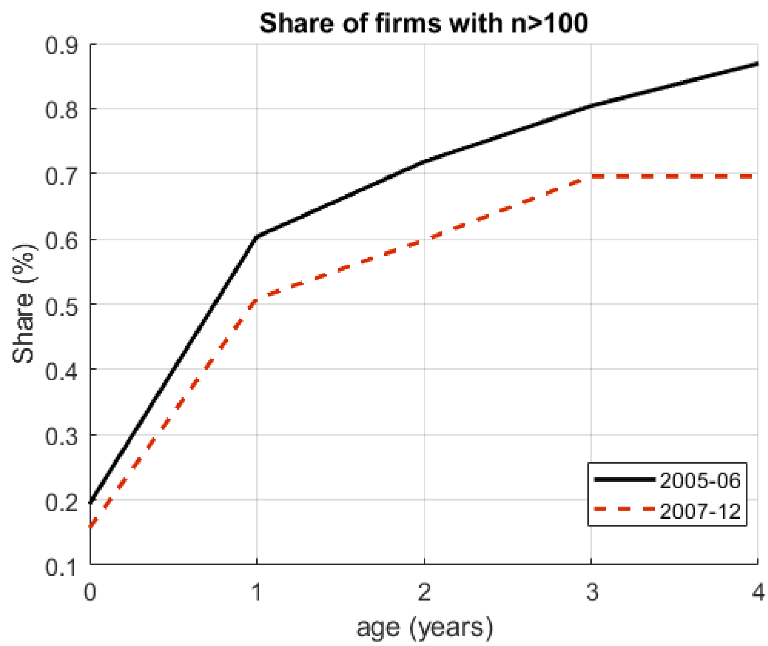
3 Firm and Labor Market Aggregate Dynamics

3.1 Firm Dynamics

First, in the spirit of Sedláček & Sterk (2017), I present evidence for procyclical entry of employer businesses and persistent average size of startups using firm-level data for the U.S. I use Business Dynamics Statistics (BDS) data between 1979 and 2016. BDS is the publicly available version of the confidential micro-level data from the Longitudinal Business Survey (LBD), which covers 98 percent of private employment. The BDS is an annual database, which allows us to follow cohorts of new firms for up to five years after they enter the economy. Thereafter, the BDS groups firms into age categories spanning five years, i.e., by windows of firms aged 6-20, 11-15, and 16-20 years.

Figure 1 presents the number of startups and their average size between 1979 and 2016, with the latter smoothed using a 3-year moving average. Both variables are covariance stationary for this period, so their cyclical components are presented as percentage deviations with respect to the mean over 1979-2016. Both variables are procyclical, with slow recoveries after recession periods. This suggests that the negative effect of recessions on business formation go beyond the period of the recession itself. This decline in the entry during recessions reduces the contribution of startups to aggregate job creation, which is reinforced by the decline in their initial size.

Next, to explore the growth performance of businesses born at different stages of the business

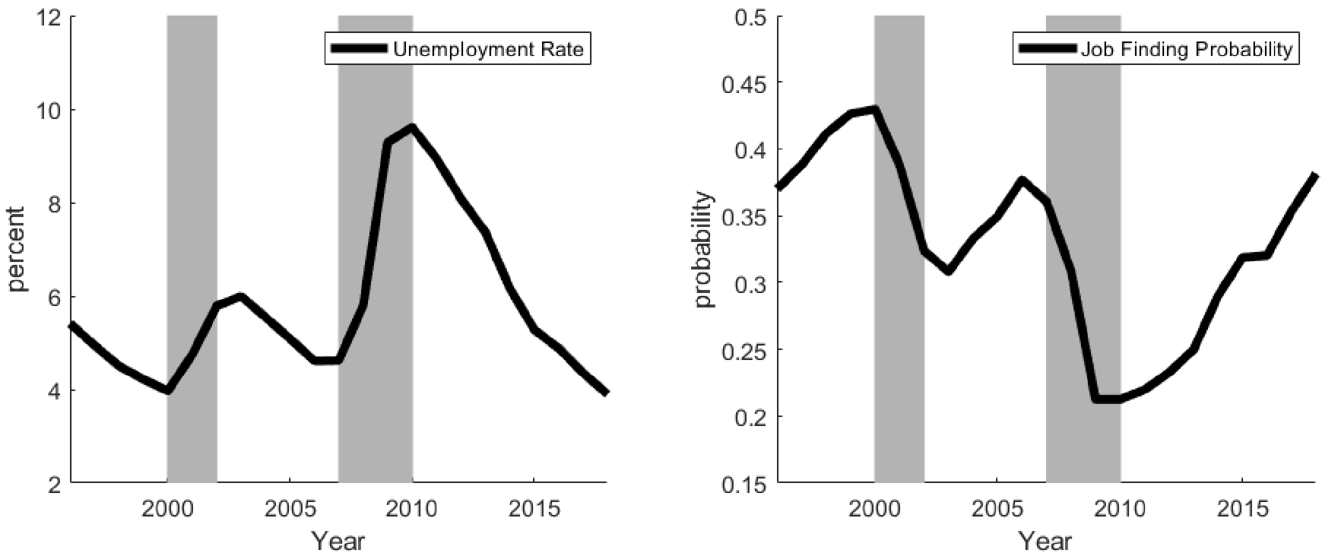


Source: author's calculations with BDS data.

Figure 2: Share of employer firms with more than 100 employees over age

cycle, Figure 2 presents the evolution of the share of businesses with more than 100 employees over firm age for two periods, 2005-2006 and 2007-2012. I choose these two periods to compare the performance of the cohorts born just before the Great Recession with those born during and in the aftermath of it. The share of startups (0-year-old businesses) with more than 100 employees is smaller in the later period due to the smaller average initial size of startups during downturns. This difference persists and even increases as businesses age, suggesting a lack of high-growth entrepreneurs in cohorts born in downturns. A similar analysis can be done by analyzing the autocorrelations between the initial average size of startups and their future size. Appendix A presents this analysis for horizons up to 5 years. Consistently, the autocorrelations for startups show that the future size of businesses is heavily correlated with their initial size. Firms that are born small during downturns are likely to remain smaller over their lifecycle. Then, I perform the same autocorrelation analysis but for a longer time horizon, using the 5-year windows cohort data from the BDS. We can see that the strong dependence of future size on initial conditions is present even 20 years later.

The findings from this section can be summarized as: (i) business creation is procyclical and highly persistent; (ii) the average size of startups is procyclical and persistent; (iii) the persistence from (i) and (ii) implies that the recovery of business entry and the average size of startups is slower than the recovery of aggregate economic conditions; (iv) the cohorts of businesses born in downturns seem to grow less, possibly due to the lack of high-growth entrepreneurs.



Source: author's calculations with CPS data.

Figure 3: Unemployment Rate and Job Finding Probability

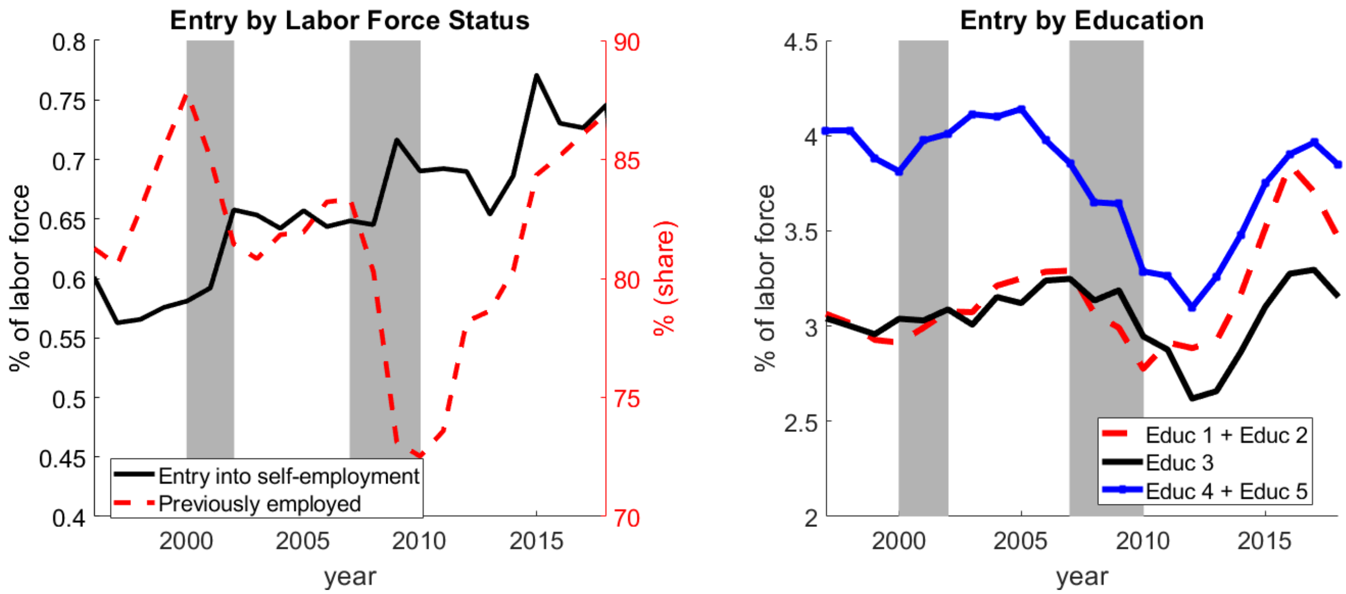
3.2 Labor Market Dynamics: Entry and Composition

Research studying business formation and growth of young businesses uses primarily firm-level data, which makes no possible to add information about the owners of those businesses into the analysis. Because the goal of this paper is precisely to study how the entry and composition of startups in terms of business founders characteristics change over the cycle, I need to relate the decision of entry to the business founder characteristics. To overcome this problem, I complement the firm-level analysis with individual-level data for the U.S. from the Current Population Survey (CPS) for the period 1996-2018. The CPS is the primary source of monthly labor force statistics in the U.S., and its sample size is about 60,000 households. First, I document the dynamics of the unemployment rate and job finding probability, and then I turn to analyze the entry and compositional dynamics in terms of previous labor force status and educational attainment of business founders.

Figure 3 shows that the unemployment rate increases heavily and persistently in recessions. The job finding probability mirrors this path but in the opposite direction.[9] This implies that more people solve the occupational problem from unemployment, and individuals make their decisions facing a persistently lower job finding rate during economic downturns.

In Figure 4, the left panel presents the total entry into self-employment and the composition of entrants in terms of their previous labor force status for the period 1996-2019. The full set

[9]Gray-shaded regions indicate NBER recession periods.



Notes: Left panel: author's calculations with CPS. Entry into self-employment is calculated as the total number of monthly transitions from employment and unemployment into self-employment as share of the labor force. Entry by previously employed individuals corresponds to the share of entrants coming from employment only. Right panel: Author's calculations with CPS ASEC. It includes only individuals who worked during the previous year and corresponds to transitions rates from year t to year t+1. "Educ 1 + 2", "Educ 3", and "Educ 4 + 5" represent individuals with high-school or less, incomplete college, and college or graduate studies, respectively.

Figure 4: Entry and Composition of Business Founders

of nine transition rates between employment, unemployment and self-employment is included in the Appendix B. Entry into self-employment exhibits an upward trend with a suggestive countercyclical behavior.[10] This kind of countercyclical behavior of entry in the CPS contrasts with the procyclical entry rate from the BDS. Self-employment in the CPS accounts for both employer and nonemployer businesses, while the universe of firms in the BDS only corresponds to employer firms. The dissimilar patterns in the entry of these two types of businesses suggest heterogeneous motivations to start businesses over the cycle at the individual level. The left panel also shows the share of new businesses started by previously employed individuals with respect to the total entry from employment and unemployment. The composition shifts sharply toward more people starting businesses from unemployment. This change is driven by the increase in the number of people solving the occupational problem from unemployment ("labor force composition" channel), and by the decrease in transitions from employment due to the decline in both the job finding probability ("labor market tightness" channel) and aggregate demand ("profitability" channel).

The right panel, using annual data from the CPS ASEC, presents the time path of the transition rates into self-employment by educational attainment, considering only individuals who

[10] In the data, this upward trend is matched by an upward trend in the exit rate, which makes the self-employment rate roughly constant over time.

reported to work during the previous calendar year.[11] Here, a transition into self-employment is identified as a person that reported waged work as the main activity in year "t" and then reported self-employment in the year "t+1". I present the entry rates by education at an annual frequency to focus the analysis on transitions cleaned from most of the stopgap activity. This makes business entry more comparable to the firm-level data.[12] The dashed red line corresponds to individuals with complete or incomplete high-school, the continuous black line to individuals with incomplete college, and the blue line with dots to individuals with complete college or graduate studies. We observe a decline in entry across all educational levels during and after the Great Recession, with a relatively larger fall for highly educated individuals, which almost double the fall of the other education levels. This pattern is consistent with the idea that the decrease in the job finding probability discourages employed workers from quitting their jobs to start a business during downturns, especially for highly educated individuals. Thus, this can be seen as suggestive evidence to support the existence of the labor market tightness channel. Regarding the composition, the larger decline in the entry for higher education levels suggests the composition shifts toward fewer high skill individuals during and after recessions.

These results are consistent with previous findings in the literature. Fairlie & Fossen (2019) document that transitions into self-employment increase during recessions in the U.S., mostly driven by the rise in transitions from unemployment to self-employment. Galindo Da Fonseca (2019), using Canadian tax data, shows that differences in outside options imply that unemployed workers are more likely to become self-employed than wage workers, but they create smaller firms and are more likely to exit. The findings from these papers are consistent with both the "labor force composition" and the "labor market tightness" channel proposed in my framework. Regarding the entry rate by education levels, to the best of my knowledge, the only work with a similar analysis is Kozeniauskas (2018). He documents a decline in the entrepreneurship rate trend across all education levels, but more pronounced for higher education levels. My analysis can be seen as an extension, which is only focused on the inflows into entrepreneurship. There is no evident decreasing trend for the entry side at any education level, which suggests that the trend of entrepreneurship might be being driven by the exit rates.

Overall, these empirical patterns suggest a role for the "labor force composition" and the "labor market tightness" channels as forces shaping the entry and composition of new businesses through the unemployment rate and the job finding probability dynamics, respectively. Entry and composition dynamics also exhibit a high persistence after the Great Recession, which

[11] CPS ASEC: Current Population Survey Annual Social and Economic Supplement

[12] Here, the annual transitions are constructed considering the occupations that are hold for the longest time during each year. This kind of analysis cannot be done with the monthly basic CPS data because individuals only report their occupation for a period of four months in the year. In Section 5, the formal empirical analysis is performed using monthly frequency data from the Survey of Income and Participation Program (SIPP).

is consistent with the firm-level analysis. This plays in favor of the idea that the declining employer business entry and the lower growth potential of startups might be driven by a selection mechanism arising from the labor market dynamics rather than by demand or financial conditions, which recover faster in the aftermath of recessions.

4 The Model

This section outlines a dynamic occupational choice model with labor market frictions and firm dynamics, in which heterogeneous individuals choose between being employed/unemployed workers, subsistence self-employed, or entrepreneurs with potential to grow.

4.1 Environment

Time is discrete, and the horizon is infinite. The economy is populated by a unitary mass of risk-neutral individuals, who are heterogeneous in labor skills and entrepreneurial ability.

Occupational choice structure Individuals start every period either matched or unmatched to an employer business, and the occupational decisions they can make depend on this condition. Unmatched workers can choose to be unemployed workers to search for a job with the best available search efficiency, or to start (or continue running) a business either as subsistence self-employed getting access to an inferior technology but searching for a job with an intermediate search efficiency or as an entrepreneur with access to the best possible technology but with a relatively low search efficiency. Those who choose to own a business must also decide how much labor units to hire. Matched workers can choose to stay on the job or quit to start a business at the cost of permanently losing the match. Workers becoming unmatched can start a business immediately in the current period. If they decide to keep the job, they can also become unmatched workers at the end of the period through exogenous separations. In this environment, individuals choose their occupations conditional on their current labor force status (matched or unmatched), labor skills, entrepreneurial ability, and aggregate productivity. This occupational choice structure allows the model to account for endogenous entry/exit in both technologies, and endogenous quits of workers to start businesses. The distinction between the two possible technologies is the key ingredient that captures the different motivations to start a business. Individuals starting businesses because of good entrepreneurial ideas are more likely to choose the entrepreneurial technology, while those starting business because of a lower outside option (e.g., unemployed workers) are more likely to start the business as subsistence self-employed.

Labor Skills Heterogeneity in labor skills is also a key ingredient in the model. Labor skills are indexed by $h \in H$, are time-invariant for a given individual, and are distributed among the population according to a logarithmic distribution. This produces a wage distribution for workers, which generates a heterogeneous pool of potential entrants. In other words, the outside options of business owners are heterogeneous, which leads to a selection at entry mechanism: highly skilled individuals only decide to start a business when the entrepreneurial idea is good enough to compensate for the forsaken wage. At the same time, the labor skills determine the value of the fallback option in the event of a business failure. This is the potential wage that the individual would receive in the job found in a business closure event.

Entrepreneurial ability of incumbents (current business owners) For current subsistence self-employed and entrepreneurs, the idiosyncratic entrepreneurial ability of an individual i, z_i, evolves stochastically over time according to the following AR(1) process:

$$\begin{aligned} \ln z_i' &= \mu_{zh} + \rho_z \ln z_i + \sigma_z \epsilon_z' \\ \epsilon_z &\sim N(0,1) \end{aligned}$$

The stochastic realizations of the entrepreneurial ability will generate endogenous exit. In the presence of a fixed operational cost and a valuable outside option, individuals will decide to close the business if the draw of z is below some certain threshold $z^\star$. The constant μ_{zh} is used to introduce permanent heterogeneity in the model, by allowing the mean of the entrepreneurial ability to correlate with the labor skills. In particular, this parameter allows the model to capture the larger size of businesses owned by high-skill individuals that we see in the data.

Entrepreneurial ability of potential entrants Potential entrants are uncertain about their initial productivity if they decide to start a business either as a subsistence self-employed or as an entrepreneur. At the beginning of every period, before the occupational choice is made, employed and unemployed individuals receive a signal ξ about the post-entry initial productivity that they would have if they decide to start a business. The signal is drawn from a Pareto distribution $q \sim Q(q) = (\underline{q}/q)^{\xi}$. Conditional on entry, the distribution of the idiosyncratic productivity in the first period of operation is given by

$$\begin{aligned} \ln z_0 &= \rho_z \ln q + \sigma_q \epsilon_q \\ \epsilon_q &\sim N(0,1) \end{aligned}$$

Given this process, the value of starting a business is increasing in the signal q, which means that there will be a threshold $q\star$ above which the prospective entrants will decide to enter. Differently from Hopenhayn (1992), where potential entrants are identical, and there is a unique cutoff $z\star$ above which individuals decide to start businesses, the heterogeneity in the outside option in my model generates dispersion in the initial productivity of the entrants. This is a novel feature of my framework. On top of that, as in Clementi & Palazzo (2016), the uncertainty regarding the initial productivity generates heterogeneity even within individuals with the same outside option. Because of the labor market frictions, when an individual decides to quit a job to start a business, the match with the employer firm is severed. This makes that even if the entrepreneurial ability draw makes the value of being a business owner lower than the value of being a waged worker, the individual might get stuck as a business owner until get a job offer because now the relevant outside option is unemployment. This feature triggers the "fear to fail" effect in the model.

