Unemployment Risk and Entrepreneurship*

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Abstract

This paper examines the dynamics of entrepreneurial entry during recessions, with heightened unemployment risk. Empirically, I find that in response to increasing unemployment rate, the propensity for employed workers to become entrepreneurs rises, whereas it diminishes for unemployed individuals. I develop an equilibrium search model of entrepreneurship and unemployment with endogenous job destruction. The decision to enter entrepreneurship is influenced by both opportunistic and separation effects, the latter of which is strengthened by higher unemployment risk. I demonstrate that the absence of separation-induced entry would have led to up to two-percentage-point increase in the unemployment rate during the Great Recession.

JEL classification: E24, J64, L26

Keywords: entrepreneurship, unemployment, business cycle, layoff risk, entry rate

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1 Introduction

How does an individual's previous employment status affect the decision to enter entrepreneurship? How does the aggregate economic condition affect this decision? Understanding the decision of individuals to become an entrepreneur has long been an important topic among economists. Theoretically, there is a close link between entrepreneurship and aggregate economic fluctuations. For example, business formation can amplify the propagation of macroeconomic shocks (Bernanke and Gertler, 1989; Rampini, 2004). In addition, Schumpeter's theory of creative destruction implies that most of the job creation and destruction would concentrate in recessions (Caballero and Hammour, 1996; Parker, 2012). More importantly, discerning how nascent entrepreneurial activities relate to business cycle fluctuations is of paramount importance because much of the job creation is driven by new firms (Adelino, Ma and Robinson, 2017; Decker et al., 2014; Haltiwanger, Jarmin and Miranda, 2013). Moreover, the employment growth of startups is much more sensitive to business cycle fluctuations (Sedláček and Sterk, 2017). While there is ample evidence that shows entrepreneurship is an important driver of economic growth[1], the relationship between entrepreneurship and the business cycle has been less clear[2]. As an illustration, Figure 1 shows the entry rate of entrepreneurship and the unemployment rate over time. While it is less clear how they are correlated in good times, it appears that the entry rate rises significantly in recessions.[3]

Much of the literature, however, has overlooked the underlying heterogeneity across different types of workers. In particular, the previous employment status of prospective entrepreneurs can play an important role in the entry decision because, for instance, unemployed individuals facing worse job market prospects may be more likely to become entrepreneurs

[1]See Acs and Szerb (2007); Galindo and Méndez (2014); Mueller (2007); van Stel, Carree and Thurik (2005); Wennekers and Thurik (1999); Wennekers et al. (2005); Wong, Ho and Autio (2005); and the references therein.

[2]See Section 2 for the related literature on entrepreneurship and business cycle.

[3]It should be noted that firm-level data using the Business Dynamics Statistics (BDS) shows a decline in the share of new firms during recessions. This is not necessarily contradictory to Figure 1. The BDS data may not solely reflect the activity of first-time entrepreneurs but also includes businesses started by existing entrepreneurs who may be scaling down or pivoting in response to economic downturns. In addition, the BDS covers employer firms only, whereas the CPS measure includes many nonemployer or very small owner-operated businesses.

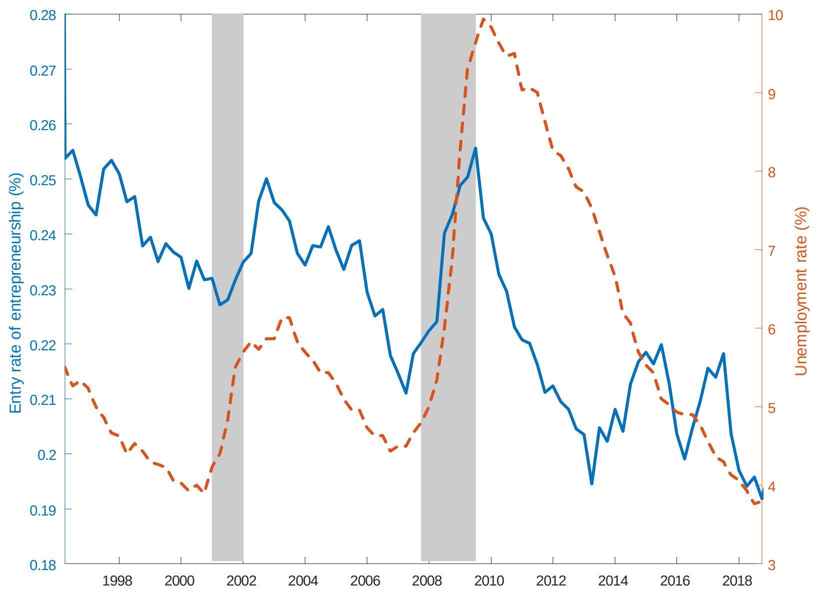

Figure 1: Entrepreneurship Entry and Aggregate Unemployment in the US

Notes: This figure shows the relationship between the entry rate into entrepreneurship (solid line, left scale) and the aggregate unemployment rate (dotted line, right scale) using the CPS data. Entrepreneurs are defined as self-employed business owners. The entry rate is calculated as the fraction of non-entrepreneurs who become an entrepreneur in the next month. The time series is adjusted for seasonal factors. NBER recessions are in shaded areas. See Section 3 for the detailed data construction.

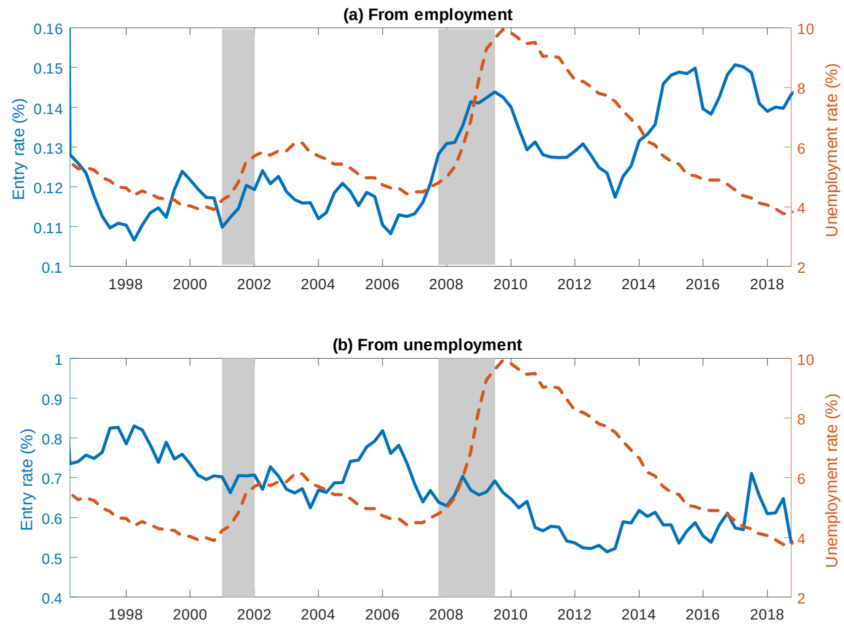

Figure 2: Entrepreneurship Entry by Previous Employment Status in the US

Notes: This figure shows the relationship between the entry rate into entrepreneurship (solid line, left scale) from employment (panel (a)) and unemployment (panel (b)) and the aggregate unemployment rate (dotted line, right scale) using the CPS data. Entrepreneurs are defined as self-employed business owners. The entry rate is calculated as the fraction of non-entrepreneurs who become an entrepreneur in the next month. The time series is adjusted for seasonal factors. NBER recessions are in shaded areas. See Section 3 for the detailed data construction.

than those employed workers. Also, they may respond differently to a rising unemployment rate. Figure 2 shows the time-series relationship between entrepreneurship entry rate and the aggregate unemployment for unemployed and employed individuals, respectively. The behavior of entrepreneurship entry from both employment groups appears to be vastly different. In fact, while we do not observe a surge in the entry rate for the unemployed individuals, it is the employed workers who are more likely to pursue entrepreneurship during economic downturns. This contrasting cyclicality between the employed and unemployed workers merits further investigation.[4]

Figure 3 shows the quit and layoff rates in the US from 2001 to 2018. In bad times, the quit rate drops while the layoff rate spikes. Note that any employment-entrepreneurship

[4]Since the entry rate for the unemployed is much higher than that for the employed, part of the surge of the aggregate entry rate can be due to the compositional effect. In Section 3, I conduct micro-level regressions to isolate within-group cyclicality of the entry rate.

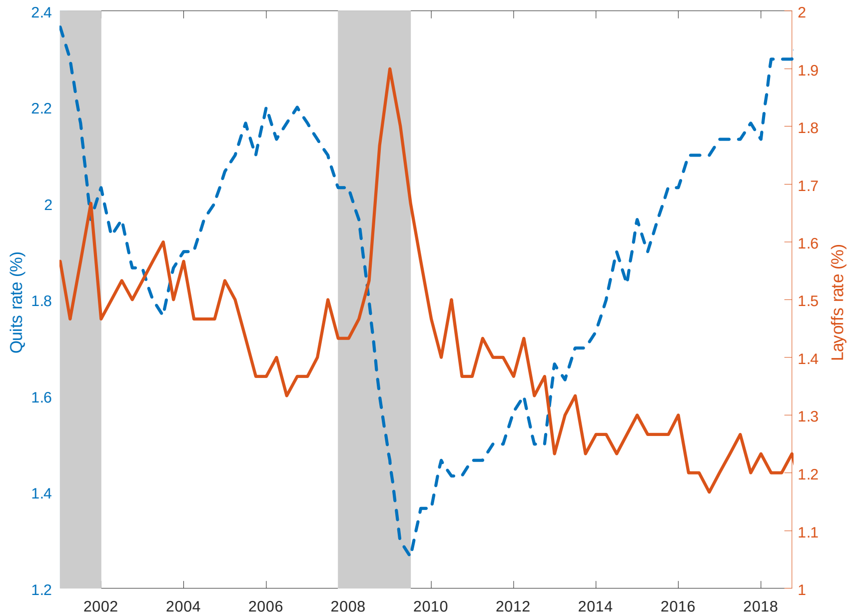

Figure 3: Quits and Layoffs in the US

Notes: This figure shows the layoff rate (solid line, right scale) and quit rate (dotted line, left scale) over time from the Job Openings and Labor Turnover Survey data. NBER recessions are in shaded areas.

transition involves either a quit or a layoff. The cyclicality of quits and layoffs then suggests that it is the increasing layoff rate during economic downturns that is responsible for the increase in the entrepreneurial entry in bad times. This is supported by an empirical literature showing that mass layoffs increase the likelihood of becoming an entrepreneur for the displaced workers. For example, von Greiff (2009) and Røed and Skogstrøm (2014) find that employed workers are substantially more likely to become an entrepreneur after a job displacement. Moreover, Nyström (2020) finds that employees displaced from smaller firms are more likely to transition to entrepreneurship. Therefore, it is important to explore the role of layoff separations on entry into entrepreneurship, which is often ignored in the literature.

In this paper, I study the dynamics of entrepreneurial entry in bad times with increasing unemployment risk. I evaluate the quantitative importance of the type of entrepreneurship induced by increasing layoff separation risk in recessions and its policy implications on entrepreneurship over the business cycle. Using the microdata from the Current Population Survey (CPS), I show that the entrepreneurial entry rate is positively associated with the unemployment rate for those previously employed, but negatively associated for those previously unemployed. This is true for the aggregate time series (as shown in Figure 2) and at the cross-sectional state level. I then perform micro-level regressions of entrepreneurship entry decision on an individual's employment status and their demographic characteristics. There are several findings. First, unemployed individuals are more likely to become an entrepreneur compared to the employed, likely due to the lower outside option value of unemployment. Second, in response to increasing unemployment rate, the propensity to become entrepreneurs increases for employed workers but decreases for unemployed individuals. Third, an examination of business outcomes reveals that entrepreneurs from employment are more likely to be incorporated, achieve higher business sales, exhibit lower one-year exit rates, and hire more employees. Overall, firms founded by employed workers tend to be more successful than those initiated by unemployed individuals.

To explain the empirical findings, I construct an equilibrium model of entrepreneurship and unemployment with endogenous job destruction. In this model, the entrepreneurship decision (Lucas, 1978) is incorporated into a standard search and matching model (Mortensen and Pissarides, 1994). There are three labor market states in the model: employment, unemployment, and entrepreneurship in a firm. In each period, firms make hiring and firing decisions, following which both employed and unemployed individuals may encounter an entrepreneurial opportunity. Upon identifying an opportunity, they must decide whether to establish a new business. Due to the lower profitability in new businesses, the entry rate from unemployment decreases during economic downturns. However, the entry rate from employment is affected by changes both in the profitability (*opportunistic effect*) and in the layoff separation rate (*separation effect*). During recessions when the unemployment rate is high, separation-induced entry surges, leading to an overall increase in the entry rate from employment.

The model is then calibrated to the US economy to evaluate the quantitative importance of separation-induced entrepreneurship in bad times and to study policy analysis regarding entrepreneurship. In this model, consistent with the data, the entry rate from unemployment is decreasing with the unemployment rate, while that from employment is increasing with the unemployment rate. The effect on the entry from employment can be decomposed into pure separation effect as well as the opportunistic effect. Quantitatively, the entry rate would increase from 0.124% to 0.150%, a 20% increase, as the unemployment rate rises from 4%

to 10% due to the increased layoff risk. Conversely, the entry rate would decrease to 0.12% because of the opportunistic effect. This illustrates that separation-induced entry plays a relatively more significant role in explaining the dynamics of the entry rate from employment. I demonstrate that, without the separation-induced entry, the unemployment rate during the Great Recession would have been one to two percentage points higher. This shows that the existence of the separation-induced entrepreneurs can serve to *mitigate* business cycle fluctuations, unlike the typical amplification mechanism in Bernanke and Gertler (1989).

The model developed provides us with a laboratory to evaluate the impact of public policies on entrepreneurial entry and the aggregate economy. I first evaluate the effects of changes in unemployment benefits. I find that the contractionary effect of unemployment benefits on output is attenuated by additional separation-induced entrepreneurial entry, so unemployment insurance affects the economy not only through job-search incentives but also through firm creation. I also find that a mild labor income tax raises entrepreneurship mainly through the employment-to-entrepreneurship margin and can potentially raise output. These findings are not seen in the canonical model with no entrepreneurship, where unemployment benefits and income tax are often detrimental to the aggregate output. Finally, a self-employment subsidy shows a positive impact on the aggregate economy. It increases opportunistic entry while lowering the aggregate unemployment rate and, consequently, the separation-induced entry. As a result, the number of entrepreneurs in the economy increases. Quantitatively, a subsidy equivalent to one unit of labor productivity could boost the aggregate output by up to 0.6%.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the empirical evidence at the micro-level. Then in Section 4, I build an equilibrium model of entrepreneurship and unemployment. I study the quantitative importance of separation-induced entrepreneurship in bad times in Section 5. Section 6 studies policy experiments. Section 7 concludes.

2 Related Literature

This paper contributes to several branches of the literature. First, it relates to the literature on the relationship between entrepreneurship and the business cycle. The empirical evidence on the cyclical properties of entrepreneurship is limited and remains contested. For example, using a panel of 22 OECD countries, Koellinger and Thurik (2012) find that while the global unemployment fluctuation has no effects on entrepreneurship measured by the share of business owners, an increase in national unemployment leads to an upswing in entrepreneurship. Also, Hacamo and Kleiner (2022) show that an increase in the national unemployment rate increases the likelihood of entering entrepreneurship. On the other hand, Yu, Orazem and Jolly (2014) show that college graduates entering the labor market during an economic downturn have a lower probability of starting a business. Fritsch and Kritikos (2016) find a cyclical relationship between unemployment and new business formation as well. Also, Faria, Cuestas and Gil-Alana (2009) estimate an empirical model where entrepreneurship and unemployment affect each other and find that the model can generate a limit cycle. Congregado, Golpe and Parker (2012) find that in Spain, cyclical fluctuation in the aggregate output significantly affects future rates of entrepreneurship. Also, the decision to become self-employed is procyclical, regardless of the original job status in Spain (Garcia-Cabo and Madera, 2019). Payne (2015) finds that a rise in the self-employment rate is causally related to an increase in the unemployment rate at the aggregate level in the US. Entrepreneurs create businesses in response to favorable local demand shocks using Brazilian administrative data (Bernstein et al., 2018). Blau (1987) finds that changes in technology and industrial structure explain much of the change in the fraction of self-employed workers in the 70s and 80s. As we see in Figure 2 and later in Section 3, in the US, the entry rate into entrepreneurship from employment rises in bad times, while that from unemployment decreases in recessions.

Several complementary mechanisms, beyond the separation channel emphasized in this paper, have been proposed to link entrepreneurship and the business cycle. One branch of the literature emphasizes reallocation and the cyclical cost of inputs: downturns can lower some factor costs and change the relative attractiveness of opening a business (Caballero and Hammour (1996); Parker (2012)). Another class emphasizes financial conditions: weaker balance sheets, tighter collateral constraints, and more difficult external finance can discourage startup formation, especially for marginal or externally financed entrepreneurs (Bernanke and Gertler (1989); Evans and Jovanovic (1989)). The present paper does not attempt to combine all of these forces in a single framework. Instead, it asks whether time-varying unemployment risk and layoff separations can account for the opposite cyclical responses of entry from employment and entry from unemployment documented in the data.

Also, there is a literature on comparing different types of entrepreneurship and their business performance. For example, using the NLSY data, Light and Munk (2016) find that 68% of jobs classified as self-employment are not reported as self-owned businesses, and they tend to possess different business characteristics. The level of skills possessed by the workers matters for the entry decisions as well. For example, Salgado (2020) finds that the decline in the entry rate into entrepreneurship is much more pronounced among college graduates. Using the Canadian matched owner-employer-employee dataset, da Fonseca (2019) find that unemployed workers are more likely to become an entrepreneur and that firms created by the unemployed perform relatively poorly compared to those created by employed workers. Also, Pfeiffer and Reize (2000) find that Startups from unemployment in the new German federal states have a slightly significant, lower one-year survival probability. In this paper, I find similar results in the US labor market regarding the business outcomes for nascent entrepreneurs transitioning from different employment statuses.

More recently, researchers in the literature have distinguished different groups of entrepreneurs and found different cyclical properties. For example, Schweitzer and Shane (2016) find that while entry into incorporated self-employment displays no cyclical pattern, people are more likely to enter unincorporated self-employment during economic expansion. Similarly, Levine and Rubinstein (2017) find that the share of incorporated entrepreneurs is procyclical, while that of the unincorporated self-employment is countercyclical. In addition, Schweitzer and Shane (2016) find that in response to a decrease in demand, the entry into entrepreneurship is higher from employment than from unemployment. This paper is most closely related to Fairlie (2013) and Fairlie and Fossen (2018), who similarly show that workers with different previous employment status respond differently to changing aggregate economic conditions. Fairlie and Fossen (2018) explain the ambiguous cyclical property of entrepreneurship by proposing that there exist both opportunity and necessity entrepreneurship.[5] They define the two types of entrepreneurship by an individual's previous employment

[5] According to the theory of necessity entrepreneurship, which is concentrated in non-employed workers, individuals become self-employed in the face of limited alternative opportunities. As a result, business creation of this type should surge in bad times. On the other hand, opportunity entrepreneurship refers to those business creations when there is an entrepreneurial opportunity, which is less likely in bad times.

status. In this paper, I also compare the previous employment status and show that, in fact, unemployed workers are less likely to become entrepreneurs in bad times, which shows that the hypothesis of necessity entrepreneurship is not apparent in the data.[6] Finally, Fossen (2021) finds that much of the variation in the entry rate over the business cycle can be explained by changes in the unemployment rate due to compositional effects. In this paper, I focus on the within-group variation and find an increase in the entry rate among employed workers. Also, this paper evaluates the quantitative effect through the lens of a general equilibrium model with search frictions and entrepreneurship choices.

Finally, this paper contributes to the theoretical literature on entrepreneurship and unemployment. The standard search and matching model has been extended with multiple workers (Acemoglu and Hawkins, 2014; Cooper, Haltiwanger and Willis, 2007; Elsby and Michaels, 2013; Hawkins, 2011). Also, there have been attempts to discuss entrepreneurship in a search model (Fonseca, Lopez-Garcia and Pissarides, 2001; Gaillard and Kankanamge, 2019; Masters, 2017; Poschke, 2019; Shapiro, 2014). However, they are mostly static models and do not feature job separation decisions.[7] In this paper, I embed the entrepreneurship decisions (Lucas, 1978) into a standard search and matching model (Mortensen and Pissarides, 1994) featuring both *endogenous job destructions* and *entrepreneurship decisions* to meaningfully discuss the impact of job separation on the entry into entrepreneurship. To the best of my knowledge, this is the first attempt to obtain differential cyclical properties of entry rates from workers with different employment statuses.

3 Empirical Analysis

In this section, I explore the cyclical properties of the entry rate of entrepreneurship empirically. In the Introduction, I have shown that the cyclicality appears to be different for workers with different employment statuses. I confirm the results by also performing micro-level regressions to understand the importance of the previous employment status to the

[6] In their regression analysis, Fairlie and Fossen (2018) look at the level of new entrepreneurs coming from employment and non-employment, whereas I look at the *entry rate* from employment and unemployment. As a result, their results may include the compositional effect due to the increasing share of unemployment.

[7] Albrecht, Navarro and Vroman (2009) discuss formal employment and informal self-employment in a search model with endogenous separations. However, in their model, self-employed workers act like employees and do not engage in entrepreneurial decisions such as hiring other employees.

entrepreneurial decision in response to changes in aggregate and local unemployment. I then show that the business outcomes of the new businesses created by workers with different previous employment statuses are vastly different as well. Appendix A contains additional empirical results.

3.1 Data

To investigate an individual's decision to become an entrepreneur, I use the microdata from the Current Population Survey (CPS). Specifically, I use the monthly CPS Outgoing Rotation Groups (ORG), which has a rotating panel structure: Each household is interviewed consecutively for four months, then dropped from the sample for the following eight months, and finally re-visited for another spell of four consecutive monthly interviews. This rotation structure allows us to match individuals from one month to another using the information on their race, sex, and age (Nekarda, 2009). My ORG sample covers individuals aged 16 to 64 over the 20-year period from 1996 until 2018.[8] Individuals are weighted by the Composited Final Weight for CPS when computing labor market statistics. The CPS data also contains information about the location of each individual at the state or county level. This is useful when looking at the state-level cross-sectional relationship and when constructing the local unemployment rate.

Unfortunately, while it is well-known that self-employment is a weak proxy of entrepreneurship, there is no universal definition of entrepreneurship in the literature. Accordingly, in the CPS data, I define individuals as entrepreneurs if they are self-employed business owners. Note that self-employment and business ownership are two different concepts.[9] The definition used here represents the intersection between them. The reason I use a relatively stricter definition than those in the literature is that I would like to exclude casual contract workers and freelancers such as Uber drivers in the data. In this definition, I also exclude employees who own a business[10]. It can be shown in Appendix A that the results below

[8] The CPS underwent a major redesign in 1994-1995, altering self-employment measurement and complicating comparisons with prior years.

[9] For example, Light and Munk (2016) find that 68% of jobs classified as self-employment are not reported as self-owned businesses, and they tend to possess different business characteristics

[10] Using the CPS data, I find that fewer than 10% of employee business owners transition to self-employment within two years. This suggests that most employee business owners do not become operational entrepreneurs, validating the exclusion of this group.

are robust to different definitions of entrepreneurs. Some may argue that entrepreneurs, especially those mature and successful ones, may not be self-employed at all. This is less of a concern since my focus is on those nascent entrepreneurs.

To capture the real entry rate into entrepreneurship, I follow Elsby, Hobijn and Şahin (2015) to remove possible spurious transitions between employment and self-employment states. For example, if a worker is employed in the first and the third month, but self-employed in the second month in the survey, I treat her as employed in all three months instead. The case of a worker who is self-employed in the first and the third month but employed in the second month is similar: I consider her self-employed in all three months.

