Unemployment Risk and Entrepreneurship*

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[Job Market Paper]

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Abstract

Understanding the decision of individuals to become a new entrepreneur has long been an important topic among economists. Empirically, I find that (i) unemployed individuals are more likely to become an entrepreneur compared to the employed, and (ii) in response to increasing unemployment rate, the propensity to become entrepreneurs increases for employed workers but decreases for unemployed individuals. To explain these findings, I build an equilibrium search model of entrepreneurship and unemployment with endogenous job destructions. Entry decision into entrepreneurship is affected by an opportunistic effect and a separation effect, which is strengthened by surging unemployment risk in recessions. I show that the unemployment rate during the Great Recession would have been two percentage points higher if separation-induced entry is absent in the model. Also, unemployment benefits can be beneficial to the economy by inducing more nascent entrepreneurs from employment. A self-employment subsidy can boost the aggregate output as well. Finally, a decline in labor share would discourage entry from employment resulting in a smaller average firm size.

JEL classification: E24, J64, L26

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

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1 Introduction

How does the previous employment status of individuals affect the decision into entrepreneurship? How would such a decision change with the aggregate economic condition? Understanding the decision of individuals to become a new entrepreneur has long been an important topic among economists. Theoretically, there is a close link between entrepreneurship and the aggregate 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, employment growth of startups are 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 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.

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 self-employed than those employed workers. Moreover, 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. We can see that the behavior of entrepreneurship entry from both employment

[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.

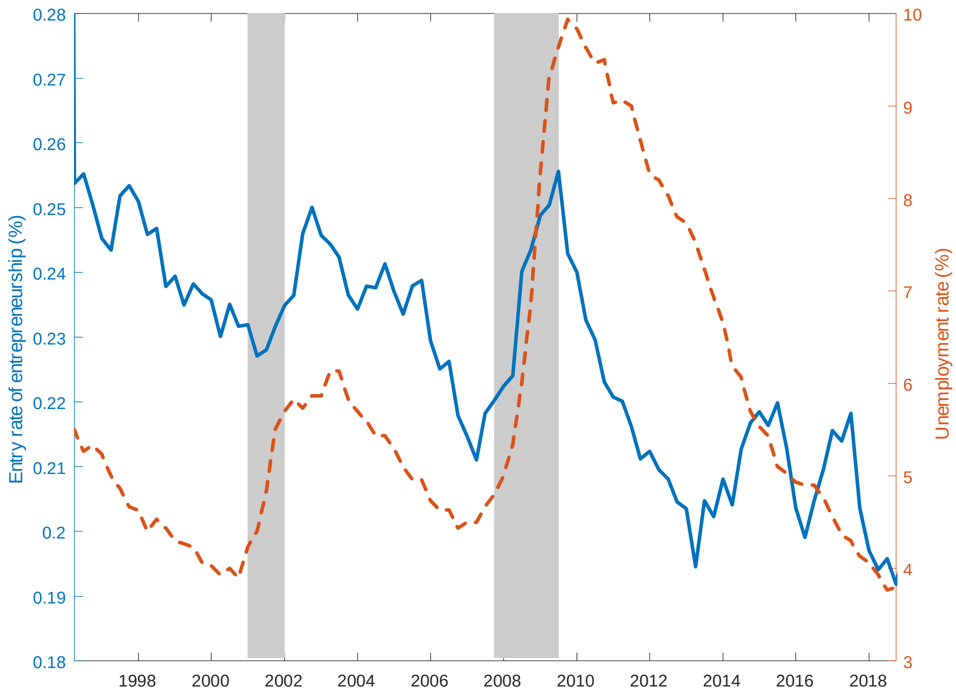

Figure 1: Entrepreneurship Entry and Aggregate Unemployment in the US

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.