If the job finding probability is lower, then the "fear to fail" effect becomes bigger discouraging the entry from employment. This effect is stronger for high-skilled workers for whom the wage loss will be larger. This is the mechanism by which the "labor market tightness" channel works in the model.

Aggregate Productivity There is no aggregate uncertainty. Aggregate productivity A is assumed to take value 1 in the stationary equilibrium. Then, to analyze cyclical fluctuations in the entry and composition of business founders, two perfect foresight transitional dynamics exercises are performed. First, to validate the model dynamics, the model is fed with an exogenous aggregate productivity path. Then, a counterfactual exercise is performed to quantify the effects of the labor market dynamics on the entry and composition of startups. Here, I apply a one-time unanticipated shock to the path of the aggregate state, which is thereafter deterministic and perfectly known by everyone (MIT shock). In both cases, to run these exercises, I first compute the stationary equilibrium and then the perfect foresight transition dynamics consistent with the exogenous path of A using a shooting algorithm.

Labor market frictions To introduce searching and matching frictions in a tractable way, I use the assumption that firms managed by subsistence self-employed or entrepreneurs do not directly hire workers but instead buy labor efficiency units n from labor agencies. These labor agencies are subject to search frictions to hire workers.[13] Labor agencies produce labor efficiency units after a worker-firm match is realized. A labor agency transforms the indivisible h units

[13] In the same fashion as Galindo Da Fonseca (2019).

of a worker's skilled labor into n labor efficiency units, with a one-to-one technology ($n = h$), and sells these units in a competitive market to the entrepreneurs. This implies that the size of businesses can effectively be measured in units of n. I also assume that worker ability is observable to the labor agencies, and thus these firms can direct their search to a particular worker type. These two assumptions allow for two desirable simplifications. First, because the labor agencies facing the search frictions are one-firm-one-worker matches, a standard search and matching mechanism can be used to avoid the complexities from a framework where a multi-worker firm faces search frictions.[14] Second, the challenge of dealing with heterogeneous worker skills is simplified by the directed search assumption. Each type of worker is seen as a different segment of the labor market to which labor agencies direct their search, and where different wages are set according to Nash Bargaining, generating a distribution of wages $w_h(A)$ (as in Mueller (2017) and Hagedorn, Manovskii & Stetsenko (2016)).

4.2 Timing and model overview

Figure 5 summarizes the structure of the model. The timing is as follows.

- The economy starts each period with the occupational distribution from the end of the previous period.
- Signals for initial productivity of potential entrants and idiosyncratic shocks to entrepreneurial ability for incumbents are realized.
- Individuals choose occupations. Businesses also decide labor hiring. The occupational distribution for the current period, after applying the decision rules, is given by $\Psi(h, z_t, n_t, o_t)$.
- Wages are set following a Nash bargaining rule and also the market of labor efficiency units clears.
- Production and payments are carried out.
- Job findings and separations are realized according to $f(\theta_{h,t})$ and s. The occupational distribution for the beginning of the next period is determined.

Next, I turn to describe the individuals' decision problems, how the labor market works, and the equilibrium definition.

[14] Elsby & Michaels (2013) introduce a notion of firm size directly into a search and matching model with endogenous job destruction.

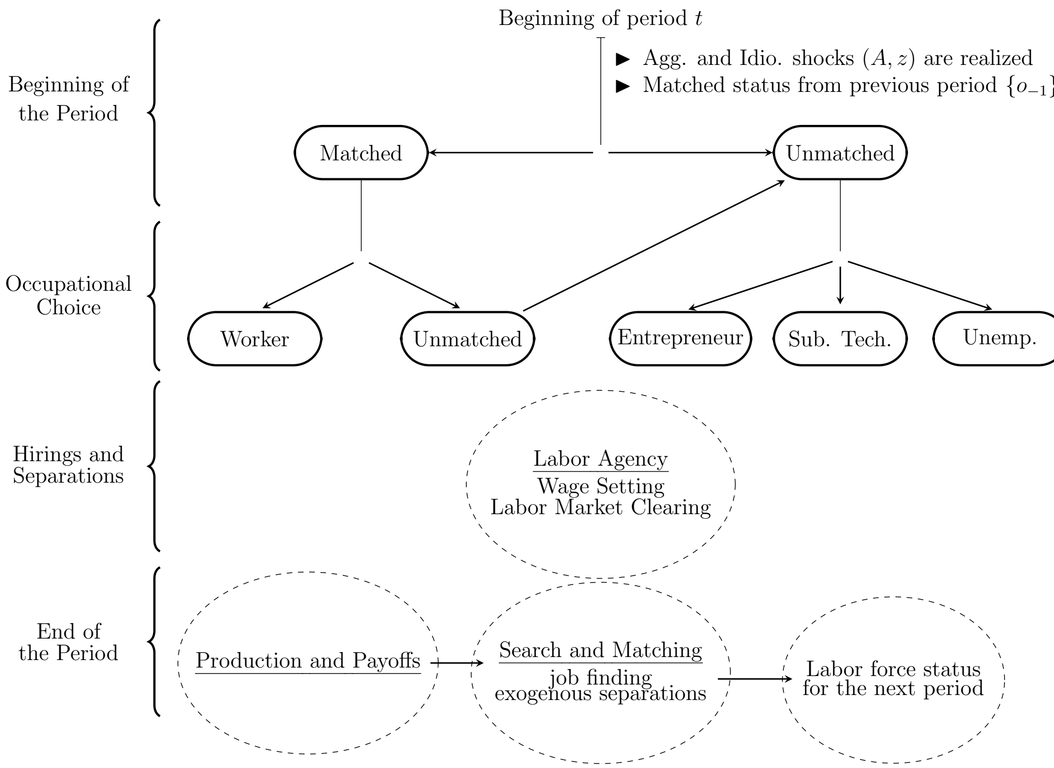


Figure 5: Model overview

4.3 Individual's Decision Problem

First, I describe the occupational choice problem faced by matched and unmatched workers. Then, I develop expressions for the value functions associated with each possible occupation: wage worker, unemployed worker, subsistence self-employed, and entrepreneur.

4.3.1 Occupational Choice Problem

Individuals start each period being matched or unmatched to an employer business. The occupational choice problem for an individual with labor skills (h), signal of initial entrepreneurial ability (q), business size in $t-1$ (n_{-1}), conditional on aggregate productivity (A), is given by:[15]

Matched worker

$$W(h, q, n_{-1}; A) = \max \mathbf{E}_{z/q}\Big[V^E(h, z, 0; A), U(h, z, n_{-1}; A)\Big] \tag{1}$$

[15]If the individual was a business owner in $t-1$, then the signal q is just the productivity realization z. If the individual was not a business owner in $t-1$, then $n_{-1} = 0$.

where $V^E(h,z;A)$ and $U(h,z;A)$ correspond to the value functions of being a wage worker and an unmatched worker, respectively.

A matched worker can decide to stay as a waged worker or to quit to solve the problem of an unmatched worker. The only way in the model to start a business, either as subsistence self-employed or as an entrepreneur, is by quitting the job first.

Unmatched Worker

$$U(h,q,n_{-1};A) = \max \mathbf{E}_{z/q}\Big[V^U(h,z,0;A), V^S(h,z,n_{-1};A), V^F(h,z,n_{-1};A)\Big] \tag{2}$$

where V^U is the value of being an unemployed worker, V^S is the value of being subsistence self-employed, and V^F is the value of being an entrepreneur.

An unmatched worker can choose to be an unemployed worker or start a business either as a subsistence self-employed or an entrepreneur.

Value of being a Wage Worker

$$V^E(h,q,0;A) = w_h(A) + \beta\Big[\Big(1-s\Big)\mathbf{E}_{q'}W(h,z',0;A') + s\mathbf{E}_{q'}U(h,z',0;A')\Big] \tag{3}$$

where $w_h(A)$ is the wage of a worker type h and s is an exogenous separation probability.[16] A wage worker receives a wage according to his type h, which is determined by Nash Bargaining with labor agencies, as will be explained below.

Value of being an Unemployed Worker

$$V^U(h,q,0;A) = Y^{ss} * w_h^{ss} + \beta\Big[f(\theta_h)\mathbf{E}_{q'}W(h,z',0;A') + \Big(1-f(\theta_h)\Big)\mathbf{E}_{q'}U(h,z',0;A')\Big] \tag{4}$$

where $Y^{ss} * w_h^{ss}$ is the unemployment benefit that a worker type h receives, which is proportional to the equilibrium wage, and $f(\theta_h)$ is the job finding probability for a type h worker.[17] θ_h corresponds to the labor market tightness in segment h.

[16] Same separation probability s across all labor skills is a conservative assumption considering that high-skill workers have a lower separation probability in the data.

[17] The model allows for heterogeneity in θ_h, however for simplicity, it is calibrated to the same value in the stationary equilibrium. In the data, $f(\theta_h)$ for high-skill workers is hire, but the magnitude of the decline in recessions is proportionally equivalent across all education levels.

Value of being an Entrepreneur

$$\begin{aligned} V^F(h,z,n_{-1};A) &= \pi(z,n_{-1};A) \\ &+ \beta\Big[\varphi^F f(\theta_h)\mathbf{E}_{z'/z}W(h,z',n;A') + \Big(1-\varphi^F f(\theta_h)\Big)\mathbf{E}_{z'/z}U(h,z',n;A')\Big] \\ s.t. & \\ \pi(h,z,n_{-1};A) &= \max_n \Big\{zAn^\alpha - \rho(A)n - \phi - g(\chi)\Big\} \\ g(\chi) &= \frac{\kappa}{\gamma}\chi^\gamma n; \quad \chi = \max\Big\{0, \frac{n-n_{-1}}{n_{-1}}\Big\} \end{aligned} \tag{5}$$

where ϕ is a fixed operational cost as in Hopenhayn (1992), φ^F is the search efficiency of entrepreneurs, n is the number of labor efficient units hired to produce the final good and ρ is its price, and (κ, γ) are the parameters in the hiring costs function. Relative to a model with linear recruitment costs, convex costs $\gamma > 1$ generate a pronounced labor market propagation, featuring sluggish adjustments of the job-finding rate and of the vacancy-unemployment ratio.

Entrepreneurs produce by using labor efficiency units n as input according to a technology that depends on their entrepreneurial ability z and aggregate productivity A. I assume decreasing returns, so that $0 < \alpha < 1$. Because starting and closing a business correspond to occupational decisions of unmatched individuals, the entry and exit are endogenous outcomes in the model.

Value of being a Subsistence Self-Employed

$$\begin{aligned} V^S(h,z,n_{sub_{-1}};A) &= \pi_{sub}(z,n_{sub_{-1}};A) \\ &+ \beta\Big[\varphi^S f(\theta_h)\mathbf{E}_{z'/z}W(h,z',n;A') + \Big(1-\varphi^S f(\theta_h)\Big)\mathbf{E}_{z'/z}U(h,z',n;A')\Big] \\ s.t. & \\ \pi_{sub}(z;A) &= \max_{n_{sub}} \Big\{A_{sub}A^\nu z n^{\alpha_{sub}} - \rho(A)n_{sub} - g(\chi_{sub})\Big\} \\ g(\chi_{sub}) &= \frac{\kappa}{\gamma}\chi_{sub}^\gamma n_{sub}; \quad \chi_{sub} = \max\Big\{0, \frac{n_{sub}-n_{sub_{-1}}}{n_{sub_{-1}}}\Big\} \end{aligned} \tag{6}$$

where $A_{sub} < 1$ is a scale parameter that allows the model to discipline the inferior technology and A^ν, with $\nu < 1$, is used to allow for a different sensitivity for the subsistence activity with respect to the aggregate shock. The parameter α is the span of control measure. φ^S is the search efficiency of subsistence self-employed, with $1 > \varphi^S > \varphi^F$.

Given the trade off in terms of technology and search efficiency between the subsistence self-employment and entrepreneurship alternatives, individuals with different motivations will choose different options. In the model, individuals that fall into unemployment and are relatively low-skilled workers are more likely to start businesses as a subsistence self-employed, while employed individuals that with high labor skills are more likely to start businesses as an entrepreneur.

4.4 Labor Market Frictions

4.4.1 Matching function, Job Finding rate, and Job Filling rate

Similar to Bils, Chang & Kim (2009) and Mueller (2017), I assume worker ability is observable to the labor agencies and thus labor agencies can direct their search to a particular worker type. I assume a finite number of types $h \in H$, and for each there are unemployed workers searching for a job and a continuum of labor agencies searching for workers of type h. Workers and labor agencies are matched in each segment $h \in H$ according to the following matching function:

$$M_h(v_h, S_h) = m u_h^{\psi} v_h^{1-\psi} \tag{7}$$

where m is the matching efficiency common across all segments, u_h the number of unemployed workers in segment h, and v_h the number of vacancies posted by labor agencies in segment h. The labor market tightness in each segment h is given by $\theta_h = \frac{v_h}{S_h}$. Then, the job finding probability for an unemployed worker of type h is given by $f(\theta_h) = \frac{M_h}{S_h} = m\theta_h^{1-\psi}$. The job filling rate is given by $q^h(\theta_h) = \frac{M_h}{v_h} = m\theta_h^{-\psi}$.

4.4.2 Labor Agencies

Labor Agencies direct their search by posting vacancies in each segment $h \in H$. The value of posting a vacancy in segment h is:

$$V_h(A) = -c + \beta[q^h(\theta_h)J_h(A') + (1 - q^h(\theta_h))V_h(A')] \tag{8}$$

The value of a filled vacancy in segment h is:

$$J_h(A) = \rho(A)h - w_h(A) + \beta[(1-s)J_h(A') + sV_h(A')] \tag{9}$$

The zero profit condition of posting vacancies in segment h is given by $V_h = 0, \forall h \in H$.

4.4.3 Market Clearing Conditions / Wage Determination

The selling price $\rho(A)$ is determined by the market clearing condition of the labor good:

$$\int h \, d\Psi^E(h, z_t; A) = \int n(h, z_t, n_{t-1}; A) \, d\Psi^F(z_t, n_{t-1}; A) \quad \forall t \tag{10}$$

The total production of labor efficiency units across all segments $h \in H$, which is equivalent to the integral of h over the type distribution of wage workers, must be equal to the total demand for labor efficiency units which corresponds to the integral of the demand of subsistence self-employed and entrepreneurs $n(z_t, n_{t-1}; A)$ over their type distribution over (z, n_{-1}).

Wages are determined by centralized Nash Bargaining separately in each segment h. In each segment h, individuals differ by entrepreneurial productivity. Thus, following Nakajima (2012), I use a representative agent of each segment for the wage bargaining. Then, wages are determined by splitting the joint surplus from an employment relationship in the segment h according to the following Nash Bargaining process:

$$[\tilde{W}(h, A) - \tilde{U}(h, A)] = \frac{\eta}{1-\eta}[J_h(A) - V_h(A)] \tag{11}$$

where $\tilde{W}(h, A)$ and $\tilde{U}(h, A)$ correspond to the value functions of the representative agent of type h, which are determined as the probability-weighted averages of the individual value functions over the distributions of z and o_{-1}.

4.5 Equilibrium

Define $i = \{E, U, S, F\}$ and o_t as the current occupational status. Then, given an initial distribution $\Psi(h, z, o_{-1}, n_{-1})$ and a sequence of aggregate productivity $\{A_t\}_{t=0}^{\infty}$, an equilibrium for this economy can be defined as a sequence of value functions $\{V_t^i\}_{t=0}^{\infty}$, prices for labor efficiency units $\{\rho_t(A)\}_{t=0}^{\infty}$, wage distributions $\{w_t(h, A)\}_{t=0}^{\infty}$, labor market tightness $\{\theta_h\}_{t=0}^{\infty}$, decision rules $\{o_t^i(h, z_t, o_{t-1}, n_{t-1}), n_{sub,t}(z_t, n_{t-1}; A), n_t(z_t, n_{t-1}; A)\}_{t=0}^{\infty}$ and distribution of individuals $\{\Psi(h, z_t, o_{t-1}, n_{t-1})\}_{t=0}^{\infty}$ that solve:

1. Given $\{\rho_t(A), w_t(h, A), \{f(\theta_h)\}\}_{t=0}^{\infty}$, decision rules $\{o^i(h, \theta_t, o_{t-1}, n_{t-1}), n_{sub,t}^E(z_t, n_{t-1}, A), n^E(z_t, n_{t-1}, A)\}_{t=0}^{\infty}$ solve equations (1), (2), (3), (4), (5), and (6).

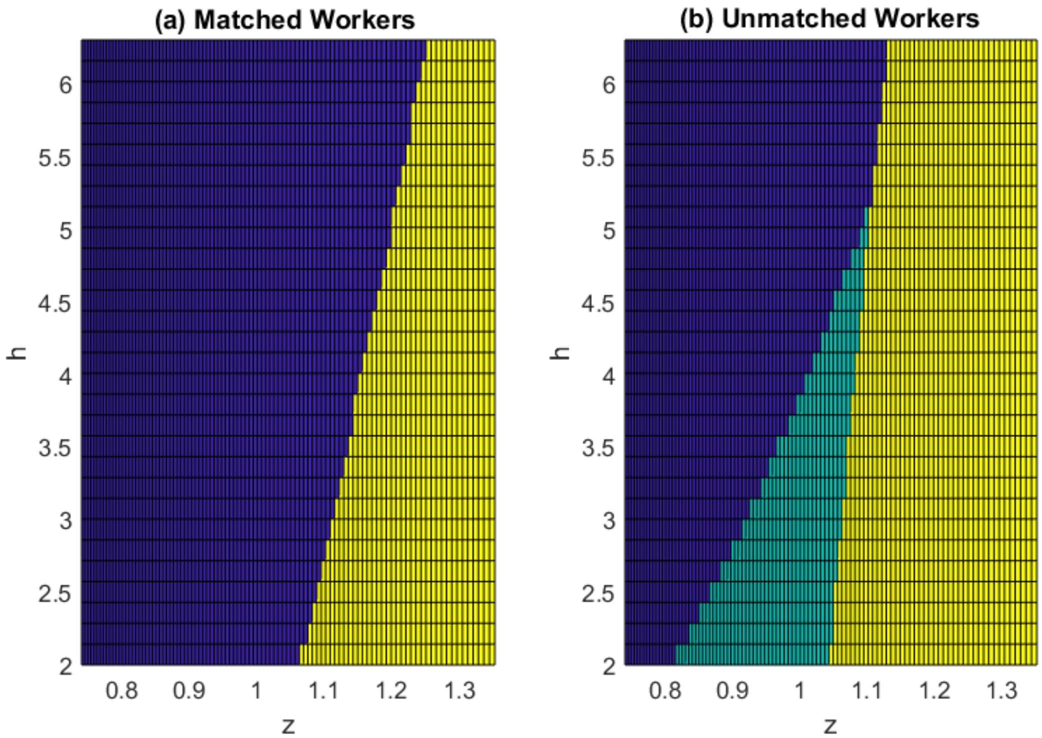
2. Given $\{\rho_t(A), w_t(h, A)\}_{t=0}^{\infty}$ and the zero profit condition, job filling rates $\{q^h(\theta_h)\}_{t=0}^{\infty}$ solve equations (8) and (9).