In the baseline, I restrict the sample to those who are in the labor force but not an entrepreneur in the current month (t). I then investigate their decision whether or not to become an entrepreneur in the following month ($t+1$). In particular, I define the variable $entre_{t+1}$ as the dummy variable which equals one if the worker becomes an entrepreneur in the following month and zero otherwise. On the aggregate level, the entry rate into entrepreneurship can then be computed by taking the average of $entre_{t+1}$. As mentioned in the Introduction, Figure 1 shows the entry rate of entrepreneurship and unemployment over time using the CPS data. While the entry rate appears to be correlated with the aggregate unemployment rate in the early years, the correlation breaks down in more recent times, especially after the Great Recession. The importance of previous employment status is shown in Figure 2, when the sample is partitioned into those previously unemployed and employed respectively. Also, Appendix A shows the state-level cross-sectional evidence.

Table A.1 in Appendix A shows the summary statistics of the samples.

3.2 Entrepreneurial Entry Decision and Unemployment

While both the time series and state-level cross-sectional evidence suggest that one's previous employment status matters for the cyclicality of entrepreneurship entry, both of the aggregate results suffer from the usual pitfall that the correlation may be due to composition change among workers over time or across states. My next step is to perform formal regression analysis at the individual level.

The baseline regression model is as follows.

$$G\left(entre_{i,t+1}\right) = \beta_0 + \beta_1 unemployed_{i,t} + \beta_2 unemployed_{i,t} \times u_{i,t}^{state} + \beta_3 employed_{i,t} \times u_{i,t}^{state} + \alpha X_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $entre_{i,t+1}$ is the dummy variable which equals one if individual i becomes an entrepreneur at time $t+1$, $G(\cdot)$ is a function which corresponds to logit, OLS, and probit regression models respectively, $unemployed_{i,t}$ and $employed_{i,t}$ are the dummy variables indicating the employment status of individual i at time t, $u_{i,t}^{state}$ is the state-level unemployment rate at time t, and $X_{i,t}$ is a vector of demographic control variables. Control variables in $X_{i,t}$ include sex, race, age, education group dummies (less than high school, high school diploma, some college, college graduate, more than college), marital status, and state fixed effects.

Table 1 shows the logit regression results using the CPS data. For columns (1) to (5), the sample is restricted to those who are in the labor force, while column (6) includes those who are out of the labor force as well. Now column (1) shows that unemployed people have on average significantly higher propensity to become an entrepreneur. This is perhaps not surprising since most of the unemployment spells are transitory in nature. Column (2) shows the pure business cycle effect of entrepreneurship entry. The coefficient associated with the state-level unemployment rate is significantly positive, which suggests that entrepreneurship entry is countercyclical. However, the cyclicality disappears once I also control for the employment status in column (3). The result is qualitatively the same in (4), where I also control for the demographic characteristics.

The result for the baseline specification is shown in column (5). Conditional on previous employment status, the entry decision responds differently to state-level labor-market conditions. Specifically, the interaction between employment and the state unemployment rate is positive and statistically significant, while the interaction between unemployment and the state unemployment rate remains negative and highly significant. Thus, worsening local labor-market conditions increase entrepreneurial entry from employment but reduce it from unemployment. Lastly, I also include those out of the labor force in the regression in (6). We can see that the behavior of those non-participants is similar to the unemployed. In particular, the entrepreneurship entry rate of those out of the labor force is on average higher

Table 1: Logit Regression Results (CPS)

Logit model	$entre_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
$unemployed_t$	1.731***		1.740***	2.065***	2.444***	2.503***
	(0.0325)		(0.0356)	(0.0378)	(0.0594)	(0.0584)
$u_{i,t}^{state}$		2.696***	-1.081	-0.638		
		(0.852)	(0.910)	(0.535)		
$employed \times u_{i,t}^{state}$					1.368**	2.621***
					(0.650)	(0.733)
$unemployed \times u_{i,t}^{state}$					-4.922***	-3.839***
					(0.880)	(0.925)
$nilf$						1.939***
						(0.0684)
$nilf \times u_{i,t}^{state}$						-4.613***
						(0.663)
Constant	-6.659***	-6.573***	-6.599***	-8.699***	-8.816***	-8.970***
	(0.0357)	(0.0544)	(0.0533)	(0.0787)	(0.0954)	(0.0912)
Observations	10,870,644	10,870,644	10,870,644	10,870,644	10,870,644	14,298,585
Controls	NO	NO	NO	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors clustered at the state level in parentheses. This table shows the logit regression results of $entre_{t+1}$. Column (6) includes the individuals out of labor force, with $nilf$ being the dummy variable for the not-in-labor-force status. The logit regression coefficients show the effects on the log of odds ratio of $entre_{t+1}$. See Appendix A for the average marginal effects on the entry probability. See Section 3 for the data construction and definitions.

than that of the employed, and responds negatively to the unemployment rate. Therefore, I restrict the focus on those who are in the labor force thereafter.

Table A.2 in the Appendix shows the average marginal effects associated with the logit regressions shown above. Consider the baseline specification (5). The average marginal effects show that for every ten-percentage-point increase in unemployment rate, the entry rate from employment would increase by 0.022 percentage point, which corresponds to an 18% increase from the mean level. On the other hand, the entry rate from unemployment would drop by 0.080 percentage point, which corresponds to a 12% decrease from the mean level. This shows that the business cycle effects on the entry rates are different and quantitatively significant.

3.3 Robustness

The results shown above are robust to a number of different specifications and definitions of entrepreneurs. Table A.3 in Appendix A shows various robustness checks. For example, the results are similar when I use OLS and probit models. Also, when I define entrepreneurs as self-employed workers, I get similar but relatively stronger results. The coefficients are also similar when I restrict the definition to only incorporated business or unincorporated business. Finally, if I use only business ownership as the definition, then I get a negative coefficient associated with the cross term between employed and unemployment rate. However, this definition is much broader, and the resulting entry rate may be misleading since many of the business owners are actually employed in different firms while owning some business on the side. The results are also robust to additional controls such as unemployment insurance generosity. Lastly, I exploit the rotating-panel structure of the CPS to include individual fixed effects. The point estimates preserve the same sign pattern as in the baseline specification. However, the interaction coefficients are no longer statistically significant in this specification. This is because the CPS follows individuals for only a short period, and entrepreneurship entry is very rare at the monthly frequency. Consequently, once the identification comes only from within-individual variation, the sample falls sharply.

Table A.4 shows similar regressions in Table 1 using the national *EU transition rate* (i.e. the probability that an employee becomes unemployed in the next period) instead of the unemployment rate. The regression results show a stronger impact on the employed workers, but less so for the out-of-labor-force individuals. This shows higher separation rates have robust effects on the employment entry decisions.

In addition, Table A.6 shows the results using the National Longitudinal Survey of Youth 1979 (NLSY79) data where I can control for individual fixed effects. Also, the NLSY79 data cover a longer horizon from 1979 to 2014, which spans earlier recessions, allowing us to assess validity beyond the baseline CPS window. Table A.7 shows the regression models when, instead of using the state-level unemployment rate, I use the local unemployment rate at the commuting zone level. In general, the sign of the point estimates of the parameters is unchanged in the different specifications.

3.4 Business Outcomes

Given the different cyclical properties of entrepreneurship entry for people with different employment statuses, it is natural to think that they produce different business outcomes as well. Table 2 shows a number of business outcome measures of nascent entrepreneurs. The upper panel shows the outcomes for the CPS data. First, the exit rate is defined as the probability that a nascent entrepreneur becomes either employed, unemployed, or out of the labor force in the following period. We can see that nascent entrepreneurs from unemployment possess a significantly higher one-month exit rate than those from employment (42% vs. 33%). It is true also for the one-year exit rate. Also, the businesses created by nascent entrepreneurs from employment are much more likely to be incorporated (33% vs. 19%). The row "Manager" refers to the proportion of nascent entrepreneurs whose occupation belongs to management. We can see that they are equally likely to be managers when creating their own businesses. Finally, nascent entrepreneurs from employment are much more likely to hire employees (28% vs. 6%). In fact, those from employment hire on average two employees (excluding the entrepreneur), while those from unemployment hire merely 0.4 employee on average.

The lower panel of Table 2 shows the business outcomes using the NLSY79 data. Note that here only the exit rates and the probability of being incorporated are derived from longitudinal questions. All other business outcome variables are from the Business Ownership questions, which were asked to each current or former business owner starting from 2010.[11] A few observations are in order. First, the probability of the business being incorporated is similar across employment status, with a slight edge for those coming from employment. Second, the amount of capital the nascent entrepreneur used to create the business is more than three times larger for those from employment than for those from unemployment.[12] Third, similar to the CPS data, those businesses created by employees are more likely to hire other employees. In fact, in the NLSY79 data, the average number of employees for nascent entrepreneurs from employment is more than six versus only about one employee for those from unemployment. Also, the business sales or revenue of those businesses created by

[11] Specifically, I attached the cross-sectional information of business ownership to each spell of self-employment entry. The results are then the average of those variables across all spells of self-employment entry.

[12] The relevant question is "About how much money did you use to establish or acquire the business?".

employees are much larger than those created by unemployed workers. Lastly, those nascent entrepreneurs are more likely to consider themselves to be an entrepreneur if they are coming from employment, and more likely to be a manager of the business.

These findings are consistent with those in the literature. For example, Evans and Leighton (1990) and da Fonseca (2019) find that unemployed workers are more likely to become an entrepreneur and that firms created by the unemployed perform relatively poorly compared to those created by employed workers. Also, Pfeiffer and Reize (2000) find that Startups from unemployment in the new federal states have a slightly significant, lower one-year survival probability.

Table A.5 in the Appendix presents the same set of business outcomes during recessions. Interestingly, the CPS sample indicates that nascent entrepreneurs during recessions exhibit exit rates and incorporation rates that are very similar to those mentioned above. The NLSY79 data, which encompasses older recessions, shows that businesses established during these earlier downturns typically fared worse, with lower firm sizes and rates of being incorporated. They also reported approximately 10% lower business sales and capital compared to their counterparts in better economic times. However, it is important to highlight that nascent entrepreneurs who transition from employment to entrepreneurship during recessions generally still perform better than those transitioning from unemployment during economically stable periods. This suggests that the selection effect may not be as significant as the effect of the employment status itself. This distinction also underscores the potential value of targeted governmental support for entrepreneurship during downturns.

3.5 Job Separation and Entrepreneurial Entry

In Appendix A.7, I show the relationship between the entry rate into entrepreneurship *from employment* and job separation rate (i.e. EU transition) across different industries. We can see from Figure A.3 that industries with higher separation rate indeed have on average higher entry rate into entrepreneurship. This is also true after controlling for year and industry fixed effects (Table A.8). This is consistent with the economic mechanism that higher risk of layoff separations induce more employed workers to become an entrepreneur. In this next section, I study the mechanism of separation-induced entry in a model of entrepreneurship and unemployment.

Table 2: Business Outcomes of Nascent Entrepreneurs

CPS, 1996 - 2018			
	Nascent Entrepreneurs		
	All	Employment	Unemployment
1-month entry rate	0.23%	0.13%	0.65%
1-month exit rate	39.91%	33.37%	41.52%
1-year exit rate	60.55%	54.20%	61.12%
Incorporated	26.74%	33.11%	19.48%
Manager	22.08%	25.32%	21.76%
Have employees	19.67%	27.83%	6.36%
Number of employees	1.38	2.17	0.42
Observations	35,148	13,632	4,593
NLSY79, 1979 - 2014			
	Nascent Entrepreneurs		
	All	Employment	Unemployment
1-month exit rate	5.72%	6.29%	2.32%
1-year exit rate	62.07%	61.00%	85.51%
Incorporated	13.62%	15.32%	14.82%
Business capital	$2,926,279.60	$3,341,759.79	$1,089,646.56
Have employees	31.1%	31.6%	25.4%
Number of employees	4.50	6.49	1.05
Business sales	$28,215,603.97	$31,206,788.87	$3,921,517.05
Feel entrepreneur	44.19%	44.75%	37.44%
Manager	17.74%	19.01%	14.85%
Observations	3,832	2,721	350

Notes: The table shows the business outcomes of nascent entrepreneurs. Nascent entrepreneurs are those entrepreneurs newly transitioned from employment or from unemployment. Number of employees refers to hired employees in the business and excludes the entrepreneur/owner. See Section 3 for the data construction and definitions.

4 A Model of Entrepreneurship and Unemployment

In this section, I develop a model of entrepreneurship entry and unemployment with endogenous job destruction. I demonstrate that in this model, entry into entrepreneurship from employment can be induced by increasing layoff separation decision during bad times which would be crucial to understand the dynamics of the entry rate over the business cycle.

4.1 Environment

Here I extend the standard search and matching model of labor market (Mortensen and Pissarides, 1994) with entrepreneurship decisions (Lucas, 1978). Multiple-worker firms are allowed when there are decreasing returns (Elsby and Michaels, 2013; Acemoglu and Hawkins, 2014). Workers are infinitely lived and risk-neutral with common discount factor β.[13] In each period of their lives, they can participate in the labor market as employed, unemployed, or as entrepreneurs in a firm.[14] For simplicity, I assume that each entrepreneur can only create and manage one firm at a time. In each period, both unemployed and employed workers have a probability λ^u and λ^w respectively to receive an entrepreneurial opportunity, in which case they draw an entrepreneurial productivity z from a stationary distribution $G_0(\cdot)$ with a compact support $[z_{\min}, z_{\max}]$.[15] They may then choose to open a business upon observing z.[16] Otherwise, workers are homogeneous when working for a firm. Unemployed workers and firms are searching randomly in a single labor market. There is an aggregate productivity

[13] Appendix F.1 examines robustness to risk aversion by replacing linear flow utility with CRRA preferences; the main quantitative results remain unchanged.

[14] Following Lucas (1978), I abstract from workers' fixed effects in this model, so that the productivity of the worker depends only on the entrepreneurial ability and the size of the firm. Incorporating workers' ex-ante heterogeneity would be an interesting extension of the model so that one may talk about the distribution of worker's characteristics over the business cycle. However, the general message about the entrepreneurial entry over the business cycle would be unchanged.

[15] I consider entrepreneurial productivity as a one-dimensional object. Hence, workers who draw a high z would be more likely to become an entrepreneur. By introducing multi-dimensional skills, Lazear (2005) finds that entrepreneurs are less likely to possess specialized skills.

[16] For tractability, I abstract from capital borrowing constraints and household wealth in the model. A large literature studies startup finance and entrepreneurial wealth. Evans and Jovanovic (1989) emphasize that borrowing constraints can shape entrepreneurial choice, while Hurst and Lusardi (2004) argue that the relationship between wealth and entry is weak over much of the wealth distribution. I do not attempt to adjudicate that debate here. Instead, I abstract from wealth and startup borrowing in order to isolate a different margin: how changing unemployment risk and separation risk affect entrepreneurial entry differently for employed and unemployed workers. A common tightening of financing conditions would typically lower startup profitability for both groups. Thus, incorporating this mechanism is unlikely by itself to overturn the main qualitative results.

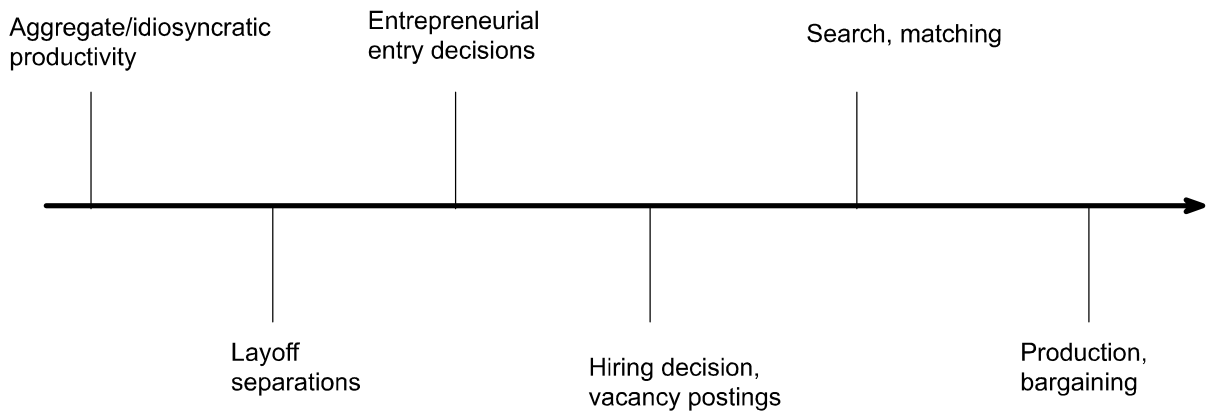

Figure 4: Timeline in the Model

y_t which is the only aggregate state variable that is changing over time.[17] Let $\theta_t = \frac{v_t}{u_t}$ be the market tightness, where v_t and u_t are the measures of vacancies and unemployed workers respectively. Figure 4 shows the timeline in the model within one period.[18]

4.2 Workers

Unemployed workers receive a flow value b_t of unemployment activity, which may include such things as leisure and home production and may depend on the aggregate state.[19] In the next period, she will search for a job in the labor market with a job finding rate of $\phi(\theta_t)$. Hence the value of being unemployed at time t is

$$U_t = b_t + \beta \mathbb{E}_t \left[(1 - \phi(\theta_t)) \hat{U}_{t+1} + \phi(\theta_t) \hat{W}_{t+1}(z_{t+1}, n_{t+1}) \right] \tag{2}$$

Note that the expectation is taken over the aggregate state, as well as the distribution of the productivity and the size of the hiring firms in the next period. The continuation values are given by

$$\hat{U}_{t+1} = \lambda^u \int \max \left\{ \Pi_{t+1}(\tilde{z}, 0), U_{t+1} \right\} dG_0(\tilde{z}) + (1 - \lambda^u) U_{t+1} \tag{3}$$

$$\hat{W}_{t+1}(z, n) = \lambda^w \int \max \left\{ \Pi_{t+1}(\tilde{z}, 0), W_{t+1}(z, n) \right\} dG_0(\tilde{z}) + (1 - \lambda^w) W_{t+1}(z, n) \tag{4}$$

[17] Hereafter, I use the subscript t to denote the dependence on y_t.

[18] In the quantitative analysis, I take one period as one month in the model.

[19] To simplify the state space of the problem, I do not distinguish between the unemployment benefits for formerly employed workers and those for formerly self-employed workers.

where $\Pi_{t+1}(\tilde{z}, 0)$ is the value of a new business with productivity $\tilde{z}$ and initial employment size of 0 at time $t+1$. Therefore, depending on whether the individual can find a job, there is a probability λ^u or λ^w that she will receive an opportunity to become an entrepreneur, with productivity drawn from the distribution G_0. The worker in this case can decide whether or not to create a new firm.

If matched with a firm, an employed worker earns a wage $w_t(z_t, n_t)$ where z_t is the entrepreneurial productivity and n_t is the size of the firm respectively. In the next period, there are both exogenous and endogenous separations. Depending on whether she separates from the firm, she will receive continuation values $\hat{U}_{t+1}$ or $\hat{W}_{t+1}(z_{t+1}, n_{t+1})$. Therefore, the value of being employed is given by

$$W_t(z_t, n_t) = w_t(z_t, n_t) + \beta \mathbb{E}_t \left[\delta_{t+1} \hat{U}_{t+1} + (1 - \delta_{t+1}) \hat{W}_{t+1}(z_{t+1}, n_{t+1}) \right] \tag{5}$$

where total separation rate is

$$\delta_{t+1} = s_{t+1} + (1 - s_{t+1}) \sigma_{t+1} \tag{6}$$

with $s_{t+1}(z_{t+1}, n_t)$ being the firm exit rate (defined below) and $\sigma_{t+1}(z_{t+1}, n_{t+1}) = \mathbf{1}\{U_{t+1} \geq W_{t+1}(z_{t+1}, n_{t+1}$ being the layoff separation rate.[20]

To be clear, the expectation is taken over the aggregate state, as well as the productivity and the size of the current firm in the next period. Similar to the case of unemployed workers, regardless of whether she separates from the firm, there is a probability that she will receive an entrepreneurial opportunity.

4.3 Entrepreneurial Firms

An entrepreneur starts by creating a firm with zero initial size. She then posts vacancy with constant marginal cost c. Due to search frictions, only q_t of those vacancies would turn into matched jobs. Therefore, a firm with productivity z_t and previous employment size n_{t-1}

[20] Since wages are determined by Nash bargaining shown later in the section, all employment-to-unemployment separations are mutually agreed to. So this is technically also the quit separation rate. See Yuen (2019) for a discussion on quit vs. layoff in the Nash bargaining solution.

chooses the optimal employment size and vacancy postings for the current period:

$$\Pi_t\left(z_t, n_{t-1}\right) = \max_{n_t, v_t} \left\{ \begin{array}{c} \xi y_t z_t f\left(n_t\right) - w\left(z_t, n_t\right) n_t - c v_t \\ +\beta \mathbb{E}_t \left[(1-\bar{s}) \int \max\left\{\Pi_{t+1}\left(z_{t+1}, n_t\right), U_{t+1}\right\} dG\left(z_{t+1}|z_t\right) + \bar{s} U_{t+1} \right] \end{array} \right\} \tag{7}$$

where y_t is the aggregate productivity, ξ is a normalizing TFP factor, $\bar{s}$ is the exogenous firm destruction rate, $G\left(z_{t+1}|z_t\right)$ is the productivity transition for incumbent firms,

$$v_t = \max\left\{ \frac{n_t - \left(1-\pi_t^w\right) n_{t-1}}{q\left(\theta_t\right)}, 0 \right\} \tag{8}$$

denotes vacancy postings and π_t^w is the fraction of workers who are becoming entrepreneurs (to be determined in equilibrium). The total firm exit rate is then given by

$$s_{t+1}\left(z_{t+1}, n_t\right) = (1-\bar{s}) \mathbf{1}\left\{U_{t+1} \geq \Pi_{t+1}\left(z_{t+1}, n_t\right)\right\} + \bar{s} \tag{9}$$

Note that the firm can reduce its size costlessly, whereas expansion is costly due to search friction. The first-order condition when there are hirings or firings of workers:

$$\xi y_t z_t f'\left(n_t\right) - w_t\left(z_t, n_t\right) - \frac{\partial w_t\left(z_t, n_t\right)}{\partial n_t} n_t + \beta \mathbb{E}_t \left[\left(1 - s_{t+1}\right) \frac{\partial \Pi_{t+1}\left(z_{t+1}, n_t\right)}{\partial n_t} \right] = \frac{c}{q\left(\theta_t\right)} \mathbf{1}_{hire_t} \tag{10}$$

The condition states that the marginal value of a worker equals its marginal cost which is the cost of posting vacancies. The existence of the asymmetric cost structure entails different cutoff productivities for hirings and firings as shown below.

4.4 Marginal Value of a Worker

Conditional on the firm's survival, we can define the marginal value of a worker as

$$J_t\left(z_t, n_t\right) = \xi y_t z_t f'\left(n_t\right) - w_t\left(z_t, n_t\right) - \frac{\partial w_t\left(z_t, n_t\right)}{\partial n_t} n_t + \beta \mathbb{E}_t \left[\left(1 - s_{t+1}\right) \frac{\partial \Pi_{t+1}\left(z_{t+1}, n_t\right)}{\partial n_t} \right] \tag{11}$$

Following Elsby and Michaels (2013), we can now derive the optimal employment size of the firm.

Proposition 1 *Conditional on the firm's survival, the optimal employment policy can be* *characterized as*

$$n_t\left(z_t, n_{t-1}\right)=\begin{cases}\left(R_t^h\right)^{-1}\left(z_t\right) & \text{if } z_t>R_t^h\left(\left(1-\pi_t^w\right) n_{t-1}\right) \\ \left(1-\pi_t^w\right) n_{t-1} & \text{if } z_t \in\left[R_t^f\left(\left(1-\pi_t^w\right) n_{t-1}\right), R_t^h\left(\left(1-\pi_t^w\right) n_{t-1}\right)\right] \\ \left(R_t^f\right)^{-1}\left(z_t\right) & \text{if } z_t<R_t^f\left(\left(1-\pi_t^w\right) n_{t-1}\right)\end{cases} \tag{12}$$

where $R_t^h(\cdot)$ and $R_t^f(\cdot)$ are defined by $J_t\left(R_t^h(n), n\right)=\frac{c}{q(\theta_t)}$ and $J_t\left(R_t^f(n), n\right)=0$.