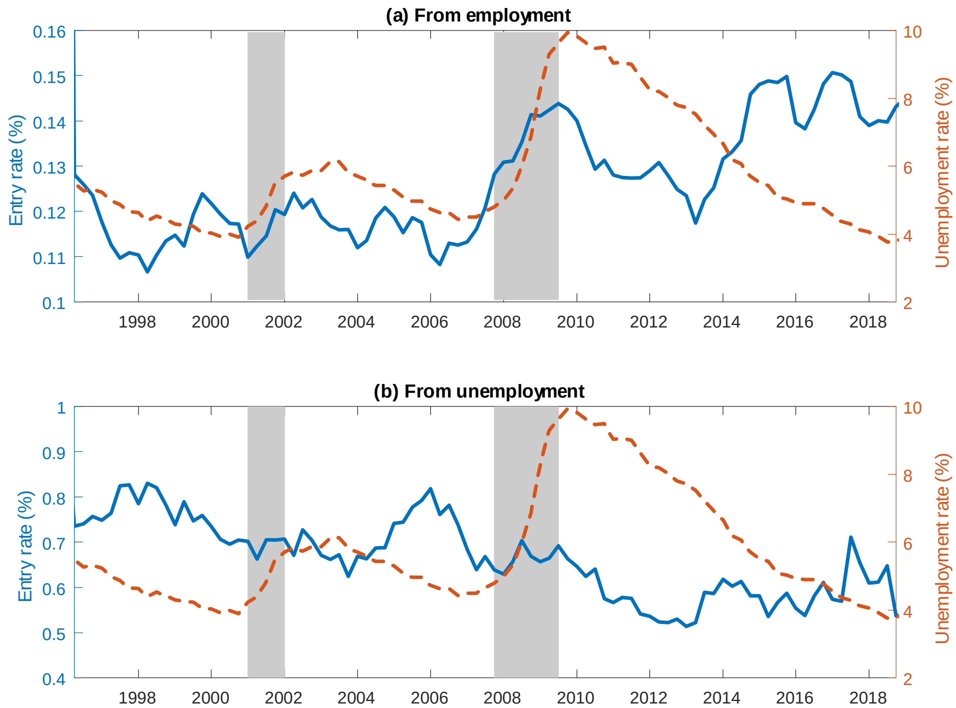

Figure 2: Entrepreneurship Entry by Previous Employment Status in the US

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.

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 group of employed workers who becomes more likely to become entrepreneurs in bad times. The different and opposite cyclicality between the employed and unemployed workers certainly warrants more explanations.

Figure 3 shows the quit rate and the layoff rate in the US from 2001 to 2018. We can see that in bad times the quit rate drops drastically while the layoff rate spikes. Note that any employment-entrepreneurship transition must be accompanied by either a quit or a layoff. The cyclicality of quits and layoffs then suggests that it is the increasing layoff rate in bad times that is responsible for the increase in the entrepreneurial entry in bad times. This is supported by an empirical literature showing that mass layoffs indeed increase the