3. Wage distribution $\{w_t(h, A)\}_{t=0}^{\infty}$ satisfies the Nash Bargaining solution in equation (11).

4. Given $\{\rho_t(A), w_t(h, A), \theta_h\}_{t=0}^{\infty}$, the sequence of distributions $\{\Psi(h, \theta_t, o_{t-1}, n_{t-1})\}_{t=0}^{\infty}$ is consistent with the decision rules and the transition matrix T:

$$\Psi(x_{t+1}) = T\Psi(x_t) \tag{12}$$

5. Price sequence $\{\rho_t(A)\}_{t=0}^{\infty}$ satisfies the labor market clearing condition (10).



Panel(a): blue color corresponds to the option of staying as an employed worker and yellow color to the choice of being an entrepreneur. Panel (b): blue color corresponds to remaining unemployed, green to being subsistence self-employed and the yellow to the choice of being an entrepreneur.

Figure 6: Occupational Decision Rules: $f(\theta) = 0.28$

Appendix C presents the set of equilibrium conditions, with 18 equations and 18 unknowns, used to solve for the stationary equilibrium and the transition dynamics of the model. Appendix D presents the algorithm used to solve for the stationary equilibrium and appendix E the algorithm used to solve for the transition dynamics.

4.6 Intuition behind the mechanisms

This section presents a simplified partial equilibrium analysis to develop intuition about how the proposed mechanisms work, which at the same time correspond to three model-implied predictions that are empirically tested in the next section. For the analysis, I compute the occupational decision rules of the individual over the space (h, z), for a given set of prices $(\rho(A), w_h(A))$ and job finding probability $f(\theta_h)$, and it is assumed that the initial productivity z is equal to the signal q.[18]

[18]For the analysis, some arbitrary prices and job finding probability are used, which are not necessarily those from the stationary equilibrium.

4.6.1 "Labor Force Composition" channel

Figure 6 shows the occupational choice of individuals over the space formed by labor skills h and entrepreneurial ability z. Panel (a) presents the optimal choices for matched workers and panel (b) shows the optimal choices for unmatched workers. In panel (a), the blue color represents choosing to remain as a wage worker and the yellow color represents becoming an unmatched worker. In panel (b), the blue color represents the choice of being an unemployed worker, green the option of subsistence self-employment, and the yellow the option of being an entrepreneur.

Panel (a) shows that only those matched workers with a relatively high entrepreneurial ability z choose to quit their jobs to become unmatched workers. Similarly, in panel (b) individuals deciding to be entrepreneurs are those who have a relatively high entrepreneurial ability, while those with higher relative labor skills prefer to keep searching for a job. The positive slope of the division between the unemployed and entrepreneur choice spaces reflects how the value of the outside option to entrepreneurship is increasing with labor skills.

From analyzing panels (a) and (b) jointly, we see that the parameter space for which an unmatched worker chooses to become an entrepreneur is larger than for a matched worker. The reason for this can be decomposed in two parts. First, matched workers can choose to be a wage worker in the current period, which is not an available option for unmatched workers. This implies a lower outside option to self-employment for unmatched workers in the current period, generating an expansion of the entrepreneurial choice space for them. Second, if the probability of finding a job is lower than 1, the value of labor skills relative to entrepreneurial ability decreases for unmatched workers. This means a steeper division line between the decision rule spaces of unmatched workers, reinforcing the expansion of the space where they choose to become entrepreneurs. The opposite happens with matched workers, for whom the division line becomes less steep. Suppose an employed worker chooses to start a business and the business fails. In that case, it is going to take more time to find another job if the job finding probability is low, which reduces the expected value of becoming an entrepreneur. The imperfect probability of finding a job affects high-skill workers disproportionately more because the difference between their wages and what they receive in unemployment is bigger than for low-skill workers. The intuition for this difference is developed further below in the explanation for the "labor market tightness" channel. In the decision rule space, this means a less steep division line. This is what I call the "fear to fail" effect. Only workers who get a high draw of entrepreneurial ability, with a low failure probability, decide to become entrepreneurs. Therefore, labor market frictions generate a wedge between the outside options to entrepreneurship of matched and unmatched workers with the same labor skills, increasing the space on which unmatched workers become entrepreneurs. Thus, we should expect unemployed workers to be more prone to transit into self-employment than matched workers.

Also, there is a substantial chance that unemployed workers decide to become subsistence self-employed. This area is characterized by combinations with low z and low h. Under this technology there is no fixed operational cost, so even individuals with low entrepreneurial ability might find this option appealing. However, conditional the prices used here, this is only true for unmatched workers. All matched workers who decide to quit become entrepreneurs. This property arises from the fact that the yellow area from panel (a) is a subset of the yellow area of panel (b). Because every matched worker who quits must then solve the unmatched worker problem, we know that they are quitting to become entrepreneurs. No matched worker decides to quit to become an unemployed worker or subsistence self-employed. This should reinforce the idea that unemployed workers are more prone to start businesses than employed workers.

Therefore, the larger set of combinations (h, z) over which unemployed workers choose to start a business either as subsistence self-employed or as entrepreneurs with respect to employed workers produce the first model-implied prediction:

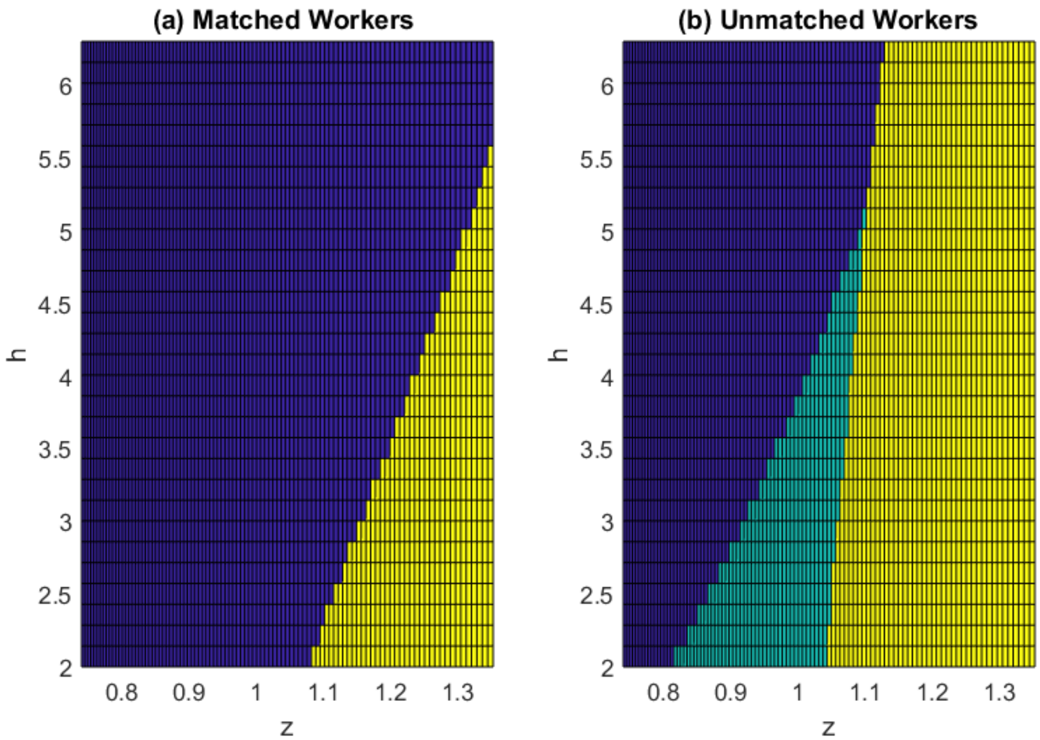
Prediction 1: *Unemployed workers are more likely to start businesses than employed workers.*

This prediction is the mechanism by which the "labor force composition" channel works. If the unemployment rate increases during recessions, then we should expect an increase in the number of individuals deciding to start businesses. In addition, if the distribution of those individuals over the space (z, h) accumulates a significant amount of people for whom the subsistence alternative is the optimal decision, then we should expect that most of that increase will take the form of subsistence self-employment. Also, because of the fall in the number of employed workers, we should expect a decrease in transitions from employment into entrepreneurship, which on average are high quality transitions.

The previous analysis may not hold in a general equilibrium context in which prices $(w_h(A), \rho(A))$ and the job finding probability $(f(\theta_h))$ adjust over the cycle.

4.6.2 "Labor Market Tightness" channel

Here, I present a comparative statistics exercise to explore how the job finding probability dynamics shape the occupational choices of matched and unmatched workers. A lower job finding probability increases the wedge between the outside options of matched and unmatched workers. This means that a fall in the job finding probability increases the space of combinations (h, z) over which an unemployed workers choose to start a business, while this space shrinks for employed workers. We can see this by comparing Figure 7, which shows the occupational decision rule with a job finding probability $f(\theta_h) = 0.1$, with the baseline case from Figure 6 that uses $f(\theta_h) = 0.28$.



Panel(a): blue color corresponds to the option of staying as an employed worker and yellow color to the choice of being an entrepreneur. Panel (b): blue color corresponds to remaining unemployed, green to being subsistence self-employed and the yellow to the choice of being an entrepreneur.

Figure 7: Occupational Decision Rules: $f(\theta) = 0.10$

The comparison between both Figures 6 and 7 shows that the decrease in the job finding probability discourages wage workers from starting businesses. This happens purely because if the business fails, it will be harder to find a job again, which decreases the value of the fallback option. In other words, there is a stronger "fear to fail" effect. Importantly, this "fear to fail" effect disproportionately affects people with higher labor skills because their future outside option is associated with a higher wage, and thus the cost of being an unemployed worker increases. In other words, the increase in the cost of failure is relatively bigger for highly skilled workers because their expected wage loss increases when the job finding probability falls. This implies that it is more likely that highly skilled workers switch their occupational decision from starting a business to staying as an employed worker because of the "fear to fail" effect.

Regarding unmatched workers, the lower job finding probability increases the incentive to enter into self-employment. This happens because the expected value of being unemployed is lower which means a lower outside option to self-employment.

Therefore, a decline in the job finding probability should discourage entry from employment, specially for high skilled workers, because of the higher "fear to fail" effect, and it should encourage the entry from unemployment. This correspond to the second testable prediction derived from the model.

Prediction 2: *A decline in the job finding probability discourages entry from employment, specially for high skilled workers, and encourage entry from employment.*

This second prediction corresponds to the mechanism through which the "labor market tightness" works.

4.6.3 "Profitability" channel

Keeping everything else constant, a decrease in aggregate productivity reduces business profits. Figure 8 shows that the space over which both matched and unmatched workers decide to be an entrepreneur shrinks after a 7% decrease in aggregate productivity. Only those individuals with high relative entrepreneurial ability still want to be entrepreneurs. This is the "profitability" channel. Through this channel recessions should lead to a decline in business entry of individuals with lower entrepreneurial ability from both unemployment and employment.

Panel(a): blue color corresponds to the option of staying as an employed worker and yellow color to the choice of being an entrepreneur. Panel (b): blue color corresponds to remaining unemployed, green to being subsistence self-employed and the yellow to the choice of being an entrepreneur.

Figure 8: Occupational Decision Rules: $A = 0.93A^{\star}$

Both the “labor market tightness” and “profitability” channels discourage the entry of employed workers. However, there are two important differences. First, the “labor market tightness” discourages disproportionately high skilled workers from starting businesses, while the effect from the “profitability” channel is the same for all types of workers. Second, in the data, the aggregate demand recovers faster than the job finding probability. For the Great Recession, the job finding probability recovered its pre-recessionary level just in October 2014. Therefore, a pure aggregate demand channel struggles to generate a persistent decline in the entry of new businesses as we saw in the aftermath of the Great Recession, which can be matched better by the “labor market tightness” channel. I will revisit these ideas in the quantitative analysis section.

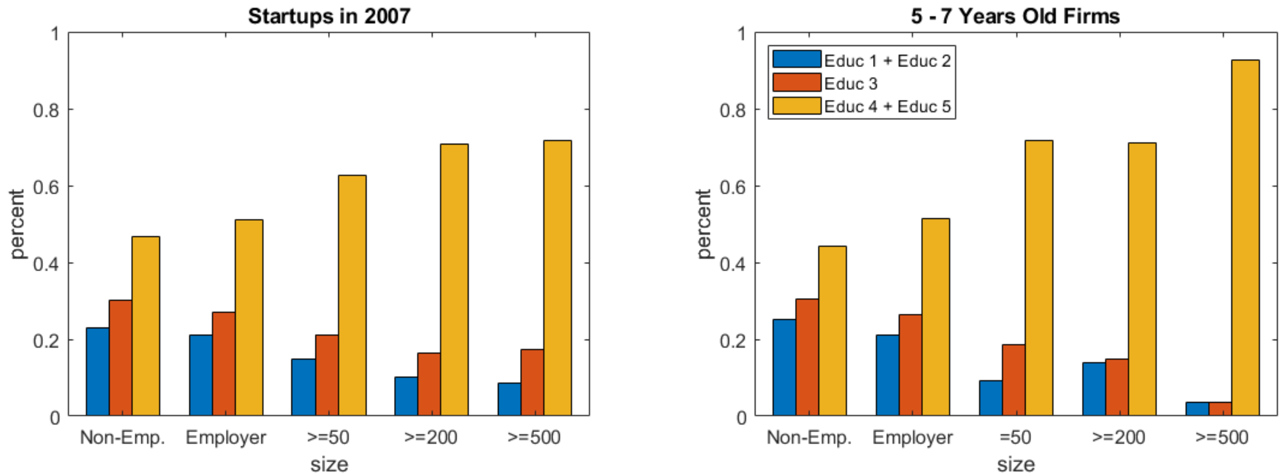
4.6.4 Initial size and growth dynamics

Now, we turn to the question of how the labor force status and educational attainment are related to the growth potential of startups.

Regarding the educational attainment of business owners, the previous analysis showed that an imperfect probability of finding a job produces a flatter division line in the decision rule space of matched workers, discouraging disproportionately the entry of high-skill workers (see Figure 6). This implies that high-skill workers only decide to start a business when the entrepreneurial idea is good enough to compensate for both the forsaken wage from quitting the current job and the potential wage loss in the event of a business failure, which depends on how much time will be needed before finding a new job. Then, high-skill workers start businesses with a higher average initial productivity z, which means a larger average initial size of startups. Regarding their growth potential, the higher threshold for z also implies that business owned by high skill workers will never become smaller because they will decide to exit before that. In addition, the permanent heterogeneity arising from the positive correlation between average productivity and labor skills ($\mu_{zh} > 0$) makes businesses owned by high-skill individuals to grow larger. Therefore, we should expect high-skill workers to start businesses with a larger average initial size and a higher potential to grow.

Prediction 3: *High-skill workers start businesses with a larger average initial size and higher potential to grow.*

Using data for the universe of nonemployer and employer firms in the U.S. from the Survey of Business Owners 2007 (SBO 2007), Figure 9 shows the firm size distribution by the founders' education level. The left panel shows the initial size distribution of startups in 2007, and the right panel shows the size distribution of 5-7-years-old firms in 2007. We see that highly



Notes: The sample only includes firms that are owned by the founder. "Educ 1 + Educ 2" is high-school or less (left bin). "Educ 3" is incomplete college (middle bin). "Educ 4 + Educ 5" is complete college or graduate studies (right bin). Author calculations with the Survey of Business Owners 2007 (SBO PUMS).

Figure 9: Firm size distribution by education of business founders

educated individuals start most of the startups with a large average initial size. For 5-7-year-old firms, we see that the differences in size found at the year of birth persist, with most large firms being owned by highly educated owners. This evidence is, in principle, consistent with prediction 3. However, in the model, if there is no permanent heterogeneity in the productivity z across labor skills, we would see just a few high skilled owners surviving in the long run. This might impede the model to reproduce the fact that high-skill individuals own most large businesses in the long run. The positive correlation between labor skills h and entrepreneurial ability z helps the model to capture this empirical regularity. A formal empirical analysis for prediction 3 will be performed in the quantitative section.

Regarding the differences in business performance between those started by previously employed and unemployed workers, the publicly available data doesn't provide the necessary information to test this prediction. However, previous works have found empirical support for this. In particular, Galindo Da Fonseca (2019), using Canadian administrative data, shows that unemployed workers are more likely to become self-employed than wage workers, but they start smaller firms that are more likely to exit.

4.6.5 Putting everything together

The first two model-implied predictions presented above give rise to a selection at entry mechanism that shapes the entry and composition of business founders over the cycle consistently with the suggestive evidence presented in Section 3. Through the "labor force composition" and the "labor market tightness" channels, the labor market dynamics should generate a decline in the entry of employer businesses in downturns and a shift in the composition of startups toward more businesses started from unemployment and fewer high-skill workers.

The missing generation of startups should account for a large part of the decline in the aggregate job creation during downturns, but also there should be an effect arising from the change in the composition of business founders. In particular, if the cohort of new businesses contains fewer high-skill founders, we should see a slower growth and a weaker contribution of new and young businesses to the recovery of the aggregate employment creation. The next section will address this using the calibrated model to take the general equilibrium effects into account in the analysis.

5 Quantitative Analysis

This section uses the proposed framework to study how the labor market dynamics affect the entry decisions and the composition of business founders over the cycle and quantify how the entry and compositional dynamics shape the recovery of aggregate job creation in the aftermath of an economic downturn.

The analysis is divided into three parts. First, I perform an empirical analysis using individual- and firm-level data for the U.S. to test the three model-implied predictions presented in Section 4. Then, in the second part, I present the calibration and stationary equilibrium results. Finally, in the third part, I performed two perfect foresight transition dynamics exercises. First, I feed the model with an exogenous aggregate productivity sequence that triggers a path of the unemployment rate that mimics the one exhibited by the U.S. during and after the Great Recession. This exercise aims to assess the ability of the model to reproduce the labor market and firm dynamics observed in the data, and quantify the effect of the labor market dynamics on the entry, composition of business founders, and aggregate job creation. Then, to understand the channels by which the labor market dynamics affect the entry and composition of business founders, I compute the impulse response functions for a one-time unexpected negative shock to aggregate productivity under perfect foresight, and I perform a counterfactual exercise keeping fixed the value of the fallback option in the event of a business failure.