Hence, there is an inactive region $\left[R_t^f\left(\left(1-\pi_t^w\right) n_{t-1}\right), R_t^h\left(\left(1-\pi_t^w\right) n_{t-1}\right)\right]$ where the firm would neither fire nor hire any worker.

Proof. See Appendix D. ■

4.5 Matching, Surplus, and Wage Bargaining

Assume a standard constant-returns-to-scale matching function $M(u, v)=A u^\alpha v^{1-\alpha}$, then the meeting rates for unemployed workers and vacant firms are respectively,

$$\phi\left(\theta_t\right) = \frac{M\left(u_t, v_t\right)}{u_t}=M\left(1, \theta_t\right)=A \theta_t^{1-\alpha} \tag{13}$$

$$q\left(\theta_t\right) = \frac{M\left(u_t, v_t\right)}{v_t}=M\left(\theta_t^{-1}, 1\right)=A \theta_t^{-\alpha} \tag{14}$$

The total surplus from matching is the difference between the sum of the marginal value of the worker and the value of being employed, and the outside of the worker, which is the unemployment of the worker:

$$S\left(z_t, n_t\right)=J_t\left(z_t, n_t\right)+W_t\left(z_t, n_t\right)-U_t \tag{15}$$

Wages are determined by Nash bargaining where firms are treating each worker as if they are the marginal workers (Stole and Zwiebel, 1996)[21]

$$(1-\eta)\left(W_t\left(z_t, n_t\right)-U_t\right)=\eta J_t\left(z_t, n_t\right) \tag{16}$$

[21] Brügemann, Gautier and Menzio (2018) emphasize that this bargaining structure can overstate within-firm bargaining distortions relative to alternative wage-setting environments. Because this paper focuses on entry and separation margins rather than on detailed wage dispersion, I retain the Stole and Zwiebel setting for tractability.

where η is the bargaining power of the worker. We are now ready to derive the wage equation.

Proposition 2 *The wage equation satisfies the ordinary differential equation*

$$w_t(z_t, n_t) = (1-\eta)(b_t + \Lambda_t(z_t, n_t)) + \eta \left\{ \xi y_t z_t f'(n_t) - \frac{\partial w_t(z_t, n_t)}{\partial n_t} n_t + \beta \phi(\theta_t) \mathbb{E}_t \left[\left(1 - \pi^w_{t+1}\right) \frac{c}{q(\theta_{t+1})} \right] \right\} \tag{17}$$

where

$$\Lambda_t(z_t, n_t) = \beta \mathbb{E}_t \left[(1 - \delta_{t+1} - \phi(\theta_t)) \begin{array}{c} \lambda^u \int_{\bar{z}^u_{t+1}}^{z_{\max}} (\Pi_{t+1}(\tilde{z}, 0) - U_{t+1})\, dG_0(\tilde{z}) \\ -\lambda^w \int_{\bar{z}^w_{t+1}(z_{t+1}, n_{t+1})}^{z_{\max}} (\Pi_{t+1}(\tilde{z}, 0) - U_{t+1})\, dG_0(\tilde{z}) \end{array} \right] \tag{18}$$

is the expected option value difference between employed and unemployed workers when given an entrepreneurial opportunity.

Proof. See Appendix D. ■

The wage expression shows the impact of entrepreneurship entry on wages. Specifically, when $\lambda^w = \lambda^u = 0$, we get back the standard wage solution in a standard search and matching model, where the wage rate is simply the weighted average of flow utility of unemployment and the marginal value of the worker. On the other hand, when $\lambda^w, \lambda^u > 0$, the possibility of becoming an entrepreneur increases the outside option of a worker and hence raises the wage.

4.6 Entrepreneurial Decisions and Entry Rates

Both employed and unemployed can choose to become an entrepreneur upon observing z. It is then clear that they employ a cutoff strategy for the entry decision. In particular, for the unemployed workers, the cutoff productivity $\bar{z}^u_t$ is determined by

$$\Pi_t(\bar{z}^u_t, 0) = U_t \tag{19}$$

above which the unemployed worker would choose to create a business. Similarly, for the employed workers, the cutoff productivity $\bar{z}^w_t(z_t)$ depends on the productivity of the current firm and is determined by

$$\Pi_t(\bar{z}^w_t(z_t, n_t), 0) = W_t(z_t, n_t) \tag{20}$$

where z_t is the productivity of the current firm.

We can then compute their entrepreneurial entry rates. Specifically, an unemployed worker would choose to become an entrepreneur when she receives an entrepreneurial opportunity and when the productivity is higher than the cutoff $\bar{z}_t^u$. Hence, the entry rate is

$$entry_{t+1}^u = \lambda^u \left(1 - G_0\left(\bar{z}_{t+1}^u\right)\right)$$

For the employed workers, however, the entry decision depends on whether the worker is separated from the firm. Therefore, the entry rate in this case is given by

$$\begin{aligned} entry_{t+1}^w\left(z_{t+1}, n_{t+1}\right) &= \delta_{t+1}\lambda^u\left(1 - G_0\left(\bar{z}_{t+1}^u\right)\right) \\ &\quad + \left(1-\delta_{t+1}\right)\lambda^w\left(1 - G_0\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right)\right) \end{aligned} \tag{21}$$

To examine the cyclicality of entrepreneurial entry, I impose the following assumption on the cyclicality of the entry cutoffs. For notational simplicity, I suppress time subscripts and express the explicit dependence on the aggregate productivity y.

Assumption 3 *For any state (z, n), the cutoff productivities $\bar{z}^u(y)$ and $\bar{z}^w(z, n; y)$ are decreasing in aggregate productivity y.*

Assumption 3 states that when aggregate productivity is low, both unemployed and employed workers require a higher entrepreneurial draw in order to start a business. The intuition is that a fall in aggregate productivity lowers the value of opening a new firm directly through current and future profits. By contrast, the values of unemployment and continued employment move through equilibrium objects such as wages, job-finding rates, and separation rates. Moreover, since the impact on the value of the firm is first-order, the decline in the value of creating a new firm is more than that in the values of being employed and unemployed. Hence, in bad times entrepreneurship becomes less attractive relative to the worker's outside option. Section 5 verifies this numerically in the calibrated model.

By Assumption 3, we have that the entry rate from unemployment $entry_{t+1}^u$ would decrease since the probability of drawing a productive enough firm $1-G_0\left(\bar{z}_{t+1}^u\right)$ is lower. Fixing the value of δ_{t+1}, there is the same negative effect on $entry_{t+1}^w$. In what follows, I refer to the impact due to changes in the cutoff productivities as the *opportunistic effect*.

Note that when the aggregate productivity is low, the separation rate δ_{t+1} is also higher. It is because the match surplus, if any, shared by the firm and the workers are now smaller. Now since $\bar{z}^u_{t+1} < \bar{z}^w_{t+1}(z_{t+1})$ (due to the fact that the value of being employed is higher than that of being unemployed) and so $1 - G_0\left(\bar{z}^u_{t+1}\right) > 1 - G_0\left(\bar{z}^w_{t+1}(z_{t+1})\right),$ the increase in δ_{t+1} leads to an overall higher entry rate for the employed worker if the cutoff productivities are fixed. This is referred to as *separation effect*.

I summarize the findings in the following proposition.

Proposition 4 *Suppose there is a decline in aggregate productivity y and that $\lambda^u \geq \lambda^w$. Under Assumption 3:*

*(i) The entry rate from unemployment decreases (**opportunistic effect**);*

*(ii) If the separation rate is fixed, the entry rate from employment decreases (**opportunistic effect**);*

*(iii) If the cutoff productivities are fixed, the entry rate from employment increases (**separation effect**).*

Proof. See Appendix D. ■

Therefore, the overall changes in the entry rate from employment depend on the relative strength between the opportunistic effect and the separation effect. I answer this quantitative question in the next section when the model is calibrated to the US economy.

5 Quantitative Analysis

In this section, I calibrate the model to the US labor market and evaluate the quantitative impact of the separation-induced entry into entrepreneurship. Details of the computation strategy are in Appendix E. First, I show the quantitative relationship between the entry rates and the aggregate unemployment in the economy. Then I evaluate the quantitative impact of the separation-induced entry into entrepreneurship from employment by matching the unemployment dynamics during the Great Recession. Finally, I perform several policy experiments in the model to highlight the importance of entry into entrepreneurship to the aggregate economy.

5.1 Calibration and Specifications

As is standard in the literature, I use a production function with decreasing returns to scale to allow for multiple workers in a firm:

$$f(n) = n^{\alpha_f} \tag{22}$$

where the parameter α_f governs the degree of decreasing returns to labor in production. The entrant draw distribution G_0 of the idiosyncratic productivity is taken to be a truncated log-normal distribution with mean μ_{z_0} and variance σ^2_{z0} on support $[z_{\min}, z_{\max}]$.[22]

The aggregate and incumbent idiosyncratic productivities $\{y_t, z_t\}$ both follow AR(1) processes

$$\ln y_{t+1} = \rho_y \ln y_t + \varepsilon^y_{t+1} \tag{23}$$

$$\ln z_{t+1} = \rho_z \ln z_t + \varepsilon^z_{t+1} \tag{24}$$

where $\varepsilon^y_{t+1} \overset{iid}{\sim} N\left(0, \sigma^2_y\right)$ and $\varepsilon^z_{t+1} \overset{iid}{\sim} N\left(0, \sigma^2_z\right)$.

I use standard calibration values of parameters as far as possible. Each period in the model corresponds to one month. The discount factor β is taken to be 0.996, which is equivalent to an annual discount rate of 4%. The flow utility of unemployment is taken to be $b = 0.71$, which follows the derivation of Hall and Milgrom (2008) and is based on a replacement ratio of 0.25. The output elasticity of labor is set to be $\alpha_f = 0.72$, which is broadly in line with the literature[23]. In Appendix F.2, I discuss the sensitivity of the quantitative results to α_f. The matching elasticity α_m is chosen to be 0.5, which is consistent with the range of estimates in Petrongolo and Pissarides (2001). On the dynamic processes of labor productivity, the persistence parameters are taken to be $\rho_y = 0.983$ and $\rho_z = 0.95$, in line with Fujita and Nakajima (2016), Hagedorn and Manovskii (2008), and the convention of the business cycle literature. Finally, the cost of opening a job vacancy is assumed to be $c = 0.133$, which is consistent with the estimates in Elsby and Michaels (2013) and Hall and

[22] Quantitative results assuming a Pareto distribution for the idiosyncratic productivity are largely unchanged.

[23] For example, Gomme and Rupert (2007) estimate a labor share of 0.72. Cooper, Haltiwanger and Willis (2004) find a similar estimate (0.64) using plant-level employment data.

Milgrom (2008).

The rest of the parameters are then jointly calibrated to target the labor market moments in the US economy using the CPS dataset I construct in the empirical analysis as well as from other sources. The worker bargaining power η is chosen to target the entrepreneurship rate. The exogenous firm destruction rate $\bar{s}$ targets the one-year survival rate from the Business Dynamics Statistics (BDS) data, while the dispersion of entrant productivity σ_{z_0} targets the three-year survival rate. The mean of entrant productivity μ_{z_0} is chosen to match the firm-size gradient (defined as the ratio between the firm size of one-year-old firms to that of the newborn firms) using the BDS data. The standard deviations of aggregate and idiosyncratic shocks, σ_y and σ_z, target the cyclical volatilities of output and unemployment, respectively. The matching efficiency parameter A is chosen to target the average unemployment rate, and the labor-force size L is chosen to target average firm size. The entrepreneurial opportunity rates λ^w and λ^u target the average monthly entry rates from employment and unemployment, respectively. Finally, the normalizing TFP term ξ pins down the scale of average productivity in the model.

A summary of the calibration values is reported in Table 3, while the targeted moments are presented in Table 4. Overall, the model provides a reasonably good fit to the targeted moments. For additional validation, Figure B.1 illustrates the distribution of employment growth, and Table C.1 reports the business cycle statistics. The model generates a distribution of employment growth and business statistics that are consistent with the data.[24]

Further evidence is provided in Figure B.2 and B.3 in the Appendix, which show, respectively, the exit rate by age and the average establishment size by age. While the model understates exit rates and overstates average firm size, it successfully captures the key selection effect: entrants tend to be smaller and exhibit higher exit rates than incumbents. Taken together, these results suggest that the model captures firm dynamics well along this dimension.

[24] This model departs from the free-entry condition of standard DMP environment. This makes labor demand on the extensive margin less elastic and allows recessionary separation shocks to translate into larger movements in vacancies and unemployment. This is consistent with Coles and Moghaddasi Kelishomi (2018), who show that relaxing free entry makes vacancy creation less than infinitely elastic and allows job-destruction shocks to drive unemployment volatility.

Table 3: Calibration Parameters

Parameter	Meaning	Value	Target/source
b	Flow utility of unemployment	0.71	Hall and Milgrom (2008)
β	Discount factor	0.996	4% annual discount rate
α_f	Labor elasticity in production	0.72	Gomme and Rupert (2007)
α_m	Matching elasticity	0.5	Petrongolo and Pissarides (2001)
ρ_y	Persistence of aggregate productivity	0.983	Fujita and Nakajima (2016)
ρ_z	Persistence of idiosyncratic productivity	0.95	Fujita and Nakajima (2016)
c	Cost of opening a job vacancy	0.133	Elsby and Michaels (2013)
η	Worker's bargaining power	0.845	% entrepreneurs
$\bar{s}$	Exogenous firm destruction rate	0.016	One-year survival rate
σ_y	Standard deviation of aggregate shock	0.0105	Cyclical volatility of productivity
σ_z	Standard deviation of idiosyncratic shock	0.0140	Cyclical volatility of unemployment rate
σ_{z_0}	Standard deviation of entrants' productivity	0.50	Three-year survival rate
μ_{z_0}	mean of entrants' productivity	-0.05	Firm size gradient
A	Matching efficiency	0.60	Unemployment rate
L	Size of labor force	14.0	Average firm size
λ^w	Entrepreneurial opportunity rate	0.0002	Monthly entry rate from employment
λ^u	Entrepreneurial opportunity rate	0.0067	Monthly entry rate from unemployment
ξ	Aggregate TFP	2.47	Average labor productivity = 1

Table 4: Target Moments

Moment	Data	Model
Entry rate from unemployment	0.00651	0.00622
Entry rate from employment	0.00127	0.00129
Average productivity	1.00	1.08
Firm size	15.0	15.0
Unemployment rate	0.0568	0.0596
Entrepreneurship rate	0.0478	0.0426
Unemployment volatility	0.110	0.0942
Output volatility	0.0130	0.0158
One-year survival rate	0.786	0.822
Three-year survival rate	0.599	0.534
Firm size gradient	1.28	1.13

5.2 Entrepreneurial Entry Rates and Unemployment

What is the relationship between entrepreneurial entry and unemployment predicted by the model? We first look at the entry rate from unemployment. Intuitively, when the unemployment rate is high, it becomes harder for the unemployed to find a job. Also, since the productivity is now lower, it is at the same time less attractive to open a new business. Hence, the dynamics of the cutoff productivity depends on the relative decline of the value of opening a business with respect to being unemployed. Panel (a) of Figure 5 shows how the cutoff productivity from unemployment is changing with the aggregate unemployment.[25] We can see that the cutoff productivity is monotonically increasing with the unemployment rate. This shows that in bad times, while both the values of being unemployed and opening a new business decline, the latter is decreasing faster so that the productivity threshold is increasing. It is because the decreasing productivity in bad times has a first-order and direct impact on the profitability of a new business, whereas it has only a general equilibrium effect on the job finding probability. This captures the idea of pure opportunistic entrepreneurial entry.

Given the dynamics of the cutoff productivity, we can then derive the entry rate from unemployment, which is the solid line in panel (b) of Figure 5. Note that since the cutoff productivity is *increasing* with the unemployment rate, the entry rate is *decreasing* with it. Again it is because the entry from unemployment only has the opportunistic component which is reduced in bad times. Shown in the same graph are the entry rate in the data (dotted line) and its 95% confidence interval (shaded area). We can see that the entry rate predicted in the model is in line with the data.

We now turn to the entrepreneurship entry decision for the employed workers. The cutoff productivity is omitted here since it depends on the current firm's productivity and size. Figure 6 shows the entry rate from employment (solid line labeled "Model(total)"). We can now see that unlike that from unemployment, the entry rate from employment is actually higher in bad times. Recall that there are now two components in the entrepreneurial entry: the separation-induced entry and the opportunistic entry. At times when the unemployment rate is higher, the separation-induced entry becomes larger since the workers are now facing

[25] To obtain this, I simulate the economy for a large number of periods according to the aggregate TFP process. The figure shows the relationship over time.

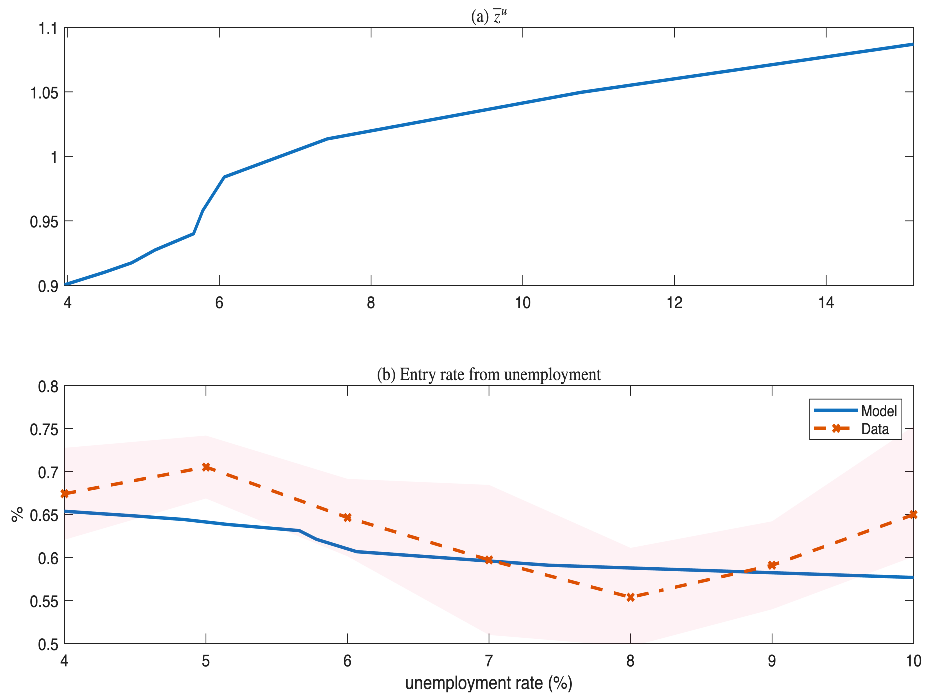

Figure 5: Entry Rate from Unemployment

Notes: This figure shows the cutoff productivity (a) and the entry rate from unemployment (b) against the unemployment rate in the model. The data series in panel (b) is derived from the same CPS data in Section 3, which shows the average entry rate for each unemployment rate. The 95% confidence interval is given in the shaded area.

higher layoff separation risk. Increasing layoff separations push workers to become an entrepreneur. On the other hand, as in the case for the unemployed, the opportunistic entry is smaller now since the productivity, and hence the profitability, of the new firm becomes lower. Combining the two components, the entry rate from employment is increasing with aggregate unemployment. Therefore, we can say that the separation-induced effect dominates the opportunistic effect in bad times. The entry rate predicted in the model is also consistent with the increasing trend in the data and is mostly within the 95% confidence interval.

To see the dynamics of the two types of entrepreneurial entry quantitatively, I decompose the entrepreneurial entry from employment into two components, which are shown in the same figure. The curve labeled "Model(separation)" shows the dynamics of entry rate when the cutoff productivities are kept the same. Hence, only the layoff separation rate is changing with aggregate unemployment. We can see that the entry rate now increases from about 0.124% to 0.150% as the unemployment rate increases from 4% to 10%. Similarly, the curve labeled "Model(opportunistic)" shows the dynamics of opportunistic entry with aggregate unemployment. Specifically, now I allow the cutoff productivities to vary while keeping the separation rate unchanged. As a result, we see that the entry rate decreases to 0.116% as the unemployment rate rises to 10%. This shows the relative importance of the two types of entrepreneurial entry as the unemployment rate rises.

5.3 The Great Recession

What is the aggregate consequence of the separation-induced entry from employment? How important quantitatively is it during recessions? To quantify the effect on aggregate unemployment, I use the baseline calibration of the model to match the unemployment rate during the Great Recession. Specifically, I match the unemployment rate in the model with that in the data by choosing the time series of the aggregate productivity shock in the process 23. The matching of the unemployment rate from 2007 to 2011 is given in Figure 7, where the Great Recession defined by the NBER is the grey area. It can be shown that the resulting labor productivity process matches well with that in the data.

To simulate the model without the separation-induced entry, I set $\lambda^w = 0$ when the economy enters the Great Recession and solve for the unemployment dynamics using the

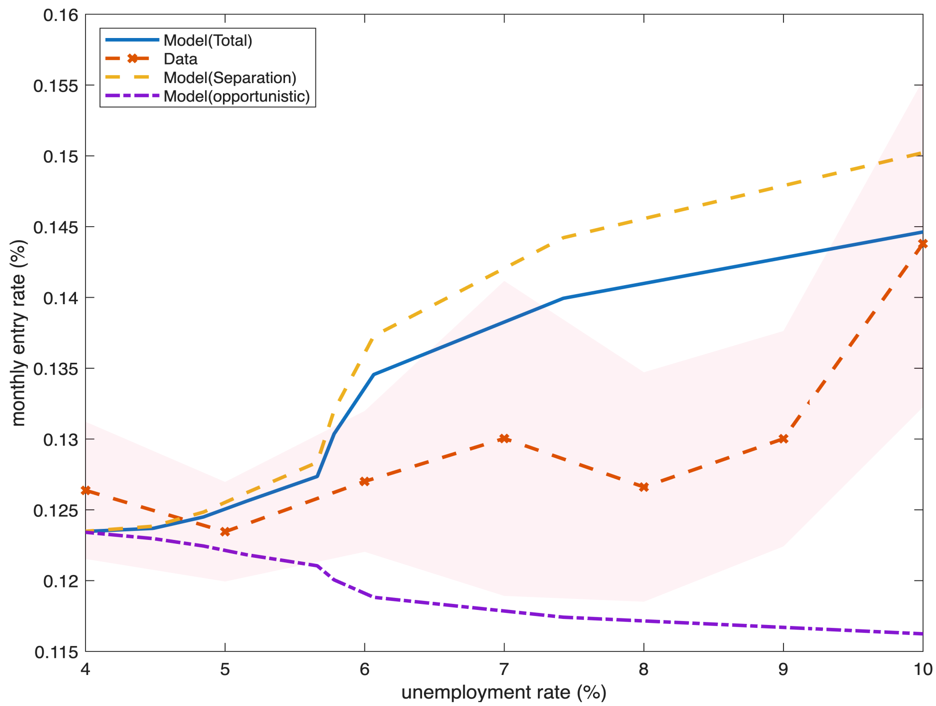

Figure 6: Entry Rate from Employment

Notes: This figure shows the entry rate from employment against the unemployment rate in the model. "Model(separation)" shows the entry rate when the cutoff productivities are fixed. "Model(opportunistic)" shows the entry rate when the separation rate is fixed. The data series is derived from the same CPS data in Section 3, which shows the average entry rate for each unemployment rate. The 95% confidence interval is given in the shaded area.

same aggregate productivity process. The resulting time series of the unemployment rate when there is no separation-induced entry is shown in the same figure where it is labeled by "Model(no sep. entry)". Note that as the economy goes into the Great Recession, the gap between the two unemployment rates, which shows the extra unemployment due to the lack of separation-induced entry, is persistently around one to two percentage points during the recession. This shows that the quantitative importance of the separation-induced entry is especially pronounced in bad times when the unemployment rate is high. We conclude that the unemployment rate during the Great Recession would have been one to two percentage points (or $10-20\%$) higher when there is no separation-induced entry.