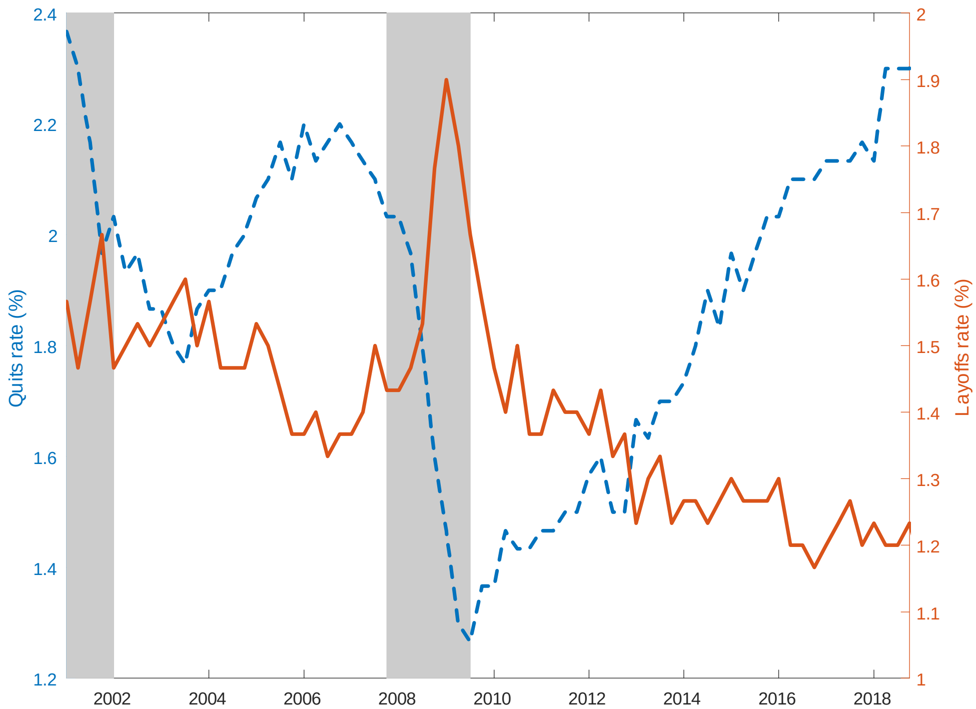

Figure 3: Quits and Layoffs in the US

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.

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. Moreover, 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 aggregate 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. This can be explained by the lower outside option of unemployment. Second, in response to the increasing unemployment rate, the propensity to become entrepreneurs increases for employed workers but decreases for unemployed workers. Third, by looking at the business outcomes of the business created by employed workers and unemployed workers, I find that entrepreneurs from employment are more likely to be incorporated, report higher business sales, have lower exit rates, and hire more employees. In general, these firms are more successful than those started by unemployed individuals.

To explain the empirical findings, I build an equilibrium model of entrepreneurship and unemployment with endogenous job destruction, where I incorporate the entrepreneurship decision (Lucas, 1978) into a standard search and matching model (Mortensen and Pissarides, 1994). There are three labor market states in the model: employed, unemployed, and entrepreneur in a firm. In each period, firms make hiring and firing decisions. Then each employed or unemployed individual has some chance to draw an entrepreneurial opportunity. Upon observing the opportunity, they can choose whether to open a new business. I show that due to the lower profitability in new businesses, the entry rate from unemployment decreases in bad times. However, the entry rate from employment is affected by both changes in the profitability (*opportunistic effect*) and in the layoff separation rate (*separation effect*). In recessions when the unemployment rate is high, separation-induced entry surges which could lead 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 the separation-induced entrepreneurship in bad times and to study policy analysis regarding entrepreneurship. I show that, consistent with the data, the entry rate from unemployment is decreasing with the aggregate unemployment rate, while the entry rate from employment is increasing with it. 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 0.125% to 0.150% as the unemployment rate increases from 5.5% to 10% due to the increasing layoff risk, whereas the entry rate would drop to 0.11% due to the opportunistic effect. This shows the separation-induced entry is relatively more important in explaining the dynamics of the entry rate from employment. I show that absent the separation-induced entry, the unemployment rate during the Great Recession would have been two percentage points higher.

The model developed provides us with a perfect laboratory to evaluate the impact of public policies on entrepreneurial entry and the aggregate economy. I first evaluate the effects of changing the unemployment benefits. I show that as the benefits increase, the share of entrepreneurs in the economy rises, which could have a positive impact on the aggregate output. This is not seen in the standard search model where unemployment benefits are often detrimental to the aggregate output. Also, countercyclical benefits raise the entrepreneurial entry during recessions, which would lead to a smaller average firm size due to the reverse selection effect.

A self-employment subsidy is also shown to have a positive impact on the aggregate economy. The subsidy raises the opportunistic entry but lowers the aggregate unemployment rate and thus the separation-induced entry. As a result, the number of entrepreneurs in the economy increases. I show quantitatively that a subsidy of one unit of labor productivity can boost up to one percent of the aggregate output. The multiplier associated with this policy is shown to be 1.6, which is much larger than one and unseen in the standard model.

Finally, a decline in the labor share would have significant effects on entrepreneurship. While the entry rate from unemployment is relatively constant with respect to the labor share, the entry rate from employment is significantly reduced (-0.05 percentage point, or -38%) when the labor share decreases by 10%. Also, there would be an 18% decrease in the average firm size in this case. As a result, there would be a surge in unemployment, and the aggregate output would be reduced by 17%.