5.1 Empirical Analysis

This section provides empirical support for the three model-implied predictions derived in section 4. For the analysis, I use individual-level data from the Survey of Income and Participation Program (SIPP) and firm-level data from the Survey of Business Owners 2007 (SBO).

5.1.1 Survey of Income and Participation Program

The SIPP provides a continuous series of national panels, with sample size ranging from approximately 14,000 to 52,000 interviewed households. I use the panels beginning in 1996, 2001, 2004, and 2008, providing monthly data between 1996 and 2013. The SIPP has a very rich and complex structure that includes data about occupation, education, earnings, demographics, assets, labor market history, businesses, and family, among other variables. With the labor market history, we can keep track of the whole path of occupations for all individuals in the sample. When individuals own a business, we know its legal form of organization (incorporated/unincorporated). The SIPP follows up to two wage jobs and two businesses simultaneously, with starting and ending dates for each spell, and provides the hours worked at each job or business. This allows me to account for multiple jobs and businesses, making possible a more rigorous identification of the main occupation, which is key for identifying transitions between labor force status.

For the analysis, I construct monthly transition among four labor market states: employment (E), unemployment (U), subsistence self-employment (S), and entrepreneurship (F). To take the model to the data I have to proxy S and F. From the CPS, we know that around 40-50% of incorporated businesses are employer firms, while only 10-15% of unincorporated firms have one or more employees. Consistent with this fact, and following the identification assumption from Levine and Rubinstein (2018), I approximate S with the universe of unicorporated businesses plus the incorporated businesses with owner working less than 35 hours and F with the universe of incorporated businesses with owners working 35 or more hours.

Appendix F includes a descriptive statics analysis comparing SIPP and CPS data in terms of number and size of businesses, and previous labor force status, educational attainment, and previous wages of founders.

5.1.2 Prediction 1: Transition Probabilities

To test whether the probability of transitioning to self-employment is higher from unemployment than from employment, I estimate the following Multinomial Logit Regression model, following Levine & Rubinstein (2018):

$$Ln(P_{Jit}/P_{Oit}) = \beta_{JO} + \beta_{JOX}X_i + \epsilon_{JOit} \tag{13}$$

where the dependent variable $Ln(P_{Jit}/P_{Oit})$ is the log-odds ratio of person i being subsistence self-employed (J=S) or an entrepreneur (J=F) rather than occupation O at time t. Two different

	Multinomial Logit Model		Linear Probability Model	
Previous Status	S	F	S	F
E	0.142	0.039	0.144	0.038
	(0.002)	(0.001)	(0.002)	(0.001)
U	0.604	0.055	0.543	0.055
	(0.012)	(0.004)	(0.009)	(0.004)
($\tilde{\beta}_1$ - $\tilde{\beta}_2$)	***	***	***	***
(Pseudo) R2	0.8297	0.8297	0.0004	0.0004
N obs	9,696,770	9,696,770	5,262,966	5,262,966
Individual FE	no	no	yes	yes
State and Time FE	yes	yes	yes	yes

($\tilde{\beta}_1$ - $\tilde{\beta}_2$): Difference test. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Results are expressed as percentages.

Table 1: Margins (Predicted Probabilities)

models are estimated. First, I estimate the model using only the sample of employed workers at time $t-1$ ($O = E$), and next using only the sample of unemployed workers at $t-1$ ($O = U$). X_i: is a categorical variable for education (five categories).

The results are presented in Table 1. The probability of starting a business is higher for unemployed than for employed workers, giving empirical support to prediction 1. This difference is much larger for subsistence self-employment. Figure 10 presents the probability of transitioning into S and F by the level of educational attainment. We can see that the probability of starting a business as "S" for employed workers is U-shaped. This is consistent with the findings from Poschke (2013), who using the CPS shows that there is a U-shaped relationship between the probability of entrepreneurship and both a person's schooling and wage when employed. My finding goes a little further, by distinguishing between two types of self-employment, and by showing that only ES transitions are U-shaped, while EF transitions increase monotonically with the level of education. A second interesting finding is that the probability of starting a business as "F" is steeper in education for employed than for unemployed workers.

5.1.3 Prediction 2: Cyclicality of Transition Rates

To study the effect of the dynamics of the job finding probability on the transitions between labor market states, I estimate a set of linear probability models using the job finding probability as explanatory variable. The reduced form is given by:

$$E_{JOist} = \beta_{JO} + \beta_{JOf} f(\theta_t) + \beta_{JOX} X_{it} + \beta_{JOfX} f(\theta_t) * X_{it} + \epsilon_{JOist} \tag{14}$$

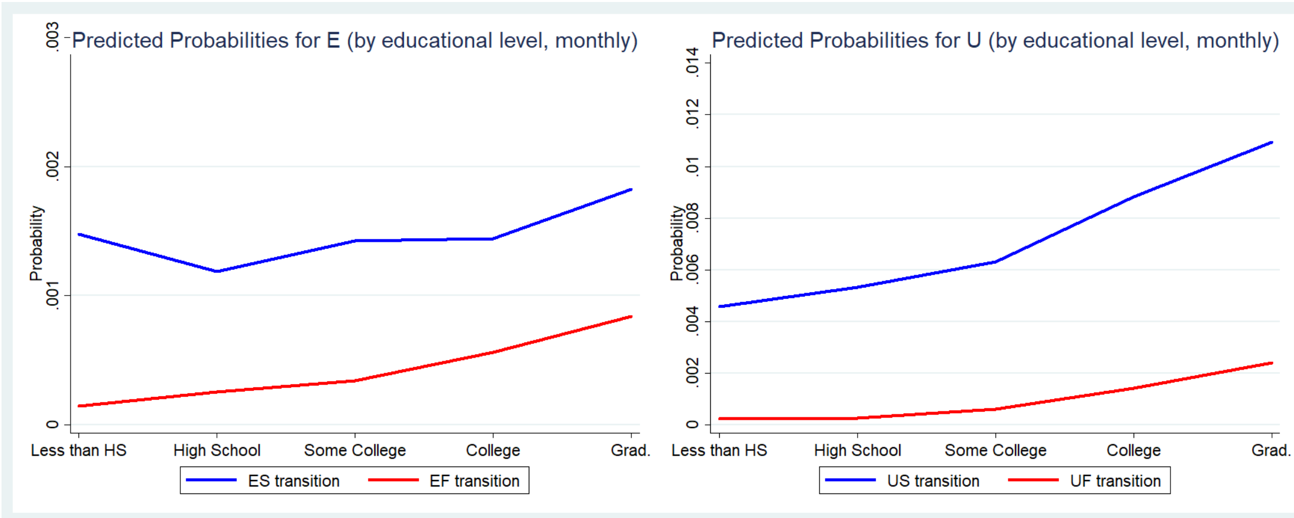


Figure 10: Transition Probabilities by Educational Attainment

where E_{JOist} is a binary indicator that equals 1 if person i in the state of residence s is observed transiting from occupation O to occupation J at time t, and 0 otherwise. $f(\theta_t)$ is the probability of finding a job in period t. X_{it} is a categorical variable for education (five categories).

Table 2 presents the marginal effects for the job finding probability at monthly frequency. The second group of specifications include the change in the state unemployment rate as a control for the aggregate demand conditions. The transition probabilities from employment to both subsistence self-employment and entrepreneurship are positively correlated with the probability of finding a job. To give an economic interpretation to the magnitude of these effects, I include the mean values for each transition. In the case of the transition probability from employment to entrepreneurship, the mean value is 0.042%. If the job finding probability goes up in 0.1, then a coefficient of 0.1449% means that the transition probability from employment to entrepreneurship increases in 0.0145%, which represent an increase of 35% with respect to the mean value.

I also explore whether the sensitivity of the transition rates with respect to the job finding probability depends on the level of human capital. The results are presented in Table 3. The probability of transitioning from employment to entrepreneurship is positively correlated with the job finding-rate for all of the five educational levels, but the effect becomes stronger as the level of education increases. This gives empirical support to prediction 2. If we believe that high skill workers are those who in average start business with a higher potential to grow, then this finding support the idea that the cohorts of businesses born in downturns contain fewer potentially high-growth entrepreneurs. The probability of transitioning from unemployment to subsistence self-employment is negatively correlated with the job finding-

	(1)				(2)			
	ES	US	EF	UF	ES	US	EF	UF
$f(\theta)$	0.2467***	0.7808	0.1449***	0.2782	0.2541***	0.7532	0.1515***	0.2967
	(0.0579)	(0.5076)	(0.0314)	(0.1807)	(0.0583)	(0.5125)	(0.0318)	(0.1840)
Mean	0.1444	0.6993	0.0420	0.0741	0.1444	0.6993	0.0420	0.0741
BC Controls	No	No	No	No	Yes	Yes	Yes	Yes
R-squared (pseudo)	0.0062	0.0105	0.0188	0.0494	0.0063	0.0108	0.0191	0.0494
N obs	3,932,492	248,673	3,932,492	237,562	3,903,661	245,694	3,903,661	234,720

Notes: Results are expressed as percentages. All regressions control for state, and time fixed effects. Model (2) includes change in the state unemployment rate as control. Heteroskedasticity robust standard errors are in parenthesis.

Table 2: Transition Probabilities (Marginal Effects)

rate, but not significantly.

	(1)				(2)			
$f(\theta)$	ES	US	EF	UF	ES	US	EF	UF
$EDUC = 1$	0.2708***	0.6109	0.0409	0.0005	0.2663***	0.6356	0.0413	0.0077
	(0.0987)	(0.6053)	(0.0316)	(0.1305)	(0.0992)	(0.6136)	(0.0319)	(0.1307)
$EDUC = 2$	0.2618***	0.3316	0.0585**	0.2821**	0.2726***	0.3572	0.0656**	0.2959**
	(0.0635)	(0.5549)	(0.0306)	(0.1404)	(0.0637)	(0.5622)	(0.0318)	(0.1444)
$EDUC = 3$	0.1698***	1.1477**	0.1200***	0.3796*	0.1757***	1.1127**	0.1250***	0.3955**
	(0.0680)	(0.5608)	(0.0336)	(0.2049)	(0.0684)	(0.5645)	(0.0339)	(0.2083)
$EDUC = 4$	0.2866***	1.1336	0.2491***	0.2474	0.2914***	0.9175	0.2573***	0.2957
	(0.0759)	(0.9226)	(0.0526)	(0.4444)	(0.0766)	(0.9250)	(0.0532)	(0.4545)
$EDUC = 5$	0.3676***	0.9858	0.3571***	0.6856	0.3881***	0.9391	0.3698***	0.6932
	(0.1131)	(1.4388)	(0.0795)	(0.7961)	(0.1140)	(1.4688)	(0.0803)	(0.8072)
Mean	0.1444	0.6993	0.0420	0.0741	0.1444	0.6993	0.0420	0.0741
BC Controls	No	No	No	No	Yes	Yes	Yes	Yes
R-squared (pseudo)	0.0062	0.0105	0.0188	0.0494	0.0063	0.0108	0.0191	0.0494
N obs	3,932,492	248,673	3,932,492	237,562	3,903,661	245,694	3,903,661	234,720

Notes: Results are expressed as percentages. All regressions control for state, and time fixed effects. Model (2) includes change in the state unemployment rate as control. Heteroskedasticity robust standard errors are in parenthesis.

Table 3: Transition Rates (Marginal Effects)

5.1.4 Prediction 3: Growth Potential of Startups by Founders' Education

Finally, I test empirically whether high-skill workers start businesses with a higher potential to grow (prediction 3). For the analysis, I use the Survey of Business Owners 2007 (SBO PUMS 2007), a representative survey covering the universe of 26 million employer and non-employer businesses in the U.S. The SBO provides information about both firm and business owners' characteristics. In particular, the SBO includes information about age, size, and industry of the firms, and age and level of education of the owners.

	Dependent variable: log(employment)			
Educ	Full Universe	Only Employers	Full Universe	Only Employers
High School	0.0981	0.0001	0.0714***	0.002
	(0.0033)	(0.0065)	(0.0036)	(0.0080)
Incomplete College	0.1370***	0.0545***	0.0849***	0.0181***
	(0.0035)	(0.0068)	(0.0038)	(0.0083)
College	0.2721***	0.2554***	0.1697***	0.1476***
	(0.0034)	(0.0065)	(0.0037)	(0.0080)
Graduate	0.2913***	0.2116***	0.1969***	0.0909***
	(0.0036)	(0.0071)	(0.0039)	(0.0086)
Constant	-0.2766***	1.4635***	-0.2055***	1.4937***
	(0.0091)	(0.0220)	(0.0092)	(0.0269)
R2	0.1830	0.1266	0.1285	0.1077
N obs	2,134,142	1,238,702	1,388,554	689,046
Only founded	no	no	yes	yes
Owner's age >=25	yes	yes	yes	yes
Age Fixed-Effects?	yes	yes	yes	yes
State Fixed-Effects?	yes	yes	yes	yes
Industry Fixed-Effects?	yes	yes	yes	yes

Notes: Reference category corresponds to less than high-school.

Table 4: Growth Potential of Startups by Founders' Education

Table 4 shows the result for a regression analysis using the log of employment of the firm as dependent variable and the level of education of the business owners as explanatory variable. I control for the age of the business owner, and whether the business is owned by the original founder. In terms of the firm, I use age, state and industry fixed-effects. The first two columns show the results for the total universe of businesses and for only employer firms, respectively. The last two columns show the results for the same analysis, but restricting the sample only to the universe of businesses for which the current owner is also the founder. Across all the specifications we see a positive correlation between the firm size and the educational attainment of the business owner, except for individuals with graduate studies. These results are consistent with previous finding in the empirical literature.[19]

5.2 Parametrization and Stationary Equilibrium

A first set of parameters is calibrated externally. The model frequency is assumed to be monthly, so β is set to 0.996. The standard deviation of the distribution of labor skills σ_h is set to 0.327, which allows the best possible match with the educational attainment distribution for five categories from the CPS. The separation rate s is set to 0.0149, which is the average monthly

[19] See Brown, Earle, Kim & Lee (2019).

Parameter	Value	Description	Source
β	0.996	Discount factor	CHW (2007)
σ_h	0.327	Std. dev. h (log distr.)	Educ. distr. (CPS 2016)
s	0.0149	Separation probability (monthly)	EU flows (CPS 2005-2006)
η	0.24	Workers' bargaining power	HW (2008) 0.052 - Shimer (2005) 0.72
ψ	0.24	Matching function elasticity	Hall (2005)
Y^{ss}	0.4	UI / Leisure	Standard
$A^\star$	1	Aggregate productivity (SS)	Normalization

Table 5: Externally Calibrated Parameters

rate of employment-to-unemployment flows in the CPS for the period 2005-2006. The workers' Nash bargaining power η is set to 0.24. The literature has used a wide range of values for this parameter, from Shimer (2005) using 0.72 to Hagedorn & Manovskii (2008) using 0.052. Recall that the latter work shows that low workers' bargaining power and a high unemployment benefit generates wage rigidity closer to what we see in the data. With respect to the elasticity of the matching function, I set ψ to 0.2, which is the value from Hall (2005). This parameter corresponds to one minus the elasticity of the job finding probability $f(\theta_h)$ with respect to the labor market tightness θ_h, so a lower value of ψ means a higher elasticity of $f(\theta_h)$ with respect to θ_h. The parameter Y^{ss}, which reflects the unemployment benefit or the value of leisure, is set to 0.4. This is the standard value used in the literature. In the model, $Y^{ss} * w_h^{ss}$ is not the only component of the opportunity cost of being a worker because individuals also have the option to start a business, making business earnings also a fundamental determinant for the worker's reservation utility used in the Nash Bargaining solution. Finally, the aggregate productivity A is normalized to 1 in equilibrium. Table 5 summarizes the seven externally calibrated parameters and the sources.

The remaining 17 parameters are calibrated internally. Table 6 presents the results. I discipline the model to match selected key features of the labor market and firm dynamics in the U.S. Even though every targeted moment is determined simultaneously by all parameters, I discuss each of them in relation to the parameter that, intuitively, yields the most identification power. Data moments from CPS are monthly averages over the period 2005-2006 unless otherwise specified. Data moments from BDS are annual average over the period 2001-2007.

The mean of the labor skills distribution (μ_h) determines the size of the effective labor force in terms of efficiency units, so I calibrate it to match the average size of employer businesses. The distribution of labor skills is determined by its lower and upper bounds (h_l, h_h), which I use to set the ratio of wages between high and low skilled workers.

To discipline the flows between labor market states, I use the parameters of the entrepreneurial ability stochastic process, job finding probability, and search efficiency. The span control parameter α pins down the value of owning a business relative to the wages earned as an employed worker, which determines the entrepreneurship rate in the economy. The exit rates primarily respond to the parameters related to entrepreneurial ability, and business owners can exit endogenously either into unemployment or to employment. I set the persistence of the entrepreneurial ability (ρ_z) to discipline the total exit rate from subsistence self-employment and entrepreneurship.[20] Then, I discipline the unemployment rate using the standard deviation of the entrepreneurial ability (σ_z), which pin downs the exit into unemployment. The exit into employment is determined mostly by the search efficiency parameters (φ^S, φ^F). These parameters also pin down the entry rate into both technologies since exit has to be equal to entry in the stationary equilibrium. The parameter (A_{sub}) is set to discipline the subsistence self-employment rate. The cost of posting vacancies for each labor market segment (c_h) is set to match an equal job finding probability across all the labor market segments, which determines the flows from unemployment into employment and the probabilities of receiving job offers for business owners. The flows from employment into unemployment are pinned down by the exogenous separation rate s. This calibration strategy disciplines completely the flows between labor market states and the labor force composition: employment rate, unemployment rate, subsistence self-employment, and entrepreneurship.

To discipline the firm dynamics structure in the model, I use the fixed operational cost (ϕ), the Pareto exponent (ξ), the standard deviation of the initial productivity (σ_s) to match the 5-years survival rate of employer businesses, the 1-year survival probability of entrepreneurs, and the relative size of entrants with respect to incumbent firms. In the model, employer businesses are defined as those hiring more than 1.5 units of the labor efficiency good, and the remaining businesses are classified as non-employer firms. The correlation between the mean of the entrepreneurial ability and labor skills (μ_{zh}) is used to introduced permanent heterogeneity in the size of the businesses to match the distribution by education from the SBO, where more educated individuals own larger firms on average. A second source of permanent heterogeneity is introduced with the span control parameter of the subsistence technology (α_{sub}), which allows the model to account better for the skewed firm size distribution by chosen it to match the share of total employment in firms using less than 50 units of labor.[21] The cost shifter (κ) and the elasticity (γ) from the convex hiring cost function help to discipline the share of total employment of young firms (1-5 years old) and the employment share of firms hiring more than

[20] If the draw of z is bad enough, a business owner will decide to close the business to become an unemployed worker ($z < \underline{z}$) If a business owner receives a job offer, and the realization of z makes owning a business a better option than unemployment but worse than taking the job ($\underline{z} < z < \overline{z}$), then the owner accept the offer and become an employed worker. The probability of receiving a job offer depends on the search efficiency of each technology.