Intuitively, when the employed workers are not able to open a new business upon being laid off during bad times, they have no choice but to become unemployed during the recession. This raises the unemployment rate in two ways. First, the addition of these newly separated workers contributes to the unemployment pool directly and increases the inflow of unemployment. Second, the inability of these workers to open a business reduces the hirings in the economy, which in turn lowers the outflow of unemployment. The combination of the two effects explains the quantitatively large magnitude of the extra unemployment when we shut down the separation-induced channel of the entrepreneurial entry.

The purpose of this counterfactual is to isolate the quantitative contribution of entry into entrepreneurship from employment, a margin that is central to the paper's empirical findings and often omitted in canonical search models. The comparison in the next subsection will make this interpretation more explicit: when the entrepreneurial reallocation margin is absent, the model behaves much more like the canonical benchmark and produces a substantially stronger unemployment response to the same aggregate shock path. This is important because it shows that separation-induced entrepreneurship can in fact serve to significantly mitigate business cycle fluctuations, unlike the typical amplification mechanism in Bernanke and Gertler (1989). It justifies the use of policy tools to promote entrepreneurship during recessions to alleviate the adverse impact on the labor market.

5.4 The Role of Entrepreneurship

To highlight the role of entrepreneurship in driving the quantitative results, I compare the baseline economy to the canonical model à la Elsby and Michaels (2013). The canonical

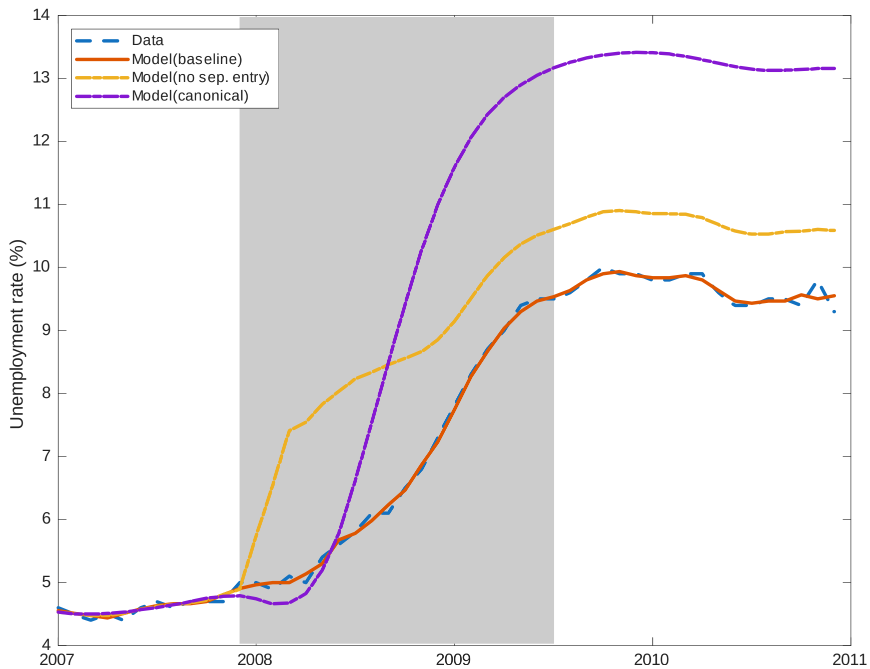

Figure 7: Unemployment Rate During the Great Recession

Notes: This figure shows the unemployment rate in the model and in the data. The aggregate productivity in the model is chosen to match the unemployment rate in the data. "Model(no sep. entry)" shows the unemployment rate in the model if $\lambda^w = 0$. "Model(canonical)" shows the unemployment rate in the canonical model. In all specifications, I maintain the same aggregate shock path. The Great Recession defined by NBER is in the shaded area.

model features a search model with decreasing returns to labor, multi-worker firms, search frictions, vacancy posting, wage bargaining, and endogenous job destruction, but abstracts from entrepreneurial entry and exit. The comparison therefore isolates what worker-state-contingent business formation adds to an otherwise standard incumbent-firm search economy. I calibrate the canonical model by targeting a similar set of moments.[26] The question is whether adding Lucas-style entrepreneurial choice changes the model's predictions once workers can respond to bad times not only by searching for jobs, but also by creating firms.

Figure 7 also shows the unemployment rate for the canonical model when I input the same aggregate shock path identified previously. When the model is disciplined to the Great Recession aggregate shock path, the canonical model generates a much larger rise in unemployment than the baseline. The reason is that, in the absence of entrepreneurial entry and exit, workers displaced in the downturn can adjust only through unemployment and subsequent incumbent-firm hiring. In the baseline model, part of those recessionary separations is converted into entrepreneurial entry, so a portion of what would otherwise become unemployment instead becomes business formation and, with a lag, additional hiring. Entrepreneurship therefore changes recession dynamics not by altering the incumbent-firm problem, but by opening an additional reallocation margin on the worker side. In other words, the canonical model likely *over-estimates* the responsiveness of unemployment relative to aggregate shocks.

Figure 8 shows this point more clearly. Panel (a) plots the unemployment rate against aggregate TFP in the baseline model and in the canonical model. We can see that the canonical benchmark features a much steeper schedule than the baseline. A common fall in TFP translates into a substantially larger increase in unemployment when entrepreneurial choice is absent. In the baseline model, the unemployment response is flatter because a rise in layoff risk no longer maps one-for-one into unemployment: some workers who lose or fear losing jobs choose to start firms instead. Entrepreneurial choice thus acts as a recession-mitigating margin that dampens the transmission of adverse aggregate shocks into unemployment. This mechanism is consistent with the paper's empirical finding that entry from employment rises in bad times, whereas entry from unemployment falls.

[26] Since there is no entry and exit in the model, I abstract from targeting the entry rates, entrepreneurship share, firm dynamics variables.

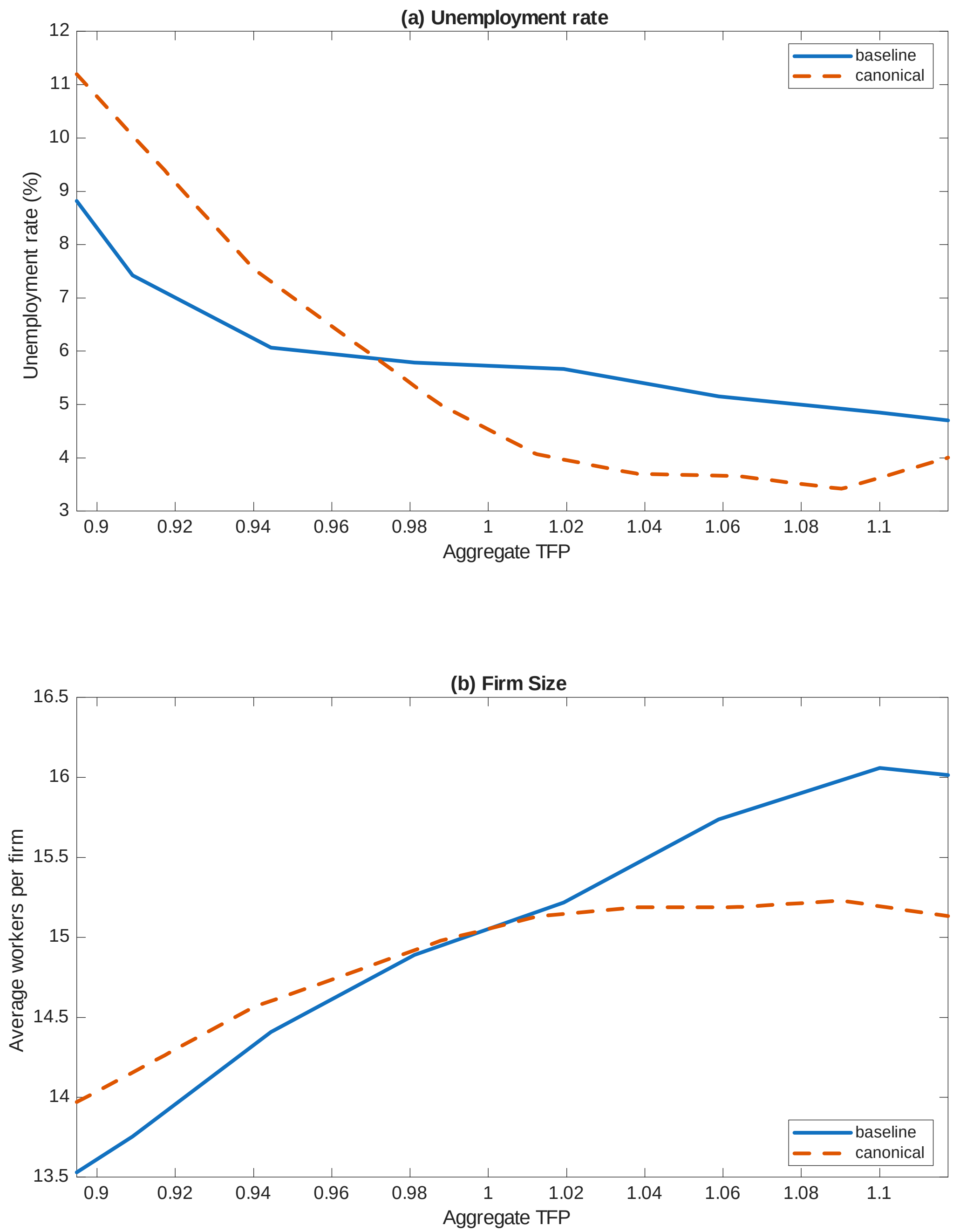

Figure 8: Comparison with the Canonical Model

Panel (b) of Figure 8 concerns firm dynamics. Elsby and Michaels (2013) emphasize that incumbent-firm heterogeneity generates meaningful cyclical reallocation across firm sizes. The baseline model preserves that force, but adds an entry margin that changes the composition of employment across firms over the cycle. Average firm size is lower in the baseline than in the canonical benchmark when aggregate TFP is low, reflecting the creation of additional small firms in downturns. As aggregate conditions improve, the gap narrows and eventually reverses as incumbent expansion dominates. Entrepreneurship therefore affects not only unemployment and vacancies, but also the cross-sectional organization of production. This shows that worker-to-entrepreneur transitions alter the way labor is reallocated across firms over the business cycle which is absent in the canonical framework.

6 Policy Analysis

The model developed in this paper provides us with a laboratory to evaluate the impact of public policies on entrepreneurial entry and the aggregate economy. In this section, I consider the impact of unemployment benefits and a self-employment subsidy on entrepreneurship and the aggregate output.

6.1 The Impact of Unemployment Benefits

In this subsection, I investigate the effects of increasing unemployment benefits financed by a lump-sum tax. Here I consider uniformly increasing a constant unemployment benefit b over the business cycle. In Appendix F.3, I discuss the case when b is countercyclical.

Figure 9 shows the impact of different b on entrepreneurship and the aggregate economy.[27] First, as the flow utility of unemployment increases from 0.71 to 0.8, the entry rate from unemployment slightly decreases. The intuition is simple: as the flow utility increases, the outside option value of opening a new business rises. As a result, there is less incentive for unemployed workers to become a nascent entrepreneur. Also, the entry rate from employment first decreases and then increases as the unemployment benefits become higher. It is because there are two effects on the entry rate. On the one hand, as the value of being

[27] For each value of b, the lump-sum tax equals the difference in the total cost of unemployment benefits compared to the baseline value.

unemployed is larger, the value of being employed is also larger due to the strong bargaining position of the wages. This lowers the incentive for the employed workers to opportunistically open a business. On the other hand, as the value of the outside option becomes larger, the layoff separation rate is also higher since there is less match surplus to share. As a result, there is more separation-induced entry from employment, which raises the overall entry rate. Combining the two effects, we get the U-shaped entry rate from employment. Moreover, we can see from (c) that the share of entrepreneurs in the economy increases from 4.26% to 4.85%. This is due to the increasing number of unemployed workers who have a higher entry rate into entrepreneurship.

Finally, panel (d) shows that GDP is U-shaped in the level of unemployment benefits in the baseline model. This is different from the canonical model with no entry or exit, which is labeled "canonical" in the same panel. This reflects two opposing channels. The first is the standard one from search models: a higher unemployment benefit raises the worker's outside option, compresses match surplus, pushes up wages, discourages vacancy posting, and therefore lowers employment and output. This explains the initial decline in GDP as b rises. The second channel is specific to the baseline model with entrepreneurial entry. By reducing match surplus, a higher b also raises the endogenous layoff separation rate, so more workers are separated from their job. Once separated, some workers may opt to enter entrepreneurship. Hence, higher unemployment benefits increase separation-induced entry, even though they reduce opportunistic entry. These additional entrepreneurs create firms that post vacancies and hire labor. This startup-creation margin partially offsets the standard decline in labor demand coming from weaker search incentives and higher wages. At low values of b, the standard search effect dominates, so GDP falls. At higher values of b, the firm-creation effect becomes quantitatively more important, which generates the U-shape in panel (d). Put differently, relative to a canonical model without entrepreneurial entry, unemployment insurance does not affect the economy only through job-search incentives; it also affects firm creation, and that additional margin mitigates the contractionary effect of higher benefits on output.[28] This shows that the inclusion of entrepreneurial entry is important in analyzing the impact of unemployment benefits on the aggregate economy.

[28] Acemoglu and Shimer (1999) show that UI may increase productivity by providing insurance to risk-averse agents in search of higher-wage jobs. In contrast, our model provides another UI channel to boost aggregate output, arising from entrepreneurship with *risk-neutral* workers.

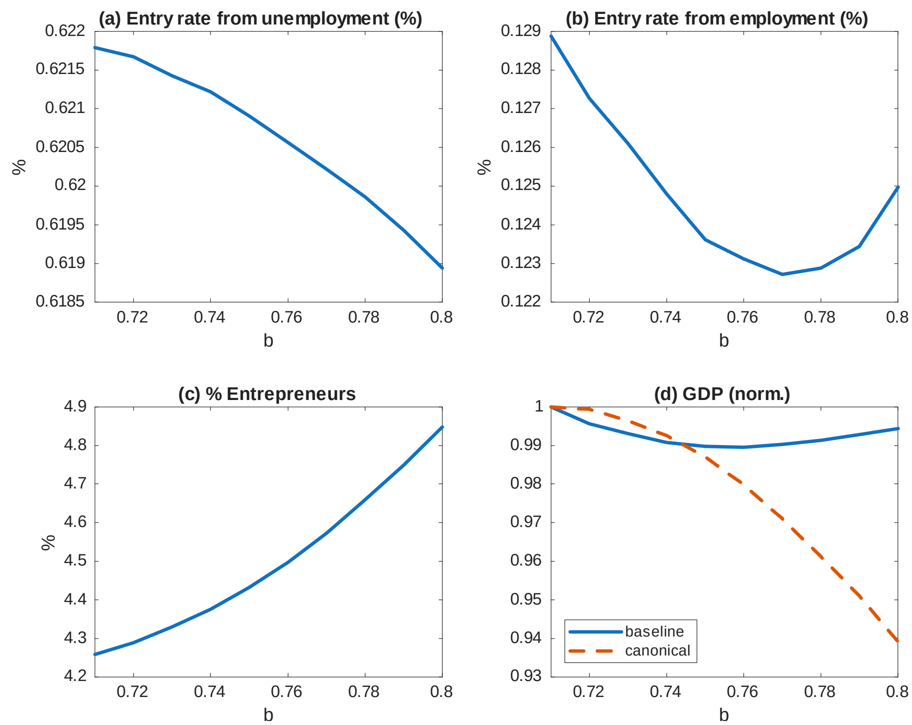

Figure 9: Effects of Unemployment Benefits

The fact that unemployment benefits may boost entrepreneurship is consistent with Hombert et al. (2020), who find that an expansion of the UI system in France leads to increased new business creation and hiring.

These results also clarify what is new relative to a canonical model such as Elsby and Michaels (2013). In that model, higher unemployment benefits affect output only through search incentives, wages, vacancy posting, and unemployment. In the present model, they also affect startup creation by changing the separation margin and by shifting more workers into unemployment, a state from which entrepreneurial entry is more likely. The comparison with the benchmark therefore isolates the entrepreneurial channel: without it, higher benefits lower output more sharply; with it, part of that decline is offset by additional separation-induced firm creation. Our model demonstrates that increased unemployment benefits, while potentially leading to a higher layoff separation rate, also encourage more separation-induced entrepreneurial entry, which positively impacts employment. We posit that UI design, traditionally concerned with the balance between consumption smoothing and maintaining job search incentives, must also consider entrepreneurship for a holistic understanding of the policy's effectiveness.

6.2 Self-employment Subsidy

Another interesting policy option regarding entrepreneurship would be the self-employment subsidy and tax credit aimed at promoting entrepreneurship, especially for the unemployed. Here I consider a simple version of the subsidy where each worker, regardless of the previous employment status, receives a one-off subsidy payment κ (in terms of one unit of labor productivity) upon opening a new business. The subsidy is financed by a lump-sum tax. Note that κ affects the cutoff productivities directly as follows.

$$\Pi_t \left(\bar{z}_t^u \left(\kappa\right), 0\right) + \kappa = U_t \tag{25}$$

$$\Pi_t \left(\bar{z}_t^w \left(z_t, n_t; \kappa\right), 0\right) + \kappa = W_t \left(z_t, n_t; \kappa\right) \tag{26}$$

It is obvious that an increase in κ would lead to a decrease in the cutoff productivities. Hence, the direct impact on the entry rate from unemployment would be positive. Moreover, there is also a general equilibrium effect on wages and hence on the firm's layoff decisions since now the option of becoming an entrepreneur is more attractive. Therefore, the impact on the entry rate from employment would depend on the effect on the separation probability as well.

Figure 10 shows the impact on entrepreneurship and the aggregate output for different values of κ from 0 to one unit of labor productivity. In the calibrated model, the average wage rate is about 85% of the labor productivity. So one unit of labor productivity can be understood as about 1.2 months of the wage bill of a worker. As expected, the entry rate from unemployment increases from 0.62% to about 1.06% purely due to the direct incentive to open a business. However, the entry rate from employment exhibits a U-shape. This reflects both the drop in the separation rate as well as the increased incentive to become an entrepreneur. As the subsidy approaches 1 unit of the labor productivity, the increased incentive due to the subsidy dominates. As a result, the overall entry from employment is higher. The effect on the number of entrepreneurs in the economy is twofold. On the one hand, the increase in the entry rate from unemployment boosts the number of nascent entrepreneurs. On the other hand, the lower unemployment rate has a negative impact on the share of entrepreneurs. Panel (c) shows that the overall effect is positive with a moderate

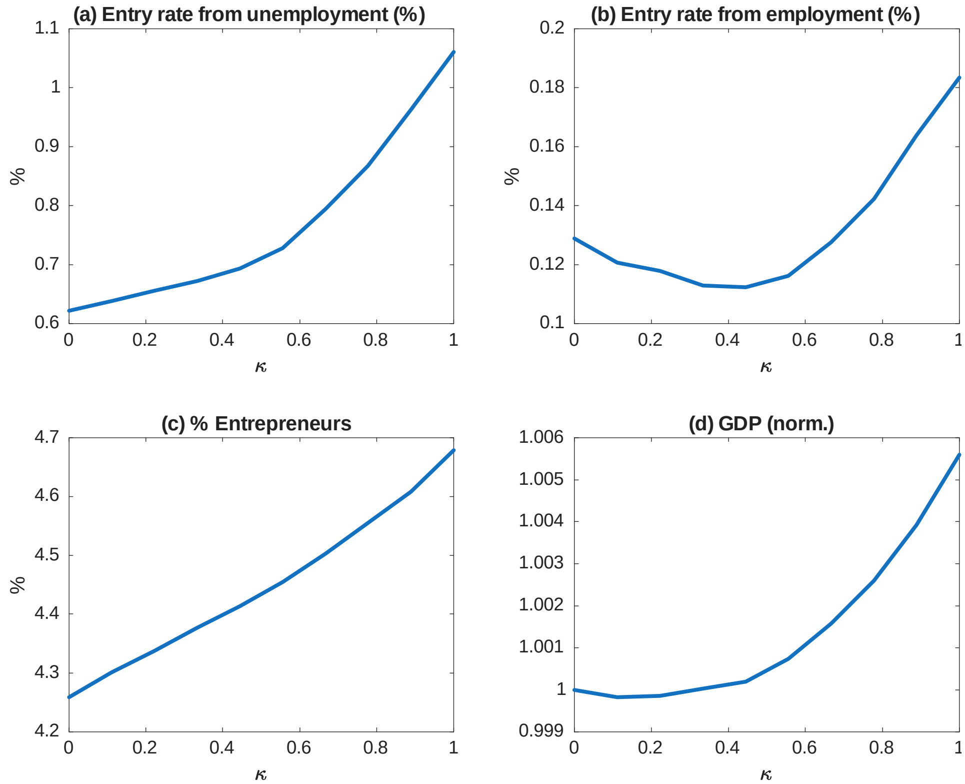

Figure 10: Effects of Self-employment Subsidy

increase in the percentage of entrepreneurs from 4.26% to about 4.68%. Finally, panel (d) shows that there is a positive impact on the aggregate output. In fact, the GDP in the model economy increases by about 0.55% when κ is close to 1. This shows that the self-employment subsidy has a quantitatively important impact on the aggregate economy.

One may then ask: what is the multiplier of the self-employment subsidy with respect to the increase in the aggregate output? To answer this, we can add up all of the subsidies from the nascent entry into entrepreneurship and divide the sum by the change in the aggregate output:

$$multiplier = \frac{\Delta GDP}{\kappa \cdot L \cdot (entry_t^u \cdot u_t + entry_t^w \cdot e_t)}$$

where u_t and e_t are the fractions of unemployed and employed workers respectively. From the model, the average multiplier associated with the policy over the business cycle is about 1.4 when $\kappa = 1$. This shows that there is a multiplier effect from the self-employment subsidy, which is unseen in a standard search model.

6.3 Labor Income Tax

Appendix F.4 studies a progressive labor income tax wedge, holding the progressivity parameter fixed and varying the tax-level parameter π^{tax}. Here lower values of π^{tax} correspond to higher effective labor taxation. Figure F.8 shows that the effects of labor-income tax are non-monotonic. For a small tax increase, entry from unemployment remains nearly flat while entry from employment rises, so the entrepreneur share increases and output can potentially rise above baseline. For sufficiently strong taxes, however, the usual distortionary effect eventually dominates: entrepreneurial entry weakens, the entrepreneur share falls, and GDP moves below baseline. Thus, the model delivers a novel local result—mild labor-income taxation can initially stimulate entrepreneurship through the employment margin, which potentially raises employment and output through subsequent hiring.

7 Conclusion

The contributions of this paper are threefold. First, I empirically demonstrate that in times of adverse labor market conditions, employed workers are more likely to transition into entrepreneurship, whereas the opposite trend is observed for unemployed individuals. Second, an equilibrium search model of entrepreneurship and unemployment with endogenous job destruction is developed to explain these empirical observations. This model reveals that an increased unemployment risk during recessions leads to a higher rate of entry into entrepreneurship from employment, attributed to a combination of opportunistic and separation effects. The significance of separation-induced entry, often overlooked in the literature, is quantitatively substantial. It is shown that without this form of entry, the unemployment rate during the Great Recession would have been one to two percentage points higher. Lastly, through policy experiments within the model, there are novel outcomes not predicted by standard models. For instance, the model posits that UI design, traditionally concerned with the balance between consumption smoothing and maintaining job search incentives, must also consider entrepreneurship as a potential benefit when evaluating the policy's effectiveness. Moreover, a subsidy for self-employment may increase aggregate output as well.