The remainder of the paper is organized as follows. In Section 2, I review the related literature. In Section 3, I study the relationship between entrepreneurship entry and unemployment empirically. I develop empirical evidence at the micro-level in the section. 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 and the effects of various public policies regarding entrepreneurship in Section 5. Section 6 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, national unemployment increases actually lead to an upswing in 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, I show that in the US, the entry rate into entrepreneurship from employment rises in bad times, while that from unemployment decreases in recessions.

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, Galindo 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 transitioned from different employment status.

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 there exist both opportunity and necessity entrepreneurship[3]. They define the two types of entrepreneurship by an individual's previous employment 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

[3] 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.

the hypothesis of necessity entrepreneurship is not apparant in the data.[4]

Finally, this paper contributes to the theoretical literature on entrepreneurship and unemployment. 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 has been attempts to discuss entrepreneurship in a search model (Fonseca, Lopez-Garcia and Pissarides, 2001; Gaillard and Kankanamge, 2019; Masters, 2017; Poschke, 2019). However, they are mostly static models and do not feature job separation decisions. In this paper, I embed the entrepreneurship decision (Lucas, 1978) into a standard search and matching model (Mortensen and Pissarides, 1994) with endogenous job destructions 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 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.

[4] In the regression analysis, Fairlie and Fossen (2018) look at the stock of entrepreneurs coming from employment and non-employment, whereas I look at the *entry rate* from employment and unemployment.

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. 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[5]. 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 causal contract workers and freelancers such as Uber drivers in the data. It can be shown in Appendix A that the results below 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 Åđahin (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

[5] 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

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 self-employed 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 previous unemployed and employed respectively. Also, Appendix A shows the state-level cross-sectional evidence.

Table 1 shows the summary statistics of the samples.

3.2 Entrepreneurial Entry Decision and Aggregate 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.

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

where $entre_{i,t+1}$ is the dummy variable which equals one if individual i becomes an en-

Table 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.

trepreneur 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_t^{agg} is the aggregate 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 year fixed effects.

Table 2 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 aggregate unemployment rate is significantly positive, which suggests that entrepreneurship entry is countercyclical. However, the cyclicality disappears once I control for also 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). Note that conditional on the previous employment status, the entry decision now shows differential responses to changes in aggregate unemployment. Specifically, the entry rate increases in bad times for the employed and decreases for the unemployed. 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 than that of the employed, and responses negatively to the aggregate unemployment rate. Therefore, I restrict the focus on those who are in the labor force thereafter.

Table A.1 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 points increase in unemployment, the entry rate from employment would increase by 0.015 percentage point, which corresponds to a 12%

Table 2: Logit Regression Results (CPS)

Logit model	$entre_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
$unemployed_t$	1.697***		1.696***	2.033***	2.401***	2.451***
	(0.0171)		(0.0173)	(0.0184)	(0.0612)	(0.0610)
u_t^{agg}		3.564***	0.185	-0.836*		
		(0.423)	(0.429)	(0.433)		
$employed \times u_t^{agg}$					0.890*	1.127**
					(0.505)	(0.504)
$unemployed \times u_t^{agg}$					-5.078***	-4.781***
					(0.812)	(0.811)
$nilf$						1.837***
						(0.0418)
$nilf \times u_t^{agg}$						-4.570***
						(0.467)
Constant	-6.626***	-6.605***	-6.637***	-9.028***	-9.128***	-9.211***
	(0.00857)	(0.0262)	(0.0262)	(0.271)	(0.271)	(0.166)
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 $entre_{t+1}$. Column (6) includes the individuals out of labor force, with $nilf$ being the dummy variable for the state. 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.

increase from the mean level. On the other hand, the entry rate from unemployment would drop by 0.084 percentage point, which corresponds to a 13% 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.2 in Appendix A shows various robustness checks. For example, the results are similar when I use OLS and probit models. However, in the OLS model, the coefficient associated with the cross term between employed and unemployment rate loses significance. Also, when I define entrepreneurs as self-employed workers. I get similar but strong 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 positive 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 owning some business on the side.

In addition, Table A.3 shows the results using the National Longitudinal Survey of Youth 1979 (NLSY79) data where I can control for individual fixed effects. Table A.4 shows the regression models when, instead of using the aggregate 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 that they produce different business outcomes as well. Table 3 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 become 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, while those from unemployment hire merely 0.4 employee on average.