[21] Gavazza, Mongey & Violante (2018) also use a similar kind of permanent heterogeneity. They argue that it helps to decouple age and size, which tend to be too strongly correlated in standard firm dynamics model with mean reverting productivity.

Parameter	Value	Description	Target	Source	Data	Model
Panel A: Labor market dynamics						
α	0.75	Span control parameter	Entrepreneurship rate	CPS	3.8%	3.6%
A_{sub}	0.48	Sub. tech. scale param.	Subsistence SE rate	CPS	6.4%	6.4%
σ_z	0.05	Standard deviation of z (log distr.)	Unemployment Rate	CPS	4.4%	4.4%
ρ_z	0.96	Persistence of z	Entrepreneurship exit rate	CPS	5.1%	3.1%
φ^S	0.45	Search efficiency sub. tech.	SE flows	CPS	6.2%	6.5%
φ^F	0.21	Search efficiency entrepreneurs	FE flows	CPS	4.2%	3.9%
m	0.496	Matching efficiency	Labor Market Tightness (θ_h)	HM 2011	0.63	0.63
c_h	Distr.	Cost of vacancies	Job Finding Rate	CPS	0.28	0.28
(h_l, h_h)	(2, 6.3)	Bounds for labor skills h	$w_{h=5}/w_{h=1}$	CPS	2.82	2.40
Panel B: Firm dynamics						
ϕ	2.50	Fixed operational cost	Employer businesses survival rate at age 5	BDS	0.49	0.41
ξ	3.2	Pareto exponent	Relative size of employer entrants	BDS	0.51	0.58
μ_{zh}	distr.	z and h dependence	Avg. size by educ of founder	SBO 2007	distr.	distr.
σ_s	0.10	Std. Dev. initial productivity	Entrepreneurs survival rate at age 1	SIPP	0.68	0.59
κ	1.5	Hiring cost scale param.	Cohort employment share at age 1-5	BDS	13.2%	20.3%
γ	2.0	Convexity of hiring costs	Employment share $n > 500$	BDS	0.47	0.40
α_{sub}	0.10	Sub. tech. span control param.	Employment share $n < 50$	BDS	0.31	0.35
μ_h	3.80	Mean of h (Labor skills)	Average employer firm size	BDS	23	22.6

Panel A: CPS data corresponds to monthly averages for period 2005-2006, except for mean and bounds of labor skills that use data from 2017.
Panel B: BDS data correspond to annual averages over the period 2001-2007. SBO data correspond to SBO PUMS 2007. SIPP data corresponds to monthly averages over period 1996-2013.

Table 6: Internally Calibrated Parameters

500 units of labor.

5.3 Cross-Sectional Implications

Now, I present the main cross-sectional implications of the calibrated model at the stationary equilibrium.

5.3.1 Labor Skills and Occupational Distributions

The labor force and educational composition shape the effects of the “labor force composition” and “labor market tightness” channels in the model. Therefore, the model needs to fit the composition of individuals in terms of these two characteristics in a good way in order to quantify the effect of the labor market dynamics on the entry and composition of business founders properly.

The results in Table 6 show that the model presents a good fit in terms of the labor force composition. In particular, the unemployment rate in the model, which drives the “labor force composition” channel, matches the target of 4.4%.

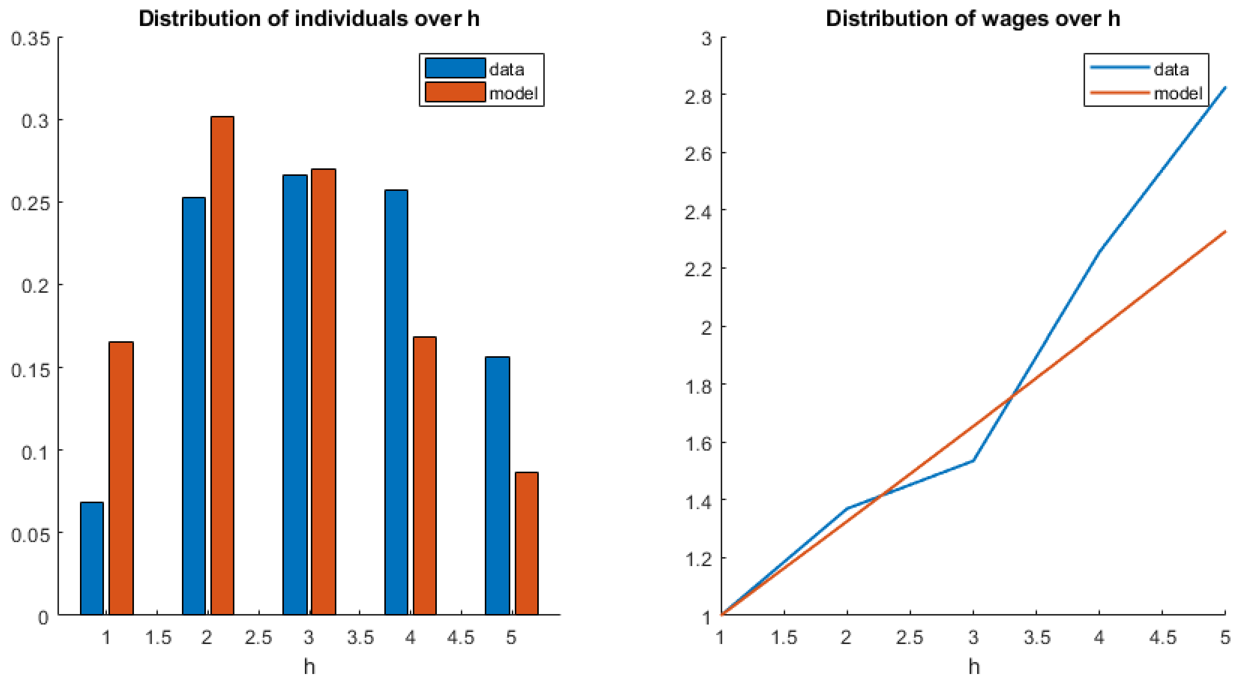


Figure 11: Labor skills distribution and equilibrium wages

The distribution of labor skills pins down the wage distribution in the model. Figure 11 presents the comparison between the model and the data. The good fit of the model matching this moment is also an important feature. It determines the distribution of outside options for potential business owners, which generates the selection at entry mechanism by education. This feature is key for the effects of the "labor market tightness" channel on entry decisions.

5.3.2 Type of business and composition by founders' characteristics

Table 7 reports some empirical compositional moments and their model-generated counterparts. The composition by type of business, which is a targeted moment, replicates the fact that subsistence self-employment is almost twice the entrepreneurship rate in the data (proxied by unincorporated and incorporated businesses, respectively). This difference increases when we look just at startups, which is a non-targeted moment that the model captures well.

The composition of entrants in terms of the previous labor force status is also well replicated by the model, which is not explicitly targeted. Subsistence self-employment exhibits a larger share of entry from unemployment than entrepreneurship. The model can also satisfactorily replicate the observed educational composition of business owners in the CPS, for both existing and new businesses. We can see that the entrepreneurial businesses are formed by a larger share of highly educated owners than subsistence self-employment, with a similar pattern for

	CPS		Model	
	Sub. Tech.	Entrep.	Sub. Tech.	Entrep.
TYPE OF BUSINESS				
All Businesses				
Share as % of labor force	6.4%	3.6%	6.4%	3.6%
Share as % of all businesses	69.6%	31.4%	69.6%	31.4%
Startups				
Share as % of labor force	0.42%	0.04%	0.50%	0.04%
Share as % of entry	91.3%	8.7%	80.5%	19.5%
COMPOSITION BY PREVIOUS LABOR FORCE STATUS				
Startups				
E	76.5%	86.4%	73.6%	86.6%
U	23.5%	13.6%	26.4%	13.4%
COMPOSITION BY HUMAN CAPITAL				
All Businesses				
<= High School	42.2%	27.5%	36.9%	29.1%
Incomplete College	27.4%	26.4%	34.2%	31.1%
>= College	30.4%	46.1%	29.0%	39.8%
Startups				
<= High School	47.0%	31.1%	44.0%	28.0%
Incomplete College	26.8%	25.1%	30.3%	33.0%
>= College	26.2%	43.8%	25.7%	39.0%

Notes: All values from CPS are weighted. Basic Monthly CPS 2005-2006.

Table 7: Compositional distribution by type of business and characteristics of business founders

both existing and new businesses. The model generates these features due to the selection at entry mechanism that makes individuals with different characteristics to choose different kinds of businesses.

5.3.3 Firm age and size distribution

Table 8 shows the composition of businesses in terms of non-employer and employer businesses. We can see that the model replicates well the larger share of non-employer businesses observed in the data, which is a non-targeted moment. All the non-employer businesses in the model are subsistence self-employed, while employer businesses are both subsistence self-employed and entrepreneurs.

Table 9 presents the age and size distribution of employer businesses only. The contribution of entrants to aggregate job creations is somewhat overestimated in the model with respect to the BDS data. The entry rate of employer businesses in the model is mainly driven by the entry

Shares (in %)	BDS and NES Data		Model
	Number	Share	Share
Non-employers	21,708,021	78.2	69.9
Employer firms	6,049,655	21.8	30.1

Notes: NES and BDS data in 2007.

Table 8: Non-employers and employer businesses

Shares (in %)	New	Young	Old	1-49	50-499	500+
BDS DATA						
Employer firms	10.6	31.7	57.7	95.6	4.0	0.4
Employment	3.0	13.2	83.8	31.0	21.5	47.5
MODEL						
Employer firms	16.2	38.6	45.2	96.2	3.5	0.3
Employment	6.2	20.3	73.5	36.2	23.5	40.3

New firms: less than 1 year old; Young firms: 1-5 years old.

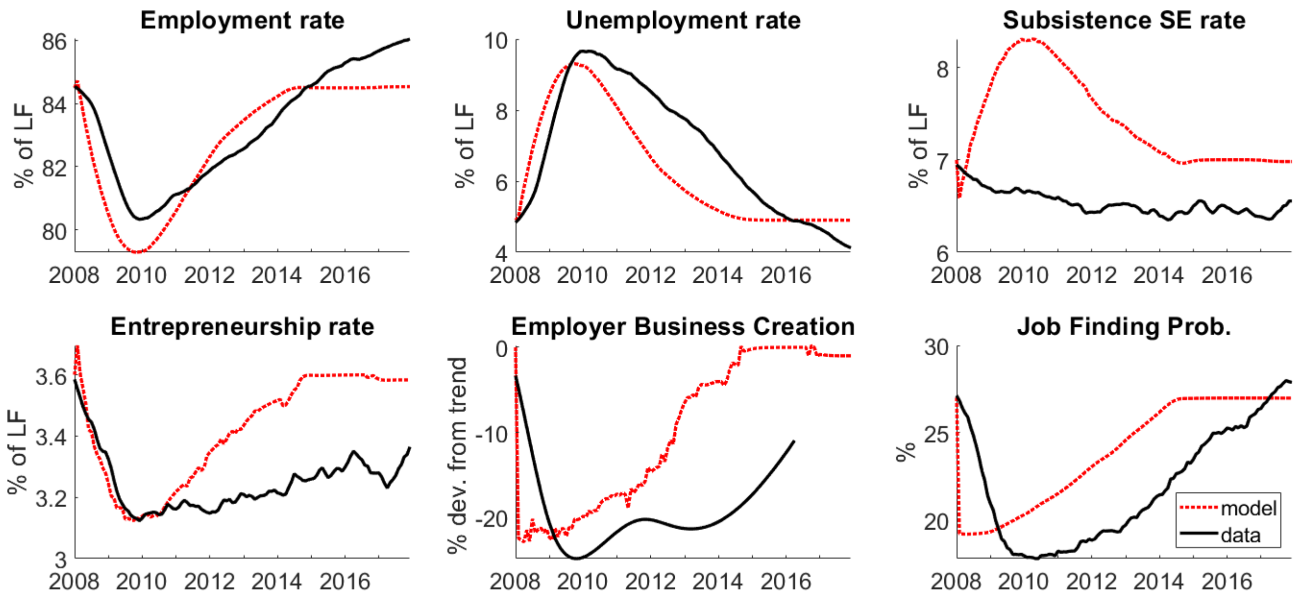
Table 9: Firm age and size distribution

rate of entrepreneurs, which is pinned down by the exit rate in the stationary equilibrium. So, the higher entry and exit rates for incorporated businesses in the CPS than in the BDS are passed on into the model. However, the lower 1-year survival rate of entrepreneurial startups helps to correct the problem, although not completely.

5.4 Great Recession: Entry, Composition, and Job Creation Dynamics

This section presents a perfect foresight transition dynamics exercise aimed, first, to validate the aggregate dynamics of the model, and, second, to quantify the effect of the labor market dynamics on entry decision, the composition of business founders, and the recovery of aggregate job creation during and after the Great Recession.

The exercise is as follows. The economy is assumed to be at the stationary equilibrium at $t = 1$. Then, in $t = 2$, the model is fed with an unexpected exogenous aggregate productivity sequence that triggers a path of the unemployment rate that mimics the one exhibited by the U.S. over January 2008 - December 2017. From $t = 3$ onwards, individuals have perfect foresight about the future path of aggregate productivity and, therefore, about the future path of the distribution of individuals, the price of the labor good, wages, and the job finding probability.



Notes: Actual and model-predicted time-paths. Labor market data corresponds to CPS and employer business creation to BDS. BDS data is transformed into monthly frequency by using cubic interpolation.

Figure 12: Actual and model-predicted time-paths

For the transition, I impose ad hoc wage rigidity as follows:

$$w_{h,t} \;=\; \gamma w_h^{Nash} + (1-\gamma) w_{h,t}^{Nash}$$

Here, w_h^{Nash} corresponds to the steady state wages. From Hagedorn & Manovskii (2008), the elasticity of wages with respect to aggregate productivity is 0.449. I discipline the value of gamma in the model to match this elasticity, which implies $\gamma = 0.93$. This feature is needed because though wages are set by Nash bargaining, their dynamics are much more volatile than what we see in the data.[22]

5.4.1 Aggregate Dynamics

Figure 12 presents the empirical and model-implied dynamics for the components of the labor force, the job finding probability, and employer business entry, which are not explicitly targeted in the transition except for the unemployment rate path. The data for employer business creation corresponds to the BDS, and the empirical counterpart for all the other variables is constructed using CPS data.

The model replicates well the persistent decline of the job finding probability during the Great

[22]The excessive volatility of wages in models with labor market frictions is known in the literature as the "Shimer puzzle".

Recession. The model is also able to satisfactorily replicate the procyclical trajectories of the employment and entrepreneurship rates. The decrease in the employment rate from $t = 3$ onwards is explained by the lower job finding rate that reduces the flows from unemployment to employment. This also explains the increase in the unemployment rate from 5% to 9%. This increase in the unemployment rate would have been even higher in the model if the flows from unemployment to subsistence self-employment did not increase during this period. The decline in the entrepreneurship rate is driven by the lower entry from employment and fewer people choosing to stay as entrepreneurs. The model predicts a contracyclical behavior for subsistence self-employment driven by the increase in the transitions from unemployment into subsistence self-employment, which is not observed in the data. The analysis performed with CPS data in Section 3 showed that during 2009 and 2010 the U.S. economy actually exhibited a higher entry into self-employment as the model predicts. However, in the data, we also observe an increase in the exit rate that is not matched by the model. Such difference makes the subsistence self-employment rate constant in the data but increasing in the model. Appendix G includes the complete set of 16 transition rate paths.

Finally, employer business creation is countercyclical consistently with its empirical counterpart from the BDS. Even though the model is able to increase persistence, the decline of employer business entry is still more persistent in the data than in the model. I will explain further how the "labor force composition" and the "labor market tightness" channels shape this decline in Section 5.5.

5.4.2 Entry of Business Founders

Figure 13 presents the distribution of entrants over their initial productivity for two periods in the transition, December 2007 and December 2009. The first row distinguishes between subsistence self-employed and entrepreneurs, and the second row between nonemployer and employer businesses.

There are two things to note here. First, the similarity between the panels in the first and second rows is because subsistence self-employed start businesses mostly as nonemployers, while all the entrepreneurs start businesses as employers. Second, entry into subsistence self-employment (new nonemployer firms) increases in recessions, mostly driven by low-quality business founders, while entry into entrepreneurship (new employers firms) decreases, especially for high-quality business founders. These dynamics are generated by the higher entry of low-skilled business founders from unemployment and lower entry of highly educated business founders from employment. Next, I turn the analysis to examine the entry composition in terms of these two business founders' characteristics.

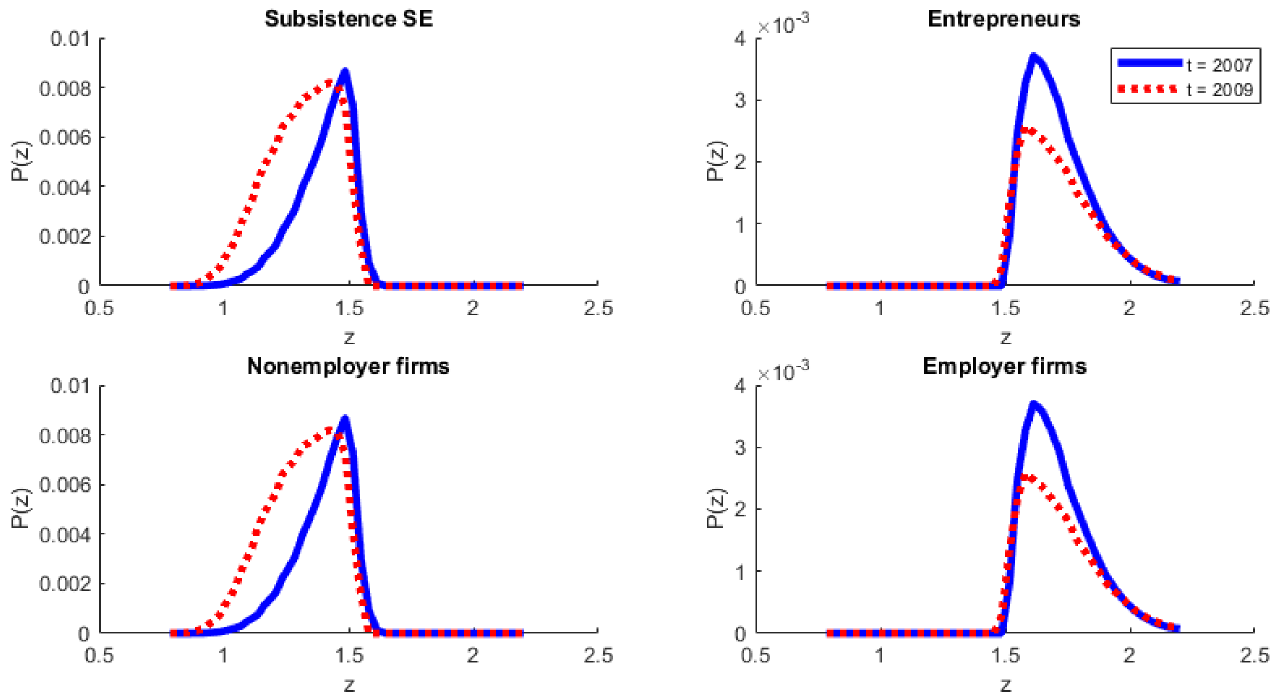


Figure 13: Initial productivity distribution

5.4.3 Composition of business founders

Figure 14 presents the composition of employer startups in terms of the previous labor force status and educational level of the founders in the model. The jump in the unemployment rate in 2009 and 2010 is passed on into the composition of business founders through the "labor force composition" channel, and the decline in the job finding probability through the "labor market tightness" channel. Both channels increase the entry from unemployment, making the share of new employer businesses starting from unemployment to increase from 16% to almost 30%. The decline in the job finding probability through the "labor market tightness" channel reduces the share of high-skill founders in the composition of employer startups from 42% to 31%.