Several promising extensions for this model are identified. Firstly, the model does not account for on-the-job search, which could present an interesting alternative to entrepreneurship. Also, the paper focuses on unemployment risk and job separation as one specific channel linking recessions to startup creation. Other recessionary forces may also matter. Lower commercial rents or other input prices can reduce startup costs; tighter credit conditions, higher default risk, and weaker collateral values can impede entry or constrain initial scale; and aggregate demand or reallocation shocks can alter the profitability of new firms independently of labor-market risk. The model abstracts from these channels in order to isolate the unemployment risk mechanism. Future research can include such factors in the model for a complete decomposition of all cyclical determinants of entrepreneurship. Finally, an important omitted margin is startup finance. The model abstracts from household wealth and startup borrowing constraints. Incorporating that margin would allow the framework to study how financing conditions interact with unemployment risk and separation risk over the business cycle, especially for the scale and composition of entrepreneurial entry.

In conclusion, further empirical validation is necessary to confirm the presence of separation-induced entry. A detailed identification of this entry mechanism using employer-employee matched data represents a valuable avenue for future research, which is part of my ongoing research agenda. The framework developed in this paper offers a useful tool for examining entry decisions into entrepreneurship and conducting further policy analysis.

References

Acemoglu, Daron, and Robert Shimer. 1999. "Efficient Unemployment Insurance." *Journal of Political Economy*, 107(5): 893–928.

Acemoglu, Daron, and William B. Hawkins. 2014. "Search with multi-worker firms." *Theoretical Economics*, 9: 583–628.

Acs, Zoltan J, and Laszlo Szerb. 2007. "Entrepreneurship, Economic Growth and Public Policy." *Small Business Economics*, 28: 109–122.

Adelino, Manuel, Song Ma, and David T. Robinson. 2017. "Firm Age, Investment Opportunities, and Job Creation." *The Journal of Finance*, 72: 999–1038.

Albrecht, James, Lucas Navarro, and Susan Vroman. 2009. "The Effects of Labour Market Policies in an Economy with an Informal Sector." *The Economic Journal*, 119: 1105–1129.

Barnichon, Regis. 2010. "Building a composite Help-Wanted Index." *Economics Letters*, 109: 175–178.

Bernanke, Ben, and Mark Gertler. 1989. "Agency Costs, Net Worth, and Business Fluctuations." *American Economic Review*, 79: 14–31.

Bernstein, Shai, Emanuele Colonnelli, Davide Malacrino, and Timothy McQuade. 2018. "Who Creates New Firms When Local Opportunities Arise?"

Blau, David M. 1987. "A Time-Series Analysis of Self-Employment in the United States." *Journal of Political Economy*, 95: 445–467.

Brügemann, Björn, Pieter Gautier, and Guido Menzio. 2018. "Intra Firm Bargaining and Shapley Values." *The Review of Economic Studies*, 86(2): 564–592.

Caballero, R. J., and M. L. Hammour. 1996. "On the Timing and Efficiency of Creative Destruction." *The Quarterly Journal of Economics*, 111: 805–852.

Coles, Melvyn G., and Ali Moghaddasi Kelishomi. 2018. "Do Job Destruction Shocks Matter in the Theory of Unemployment?" *American Economic Journal: Macroeconomics*, 10(3): 118âĂŞ36.

Congregado, Emilio, Antonio A Golpe, and Simon C Parker. 2012. "The dynamics of entrepreneurship: hysteresis, business cycles and government policy." *Empirical Economics*, 43: 1239–1261.

Cooper, Russel, John Haltiwanger, and Jonathan Willis. 2004. "Dynamics of Labor Demand: Evidence from Plant-level Observations and Aggregate Implications."

Cooper, Russell, John Haltiwanger, and Jonathan L. Willis. 2007. "Search frictions: Matching aggregate and establishment observations." *Journal of Monetary Economics*, 54: 56–78.

da Fonseca, Joao Galindo. 2019. "Unemployment , Entrepreneurship and Firm."

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda. 2014. "The Role of Entrepreneurship in US Job Creation and Economic Dynamism." *Journal of Economic Perspectives*, 28: 3–24.

Elsby, Michael W. L, and Ryan Michaels. 2013. "Marginal Jobs, Heterogeneous Firms, and Unemployment Flows." *American Economic Journal: Macroeconomics*, 5: 1–48.

Elsby, Michael W. L, Bart Hobijn, and Ayşegül Şahin. 2015. "On the importance of the participation margin for labor market fluctuations." *Journal of Monetary Economics*, 72: 64–82.

Evans, David S, and Boyan Jovanovic. 1989. "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints." *Journal of Political Economy*, 97: 808–827.

Evans, David S, and Linda S Leighton. 1990. "Some Empirical Aspects of Entrepreneurship."

Fairlie, Robert W. 2013. "Entrepreneurship, Economic Conditions, and the Great Recession." *Journal of Economics and Management Strategy*, 22: 207–231.

Fairlie, Robert W, and Frank M Fossen. 2018. "Opportunity versus Necessity Entrepreneurship : Two Components of Business Creation." *IZA Discussion Papers.*

Faria, João Ricardo, Juan Carlos Cuestas, and Luis A Gil-Alana. 2009. "Unemployment and entrepreneurship: A cyclical relation?" *Economics Letters*, 105: 318–320.

Fonseca, Raquel, Paloma Lopez-Garcia, and Christopher A. Pissarides. 2001. "Entrepreneurship, start-up costs and employment." *European Economic Review*, 45: 692–705.

Fossen, Frank M. 2021. "Self-employment over the business cycle in the USA: a decomposition." *Small Business Economics*, 57(4): 1837–1855.

Fritsch, Michael, and Alexander S Kritikos. 2016. "Entrepreneurship and the business cycle."

Fujita, Shigeru, and Makoto Nakajima. 2016. "Worker flows and job flows: A quantitative investigation." *Review of Economic Dynamics*, 22: 1–20.

Gaillard, Alexandre, and Sumudu Kankanamge. 2019. "Entrepreneurship , Labor Market Mobility and the Role of Entrepreneurial Insurance."

Galindo, Miguel-Ángel, and María Teresa Méndez. 2014. "Entrepreneurship, economic growth, and innovation: Are feedback effects at work?" *Journal of Business Research*, 67: 825–829.

Garcia-Cabo, Joaquin, and Rocio Madera. 2019. "The Self-Employment Option in Rigid Labor Markets: An Empirical Investigation."

Gomme, Paul, and Peter Rupert. 2007. "Theory, measurement and calibration of macroeconomic models." *Journal of Monetary Economics*, 54: 460–497.

Guner, Nezih, Martin Lopez-Daneri, and Gustavo Ventura. 2016. "Heterogeneity and Government revenues: Higher taxes at the top?" *Journal of Monetary Economics*, 80(C): 69–85.

Hacamo, Isaac, and Kristoph Kleiner. 2022. "Forced Entrepreneurs." *Journal of Finance*, 77: 49–83.

Hagedorn, Marcus, and Iourii Manovskii. 2008. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited." *American Economic Review*, 98: 1692–1706.

Hall, Robert E, and Paul R Milgrom. 2008. "The Limited Influence of Unemployment on the Wage Bargain." *American Economic Review*, 98: 1653–1674.

Haltiwanger, John, Ron S Jarmin, and Javier Miranda. 2013. "Who Creates Jobs? Small versus Large versus Young." *Review of Economics and Statistics*, 95: 347–361.

Hawkins, William B. 2011. "Do Large-Firm Bargaining Models Amplify and Propagate Aggregate Productivity Shocks ?"

Henly, Samuel E., and Juan M. Sánchez. 2009. "The U.S. Establishment-Size Distribution: Secular Changes and Sectoral Decomposition." *Economic Quarterly*, 95: 419–454.

Hombert, Johan, Antoinette Schoar, David Sraer, and David Thesmar. 2020. "Can Unemployment Insurance Spur Entrepreneurial Activity? Evidence from France." *The Journal of Finance*, 75(3): 1247–1285.

Hurst, Erik, and Annamaria Lusardi. 2004. "Liquidity Constraints, Household Wealth, and Entrepreneurship." *Journal of Political Economy*, 112: 319–347.

Karabarbounis, Loukas, and Brent Neiman. 2014. "The Global Decline of the Labor Share." *The Quarterly Journal of Economics*, 129: 61–103.

Koellinger, Philipp D, and A Roy Thurik. 2012. "Entrepreneurship and the Business Cycle." *Review of Economics and Statistics*, 94: 1143–1156.

Koh, Dongya, Raül Santaeulàlia-Llopis, and Yu Zheng. 2020. "Labor Share Decline and Intellectual Property Products Capital." *Econometrica*.

Lazear, Edward P. 2005. "Entrepreneurship." *Journal of Labor Economics*, 23: 649–680.

Lee, Yoonsoo, and Toshihiko Mukoyama. 2015. "Entry and exit of manufacturing plants over the business cycle." *European Economic Review*, 77: 20–27.

Levine, Ross, and Yona Rubinstein. 2017. "Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More?*." *The Quarterly Journal of Economics*, 132: 963–1018.

Light, Audrey, and Robert Munk. 2016. "Business Ownership vs. Self-Employment." *SSRN Electronic Journal.*

Lucas, Robert E. 1978. "On the Size Distribution of Business Firms." *The Bell Journal of Economics*, 9: 508.

Masters, Adrian. 2017. "Job creators, job creation, and the tax code." *Journal of Public Economic Theory*, 19: 674–691.

Moreira, Sara. 2017. "Firm Dynamics, Persistent Effects of Entry Conditions, and Business Cycles."

Mortensen, Dale T., and Christopher A Pissarides. 1994. "Job Creation and Job Destruction in the Theory of Unemployment." *The Review of Economic Studies*, 61: 397–415.

Mueller, Pamela. 2007. "Exploiting Entrepreneurial Opportunities: The Impact of Entrepreneurship on Growth." *Small Business Economics*, 28: 355–362.

Nekarda, Christopher J. 2009. "A Longitudinal Analysis of the Current Population Survey: Assessing the Cyclical Bias of Geographic Mobility."

Nyström, Kristina. 2020. "Entrepreneurship after displacement." *Small Business Economics*, 54: 475–494.

Parker, Simon C. 2012. "Theories of Entrepreneurship, Innovation and the Business Cycle." *Journal of Economic Surveys*, 26: 377–394.

Payne, James E. 2015. "The role of economic policy uncertainty in the US entrepreneurship-unemployment nexus." *Journal of Entrepreneurship and Public Policy*, 4: 352–366.

Petrongolo, Barbara, and Christopher A Pissarides. 2001. "Looking into the Black Box: A Survey of the Matching Function." *Journal of Economic Literature*, 39: 390–431.

Pfeiffer, Friedhelm, and Frank Reize. 2000. "Business start-ups by the unemployed - an econometric analysis based on firm data." *Labour Economics*, 7: 629–663.

Poschke, Markus. 2019. "Wage Employment , Unemployment and Self-Employment across Countries."

Rampini, Adriano A. 2004. "Entrepreneurial activity, risk, and the business cycle." *Journal of Monetary Economics*, 51: 555–573.

Røed, Knut, and Jens Fredrik Skogstrøm. 2014. "Job Loss and Entrepreneurship." *Oxford Bulletin of Economics and Statistics*, 76: 727–744.

Salgado, Sergio. 2020. "Technical Change and Entrepreneurship." *SSRN Electronic Journal*.

Schweitzer, Mark E., and Scott Shane. 2016. "The Ins and Outs of Self-Employment: An Estimate of Business Cycle and Trend Effects."

Sedláček, Petr, and Vincent Sterk. 2017. "The Growth Potential of Startups over the Business Cycle." *American Economic Review*, 107: 3182–3210.

Shapiro, Alan Finkelstein. 2014. "Self-employment and business cycle persistence: Does the composition of employment matter for economic recoveries?" *Journal of Economic Dynamics and Control*, 46: 200–218.

Stole, Lars A, and Jeffrey Zwiebel. 1996. "Intra-Firm Bargaining under Non-Binding Contracts." *The Review of Economic Studies*, 63: 375.

Tauchen, George. 1986. "Finite state markov-chain approximations to univariate and vector autoregressions." *Economics Letters*, 20: 177–181.

van Stel, André, Martin Carree, and Roy Thurik. 2005. "The Effect of Entrepreneurial Activity on National Economic Growth." *Small Business Economics*, 24: 311–321.

von Greiff, Jenny. 2009. "Displacement and self-employment entry." *Labour Economics*, 16: 556–565.

Wennekers, Sander, André van Wennekers, Roy Thurik, and Paul Reynolds. 2005. "Nascent Entrepreneurship and the Level of Economic Development." *Small Business Economics*, 24: 293–309.

Wennekers, Sander, and Roy Thurik. 1999. "Linking entrepreneurship and economic growth." *Small Business Economics*, 13: 27–55.

Wong, Poh Kam, Yuen Ping Ho, and Erkko Autio. 2005. "Entrepreneurship, Innovation and Economic Growth: Evidence from GEM data." *Small Business Economics*, 24: 335–350.

Yuen, C. Y. Kelvin. 2019. "Inefficient Unemployment and Bargaining Friction." *SSRN Electronic Journal*.

Yu, Li, Peter F Orazem, and Robert W Jolly. 2014. "Entrepreneurship over the business cycle." *Economics Letters*, 122: 105–110.

Online Appendix

A Additional Empirical Results

A.1 Summary Statistics

Table A.1: Summary Statistics (Demographic Variables)

		CPS, 1996 - 2018		
	All Workers	Nascent Entrepreneurs		
		All	Employment	Unemployment
Age	40.13	45.17	43.88	43.70
Female	0.51	0.47	0.36	0.30
White	0.80	0.86	0.85	0.84
College	0.28	0.34	0.39	0.29
		NLSY79, 1979 - 2014		
	All Workers	Nascent Entrepreneurs		
		All	Employment	Unemployment
Age	34.99	36.11	34.59	40.61
Female	49.22%	37.36%	35.62%	31.92%
White	79.39%	83.94%	85.68%	75.07%
College	23.25%	23.67%	25.21%	19.63%
Net Worth	$114,974.95	$151,689.73	$151,160.85	$134,699.35
Past Family Income	$55,218.02	$64,944.54	$65,460.88	$56,570.86
Past Wage Income	$26,265.04	$26,238.48	$27,925.38	$25,977.39

Notes: This table shows the summary statistics of the baseline sample of CPS and NLSY79 data in Section 3. Nascent entrepreneurs are those entrepreneurs newly transitioned from employment or from unemployment.

A.2 Average Marginal Effects

Table A.2 shows the average marginal effects associated with the logit regressions shown above. Consider the baseline specification (5). The average marginal effects show that for every ten percentage points increase in unemployment rate, the entry rate from employment would increase by 0.022 percentage point, which corresponds to an 18% increase from the mean level. On the other hand, the entry rate from unemployment would drop by 0.080

Table A.2: Average Marginal Effects (CPS)

Logit model	$entre_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
$unemployed_t$	0.00281***		0.00282***	0.00334***	0.00396***	0.00597***
	(0.000100)		(0.000101)	(6.06e-05)	(9.60e-05)	(0.000139)
$u_{i,t}^{state}$		0.00438***	-0.00175	-0.00103		
		(0.00142)	(0.00147)	(0.000866)		
$employed \times u_{i,t}^{state}$					0.00221**	0.00625***
					(0.00105)	(0.00175)
$unemployed \times u_{i,t}^{state}$					-0.00797***	-0.00915***
					(0.00143)	(0.00220)
$nilf$						0.00462***
						(0.000163)
$nilf \times u_{i,t}^{state}$						-0.0110***
						(0.00158)
Observations	10,870,644	10,870,644	10,870,644	10,870,644	10,870,644	14,298,585
Controls	NO	NO	NO	YES	YES	YES
*** p<0.01, ** p<0.05, * p<0.1						

Notes: Standard errors clustered at the state level in parentheses. This table shows the average marginal effects on $entre_{t+1}$ corresponding to the models (1) to (6) in Table 1. See Table 1 for the logit regression coefficients. See Section 3 for the data construction and definitions.

percentage point, which corresponds to a 12% decrease from the mean level. This shows that the business cycle effects on the entry rates are different and quantitatively significant.

A.3 Robustness

Table A.3 shows various robustness checks. For example, the results are similar when I use OLS and probit models. Also, when I define entrepreneurs as self-employed workers, I get similar but stronger results. The coefficients are also similar when I restrict the definition to only incorporated business or unincorporated business. Finally, if I use only the business ownership as the definition, then I get a negative coefficient associated with the cross term between employed and unemployment rate. However, this definition is much broader and the resulting entry rate may be misleading since many business owners are actually employed in different firm owning some business on the side. Since unemployment insurance generosity may affect both the employment status and the entry rate, I control for the national average UI replacement ratio, and the results remain unchanged. Finally, column (8) adds individual fixed effects using the CPS rotating panel. Relative to the baseline CPS regressions, this specification is much more demanding because it relies only on within-individual variation over a short panel. Since monthly entrepreneurship entry is rare, the usable sample drops sharply to 78,399 observations. The interaction coefficients therefore become much less precise and are no longer statistically significant, although their signs remain the same as in the baseline. Table A.4 shows similar regressions in Table 1 using the aggregate EU transition rate instead of the unemployment rate. The regression results show a strong impact on the employed workers, but less so for the out-of-labor-force individuals.

A.4 NLSY79

One potential problem with the previous regression results is that there may be unobserved heterogeneity across workers with different employment status. One solution would be to use the National Longitudinal Survey of Youth 1979 (NLSY79) data. Since NLSY79 has a panel structure, I would be able to control for the individual fixed effects, which potentially accounts for any unobserved heterogeneity. I use the micro data from the NLSY79. The NLSY79 is a nationally representative longitudinal sample of about 12,686 individuals who

Table A.3: Regression Results (Robustness)

Logit model	$entre_{t+1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	Probit	Self-employed	Incorporated	Unincorporated	Bus. Owner	UI ratio	Ind FE (CPS)
$unemployed_t$	0.00908***	0.845***	2.834***	2.222***	2.928***	-0.244***	2.511***	1.720***
	(0.000455)	(0.0199)	(0.0438)	(0.115)	(0.0460)	(0.0518)	(0.0600)	(0.118)
$employed \times u_{i,t}^{state}$	0.00559***	0.807***	2.866***	4.328***	2.310***	-2.440***	2.642***	2.588
	(0.00175)	(0.232)	(0.606)	(0.775)	(0.691)	(0.248)	(0.758)	(1.825)
$unemployed \times u_{i,t}^{state}$	-0.0300***	-1.468***	-4.734***	-4.998***	-4.607***	-4.508***	-3.962***	-1.391
	(0.00478)	(0.324)	(0.497)	(1.410)	(0.516)	(0.881)	(0.977)	(2.164)
$nilf$	0.00597***	0.643***	3.905***	3.568***	3.933***	-0.633***	1.930***	1.600***
	(0.000482)	(0.0245)	(0.0501)	(0.0638)	(0.0517)	(0.0504)	(0.0698)	(0.0893)
$nilf \times u_{i,t}^{state}$	-0.0277***	-1.709***	-4.029***	-3.282***	-4.075***	-6.002***	-4.600***	-1.918
	(0.00506)	(0.242)	(0.535)	(0.801)	(0.569)	(0.802)	(0.646)	(1.774)
Constant	-0.00348***	-3.780***	-7.288***	-9.924***	-7.330***	-6.201***	-9.953***	
	(0.000284)	(0.0300)	(0.0465)	(0.110)	(0.0473)	(0.0623)	(1.062)	
Observations	14,298,585	14,298,585	10,983,103	10,983,103	10,983,103	14,238,983	13,731,375	78,399
Controls	YES	YES	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors clustered at the state level in parentheses. This table shows the regression results using different specifications. Columns (1) and (2) show the regression coefficients of a linear regression model and a probit model respectively of $entre_{t+1}$. Column (3) shows the logit regression results when entrepreneurs are defined as workers who are self-employed. Columns (4) and (5) show the logit regressions when they have to be self-employed in an incorporated and unincorporated business respectively. Column (6) shows the logit regression results when entrepreneurs are defined as business owners. Columns (7) and (8) show the logit regression results when controlling for average unemployment insurance replacement ratio and individual fixed effects, respectively. See Section 3 for the data construction and definitions.

Table A.4: Logit Regression Results using EU rate (CPS)

Logit model	$entre_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
$unemployed_t$	1.697***		1.693***	2.026***	2.397***	2.447***
	(0.0220)		(0.0222)	(0.0236)	(0.104)	(0.105)
EU_t		22.58***	8.453**	4.540		
		(3.656)	(3.574)	(3.523)		
$employed \times EU_t$					12.01***	12.28***
					(4.162)	(4.199)
$unemployed \times EU_t$					-16.04**	-15.40**
					(6.531)	(6.534)
$nilf$						1.642***
						(0.0983)
$nilf \times EU_t$						1.710
						(5.450)
Constant	-6.626***	-6.687***	-6.734***	-9.132***	-9.227***	-9.300***
	(0.0114)	(0.0477)	(0.0466)	(0.286)	(0.288)	(0.178)
Observations	10,935,478	10,935,478	10,935,478	10,934,055	10,934,055	14,393,290
Controls	NO	NO	NO	YES	YES	YES
*** p<0.01, ** p<0.05, * p<0.1						

Notes: Standard errors clustered at the state level in parentheses. This table shows the logit regression results of $entre_{t+1}$. Column (6) includes the individuals out of labor force, with $nilf$ being the dummy variable for the not-in-labor-force status. The logit regression coefficients show the effects on the log of odds ratio of $entre_{t+1}$. See Section 3 for the data construction and definitions.

Table A.5: Business Outcomes of Nascent Entrepreneurs (Recessions)

CPS, 1996 - 2018			
	Nascent Entrepreneurs		
	All	Employment	Unemployment
1-month entry rate	0.23%	0.13%	0.68%
1-month exit rate	39.37%	32.56%	38.70%
1-year exit rate	58.65%	51.64%	58.84%
Incorporated	25.83%	33.30%	21.57%
Manager	22.16%	25.10%	25.54%
NLSY79, 1979 - 2014			
	Nascent Entrepreneurs		
	All	Employment	Unemployment
1-month exit rate	5.66%	6.29%	1.47%
1-year exit rate	55.87%	54.47%	86.00%
Incorporated	11.15%	12.04%	12.05%
Business capital	$ 2,714,387.63	$ 2,865,392.03	$ 69,315.88
Have employees	24.34%	25.00%	19.39%
Number of employees	2.09	2.78	0.52
Business sales	$ 25,278,752.54	$ 25,251,206.12	$ 1,626,410.93
Feel entrepreneur	42.44%	42.81%	38.57%
Manager	16.43%	17.36%	13.81%

Notes: The table shows the business outcomes of nascent entrepreneurs during NBER recessions. Nascent entrepreneurs are those entrepreneurs newly transitioned from employment or from unemployment. See Section 3 for the data construction and definitions. In the CPS data, variables about firm size are omitted since they are available only after 2014. Due to limited sample size, in the NLSY79, recessions are periods when the aggregate unemployment rate is above the long-run average of 6%.

Table A.6: Logit Regression Results (NLSY79)

Logit model	$entre_{t+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES							
$unemployed_t$	0.598***		0.623***	0.714***	2.900***	2.880***	2.611***
	(0.0630)		(0.0641)	(0.0669)	(0.304)	(0.297)	(0.280)
u_t^{agg}		-4.225***	-5.355***	-3.685***			
		(1.223)	(1.254)	(1.208)			
$employed$					0.0548	0.368	0.219
$\times u_t^{agg}$					(1.211)	(1.179)	(1.412)
$unemployed$					-33.72***	-32.70***	-30.33***
$\times u_t^{agg}$					(4.656)	(4.533)	(4.147)
$nilf$						2.202***	2.070***
						(0.209)	(0.203)
$nilf$						-32.06***	-30.24***
$\times u_t^{agg}$						(3.186)	(2.917)
Constant	-6.387***	-6.063***	-6.046***	-6.163***	-6.388***	-6.668***	
	(0.0252)	(0.0811)	(0.0814)	(0.146)	(0.146)	(0.136)	
Observations	1,733,286	1,733,286	1,733,286	1,733,286	1,733,286	2,185,972	436,165
Controls	NO	NO	NO	YES	YES	YES	YES
Individual FE	NO	NO	NO	NO	NO	NO	YES
Number of pid							2,357
*** p<0.01, ** p<0.05, * p<0.1							

Notes: Robust standard errors in parentheses. This table shows the logit regression results of $entre_{t+1}$ using the National Longitudinal Survey of Youth 1979 data. Column (6) includes the individuals out of labor force, with $nilf$ being the dummy variable for the not-in-labor-force status. The logit regression coefficients show the effects on the log of odds ratio of $entre_{t+1}$. See Section A.4 for the data construction and definitions.

were 14 to 22 years old as of the first survey in 1979. I use the data until 2014. The survey is conducted annually from 1979 to 1994, and biennially from 1996 to 2014. However, *weekly* employment status during the period can be deduced from the survey questions. To be consistent with the CPS data, I further aggregate the weekly employment status into *monthly* employment status[29]. My sample covers individuals aged at least 16, which are weighted by the default sampling weight in the survey. In the NLSY79 data, however, there is no longitudinal question about business ownership. As a result, I solely use self-employment as the criteria.