The lower panel of Table 4 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 owners starting from 2010[6]. 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[7]. 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 the nascent employment 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 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 Galindo 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.

Finally, in Appendix A.6, I show the relationship between the entry rate into entrepreneurship and job separation rate 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 controling for year and industry fixed effects (Table A.5). 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.

[6] 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.

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

Table 3: 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
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%

Notes: The table shows the business outcomes of nascent entrepreneurs. Nascent entrepreneurs are those entrepreneurs newly transitioned from employment or from unemployment. 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 is decreasing returns (Elsby and Michaels, 2013; Acemoglu and Hawkins, 2014). Workers are infinitely lived and risk-neutral with common discount factor β. In each period of their life, they can be participating in the labor market as employed, unemployed, or being an entrepreneur in a firm.[8] For simplicity, I assume that each entrepreneur can only create and manage one firm at the same 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 $G(\cdot)$ with a compact support $[z_{\min}, z_{\max}]$[9]. They may then choose to open a business upon observing z[10]. Otherwise, workers are homogeneous when working for a firm. Unemployed workers and firms are searching randomly in a single labor market. The firm exit probability s is assumed to be exogenous[11]. There is an aggregate productivity y_t which

[8] I abstract from worker's fixed effect in this model, so that the productivity of the worker depends on that of the firm. Incorporating worker's ex-ante heterogeneity would be an interesting extension of the model so that one can talk about the distribution of worker's ability over the business cycle. However, the general message about the entrepreneurial entry over the business cycle would be unchanged.

[9] 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.

[10] For simplicity, I abstract from the problem of liquidity constraints facing new entrepreneurs. While Evans and Jovanovic (1989) argue that liquidity constraints are binding for many start-ups, a more recent analysis by Hurst and Lusardi (2004) shows that there is no relationship between wealth and entry into entrepreneurship for much of the wealth distribution.

[11] Lee and Mukoyama (2015) show that at the margin, the entry decision of the firm is much more important than the exit decision in understanding the business cycle dynamics of the firms.

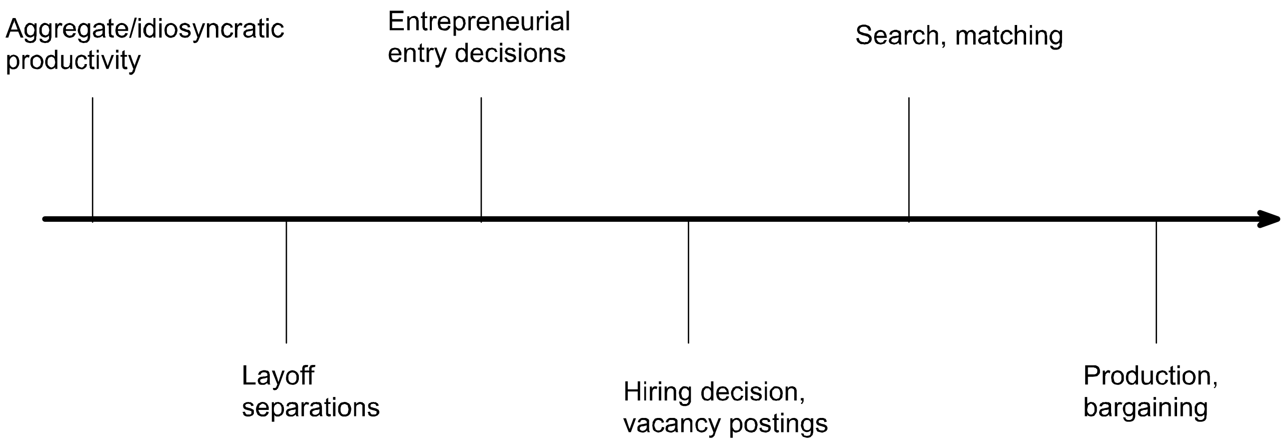

Figure 4: Timeline in the Model

is the only aggregate state variable that is changing over time[12]. 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.