Therefore, the composition of founders of employer firms shifts toward fewer highly educated individuals and more people coming from unemployment.

5.4.4 Initial productivity and growth potential of entrants

Figure 15 presents the model-predicted initial productivity distribution of employer startups by the education level of the founders for two periods in the transition, the initial stationary equilibrium in December 2007 and 24 periods later in December 2009.

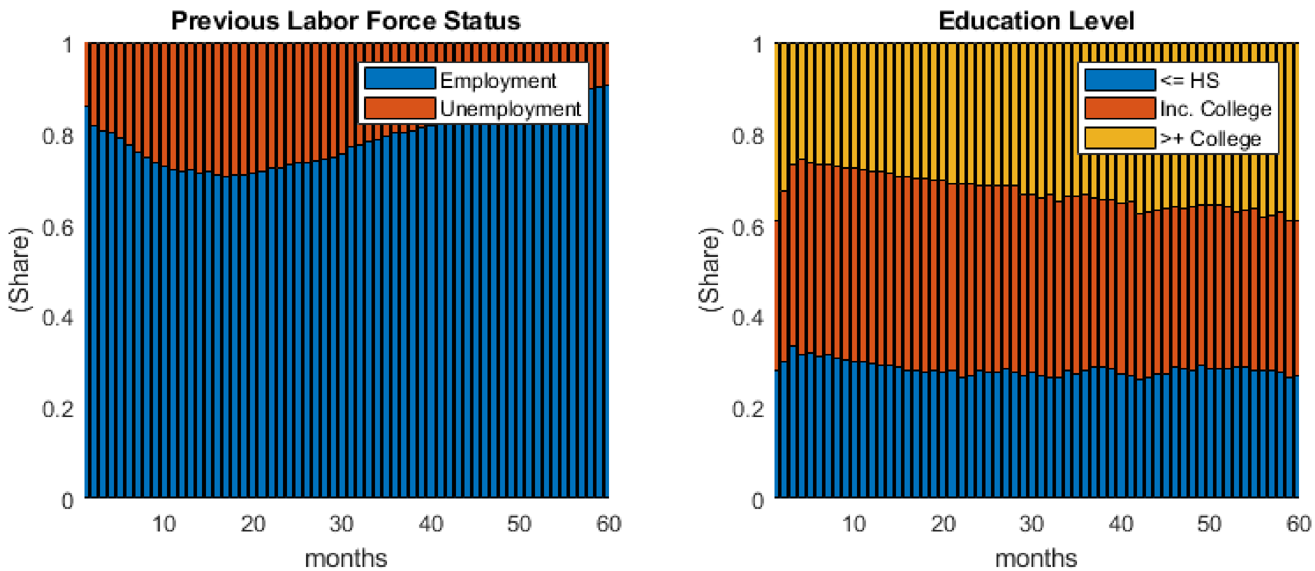


Figure 14: Composition of employer startups by founders' characteristics

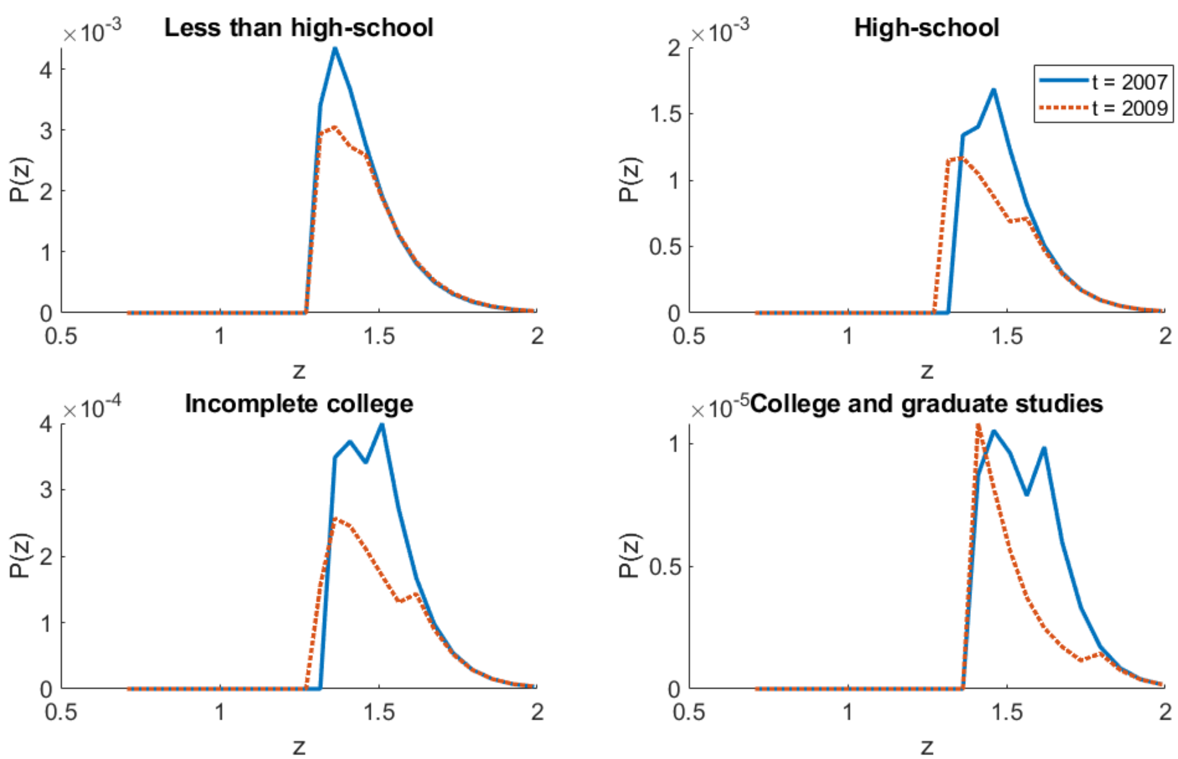


Figure 15: Distribution of entrants over initial productivity

First, we can observe that the right side of the distribution shrinks disproportionately for highly educated individuals. Second, the mass of entry falls for every level of education, but the decline increases as we increase the level of education of the founders. Because initial productivity pins down the initial average size of startups, the first result implies that new businesses will start relatively smaller, especially those owned by highly skilled individuals. The second result implies that there will be fewer high skilled individuals deciding to start businesses, which make the cohort to contain fewer high-growth entrepreneurs.

Therefore, employer businesses born in periods with a high unemployment rate and low job finding probability will start smaller and with a lower potential to grow because of the fewer highly educated individuals starting businesses. These two features will reduce the contribution of entrants and young firms to the recovery of the aggregate job creation in the aftermath of an economic crisis.

5.4.5 Job Creation Dynamics

In Figure 16, the left panel shows the model-predicted job creation and its empirical counterpart from the BDS. The model replicates well the path of the job creation, with a faster fall at the beginning of the transition, consistent with the sharp decline in the job finding probability. The magnitude and persistence of the fall in the aggregate job creation respond to the lower labor demand by existing firms, decline in entry, smaller initial size of startups, and their lower potential to grow.

The right panel presents a counterfactual exercise to quantify the role of the compositional change in the recovery of job creation. First, I fix the educational composition of entrants, and then, on top of that, I fix the previous labor force status composition. The results show that by fixing the composition of entrants, the initial fall is somewhat reduced because now the initial size of startups doesn't decline, but this improvement is small. So, the contribution of the change in founders' composition to the decline in the aggregate job creation is minimal at the beginning of the recession. However, over time, the compositional shift starts to matter because young businesses grow less, so their contribution to job creation is smaller. Therefore, slower growth of young businesses in the aftermath of the recession prevents aggregate job creation from a faster recovery.

Regarding the relative contribution between previous labor force status and educational attainment composition to the slower recovery of job creation, we can see that the educational composition change accounts for most of the effect. The effect arising from the shift in the previous labor force status, which corresponds to the "labor force composition" channel, is small.

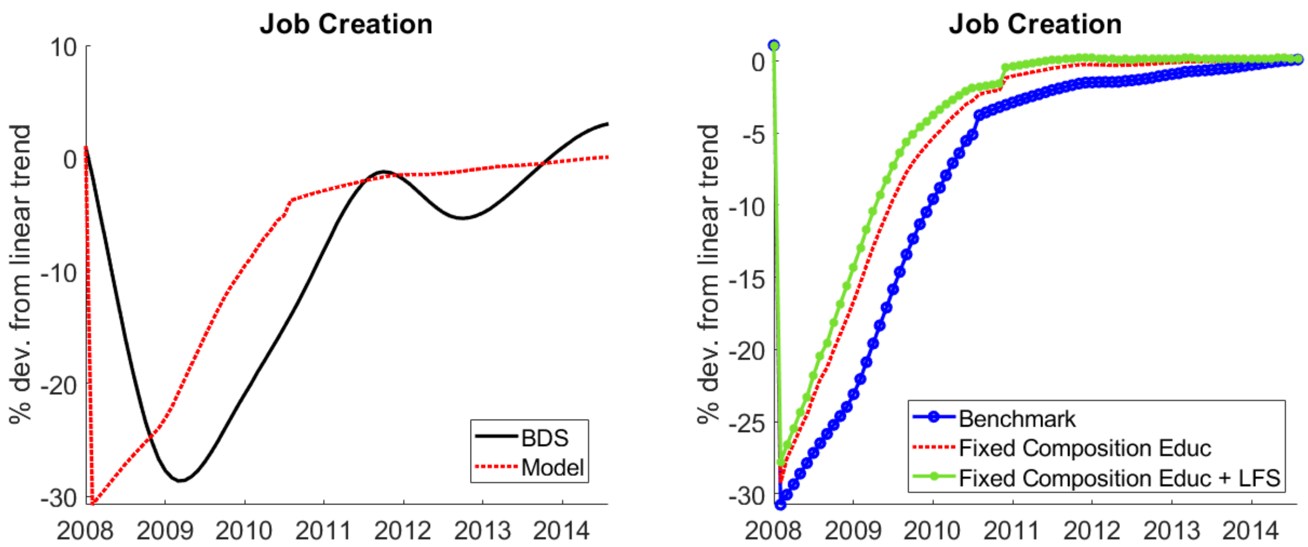


Figure 16: Aggregate Job Creation

In other words, the decline in the growth potential of startups is primarily explained by the shift in the educational composition of business founders toward fewer highly educated individuals.

We can summarize the findings of this section as follows: (i) entry due to stopgap motives into subsistence self-employment increases during downturns while entry into entrepreneurship declines, and (ii) composition of entrepreneurs shifts toward fewer highly educated individuals, making the new cohorts to contain fewer potentially high-growth startups. Both features hinder job creation recovery, keeping the labor market depressed longer, and the entrepreneurship entry persistently low.

5.5 Understanding the Mechanisms

The previous analysis showed that the "labor market tightness" channel accounts for most of the slower recovery of aggregate job creation due to its negative effect on startups' growth potential. However, the total effect depends on both the growth potential and the number of new businesses started. This section investigates further the role of the "labor force composition" and the "labor market tightness" channels in driving the aggregate dynamics.

5.5.1 "Labor Force Composition" channel

Even though the "labor force composition" channel doesn't play an important role in shaping the growth potential of startups, it is an important driver for entry into subsistence technology. Figure 17, left panel, shows the transitions from unemployment to subsistence self-employment

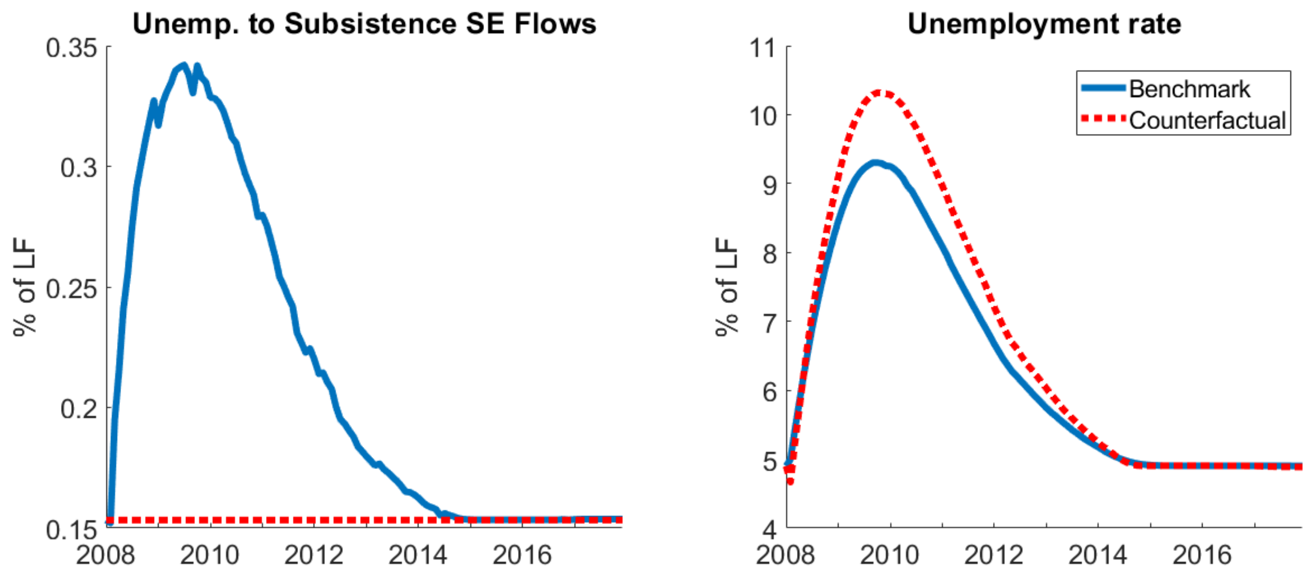


Figure 17: Transitions from Unemp. to Subsistence SE and Unemployment rate

for the transitional dynamics exercise from Section 5.4. It also includes a counterfactual exercise, in which additional flows from unemployment into subsistence self-employment are not allowed throughout the entire transition. In the model, the subsistence technology absorbs a significant fraction of the increase in unemployment during recessions. The right panel shows the unemployment rate for both cases. The difference between the benchmark and the counterfactual exercise shows that the unemployment rate would have increased by 1.5 p.p. more at the peak of the Great Recession without the subsistence alternative.

In the data, the entry into subsistence self-employment (proxied as unincorporated businesses) increases during recessions but the exit rate also follows a similar pattern, making the subsistence self-employment rate to follow a non-increasing path. This suggests that unemployed individuals use self-employment as a stopgap activity for short periods of time.

5.5.2 "Labor Market Tightness" Channel

To disentangle the role of the "labor market tightness" channel from the "profitability" channel, I perform a counterfactual exercise in which the "labor market tightness" channel is muted. To do so, I keep fixed the job finding probability at the steady state level that individuals see for their occupational choice problem throughout the transition. By doing this, I keep constant the value of the fallback option in the event of business failure for the potential entrants, canceling the "fear to fail" effect.