Table A.6 shows the logit regression results using the NLSY79 data. Column (1) to (6) follows the same specifications of those in Table 1. We can again see that unemployed workers on average have higher entrepreneurship entry rate. Note however the unemployment rate now has an opposite aggregate effect: the aggregate entry rate falls significantly as a result of increasing unemployment rate. From (5) and (6), we get similar results as before: unemployed workers and those out of labor force are less likely to become entrepreneurs in bad times, while the effect for those employed becomes insignificant. Finally, in column (7) I control also the individual fixed effects. The coefficients are almost the same as (6), though the magnitudes of the effects are slightly smaller.

A.5 Local Unemployment

In the previous section, I demonstrate the effects of changes in the state-level unemployment rate on entrepreneurship entry. Some may argue that workers respond more to the local labor market condition. Here instead of the unemployment rate at the state level, I use that at the local level. I employ the concept of commuting zone as the unit of locality. In short, commuting zones are collections of counties which economists identify as separate local labor markets. Here the 2000 definition of commuting zones defined by United States Department of Agriculture Economic Research Service is used[30]. The baseline regression

[29] Specifically, an individual is defined to be *employed* in a month if she has been employed in at least one of the weeks, *unemployed* if she has never been employed but has been unemployed in any of the weeks, and *not in labor force* otherwise.

[30] The crosswalk between counties and commuting zones can be obtained at: https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/

model now becomes

$$
\begin{aligned}
G\left(entre_{i,t+1}\right) &= \beta_0 + \beta_1 unemployed_{i,t} + \beta_2 unemployed_{i,t} \times u_t^{cz} \\
&\quad + \beta_3 employed_{i,t} \times u_t^{cz} + \alpha X_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{A.1}
$$

where u_t^{cz} is the commuting zone level unemployment rate and all other variables are the same as before.

Table A.7 shows the regression results using local unemployment rate. Note that compared to Table 1, we have very similar effects of changing unemployment rate, both qualitatively and quantitatively. Again the unemployed workers have a higher probability of becoming entrepreneurs, and the marginal propensity of entrepreneurship entry increases for the employed, but decreases for the unemployed, in response to higher local unemployment rate.

A.6 State-level Cross-sectional Relationship

While Figure 1 and 2 look at time series correlations of the relationship, there could be unexplained time trend that is driving the relationship. Another way to look at it is to explore the state variations in a particular year. Here I make use of the state information in the CPS data. Figure A.1 shows the relationship between state-level entrepreneurship entry and unemployment rate in 2017. Here each circle represents a state or DC. The size of circle corresponds to the size of the labor force of that state. The fitted line is drawn so that each state is weighted by its labor force. Essentially, Figure A.1 shows that there is no relationship between the entry and unemployment rates at state level. This is consistent with the time series evidence that the two variables are weakly related at the aggregate level.

Similar to the time series case, now I divide the sample by the previous employment status. Figure A.2 shows the relationship for those who are previously unemployed and previously employed respectively. We can see now the correlations are much stronger. The slope of the fitted line is significantly negative for those from unemployment, while it is mildly positive for those from employment. This shows that states with relatively higher unemployment levels tend to have higher entrepreneurial entry rate for the employed workers and lower for the unemployed.

Table A.7: Logit Regression Results (CPS), Local Unemployment Rate

Logit model	$entre_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
$unemployed_t$	1.697***		1.704***	2.039***	2.393***	2.443***
	(0.0194)		(0.0198)	(0.0209)	(0.0565)	(0.0561)
u_t^{cz}		2.567***	-0.867**	-1.163***		
		(0.413)	(0.427)	(0.422)		
$employed \times u_t^{cz}$					0.638	0.925*
					(0.509)	(0.512)
$unemployed \times u_t^{cz}$					-5.246***	-4.935***
					(0.766)	(0.760)
$nilf$						1.872***
						(0.0420)
$nilf \times u_t^{cz}$						-5.613***
						(0.562)
Constant	-6.626***	-6.540***	-6.578***	-9.005***	-9.095***	-9.171***
	(0.0110)	(0.0256)	(0.0259)	(0.264)	(0.265)	(0.170)
Observations	10,935,478	10,935,478	10,935,478	10,934,055	10,934,055	14,393,290
Controls	NO	NO	NO	YES	YES	YES
*** p<0.01, ** p<0.05, * p<0.1						

Notes: Robust standard errors in parentheses. This table shows the logit regression results of $entre_{t+1}$. The variable u_t^{cz} denotes the local unemployment at the commuting zone level. Column (6) includes the individuals out of labor force, with $nilf$ being the dummy variable for the not-in-labor-force status. The logit regression coefficients show the effects on the log of odds ratio of $entre_{t+1}$. See Section 3 for the data construction and definitions.

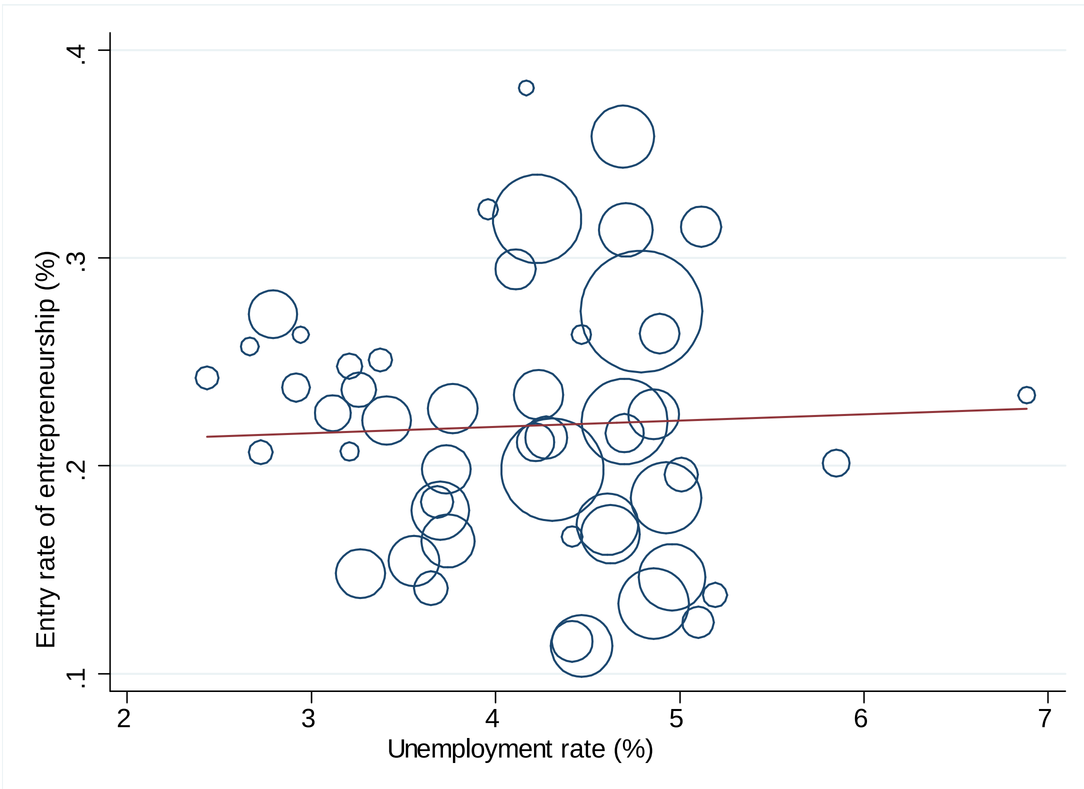

Figure A.1: Entry and Unemployment at the State Level

Notes: This figure shows the relationship between the entry rate into entrepreneurship and the unemployment rate for each state in 2017. The size of the circle represents the size of the labor force in each state. The straight line is the fitted line weighted by the labor force in each state. See Section 3 for the data construction and definitions.

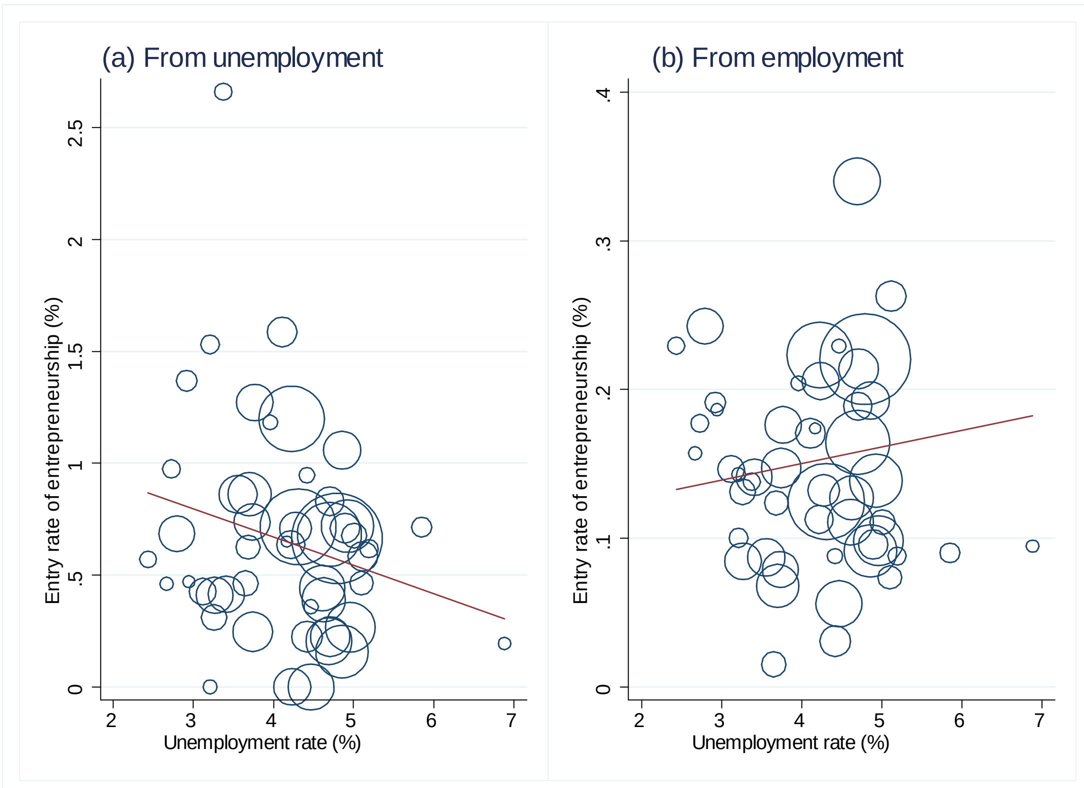

Figure A.2:
Entry and Unemployment at the State Level by Previous Employment Status

Notes: This figure shows the relationship between the entry rate into entrepreneurship from unemployment (a) and from employment (b), and the unemployment rate for each state in 2017. The size of the circle represents the size of the labor force in each state. The straight line in each panel is the fitted line weighted by the labor force in each state. See Section 3 for the data construction and definitions.

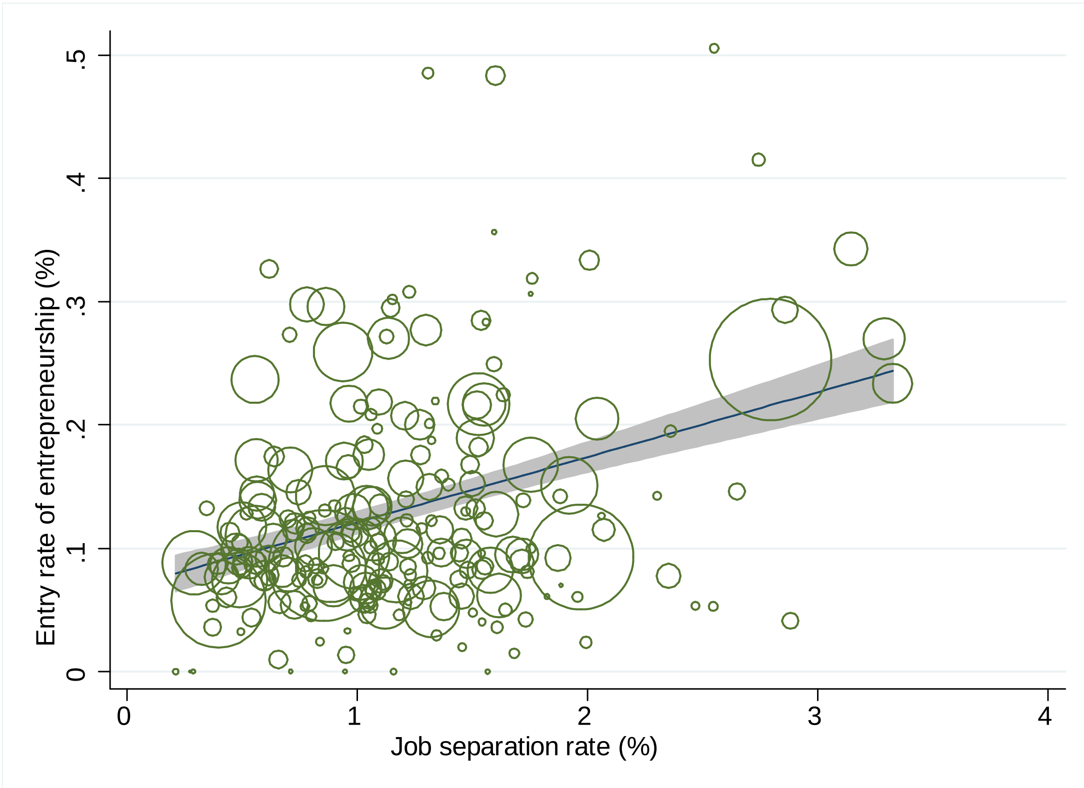

Figure A.3: Entry Rate and Job Separation Rate by Industry

Notes: This figure shows the relationship between the entry rate into entrepreneurship and the job separation rate across different industries using the CPS data. Job separation rate is the probability that an employed worker becomes unemployed in the next month. The size of the circle represents the size of the labor force in each industry. The straight line is the fitted line weighted by the labor force in each industry. See Section 3 for the data construction and definitions.

A.7 Entry and Separation by Industry

Table A.8: Entry Rate Regression by Industry

	$entre_{t+1}$	
	(1)	(2)
VARIABLES	Pooled OLS	Fixed Effects
Separation rate	0.0374***	0.0128**
	(0.00253)	(0.00503)
Constant	0.00107***	0.00140***
	(0.000119)	(0.000103)
Observations	2,952	2,952
Year FE	YES	YES
Industry FE	NO	YES
*** p<0.01, ** p<0.05, * p<0.1		

Notes: Robust standard errors in parentheses. This table shows the linear regression results of $entre_{t+1}$ across industries. Separation rate is the probability that an employed worker becomes unemployed in the next month in each industry. See Section 3 for the data construction and definitions.

B Model Validation

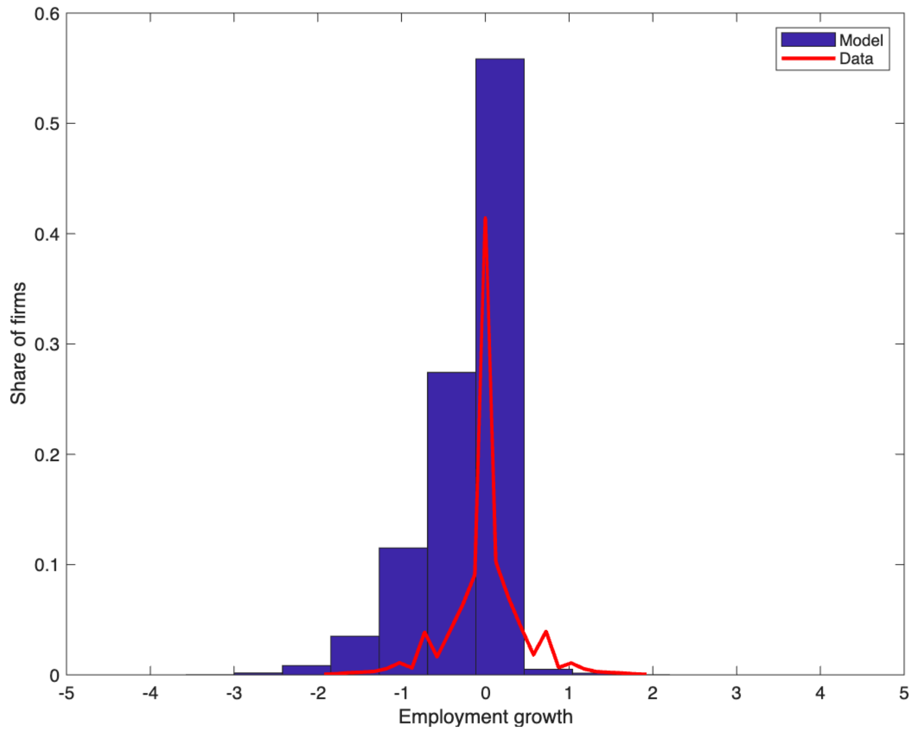

Figure B.1: Employment Growth Distribution

Notes: This figure shows the distribution of employment growth from all firms in the model and in the data. The distribution in the data is derived from the Longitudinal Business Database by Elsby and Michaels (2013).

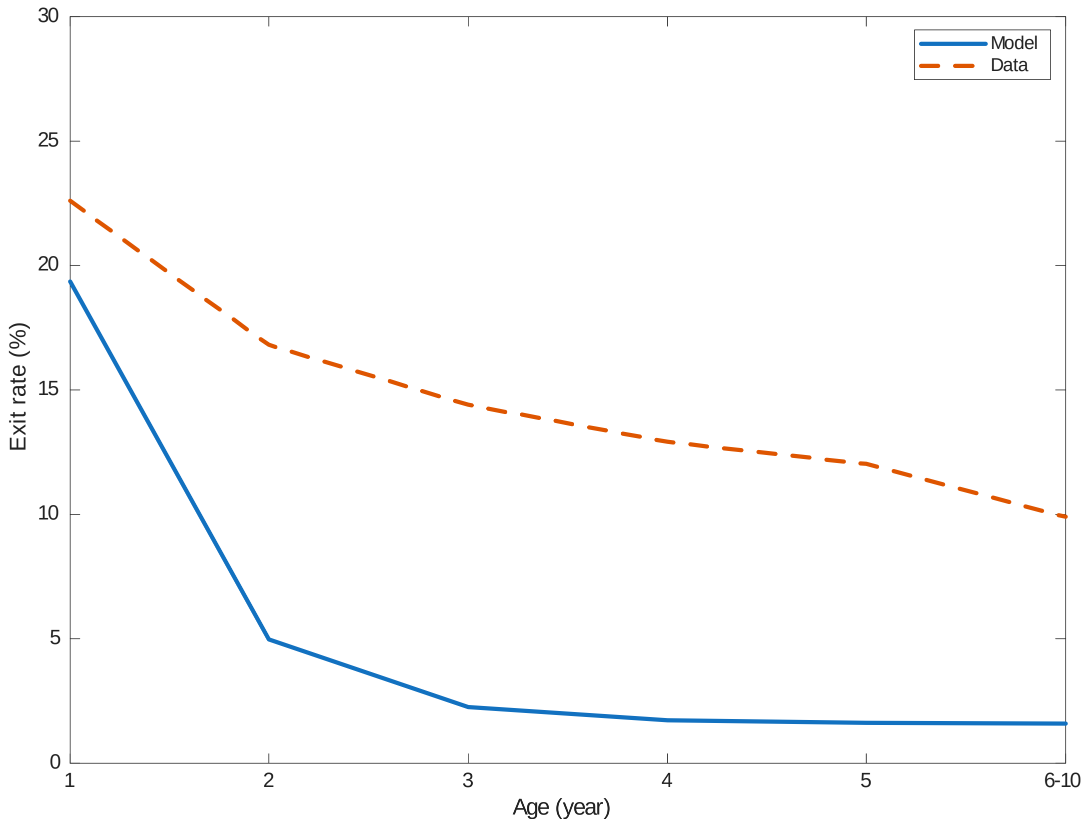

Figure B.2: Conditional Exit Rate By Age

Notes: This figure shows the conditional firm exit rate in the model and in the data. The data is derived from the Business Dynamics Statistics (BDS) dataset over the year 1996-2018.

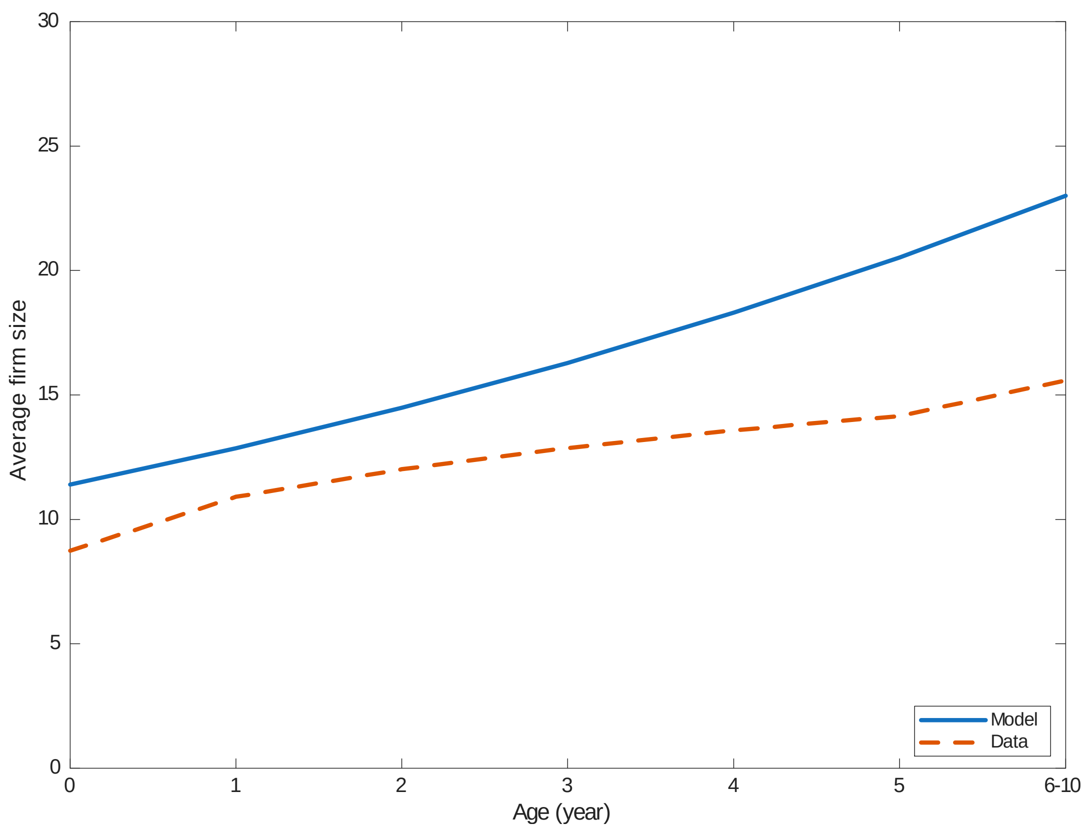

Figure B.3: Establishment Size By Age

Notes: This figure shows the establishment size by age in the model and in the data. The data is derived from the Business Dynamics Statistics (BDS) dataset over the year 1996-2018.