4.2 Unemployed 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. In the next period, there is a probability λ^u that they will receive an opportunity to become an entrepreneur. The worker in this case can decide whether or not to create a new firm. Otherwise, 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

$$U_t = b_t + \beta \mathbb{E}_t \left[\begin{array}{c} \lambda^u \int \max \left\{ \Pi_{t+1}(\tilde{z}, 0), U_{t+1} \right\} dG(\tilde{z}) \\ + (1 - \lambda^u) \left[(1 - \phi(\theta_t)) U_{t+1} + \phi(\theta_t) W_{t+1}(z_{t+1}, n_{t+1}) \right] \end{array} \right] \qquad (2)$$

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 $t+1$. Note that the expectation is taken over the aggregate state, as well as the productivity and the size of the hiring firms in the next period.

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

4.3 Employed Workers

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

$$W_t(z_t, n_t) = w_t(z_t, n_t) + \beta \mathbb{E}_t \begin{bmatrix} [s + (1-s)\sigma_{t+1}] \hat{U}_{t+1} \\ +(1-s)(1-\sigma_{t+1}) \hat{W}_{t+1}(z_{t+1}, n_{t+1}) \end{bmatrix} \tag{3}$$

where s is the exogenous firm exit rate and $\sigma_{t+1} = \mathbf{1}\{U_{t+1} \geq W_{t+1}(z_{t+1}, n_{t+1})\}$ is the endogenous layoff separation rate[13]. 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. The continuation values for the employed workers are then

$$\hat{U}_{t+1} = \lambda^u \int \max\{\Pi_{t+1}(\tilde{z}, 0), U_{t+1}\} dG(\tilde{z}) + (1-\lambda^u) U_{t+1} \tag{4}$$

$$\hat{W}_{t+1}(z, n) = \lambda^w \int \max\{\Pi_{t+1}(\tilde{z}, 0), W_{t+1}(z, n)\} dG(\tilde{z}) + (1-\lambda^w) W_{t+1}(z, n) \tag{5}$$

4.4 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 friction, only q_t of those vacancies would turn into jobs with employed workers. Therefore, a firm with productivity z and previous employment

[13]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.

size n_{t-1} chooses the optimal employment size and vacancy postings for the current period:

$$\Pi_t(z_t, n_{t-1}) = \max_{n_t, v_t} \left\{ \begin{array}{c} y_t z_t f(n_t) - w(z_t, n_t) n_t - c v_t \\ +\beta \mathbb{E}_t [(1-s)\Pi_{t+1}(z_{t+1}, n_t) + s U_{t+1}] \end{array} \right\} \tag{6}$$

where

$$v_t = \max \left\{ \frac{n_t - (1-\pi_t^w) n_{t-1}}{q(\theta_t)}, 0 \right\} \tag{7}$$

is the vacancy postings and π_t^w is the fraction of workers who are becoming entrepreneurs (to be determined in equilibrium). Note that the firm can reduce its size costlessly, whereas expansion is costly due to search friction. The first order condition when there is hirings or firings of workers:

$$y_t z_t f'(n_t) - w_t(z_t, n_t) - \frac{\partial w_t(z_t, n_t)}{\partial n_t} n_t + (1-s)\beta \mathbb{E}_t \left[\frac{\partial \Pi_{t+1}(z_{t+1}, n_t)}{\partial n_t} \right] = \frac{c}{q(\theta_t)} \mathbf{1}_{hire_t} \tag{8}$$

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.

4.5 Marginal Value of a Worker

One can then define the marginal value of a worker as

$$J_t(z_t, n_t) = y_t z_t f'(n_t) - w_t(z_t, n_t) - \frac{\partial w_t(z_t, n_t)}{\partial n_t} n_t + (1-s)\beta \mathbb{E}_t (1-\sigma_{t+1}) \left[\frac{\partial \Pi_{t+1}(z_{t+1}, n_t)}{\partial n_t} \right] \tag{9}$$

It has been shown in Elsby and Michaels (2013) that the optimal employment size can be characterized as

$$n_t(z_t, n_{t-1}) = \left\{ \begin{array}{ll} \left(R_t^h\right)^{-1}(z_t) & \text{if } z_t > R_t^h(n_{t-1}) \\ (1-\pi_t^w) n_{t-1} & \text{if } z_t \in \left[R_t^f(n_{t-1}), R_t^h(n_{t-1})\right] \\ \left(R_t^f\right)^{-1}(z_t) & \text{if } z_t < R_t^f(n_{t-1}) \end{array} \right. \tag{10}$$