The transition dynamics for this exercise is as follows. The economy is assumed to be at the

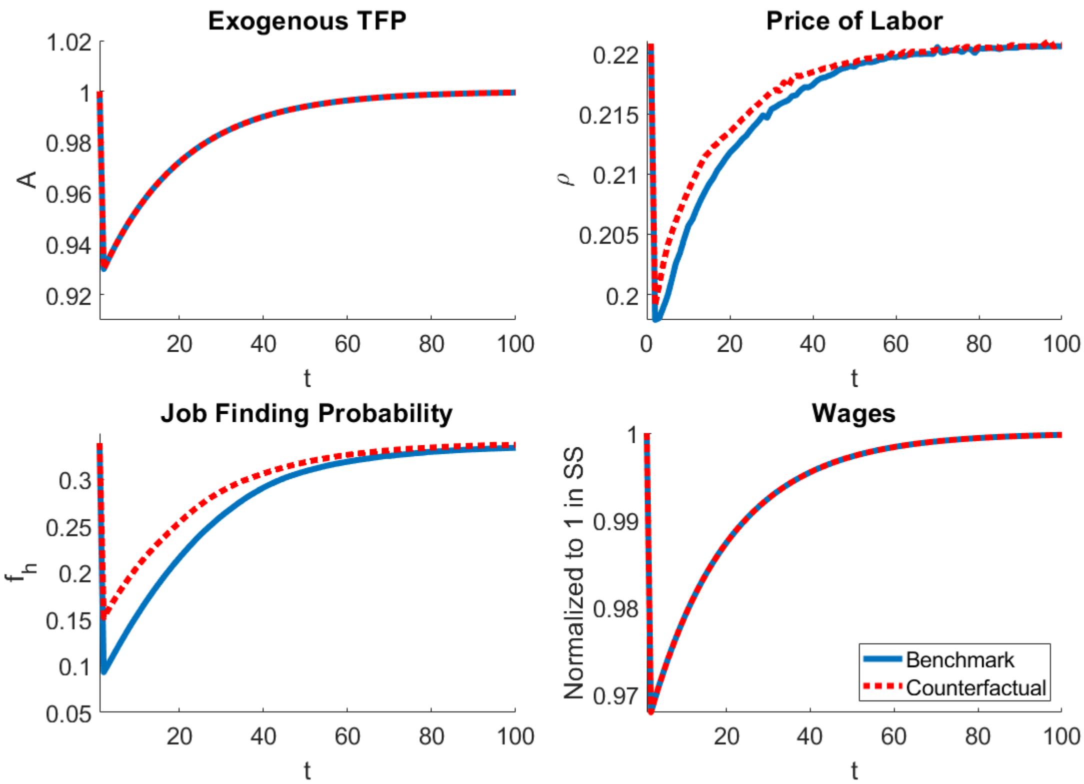


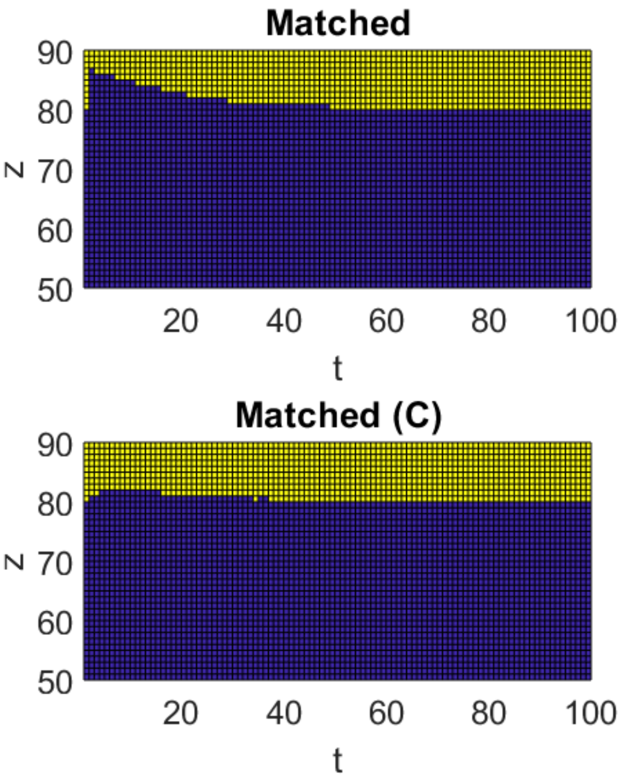
Figure 18: Aggregate productivity and job finding probability

stationary equilibrium at $t = 1$. Then, at $t = 2$ the economy is shocked by an unexpected 7% decrease in the aggregate productivity. After that, individuals have perfect foresight about the future path of aggregate productivity and, therefore, about the future path of the distribution of individuals, the price of the labor good, wages, and the job finding probability. The same kind of wage rigidity from the first exercise is used here. After the one-time initial shock, aggregate productivity follows a mean reverting AR(1) process, given by:

$$A' \quad = \quad (1 - \rho_A) * A^\star + \rho_A A \tag{15}$$

for which I use $\rho_A = 0.95$.

Figure 18 shows the exogenous path of aggregate productivity used to perform the exercise, price of labor efficiency units, wages, and job finding probability. Wages follow the path of the exogenous TFP because of the exogenous wage rigidity imposed throughout the transition. The price of labor efficiency units falls slightly less in the counterfactual because of the smaller fall in the labor demand. However, its path is also rigid because of the exogenous wage rigidity. The job finding probability falls less in the counterfactual. This happens because, without the "fear to fail" effect, the entry decisions decline less, especially for highly educated individuals,



Panel(a): blue color corresponds to the option of staying as an employed worker and yellow color to the choice of being an entrepreneur. Panel (b): blue color corresponds to remaining unemployed, green to being subsistence self-employed and the yellow to the choice of being an entrepreneur.

Figure 19: Paths of Decision Rules

making the number of new businesses to fall by less and start bigger. Moreover, because now the cohort of new businesses contains more highly educated workers, it grows faster, fostering the job creation recovery. I will explain each one of these steps next.

Figure 19 presents the occupational decision rules paths for both a matched and unmatched highly educated individuals. The first row corresponds to the benchmark transition, and the second row to the counterfactual. In the benchmark transition, we see that the cutoff $\bar{z}$ above which a highly educated matched individual decides to be an entrepreneur moves up, discouraging potential entrants with good entrepreneurial ideas from starting businesses. In the counterfactual, in the absence of the "fear to fail" effect, this shift is smaller. The remaining effect corresponds to the "profitability" channel. If we perform the same counterfactual analysis for an individual with lower educational attainment, the "profitability" effect would be larger because the "fear to fail" for low-skill workers is smaller.

Figure 20 presents the results for both the benchmark (upper panels) and the counterfactual (lower panels) exercises in terms of the initial productivity distribution of new businesses, distinguishing between the subsistence self-employment and entrepreneurship. In the counterfactual

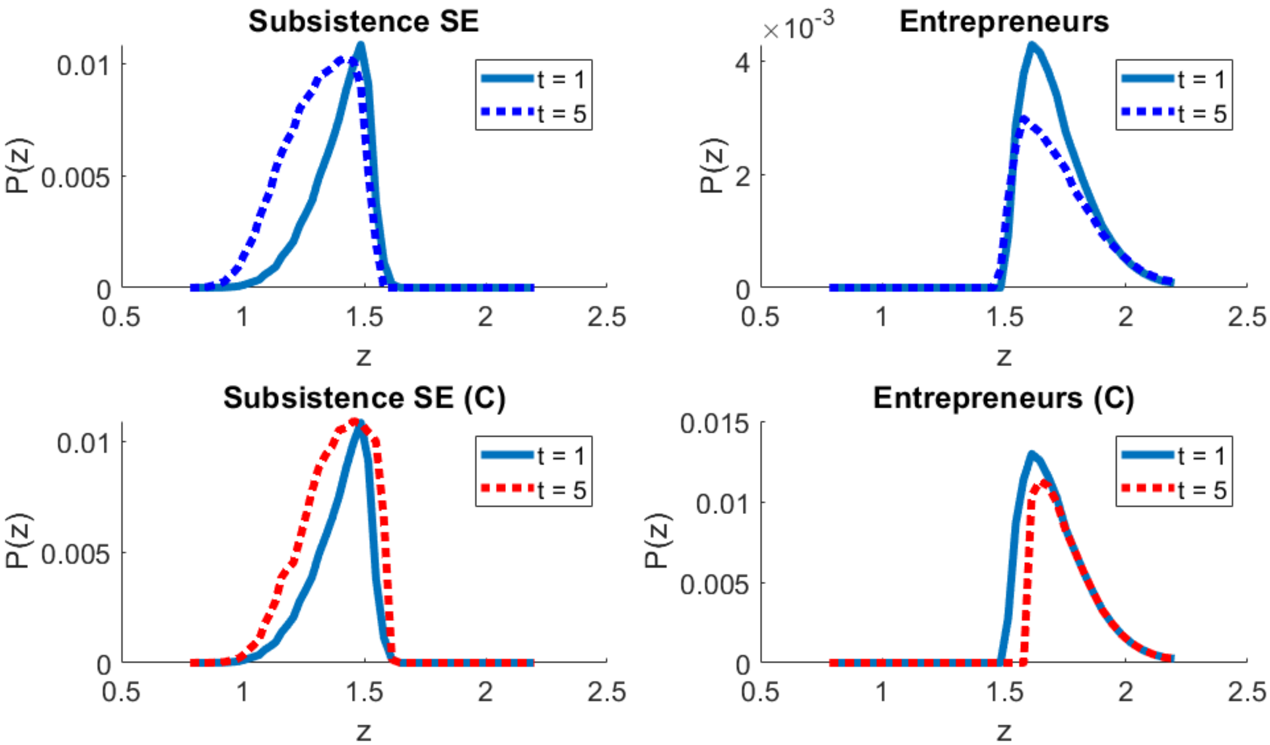


Figure 20: Initial productivity distribution of new businesses

scenario, the "profitability" channel generates a rightward shift in the left part of the quality distribution of new entrepreneurial businesses, with almost no change in the right side, difference that corresponds to the "fear to fail" effect. This means that the "fear to fail effect" makes the cohort of startups to start with a smaller average initial size and a lower potential to grow.

In Figure 21, the left panel presents the counterfactual analysis for the entry rate into entrepreneurship, which can also be thought of as the entry rate of employer businesses. The "labor market tightness" channel account almost for one-third of the total decline in the entry rate. The right panel presents the results for the aggregate job creation. At the beginning of the transition, the "labor market tightness" channel has a very small effect, but its role becomes more important as time goes by. In the model, as in the data, most of the contribution of startups to the aggregate job creation comes from their growth, so the missing generation of new business doesn't diminish the aggregate job creation contemporaneously as in the following periods. In the model, the negative effect of lower entry is reinforced by the composition change of business founders toward fewer highly educated individuals, which reduces the entry of high-growth startups disproportionately. Therefore, both the decline in entry and the change in composition hinder aggregate job creation recovery in the aftermath of an economic crisis.

Finally, Figure 22 shows the paths of the labor force components. Because fewer individuals

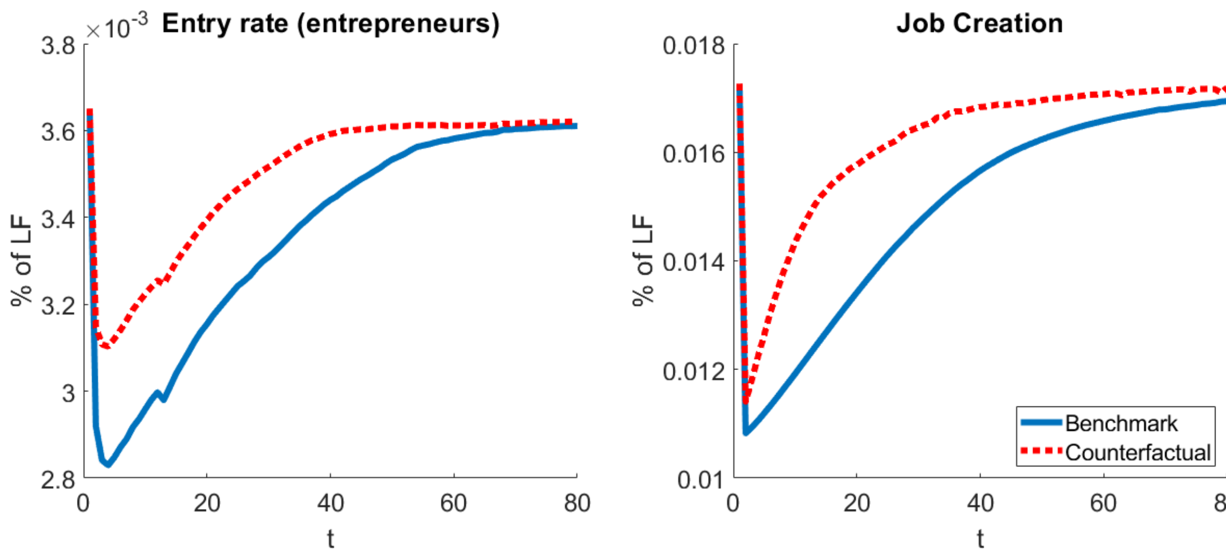


Figure 21: Entry rate of entrepreneurs and job creation

are discouraged from starting businesses, we see a smaller fall in the entrepreneurship rate. The smaller decline in entry plus the bigger size of startups helps to avoid a further decline in the job finding probability, making the unemployment rate jump less. Then, because the unemployment rate and the job funding probability respond less, the subsistence self-employment also increase slightly less.

The entrepreneurship rate, measured as a share of the labor force, falls from 0.034 to 0.028 in the benchmark model, and from 0.034 to 0.030 in the counterfactual. This means that the "labor market tightness" channel (and "fear to fail" effect) contributes to a 33% to the total decline in the entrepreneurship rate. Regarding the unemployment rate, in the benchmark model, it jumps from 5% to 8% while in the counterfactual it goes from 5% to 7%. Therefore, the "labor market tightness" channel accounts again around a 30% of the total increase. Finally, from the benchmark analysis, we can see that without the 3% increase in the subsistence self-employment rate, the unemployment rate would have gone from 5% to 11%, which highlights the role of the subsistence self-employment activity as a shock smoother during downturns.

6 Conclusions

This paper studies how labor market dynamics affect the decision to start a business and the growth potential of startups over the cycle, and the final effects on the aggregate job creation. The results show that entry due to stopgap motives increases in recessions, but entry into entrepreneurship, which is more related to employer businesses, falls. The type of

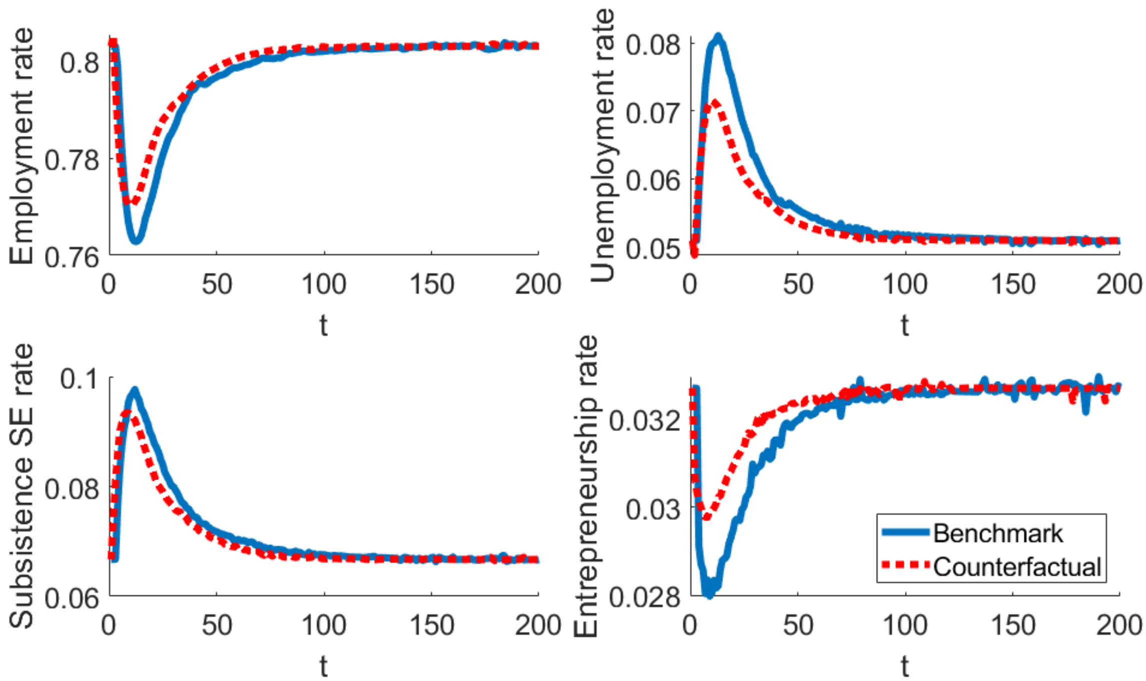


Figure 22: Path of Labor Force Components

individuals deciding to start businesses also change over the cycle. In particular, in recessions, the composition of business founders shifts toward more previously unemployed and fewer highly educated individuals. Because highly educated individuals are precisely those individuals more likely to start a business with a high potential to grow, the change in business founder composition also shifts toward businesses with a lower potential to grow.

Therefore, during downturns, there is a decline in the entry of employer firms and a shift in the business composition toward startups with a lower growth potential. The structural model shows that labor market dynamics during recessions account for a 33% of the decline in the entrepreneurship rate, and a 30% of the increase in the unemployment rate at the peak of the recession period. It also highlights that the initial decline in the aggregate job creation in downturns is mainly driven by the decline in the entry of employer businesses, but as the economy recovers, the lower growth of young businesses becomes more important. In this framework, firm and worker dynamics interact in equilibrium to amplify the effects and persistence of an aggregate productivity/demand shock: a lower job creation of startups declines further the job finding probability, deterring, even more, and more persistently, the entry of startups, especially high-growth businesses. This mechanism generates a slower recovery in the entry of employer businesses and aggregate job creation, consistent with the labor market dynamics in the aftermath of the Great Recession in the U.S.

References

Ates, S. T. & Saffie, F. E. (2020). Fewer but Better: Sudden Stops, Firm Entry, and Financial Selection. *American Economic Journal: Macroeconomics, forthcoming*.

Audoly, R. (2020). Firm Dynamics and Random Search over the Business Cycle.

Bils, M., Chang, Y., & Kim, S.-B. (2009). Comparative Advantage and Unemployment. SSRN Scholarly Paper ID 1413594, Social Science Research Network, Rochester, NY.

Brown, J. D., Earle, J. S., Kim, M. J., & Lee, K. M. (2019). Start-ups, job creation, and founder characteristics. *Industrial and Corporate Change*, *28*(6), 1637–1672. Publisher: Oxford Academic.

Choi, J. (2017). Entrepreneurial Risk Taking, Young Firm Dynamics and Aggregate Implications.

Clementi, G. L. & Palazzo, B. (2016). Entry, Exit, Firm Dynamics, and Aggregate Fluctuations. *American Economic Journal: Macroeconomics*, *8*(3), 1–41.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The Role of Entrepreneurship in US Job Creation and Economic Dynamism. *Journal of Economic Perspectives*, *28*(3), 3–24.

Elsby, M. W. L. & Michaels, R. (2013). Marginal Jobs, Heterogeneous Firms, and Unemployment Flows. *American Economic Journal: Macroeconomics*, *5*(1), 1–48.

Engbom, N. (2019). Firm and Worker Dynamics in an Aging Labor Market.

Fairlie, R. & Fossen, F. (2019). Defining Opportunity versus Necessity Entrepreneurship: Two Components of Business Creation. Technical Report w26377, National Bureau of Economic Research, Cambridge, MA.

Fossen, F. M. (2020). Self-employment over the business cycle in the USA: a decomposition. *Small Business Economics*.

Gaillard, A. & Kankanamge, S. (2019). Entrepreneurship, Labor Market Mobility and the Role of Entrepreneurial Insurance. Publication Title: TSE Working Papers.

Galindo Da Fonseca, J. A. (2019). Unemployment, Entrepreneurship and Firm Outcomes. Technical Report 04-2019, Centre interuniversitaire de recherche en économie quantitative, CIREQ. Publication Title: Cahiers de recherche.

Gavazza, A., Mongey, S., & Violante, G. L. (2018). Aggregate Recruiting Intensity. *American Economic Review*, *108*(8), 2088–2127.

Hagedorn, M. & Manovskii, I. (2008). The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited. *American Economic Review*, *98*(4), 1692–1706.

Hagedorn, M., Manovskii, I., & Stetsenko, S. (2016). Taxation and unemployment in models with heterogeneous workers. *Review of Economic Dynamics*, *19*, 161–189.

Hall, R. E. (2005). Employment Fluctuations with Equilibrium Wage Stickiness. *American Economic Review*, *95*(1), 50–65.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who Creates Jobs? Small versus Large versus Young. *Review of Economics and Statistics*, *95*(2), 347–361.

Hombert, J., Schoar, A., Sraer, D., & Thesmar, D. (2020). Can Unemployment Insurance Spur Entrepreneurial Activity? Evidence from France. *The Journal of Finance*, *75*(3), 1247–1285. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12880.