C Business Cycle Statistics

Table C.1: Business Cycle Statistics, 1996 - 2018

	p_t	u_t	jfr_t	jsr_t	v_t	θ_t
σ_x^c	0.012	0.113	0.089	0.065	0.118	0.227
$\epsilon_{x,p}$	1.000	-8.670	6.319	-4.304	9.028	17.699
			Correlation matrix			
	p_t	u_t	jfr_t	jsr_t	v_t	θ_t
p_t	1	-0.920	0.851	-0.797	0.916	0.933
u_t		1	-0.932	0.757	-0.934	-0.983
jfr_t			1	-0.670	0.889	0.925
jsr_t				1	-0.809	-0.796
v_t					1	0.984
θ_t						1

Notes: This table shows the business cycle statistics in the US from 1996 to 2018. p_t denotes the average labor productivity which is calculated as real GDP divided by the number of employed workers. jfr_t and jsr_t refer to job finding rate and job separation (EU) rate respectively from the CPS data. v_t is the number of job postings index by Barnichon (2010). σ_x^c is the standard deviation of the cyclical component of the variable x after a Hodrick-Prescott filter. $\epsilon_{x,p}$ is the elasticity of the variable x with respect to average labor productivity.

Table C.2: Business Cycle Statistics, Model

	p_t	u_t	jfr_t	jsr_t	v_t	θ_t
σ_x^c	0.016	0.098	0.035	0.186	0.068	0.078
$\epsilon_{x,p}$	1.000	-3.705	2.093	-7.900	0.279	4.237
Correlation matrix						p_t
u_t	FR_t	SR_t	v_t	θ_t	p_t	1
-0.606	0.944	-0.678	0.066	0.861	u_t	
1	-0.770	0.748	0.686	-0.689	jfr_t	
	1	-0.869	-0.207	0.786	jsr_t	
		1	0.519	-0.435	v_t	
			1	0.003	θ_t	
				1		

Notes: This table shows the business cycle statistics in the model. p_t denotes the average labor productivity which is calculated as GDP divided by the number of employed workers. jfr_t and jsr_t refer to job finding rate and job separation (EU) rate respectively. v_t is the number of vacancy postings. See Section 4 for the definitions. σ_x^c is the standard deviation of the cyclical component of the variable x after a Hodrick-Prescott filter. $\epsilon_{x,p}$ is the elasticity of the variable x with respect to average labor productivity.

D Derivations

D.1 Proposition 1: Optimal Employment Policy

$$n_t\left(z_t, n_{t-1}\right) = \begin{cases} \left(R_t^h\right)^{-1}\left(z_t\right) & \text{if } z_t > R_t^h\left(\left(1-\pi_t^w\right) n_{t-1}\right) \\ \left(1-\pi_t^w\right) n_{t-1} & \text{if } z_t \in \left[R_t^f\left(\left(1-\pi_t^w\right) n_{t-1}\right), R_t^h\left(\left(1-\pi_t^w\right) n_{t-1}\right)\right] \\ \left(R_t^f\right)^{-1}\left(z_t\right) & \text{if } z_t < R_t^f\left(\left(1-\pi_t^w\right) n_{t-1}\right) \end{cases} \tag{D.1}$$

where $R_t^h(\cdot)$ and $R_t^f(\cdot)$ are defined by $J_t\left(R_t^h(n), n\right) = \frac{c}{q(\theta_t)}$ and $J_t\left(R_t^f(n), n\right) = 0$.

Due to the concavity of the production function, it is clear that $J_t(z, n)$ is strictly decreasing in n and strictly increasing in z. If $z_t > R_t^h\left(\left(1-\pi_t^w\right) n_{t-1}\right)$, then

$$J_t\left(z_t, \left(1-\pi_t^w\right) n_{t-1}\right) > J_t\left(R_t^h\left(\left(1-\pi_t^w\right) n_{t-1}\right), \left(1-\pi_t^w\right) n_{t-1}\right) = \frac{c}{q\left(\theta_t\right)}$$

Hence, the right derivative of the objective function at $\left(1-\pi_t^w\right) n_{t-1}$ is strictly positive. Therefore, the optimum must satisfies $n_t^h > \left(1-\pi_t^w\right) n_{t-1}$. By concavity, the unique optimal employment n_t^h solves

$$J_t\left(z_t, n_t^h\right) = \frac{c}{q\left(\theta_t\right)}$$

or

$$z_t = R_t^h\left(n_t^h\right)$$

and so

$$n_t^h = \left(R_t^h\right)^{-1}\left(z_t\right)$$

This is the *hire* region.

Second, suppose $z_t < R_t^f\left(\left(1-\pi_t^w\right) n_{t-1}\right)$, then

$$J_t\left(z_t, \left(1-\pi_t^w\right) n_{t-1}\right) < J_t\left(R_t^f\left(\left(1-\pi_t^w\right) n_{t-1}\right), \left(1-\pi_t^w\right) n_{t-1}\right) = 0$$

The objective function is decreasing to the left of $\left(1-\pi_t^w\right) n_{t-1}$. Therefore, the unique optimal employment n_t^f solves

$$J_t\left(z_t, n_t^f\right) = 0$$

Equivalently

$$z_t = R_t^f \left(n_t^f \right)$$

so

$$n_t^f = \left(R_t^f \right)^{-1} (z_t)$$

This is the *fire* region.

Third, if $z_t \in \left[R_t^f \left(\left(1 - \pi_t^w\right) n_{t-1} \right), R_t^h \left(\left(1 - \pi_t^w\right) n_{t-1} \right) \right]$, then

$$0 = J_t \left(R_t^f \left(\left(1 - \pi_t^w\right) n_{t-1} \right), \left(1 - \pi_t^w\right) n_{t-1} \right) \leq J_t \left(z_t, \left(1 - \pi_t^w\right) n_{t-1} \right) \leq J_t \left(R_t^h \left(\left(1 - \pi_t^w\right) n_{t-1} \right), \left(1 - \pi_t^w\right) n_{t-1} \right)$$

and so $J_t \left(z_t, \left(1 - \pi_t^w\right) n_{t-1} \right) \in \left[0, \frac{c}{q(\theta_t)} \right]$. In this case, the objective function is decreasing to the right of $\left(1 - \pi_t^w\right) n_{t-1}$, and increasing to the left $\left(1 - \pi_t^w\right) n_{t-1}$. Therefore, the kink $n_t = \left(1 - \pi_t^w\right) n_{t-1}$ is optimal. This is the *inactive* region.

D.2 Proposition 2: Wage Equation

From the bargaining equation, we have

$$W_t (z_t, n_t) - U_t = \left(\frac{\eta}{1 - \eta} \right) J_t (z_t, n_t) \tag{D.2}$$

Let

$$\Gamma_t (x) = \int_x^{z_{\max}} \left(\Pi_t (\tilde{z}, 0) - U_t \right) dG_0 (\tilde{z})$$

From (3) and (4), we have

$$\hat{U}_{t+1} - U_{t+1} = \lambda^u \Gamma_{t+1} \left(\bar{z}_{t+1}^u \right) \tag{D.3}$$

$$
\begin{aligned}
& \hat{W}_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1} \\
= \; & \lambda^w \int \max \left\{\Pi_{t+1}(\tilde{z}, 0)-U_{t+1}, W_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right\} d G_0(\tilde{z})+\left(1-\lambda^w\right)\left(W_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right) \\
= \; & \lambda^w\left(\Gamma_{t+1}\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right)+\int_{z_{\min}}^{\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)}\left(W_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right) d G_0(\tilde{z})\right) \\
& +\left(1-\lambda^w\right)\left(W_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right) \\
= \; & \lambda^w \Gamma_{t+1}\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right)+\left(1-\pi_{t+1}^w\right)\left(W_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right) \\
= \; & \lambda^w \Gamma_{t+1}\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right)+\left(1-\pi_{t+1}^w\right)\left(\frac{\eta}{1-\eta}\right) J_{t+1}\left(z_{t+1}, n_{t+1}\right)
\end{aligned} \tag{D.4}
$$

where

$$
\pi_{t+1}^w=\lambda^w\left(1-G_0\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right)\right)
$$

From (2) and using (D.3) and (D.4), we have

$$
\begin{aligned}
U_t-\beta \mathbb{E}_t U_{t+1} & = b_t+\beta \mathbb{E}_t\left[\begin{array}{c}
\left(1-\phi\left(\theta_t\right)\right)\left[\lambda^u \int \max \left\{\Pi_{t+1}(\tilde{z}, 0)-U_{t+1}, 0\right\} d G_0(\tilde{z})\right] \\
+\phi\left(\theta_t\right)\left(\hat{W}_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right)
\end{array}\right] \\
& = b_t+\beta \mathbb{E}_t\left[\left(1-\phi\left(\theta_t\right)\right) \lambda^u \Gamma_{t+1}\left(\bar{z}_{t+1}^u\right)+\phi\left(\theta_t\right)\left(\hat{W}_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right)\right] \\
& = b_t+\beta \mathbb{E}_t\left[\begin{array}{c}
\left(1-\phi\left(\theta_t\right)\right) \lambda^u \Gamma_{t+1}\left(\bar{z}_{t+1}^u\right) \\
+\phi\left(\theta_t\right)\left(\lambda^w \Gamma_{t+1}\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right)+\left(1-\pi_{t+1}^w\right)\left(\frac{\eta}{1-\eta}\right) J_{t+1}\left(z_{t+1}, n_{t+1}\right)\right)
\end{array}\right]
\end{aligned}
$$

Note that $J_{t+1}\left(z_{t+1}, n_{t+1}\right)=\frac{c}{q\left(\theta_{t+1}\right)}$ for expanding firms. Hence,

$$
\begin{aligned}
U_t-\beta \mathbb{E}_t U_{t+1} = \; & b_t+\beta \mathbb{E}_t\left[\left(1-\phi\left(\theta_t\right)\right) \lambda^u \Gamma_{t+1}\left(\bar{z}_{t+1}^u\right)+\phi\left(\theta_t\right) \lambda^w \Gamma_{t+1}\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right)\right] \\
& +\beta \phi\left(\theta_t\right)\left(\frac{\eta}{1-\eta}\right) \mathbb{E}_t\left[\left(1-\pi_{t+1}^w\right) \frac{c}{q\left(\theta_{t+1}\right)}\right]
\end{aligned}
$$

Also, from (5), we have

$$
\begin{aligned}
& W_t\left(z_t, n_t\right)-\beta \mathbb{E}_t U_{t+1} \\
= \; & w_t\left(z_t, n_t\right)+\beta \mathbb{E}_t\left[\delta_{t+1}\left(\hat{U}_{t+1}-U_{t+1}\right)+\left(1-\delta_{t+1}\right)\left(\hat{W}_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right)\right] \\
= \; & w_t\left(z_t, n_t\right)+\left[\begin{array}{c}
\beta \mathbb{E}_t \delta_{t+1} \lambda^u \Gamma_{t+1}\left(\bar{z}_{t+1}^u\right) \\
+\beta \mathbb{E}_t\left(1-\delta_{t+1}\right) \lambda^w \Gamma_{t+1}\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right) \\
+\beta \mathbb{E}_t\left(1-\delta_{t+1}\right)\left(1-\pi_{t+1}^w\right)\left(W_{t+1}\left(z_{t+1}, n_{t+1}\right)-U_{t+1}\right)
\end{array}\right]
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
W_t(z_t, n_t) - U_t \;\; = \;\; & w_t(z_t, n_t) - b_t - \Lambda_t(z_t, n_t) - \beta\phi(\theta_t)\left(\frac{\eta}{1-\eta}\right)\mathbb{E}_t\left[\left(1-\pi^w_{t+1}\right)\frac{c}{q(\theta_{t+1})}\right] \\
& + \left[\beta\mathbb{E}_t\left(1-\delta_{t+1}\right)\left(1-\pi^w_{t+1}\right)\left(W_{t+1}(z_{t+1}, n_{t+1}) - U_{t+1}\right)\right]
\end{aligned} \tag{D.5}
$$

where

$$
\Lambda_t(z_t, n_t) = \beta\mathbb{E}_t\left(1-\delta_{t+1}-\phi(\theta_t)\right)\left(\lambda^u\Gamma_{t+1}\left(\bar{z}^u_{t+1}\right) - \lambda^w\Gamma_{t+1}\left(\bar{z}^w_{t+1}(z_{t+1}, n_{t+1})\right)\right)
$$

By the envelope theorem,

$$
\frac{\partial\Pi_t(z_t, n_{t-1})}{\partial n_{t-1}} = \begin{cases} \left(1-\pi^w_t\right)\frac{c}{q(\theta_t)} & hire \\ \left(1-\pi^w_t\right)J_t\left(z_t, \left(1-\pi^w_t\right)n_{t-1}\right) & stay \\ 0 & fire \end{cases}
$$

Hence, we have from (11)

$$
J_t(z_t, n_t) - \beta\mathbb{E}_t\left(1-\delta_{t+1}\right)\left(1-\pi^w_{t+1}\right)J_{t+1}\left(z_{t+1}, \left(1-\pi^w_{t+1}\right)n_t\right) = \xi y_t z_t f'(n_t) - w_t(z_t, n_t) - \frac{\partial w_t(z_t, n_t)}{\partial n_t}n_t \tag{D.6}
$$

Finally, combining (D.5) and the bargaining equation (D.2), and rearranging, we obtain

$$
\begin{aligned}
& J_t(z_t, n_t) - \left[\beta\mathbb{E}_t\left(1-\delta_{t+1}\right)\left(1-\pi^w_{t+1}\right)J_{t+1}(z_{t+1}, n_{t+1})\right] \\
& \quad = \left(\frac{1-\eta}{\eta}\right)\left[w_t(z_t, n_t) - b_t - \Lambda_t(z_t, n_t)\right] \quad -\beta\phi(\theta_t)\mathbb{E}_t\left[\left(1-\pi^w_{t+1}\right)\frac{c}{q(\theta_{t+1})}\right]
\end{aligned} \tag{D.7}
$$

Equating (D.6) and (D.7), we have

$$
w_t(z_t, n_t) = (1-\eta)\left(b_t + \Lambda_t(z_t, n_t)\right) + \eta\left\{\xi y_t z_t f'(n_t) - \frac{\partial w_t(z_t, n_t)}{\partial n_t}n_t + \beta\phi(\theta_t)\mathbb{E}_t\left[\left(1-\pi^w_{t+1}\right)\frac{c}{q(\theta_{t+1})}\right]\right\}
$$

If $f(n) = n^\alpha$, then we can solve the ordinary differential equation for the wage equation

$$
\begin{aligned}
w_t(z_t, n_t) \;\; = \;\; & \left(\frac{\eta\alpha}{1-\eta(1-\alpha)}\right)\xi y_t z_t n_t^{\alpha-1} + (1-\eta)b + \eta\beta\phi(\theta_t)\mathbb{E}_t\left(\left(1-\pi^w_{t+1}\right)\frac{c}{q(\theta_{t+1})}\right) \\
& + n_t^{-\frac{1}{\eta}}\left(\frac{1-\eta}{\eta}\right)\int_0^{n_t}\tilde{n}^{\frac{1}{\eta}-1}\Lambda_t(z_t, \tilde{n})\,d\tilde{n}
\end{aligned}
$$

D.3 Proposition 4: Opportunistic and Separation Effects

The entry rate from unemployment with explicit dependence on y is given by

$$entry^u(y) = \lambda^u \left[1 - G_0(\bar{z}^u(y))\right].$$

Let $y_L < y_H$, where y_L denotes a bad aggregate state and y_H a good aggregate state. By Assumption 3,

$$\bar{z}^u(y_L) > \bar{z}^u(y_H)$$

Since G_0 is increasing, its survival function $1 - G_0(\cdot)$ is decreasing. Therefore,

$$1 - G_0(\bar{z}^u(y_L)) < 1 - G_0(\bar{z}^u(y_H))$$

and hence

$$entry^u(y_L) < entry^u(y_H)$$

Thus a decline in aggregate productivity decreases the entry rate from unemployment, proving part (i).

Now consider the entry rate from employment:

$$entry^w(z, n; y) = \delta(z, n; y)\lambda^u \left(1 - G_0(\bar{z}^u(y))\right) + \left(1 - \delta(z, n; y)\right) \lambda^w \left(1 - G_0(\bar{z}^w(z, n; y))\right)$$

where $\delta(z, n; y)$ denotes the total separation rate. Holding δ fixed, we have

$$\begin{aligned} \bar{z}^u(y_L) &> \bar{z}^u(y_H) \\ \bar{z}^w(z, n; y_L) &> \bar{z}^w(z, n; y_H) \end{aligned}$$

by Assumption 3,

$$1 - G_0(\bar{z}^w(z, n; y_L)) < 1 - G_0(\bar{z}^w(z, n; y_H))$$

Therefore,

$$
\begin{aligned}
& entry^{w}(z,n;y_L) - entry^{w}(z,n;y_H) \\
= \; & \delta\lambda^{u}\left\{[1-G_0(\bar{z}^{u}(y_L))] - [1-G_0(\bar{z}^{u}(y_H))]\right\} + (1-\delta)\lambda^{w}\left\{[1-G_0(\bar{z}^{w}(z,n;y_L))] - [1-G_0(\bar{z}^{w}(z,n;y_H))\right. \\
< \; & 0.
\end{aligned}
$$

So, holding the separation rate fixed, a decline in aggregate productivity decreases the entry rate from employment. This proves part (ii).

Finally, hold the cutoff productivities fixed (with respect to y) and consider a fall in aggregate productivity that raises the separation rate from δ_H to δ_L, with $\delta_L > \delta_H$. For continuing match, we have

$$W(z,n;y) \geq U(y)$$

and hence we have $\bar{z}^{w}(z,n) \geq \bar{z}^{u}$. Thus, if $\lambda^{u} \geq \lambda^{w}$, then

$$\lambda^{u}\left(1-G_0(\bar{z}^{u})\right) \geq \lambda^{w}\left(1-G_0(\bar{z}^{w}(z,n))\right)$$

Then

$$entry^{w}(z,n;\delta_L) - entry^{w}(z,n;\delta_H) = (\delta_L-\delta_H)\left[\lambda^{u}\left(1-G_0(\bar{z}^{u})\right) - \lambda^{w}\left(1-G_0(\bar{z}^{w}(z,n))\right)\right] \geq 0$$

This proves part (iii).

E Computational Appendix

First, the stochastic processes of the aggregate and idiosyncratic productivity are discretized as follows. The AR(1) stochastic processes (23) and (24) are approximated by a finite state Markov chain with respectively Y and Z states and transition probability matrices $\left[p^y_{i,j}\right]$ and $\left[p^z_{i,j}\right]$ by using the Tauchen (1986) procedure. Also, the initial distribution of z is taken to be the truncated log-normal distribution with Z points of support $\{z_1, ..., z_Z\}$, with $G_0(z_Z) = 1$. In the computation exercise, I set $Y = 10$ and $Z = 100$.

The model is then solved recursively as follows. Given an initial guess of the market tightness θ_t, and the value functions $\Pi_t(z_t, n_{t-1})$, $W_t(z_t, n_t)$, U_t, I employ the following nested iteration algorithm:

1. Compute the meeting rates $\phi(\theta_t)$ and $q(\theta)$ using (13) and (14).

2. Compute the endogenous separation function $\sigma_t(z_t, n_t) = \mathbf{1}\{W_t(z_t, n_t) \leq U_t\}$ and the cutoff entrepreneurial abilities $\bar{z}^u_t$ and $\bar{z}^w_t(z_t, n_t)$ using (19) and (20).

3. Given an initial guess of the employment policy function $n^*_t(z_t, n_{t-1})$,

   (a) Calculate the marginal value function of workers $J_t(z_t, n_t)$ using (11).

   (b) Compute the employment cutoffs $\hat{n}_t(z_t, n_{t-1})$ and $\bar{n}_t(z_t, n_{t-1})$.

   (c) Update the employment policy function.

   (d) Repeat until convergence of $n^*_t(z_t, n_{t-1})$.

4. Given an initial guess of the equilibrium firm distribution $h_t(z_t, n_{t-1})$,

   (a) Compute the measure of employed and unemployed workers.

   (b) Simulate the firm distribution in the next period using the employment policy function $n^*_t(z_t, n_{t-1})$ above, as well as the transition probabilities of y_t and z_t derived from the dynamic processes (23) and (24) . Note that one should take into account the exogenous firm destruction and the entry from employed and unemployed workers.

   (c) Repeat until convergence of $h_t(z_t, n_{t-1})$.

5. Calculate the vacancy posted by each hiring firm using (8).

6. Update the value of being unemployed U_t using (2) and the distribution of hiring firms.

7. Update the value of being employed $W_t(z_t, n_t)$ using (5).

8. Update the value of a productive firm $\Pi_t(z_t, n_{t-1})$ using (7).

9. Update the labor market tightness $\theta_t = \frac{v_t}{u_t}$.

10. Repeat until convergence of $\{\Pi_t, W_t, U_t, \theta_t\}$.

To compute the volatility of aggregate variables, I simulate the economy over time by simulating a time series of the aggregate productivity y_t. Then I compute the time series of each aggregate variable. I choose the sample size to be $6,000$ months, which is equivalent to 2000 quarters. The monthly series is transformed to quarterly frequency by calculating the simple average in a quarter. Finally, the log deviation of the quarterly series computed by using a HP filter with a coefficient of 1600, and the cyclical part is used to measure the volatility.

F Additional Quantitative Results

F.1 Robustness Check: Risk Aversion

The baseline model assumes risk-neutral individuals, so occupational choices are based on linear comparisons of continuation values. To assess whether the main quantitative results hinge on this assumption, I solve the equilibrium under constant relative risk aversion (CRRA) preferences

$$u(c) = \begin{cases} \log c, & \gamma = 1, \\ \dfrac{c^{1-\gamma} - 1}{1-\gamma}, & \gamma \neq 1, \end{cases}$$

for alternative values of γ while keeping the rest of the environment as close as possible to the baseline. In particular, the flow values of the Bellman equations (2), (5), (7) are now given by the utility flow values. For tractability, I keep the linear approximation of the wage function as well as firm's employment policy unchanged.

Figure F.4 reports the entry rate from unemployment and the entry rate from employment against the unemployment rate for alternative values of γ. Panel (a) shows that introducing risk aversion shifts the unemployment-entry schedule downward, but leaves its qualitative shape essentially unchanged. For every value of γ, entry from unemployment remains decreasing in the unemployment rate. Quantitatively, higher γ lowers entry from unemployment by a modest amount at all unemployment rates, and the schedules are close to parallel. The economic intuition is straightforward. Relative to unemployment benefits, entrepreneurship delivers a more risky payoff. Concavity therefore lowers the certainty-equivalent value of entrepreneurial entry for unemployed workers in every aggregate state. This indicates that risk aversion mainly changes the level of entry from unemployment but not its cyclical sensitivity.

Panel (b) shows that the positive relationship between entry from employment and the unemployment rate survives for every value of γ. At the same time, the level response is non-monotonic in γ. For small values of γ, the entry-from-employment schedule lies slightly below the baseline. This reflects the direct effect of risk aversion on *opportunistic* entrepreneurship: holding the employment relationship fixed, a worker is less willing to leave a relatively safe wage for a risky business. For larger values of γ, however, the schedule shifts upward.