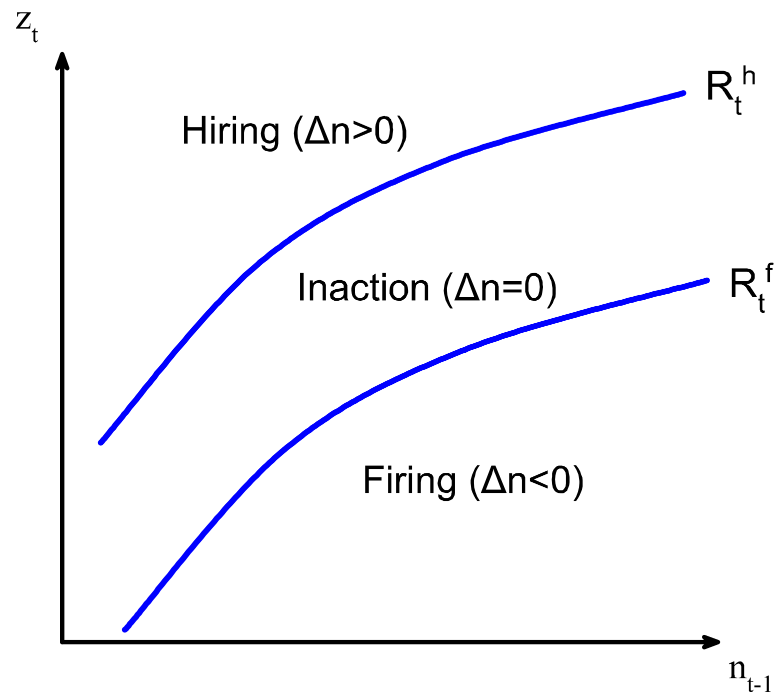

Figure 5: Optimal Employment Policy

where $R_t^h(\cdot)$ and $R_t^f(\cdot)$ are defined by $J_t\left(R_t^h(n),(1-\pi_t^w)n\right)=\frac{c}{q(\theta_t)}$ and $J_t\left(R_t^f(n),(1-\pi_t^w)n\right)=0$. Hence, there is an inactive region $\left[R_t^f(n_{t-1}),R_t^h(n_{t-1})\right]$ where the firm would neither fire nor hire any worker, as shown in Figure 5.

4.6 Matching, Surplus, and Wage Bargaining

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

$$\phi(\theta_t) = \frac{M(u_t,v_t)}{u_t}=M(1,\theta_t)=A\theta_t^{1-\alpha} \tag{11}$$

$$q(\theta_t) = \frac{M(u_t,v_t)}{v_t}=M\left(\theta_t^{-1},1\right)=A\theta_t^{-\alpha} \tag{12}$$

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:

$$S(z_t, n_t) = J_t(z_t, n_t) + W_t(z_t, n_t) - U_t$$

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

$$(1-\eta)(W_t(z_t, n_t) - U_t) = \eta J_t(z_t, n_t) \tag{13}$$

We are now ready to derive the wage equation of the workers.

Proposition 1 *The wage equation satisfies the ordinary differential equation*

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

where

$$\Lambda_t(z_t, n_t) = \beta(1-s)\mathbb{E}_t(1-\sigma_{t+1}) \left[\begin{array}{c} \lambda^u \int_{\tilde{z}^U_{t+1}}^{z_{\max}} (\Pi_{t+1}(\tilde{z}, 0) - U_{t+1}) \, dG(\tilde{z}) \\ -\lambda^w \int_{\tilde{z}^W_{t+1}(z_{t+1}, n_{t+1})}^{z_{\max}} (\Pi_{t+1}(\tilde{z}, 0) - U_{t+1}) \, dG(\tilde{z}) \end{array} \right]$$

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.