Hopenhayn, H. A. (1992). Entry, Exit, and firm Dynamics in Long Run Equilibrium. *Econometrica*, *60*(5), 1127–1150. Publisher: [Wiley, Econometric Society].

Kozeniauskas, N. (2018). What's Driving the Decline in Entrepreneurship?

Levine, R. & Rubinstein, Y. (2018). Selection into Entrepreneurship and Self-Employment. Technical Report w25350, National Bureau of Economic Research, Cambridge, MA.

Menzio, G. & Shi, S. (2010). Block recursive equilibria for stochastic models of search on the job. *Journal of Economic Theory*, *145*(4), 1453–1494.

Moreira, S. (2016). Firm Dynamics, Persistent Effects of Entry Conditions, and Business Cycles. SSRN Scholarly Paper ID 3037178, Social Science Research Network, Rochester, NY.

Moscarini, G. & Postel-Vinay, F. (2013). Stochastic Search Equilibrium. *The Review of Economic Studies*, *80*(4 (285)), 1545–1581. Publisher: [Oxford University Press, The Review of Economic Studies, Ltd.].

Mueller, A. I. (2017). Separations, Sorting, and Cyclical Unemployment. *American Economic Review*, *107*(7), 2081–2107.

Nakajima, M. (2012). Business Cycles in the Equilibrium Model of Labor Market Search and Self-Insurance*. *International Economic Review*, *53*(2), 399–432. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-2354.2012.00686.x.

Poschke, M. (2013). Who becomes an entrepreneur? Labor market prospects and occupational choice. *Journal of Economic Dynamics and Control*, *37*(3), 693–710.

Poschke, M. (2019). Wage Employment, Unemployment and Self-Employment Across Countries. SSRN Scholarly Paper ID 3401135, Social Science Research Network, Rochester, NY.

Pugsley, B., Sedláček, P., & Sterk, V. (2020). The Nature of Firm Growth. *American Economic Review, forthcoming*.

Salgado, S. (2020). Technical Change and Entrepreneurship. SSRN Scholarly Paper ID 3616568, Social Science Research Network, Rochester, NY.

Schaal, E. (2017). Uncertainty and Unemployment. *Econometrica*, *85*(6), 1675–1721. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA10557.

Sedláček, P. (2020). Lost generations of firms and aggregate labor market dynamics. *Journal of Monetary Economics*, *111*, 16–31.

Sedláček, P. & Sterk, V. (2017). The Growth Potential of Startups over the Business Cycle. *American Economic Review*, *107*(10), 3182–3210.

Shimer, R. (2005). The Cyclical Behavior of Equilibrium Unemployment and Vacancies. *American Economic Review*, *95*(1), 25–49.

Shimer, R. (2006). On-the-job search and strategic bargaining. *European Economic Review*, *50*(4), 811–830.

Siemer, M. (2014). Firm Entry and Employment Dynamics in the Great Recession.

Smirnyagin, V. (2020). Compositional Nature of Firm Growth and Aggregate Fluctuations.

Vardishvili, I. (2020). Entry Decision, the Option to Delay Entry, and Business Cycles, 100.

A Autocorrelation: Initial and Future Size of Startups

Figure 23: Autocorrelation: Initial and Future Size of Startups

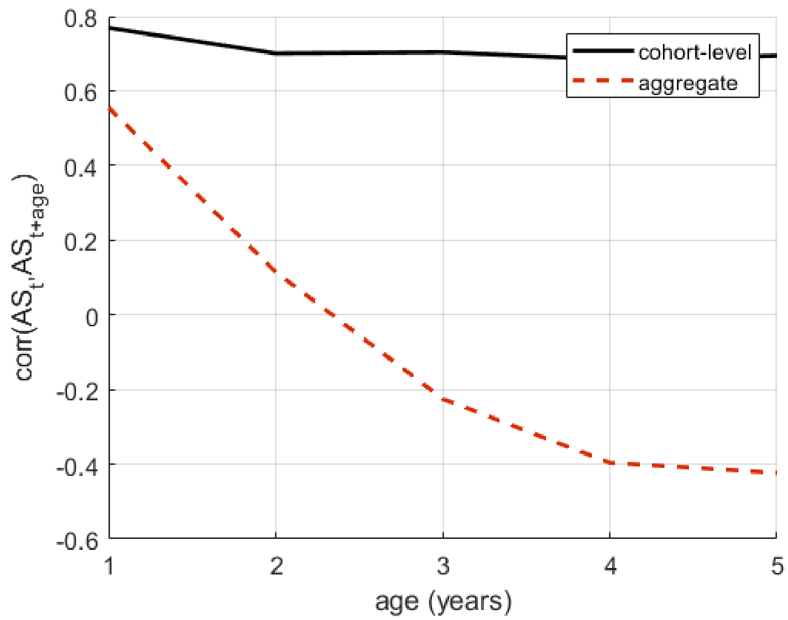


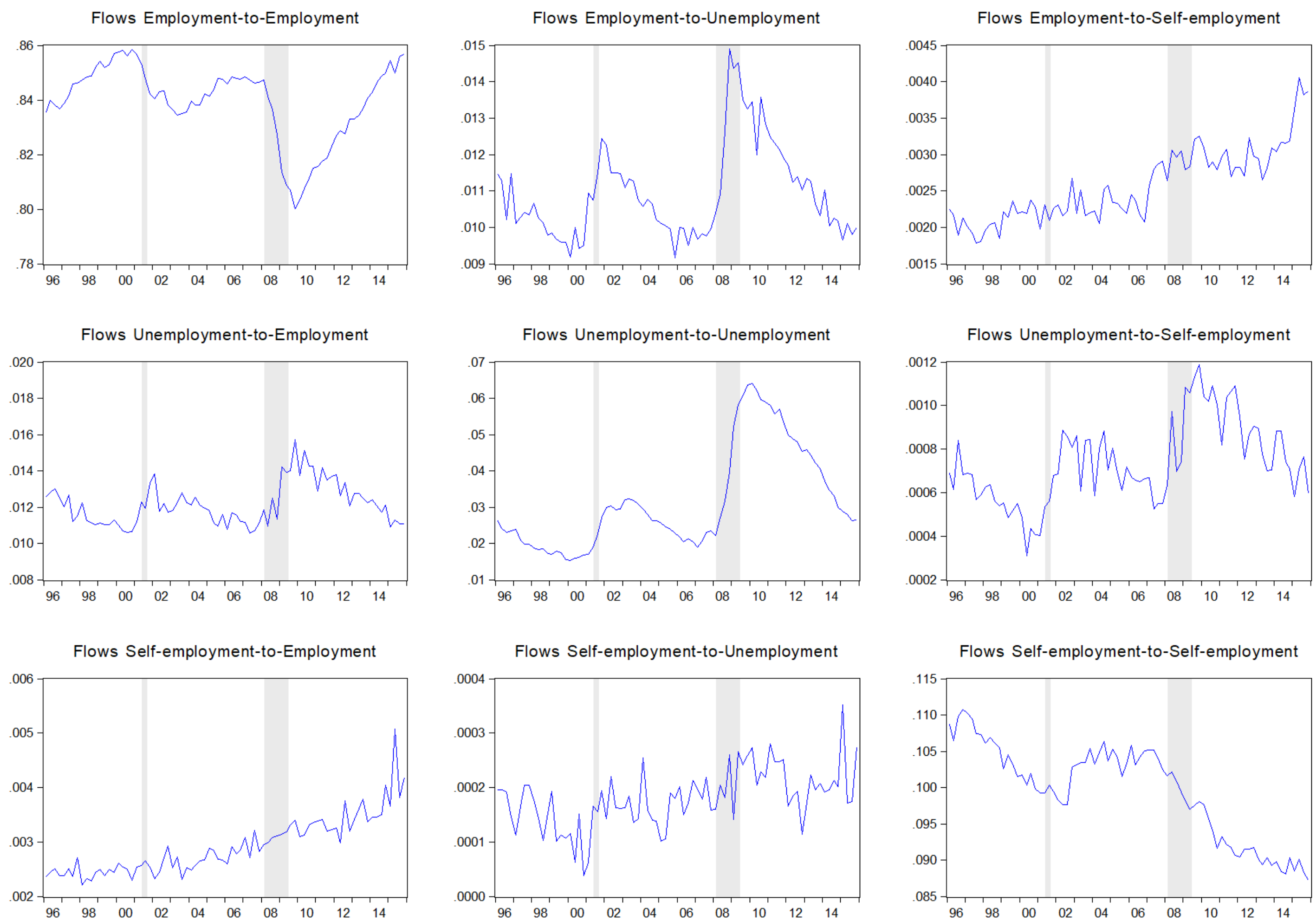
Table 10: Correlation 5-year window: Average size

years window	6-10	11-15	16-20
0-5	0.4196	0.5450	0.4408

Source: author's calculation with BDS data.

B Empirical Transition Rates

Transition Rates



(as percentage of total labor force)

Transition rates are computed as the number of transitions over the total labor force. All series are seasonally adjusted.

C Equilibrium Conditions

$Endogenous\,(18) = \{W_t, U_t, V_t^E, V_t^U, V_t^S, V_t^F, Opol\_W_t, Opol\_U_t, n_{sub,t}, n_t, w_{ht}, \theta_{ht}, f_{ht}, q_{ht}, V_{ht}, J_{ht}, \rho_t, \Psi_t\}$
$Exogenous\,(1) \quad = \{A_t\}$

$$W(h,z,n_{-1};A) = \max[V^W(h,z,n_{-1};A), U(h,z,n_{-1};A)] \tag{16}$$
$$DR : Opol\_W \tag{17}$$

$$U(h,z,n_{-1};A) = \max[V^U(h,z,0;A), V^S(h,z,n_{-1};A), V^F(h,z,n_{-1};A)] \tag{18}$$
$$DR : Opol\_U \tag{19}$$

$$V^E(h,z,0;A) = w_h(A) + \beta[(1-s)\mathbf{E}_{z'/z}W(h,z',n;A') + s\mathbf{E}_{z'/z}U(h,z',o,n;A')] \tag{20}$$

$$V^U(h,z,0;A) = Y^{ss} + \beta[f(\theta_h)\mathbf{E}_{z'/z}W(h,z',o,n;A') + (1-f(\theta_h))\mathbf{E}_{z'/z}U(h,z',o,n;A')] \tag{21}$$

$$V^S(h,z,o_{-1},n_{-1};A) = A_{sub}A^{\gamma}zn_{sub}^{\alpha} - \rho(A)n_{sub} + \beta\mathbf{E}_{z'/z}U(h,z',o,n;A')] \tag{22}$$
$$n_{sub}(z;A) = \underset{n_{sub}}{\text{argmax}}\left\{A_{sub}A^{\nu}zn^{\alpha_{sub}} - \rho(A)n_{sub} - g(\chi_{sub})\right\} \tag{23}$$

$$V^F(h,z,o_{-1},n_{-1};A) = zAn^{\alpha} - \rho(A)n - \phi + \beta\mathbf{E}_{z'/z}U(h,z',o;A')] \tag{24}$$
$$n(z,n_{-1};A) = \underset{n}{\text{argmax}}\left\{zAn^{\alpha} - \rho(A)n - \phi - g(\chi)\right\} \tag{25}$$

$$f(\theta_h) = \frac{M_h}{S_h} = m\theta_h^{1-\psi} \tag{26}$$
$$q^h(\theta_h) = \frac{M_h}{v_h} = m\theta_h^{-\psi} \tag{27}$$

$$V_h(A) = -c + \beta[q(\theta_h)J_h(A') + (1-q(\theta_h))V_h(A')] \tag{28}$$
$$V_h(A) = 0 \tag{29}$$

$$J_h(A) = \rho(A)h - w_h(A) + \beta[(1-s)J_h(A') + sV_h(A')] \tag{30}$$

$$\int h\,d\Psi^W(h,z_t,A) = \int n(h,z_t,A)\,d\Psi^E(z_t,A) \quad \forall t \tag{31}$$

$$w_h(A) = \eta[\rho(A)h + \beta(1-s)\mathbf{E}_{z'/z}J_h(A')] + (1-\eta)[\tilde{U}(h;A) - \beta\tilde{W}_c(h;A')] \tag{32}$$
$$\tilde{W}_c(h;A') = (1-s))\mathbf{E}_{z'/z}\tilde{W}(h;A') + s\mathbf{E}_{z'/z}\tilde{U}(h;A')$$

$$\Psi(x_{t+1}) = T\Psi(x_t) \tag{33}$$

D Algorithm to solve Stationary Equilibrium

Assumptions:

- Economy is in stationary equilibrium associated with $A = 1$

Algorithm:

1. Set A=1.

2. **Outer loop on $\boldsymbol{\rho(A)}$.** Make a guess for the labor efficiency unit price $\rho(A)$.

3. **Inner loop on $\boldsymbol{w(h, A)}$.** Make a guess for the distribution of wages $w(h, A)$.
   Given the guesses $\rho(A)$ and $w(h, A)$, compute:

   - Labor Market elements: $\theta(h, A), f_h(\theta(h, A)), q_h(\theta(h, A))$ (eq. 6)
   - Do VFI over (eqs. 1-5, 7-8) to compute:
     - Value Functions: $W(h, z, o_{-1}, A)$, $U(h, z, o_{-1}, A)$ and $J(h, A)$
     - Occupational Decision Rules: $o(h, z, o_{-1}, A)$
   - Using Value Functions, compute the implicit wage from Nash Bargaining Solution (eq. 10)
   - Compute $diff_w = w_{implict}(h, A) - w_{old}(h, A)$
   - **Update $\boldsymbol{w(h, A)}$**.If $diff_w > tol_w$, update $w(h, A)$ using a weighted average of previous guess ($w_{old}(h, A)$) and model implied values ($w_{implict}(h, A)$).
   - Go back to step beginning of step 3 and repeat until convergence.

4. **Compute Time Invariant Distribution.** Given the decision rule $o(h, z, o_{-1}, A)$ and the transition matrix for the idiosyncratic productivity Pz, compute the time invariant firm distribution $\Psi(h, z, o)$.

5. **Update guessed $\boldsymbol{\rho(A)}$**:

   - Compute the excess of demand/supply for labor efficiency units (eq. 9)
   - Update bounds of $\rho(A)$ for bisection.
   - Compute $diff_\rho = ub_\rho - lb_\rho$
   - If $diff_\rho > tol_\rho$, go back to step 2 and repeat until convergence.

E Algorithm to solve Transition Dynamics

Assumptions:

- Economy is in stationary equilibrium at $t = 0$, associated with $A = 1$
- Economy is in stationary equilibrium at $t = T$, associated with $A = 1$
- There is a full exogenously given sequence of A_t for t=1...T.

Algorithm:

1. Compute stationary equilibrium with A=1. It corresponds to the initial and final equilibrium. Fix T. Set the exogenously given sequence $\{A_t\}_{t=1}^{T}$, with a 7% decrease in $t = 2$ and a recovery following the following AR(1) process: $A_t = (1 - \rho_A) * \bar{A} + \rho_A * A_{t-1}$.
2. **Outer loop on $\rho(A_t)$.** Make a guess for the path of equilibrium object $\{\rho(A_t)\}_{t=1}^{T}$.
3. **Inner loop on $w(h, A_t)$.** Make a guess for the path of equilibrium object $\{w(h, A_t)\}_{t=1}^{T}$.
4. **Backward Iteration Loop.** Given $\rho_(A_t), w(h, A_t)$ compute for each $t = T...1$:
   - Labor Market elements: $\theta(h, A_t), f_h(\theta(h, A_t)), q_h(\theta(h, A_t))$ (eq. 6)
   - Value Functions: $W(h, z_t, o_{t-1}, A_t)$, $U(h, z_t, o_{t-1}, A_t)$ and $J(h, A_t)$ (eqs. 1-5, 7-8)
   - Occupational Decision Rules: $o(h, z_t, o_{t-1}, A_t)$ (from W and U)
   - Implicit wage from Nash Bargaining Solution (eq. 10)
   - Compute $diff_w = w_{implict}(h, A_t) - w(h, A_t)$
   - **Update $w(h, A_t)$** using a weighted average of previous guess and model implied values.
   - While $diff_w > tol_w$, iterate until convergence.
5. **Forward Iteration Loop.** Given the initial distribution $\Psi(h, z_1, o_1)$, the sequence of prices $\{\rho(A_t), w(h, A_t)\}_{t=1}^{T}$ and the decision rules $\{o(h, z_t, o_{t-1}, A_t)\}_{t=1}^{T}$, compute the firms distribution forward $\{\Psi(h, z_t, o_t)\}_{t=1}^{T}$.
6. **Update guessed $\rho(A_t)$**:
   - Compute the excess of demand/supply for labor efficiency units (eq. 9)
   - Update bounds of $\rho(A)$ for bisection.
   - Compute $diff_\rho = ub_\rho - lb_\rho$
   - If $diff_\rho > tol_\rho$, go back to step 2 and repeat until convergence.

F Descriptive Statistics

Year 2005	CPS		SIPP	
	Uninc.	Inc.	Uninc.	Inc.
NUMBER OF BUSINESSES				
All Businesses	10,496,226	5,264,196	10,855,594	5,088,705
	66.6%	33.4%	68.1%	31.9%
Startups	610,730	138,322	326,900	79,315
	81.5%	18.5%	80.5%	19.5%
PREVIOUS OCCUPATION				
Startups				
E	35.8%	59.3%	48.2%	83.0%
NE	64.2%	40.7%	51.8%	17.0%
HUMAN CAPITAL				
All Businesses				
<= High School	42.2%	27.5%	34.9%	21.7%
Incomplete College	27.4%	26.4%	36.2%	34.1%
>= College	30.4%	46.1%	29.0%	44.2%
Startups				
<= High School	47.0%	31.1%	37.0%	27.0%
Incomplete College	26.8%	25.1%	38.3%	32.7%
>= College	26.2%	43.8%	24.6%	40.3%

	CPS		SIPP	
	Uninc.	Inc.	Uninc.	Inc.
EMPLOYEES (% of firms)**				
All Businesses				
N>=1	13.2%	38.8%	NA	NA
N>=25	2.3%	10.1%	1.3%	5.4%
P50	0	0	under 25	under 25
Mean	0.79	3.96	NA	NA
Startups				
N>=1	7.5%	30.3%	NA	NA
N>=25	3.9%	9.5%	2.9%	12.4%
p50	0	0	under 25	under 25
Mean	0.66	2.37	NA	NA
PREVIOUS WAGE* (annual, thousands)				
p25				
p50				
p90	$80.0	$127.0	$54.9	$96.0
Mean	$39.3	$66.2	$27.0	$47.9

Notes: All values are weighted. * Previous wages are from CPS ASEC. ** Basic Monthly CPS 2014-2018 and SIPP 2012.

G Model Implied Transition Rates

Figure 24: Model Implied Transition Rates (as % of Labor Force)