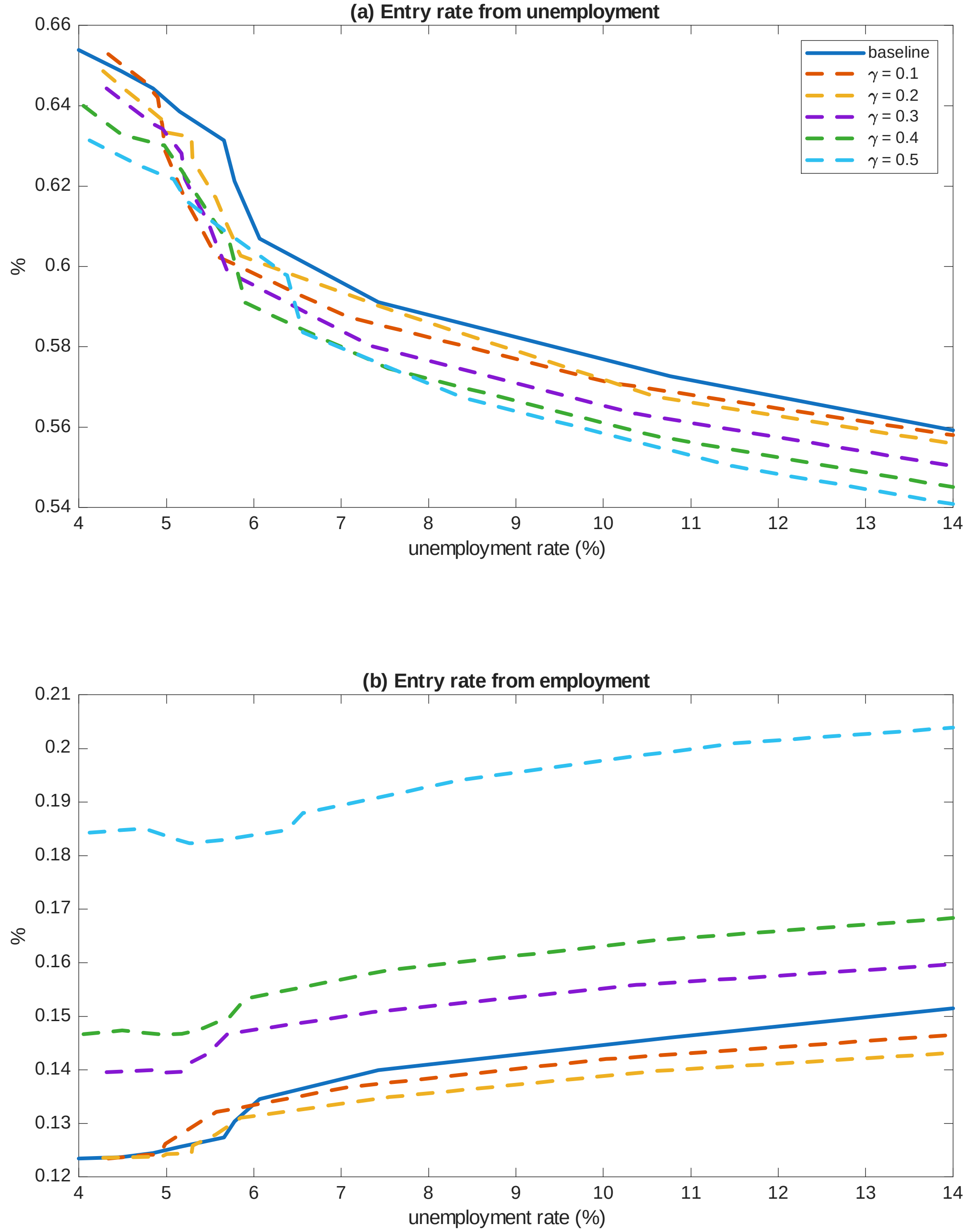

Figure F.4: Robustness Check: Risk Aversion

Intuitively, once curvature is strong enough, it lowers the value of remaining in marginal low-surplus jobs and weakly profitable businesses, so the *separation-induced* component of entrepreneurship becomes more important. Thus, risk aversion reduces voluntary job-to-business switching, but it also increases entrepreneurship that occurs after separation from employment.

Therefore, I conclude that the quantitative results of the cyclicality of the entry rates are robust to the introduction of risk aversion in the model.

F.2 Robustness Check: Output Elasticity of Labor α_f

In the production function,

$$f(n) = n^{\alpha_f},$$

α_f is the output elasticity of labor and therefore governs the degree of decreasing returns, or equivalently the entrepreneur's span of control. To assess the sensitivity of the quantitative results to this parameter, I solve the model for alternative values of $\alpha_f \in \{0.64, 0.68, 0.72, 0.76, 0.80\}$ and report the resulting steady-state statistics in Table F.3. Throughout this exercise, all other parameters are kept at their baseline values. Note that the measure of welfare is the weighted sum of all the value functions as follows.

$$welfare_t = \int W_t(z_t, n_t)\, n_t dH(z_t, n_t) + U_t \cdot u_t + \int \Pi_t(z_t, n_{t-1})\, dH(z_t, n_{t-1})$$

Several patterns emerge. First, the entry rate from unemployment is essentially unchanged across specifications, remaining at about 0.6% per month. This reflects two offsetting forces. A lower α_f implies stronger decreasing returns, which lowers the profitability of creating and expanding a new firm and therefore discourages entrepreneurial entry. At the same time, stronger decreasing returns reduce firms' labor demand and worsen job-finding prospects, lowering the outside option of unemployment and making entrepreneurship relatively more attractive. Second, entry from employment becomes weaker as α_f rises. The intuition is that a higher α_f allows incumbent firms to expand more easily on the intensive margin, which lowers unemployment and reduces the separation risk faced by employed workers. Consistent with this mechanism, the overall share of entrepreneurs declines sharply, from 6.5 percent at $\alpha_f = 0.64$ to 3.4 percent at $\alpha_f = 0.80$. Third, α_f has a large effect on firm size and labor-market outcomes. As α_f increases from 0.64 to 0.80, average firm size rises from 8.2 to 19.3 workers, while the unemployment rate falls from 17.7 percent to 4.4 percent. Vacancies decline somewhat at higher values of α_f, but unemployment declines even more. This is straightforward: when decreasing returns are weaker, the marginal product of labor falls more slowly with firm size, so productive firms hire more aggressively on the intensive margin and the economy relies less on the creation of many small firms to absorb workers. Fourth, the aggregate and distributional implications move in the same direction. GDP rises monotonically with α_f, and welfare increases substantially. At the same time, the Gini coefficient rises, consistent with weaker decreasing returns allowing successful firms to operate at larger scale and increasing dispersion in firm outcomes. In summary, lower values of α_f correspond to stronger decreasing returns and a smaller span of control, leading to smaller firms, more entrepreneurs, and substantially higher unemployment. Higher values of α_f imply fewer but larger firms, lower unemployment, and higher output.

Figure F.5 shows how the cyclical behavior of entrepreneurial entry varies with α_f. Panel (a) shows that the entry rate from unemployment is decreasing in the aggregate unemployment rate for all values of α_f considered. Moreover, the slope becomes steeper as α_f rises. This implies that when decreasing returns are weaker, the opportunistic component of entrepreneurial entry from unemployment becomes more sensitive to aggregate conditions: opening a new business is relatively more attractive in good times, when firms can expand more easily, and falls more sharply in bad times.

Panel (b) shows that the entry rate from employment is mostly increasing in the unemployment rate, consistent with the separation-induced entry channel emphasized in the main text. For higher values of α_f, this positive relationship becomes much flatter and close to acyclical. The intuition is that a higher α_f allows incumbent firms to operate at larger scale and lowers equilibrium unemployment and separation risk, thereby weakening the separation-induced motive for employed workers to switch into entrepreneurship.

Overall, Figure F.5 shows that the paper's main cyclical distinction between entry from unemployment and entry from employment is robust to alternative values of α_f.

Table F.3: Sensitivity to α_f (Summary Statistics)

			α_f		
Variable	0.640	0.680	0.72 (baseline)	0.760	0.800
$entry\_u$	0.006	0.006	0.006	0.006	0.006
$entry\_w$	0.001	0.001	0.001	0.000	0.000
$\%\ entre$	0.065	0.053	0.043	0.034	0.034
$firm\ size$	8.214	11.068	14.981	19.342	19.346
u	0.177	0.120	0.060	0.045	0.044
v	0.023	0.023	0.021	0.015	0.015
$theta$	0.144	0.206	0.369	0.344	0.352
$gini$	0.010	0.012	0.016	0.026	0.027
GDP	11.255	12.280	13.639	14.799	16.912
$welfare$	240.200	240.193	239.900	253.633	254.138

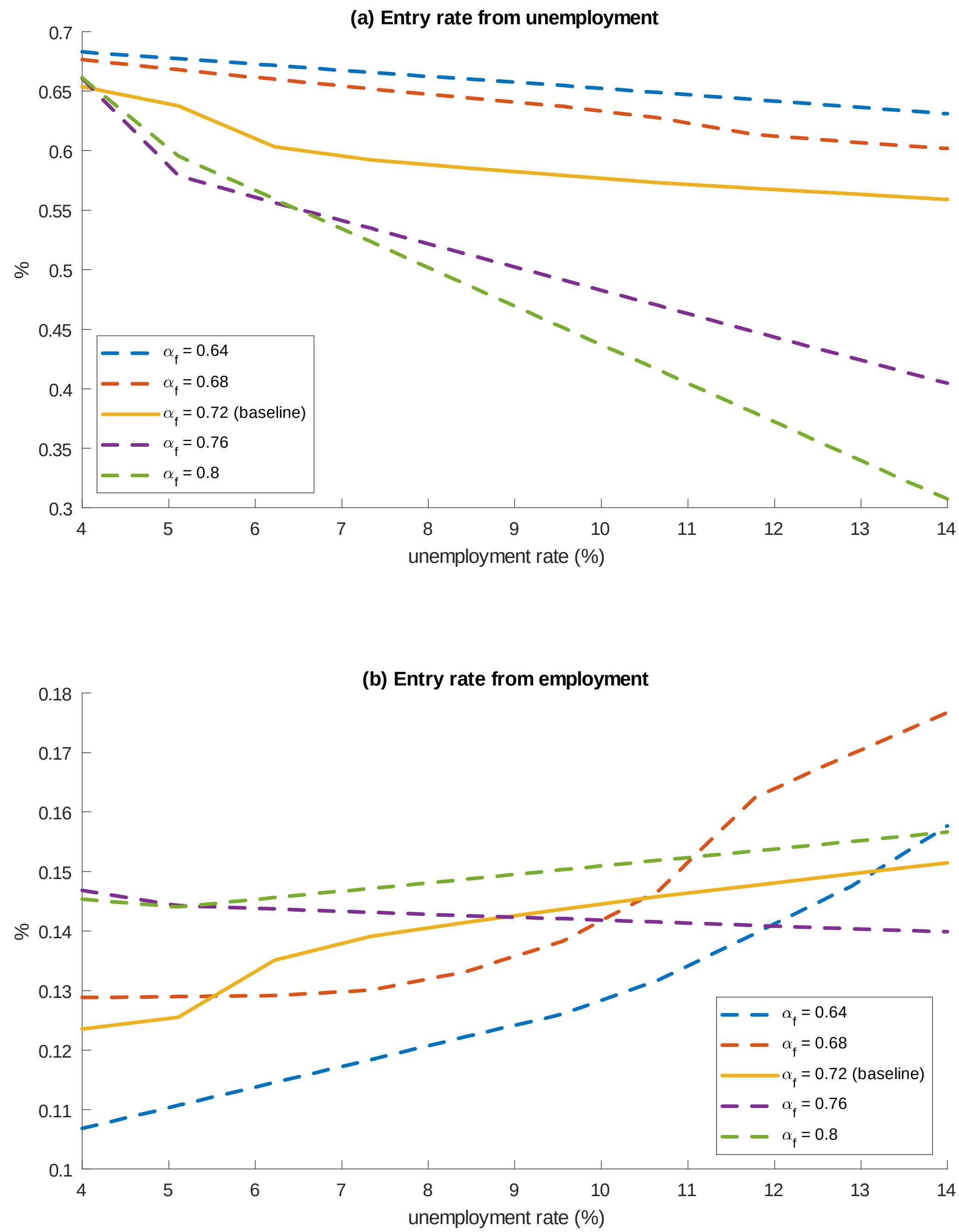

Figure F.5: Sensitivity to α_f (Cyclicality of Entrepreneurial Entry)

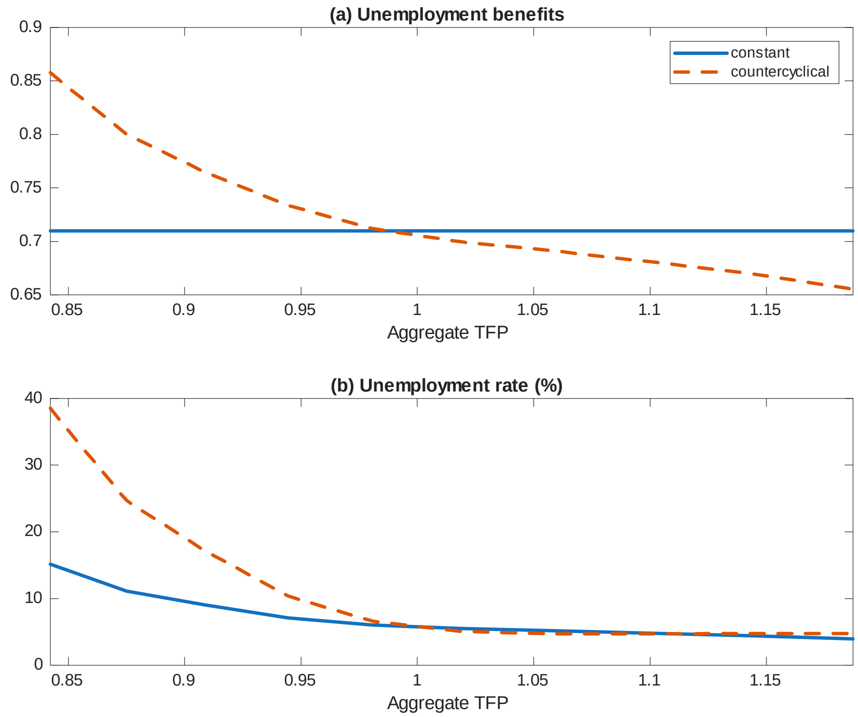

Figure F.6: Countercyclical Unemployment Benefits and Unemployment Rate

F.3 Countercyclical Unemployment Benefits

Instead of having a constant rate, unemployment benefits are often extended and boosted during recessions and reduced in good times. Here, I analyze the impact of countercyclical unemployment benefits as a policy option. Panel (a) of Figure F.6 shows the flow utility of unemployment against the aggregate productivity in the baseline (constant) case versus the countercyclical case. In this quantitative exercise, the flow utility of unemployment goes as high as 0.85 in bad times and as low as 0.65 during expansions. The resulting aggregate unemployment is shown in panel (b). We can see that with the countercyclical benefits, unemployment becomes much more volatile. In fact, the unemployment rate now rises sharply in bad times, while the reduction in unemployment is more muted.

How would the countercyclical benefits affect entrepreneurship over the business cycle? Figure F.7 shows the impact on entry rate, the share of entrepreneurs, and the average firm size versus a constant rate of benefits. We can see from panel (a) that the entry rate into entrepreneurship increases in bad times and decreases in good times. This is because in bad times there is a surge in the number of unemployed workers who are far more likely to open a new business. Hence, the compositional changes between employment statuses lead

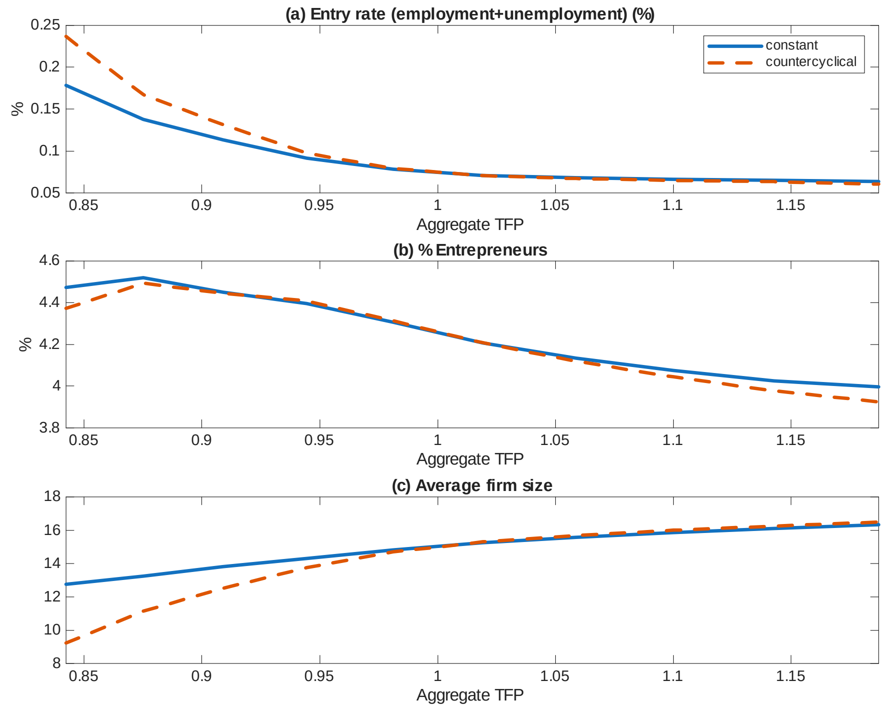

Figure F.7: Effects of Countercyclical Unemployment Benefits on Entrepreneurship

the overall entry rate to rise in bad times even when not every within-status entry margin moves one-for-one. As a result, the entry rate becomes more volatile over the business cycle. Panel (b) shows that the entrepreneur share is redistributed toward downturn states: it is modestly higher around the recession region, while becoming lower in better aggregate states. Finally, the average firm size increases over the business cycle. Hence, the model predicts a procyclical average firm size: firms are smaller in recessions and larger in expansions.[31]

F.4 Policy: Labor Income Tax

In this section, I consider a labor income tax experiment. Following Guner, Lopez-Daneri and Ventura (2016), I model after-tax labor income using a progressive power schedule:

$$w^{net} = \min\left\{w, \pi^{tax} w^{\tau}\right\}$$

[31] On the other hand, Moreira (2017) and Lee and Mukoyama (2015) show the selection effects in firm dynamics over the business cycle, which predict larger firms in recessions. Our analysis shows that the productivity effect dominates the selection effect.

where τ is the progressivity parameter and π^{tax} controls the level of taxation. This tax enters the worker's value through after-tax wage income, while the firm side continues to pay the gross wage bill. I take $\tau = 0.947$ from the estimates of Guner, Lopez-Daneri and Ventura (2016), and vary the value of π^{tax}. For each level of π^{tax}, I compute the equilibrium under the baseline calibration.[32] Notice that larger values of π^{tax} lower the effective tax rate. Quantitatively, $\pi^{tax} = 1.5$ achieves an outcome close to the baseline, and moving to lower values of π^{tax} corresponds to higher effective labor taxation.

Figure F.8 shows the effects of varying π^{tax}. The first notable result is that mild labor taxation can have positive effects on entrepreneurship and aggregate activity. Panel (a) shows that entry from unemployment is nearly flat over the range of π^{tax} from 1.5 to 1, while panel (b) shows that entry from employment rises. Panels (c) and (d) show that these changes translate into a higher entrepreneur share and higher aggregate output: the share of entrepreneurs rises from about 4.25% to about 4.5%, while GDP rises by roughly 1.2%.

The economic intuition is straightforward. A labor income tax lowers the disposable return to paid employment, and therefore lowers the value of remaining a wage worker relative to opening a business. In addition, the model's separation mechanism amplifies the response of employed workers. When after-tax wage income falls, the value of employment declines, more matches become fragile, and the separation-induced entry channel becomes stronger. As a result, a higher labor tax primarily raises entrepreneurship through the employment-to-entrepreneurship margin. The positive GDP response deserves emphasis. In a conventional model, higher labor taxes often reduce output. The dominant effect in this environment is a reallocation effect: as wage employment becomes less attractive, more individuals select into entrepreneurship, firm creation rises, and the increase in entrepreneurial activity is strong enough to offset the contractionary force from lower disposable wages.

This positive effect is not monotone, however. Once π^{tax} falls sufficiently far (i.e. when the effective tax rate is sufficiently high), the economy begins to resemble the traditional tax-distortion environment. Entry from unemployment declines, entry from employment eventually turns down sharply, the entrepreneur share falls, and GDP moves below baseline. Thus, the model delivers a hump-shaped response: small labor-income taxes can stimulate

[32] Since there is no labor income tax in the baseline calibration, and that the income tax only applies to employees but not entrepreneurs, this experiment should be interpreted as the implementation of *additional* labor income tax relative to the entrepreneurs.

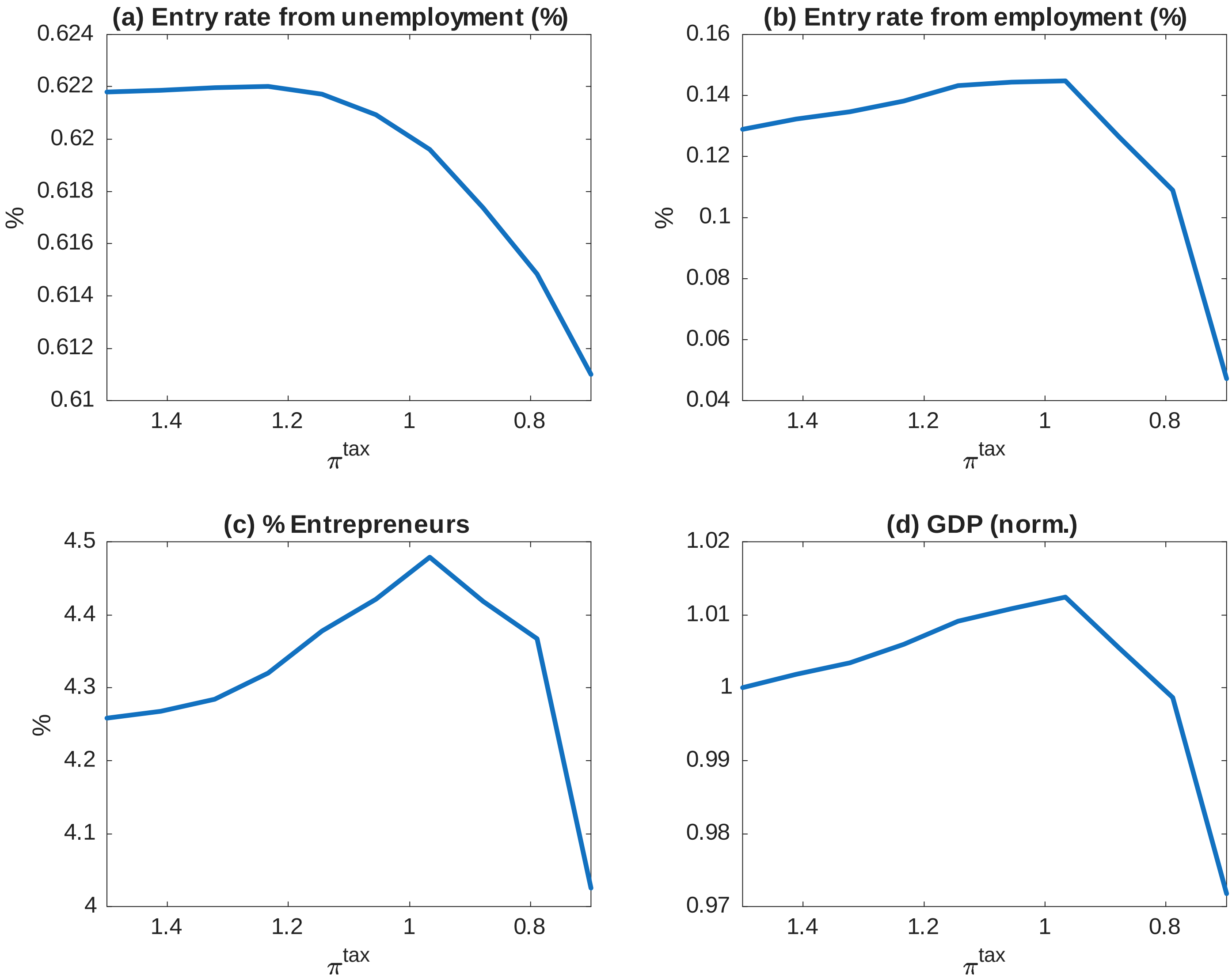

Figure F.8: Effects of Labor Income Tax

entrepreneurship and temporarily raise output, but sufficiently strong labor-income taxation eventually reduces output. Traditional public-finance models emphasize that stronger labor-income taxation depresses labor supply and output (Guner, Lopez-Daneri and Ventura (2016)). The novelty of this model here is that in an environment with entrepreneurial entry, a modest labor-income tax can initially raise business formation and generate a small positive effect on output.