4.7 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 $\bar{z}_t^u$ is determined by

$$\Pi_t\left(\bar{z}_t^u, 0\right) = U_t \tag{14}$$

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

$$\Pi_t\left(\bar{z}_t^w\left(z_t, n_t\right), 0\right) = W_t\left(z_t, n_t\right) \tag{15}$$

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

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

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

$$\begin{aligned} entry_{t+1}^w\left(z_{t+1}, n_{t+1}\right) &= \left[s + (1-s)\,\sigma_{t+1}\right]\lambda^u\left(1 - G\left(\bar{z}_{t+1}^u\right)\right) \\ &\quad + (1-s)\left(1-\sigma_{t+1}\right)\lambda^w\left(1 - G\left(\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)\right)\right) \end{aligned} \tag{16}$$

In bad times where the aggregate productivity y_t is low, the profitability and hence the value of creating a business drops. 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. both cutoffs $\bar{z}_{t+1}^u$ and $\bar{z}_{t+1}^w\left(z_{t+1}, n_{t+1}\right)$ increase. Thus, we have that the entry rate from unemployment $entry_{t+1}^u$ would decrease since the probability of drawing a productive enough firm $1-G\left(\bar{z}^{u}_{t+1}\right)$ is lower. Fixing the value of σ_{t+1}, there is the same negative effect on $entry^{w}_{t+1}$. 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 σ_{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 $\bar{z}^{u}_{t+1} < \bar{z}^{w}_{t+1}\left(z_{t+1}\right)$ (due to the fact that the value of being employed is higher than that of being unemployed) and so $1-G\left(\bar{z}^{u}_{t+1}\right) > 1-G\left(\bar{z}^{w}_{t+1}\left(z_{t+1}\right)\right)$, the increase in σ_{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 2 *Suppose there is a decline in aggregate productivity y_t. Then*

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

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

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

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:

$$f(n) = n^{\alpha_f} \tag{17}$$

The aggregate and idiosyncratic productivities $\{y_t, z_t\}$ both follows AR(1) process

$$\ln y_{t+1} = \rho_y \ln y_t + \varepsilon^y_{t+1} \tag{18}$$

$$\ln z_{t+1} = \rho_z \ln z_t + \varepsilon^z_{t+1} \tag{19}$$

where $\varepsilon^y_{t+1} \overset{iid}{\sim} N\left(0, \sigma^2_y\right)$ and $\varepsilon^z_{t+1} \overset{iid}{\sim} N\left(0, \sigma^2_z\right)$. Hence, the initial opportunistic draw of the idiosyncratic productivity is taken to be truncated log-normal distribution with mean 0 and variance σ^2_z.

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 labor share is assumed to be $\alpha_f = 0.72$, which is broadly in line with the literature[14]. Later in the quantitative analysis, I consider the impact on entrepreneurship when the labor share is lower. The matching elasticity α_m is chosen to be 0.5, which is consistent with the range of estimates in Petrongolo and Pissarides (2001).

[14] 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.

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 Milgrom (2008).

The rest of the parameters are then jointly calibrated to match the labor market moments in the US economy using the CPS dataset I construct in the empirical analysis. First, the bargaining power of the worker is calibrated to match the fraction of entrepreneurs in the economy, which is about 6.2% in the CPS data. Also, the coefficient of matching efficiency A is chosen to fit the monthly job finding rate of 23% in the CPS data. The size of the labor force L in the economy is calibrated to match the average firm size of 15 (Henly and Sánchez, 2009). The standard deviation of aggregate and idiosyncratic shocks σ_y and σ_z are taken to fit the cyclical volatilities of labor productivity and unemployment in the data. The rates of entrepreneurial opportunity λ^w and λ^u are then chosen to match the average monthly entry rates from employment and unemployment respectively. The exogenous firm destruction rate s is taken to match the steady-state unemployment rate of 5.68% in the data. Finally, the aggregate TFP ξ is used to normalize the average labor productivity to one in the model.

A summary of the calibration values is given by Table 4. The distribution of employment growth is shown in Figure B.1. Also, the business cycle statistics are given in Table C.1. In general, the model generates a distribution of employment growth and business statistics that are consistent with the data.

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.

Table 4: 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 share	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	0.70	% entrepreneurs
σ_y	Standard deviation of aggregate shock	0.014	Cyclical volatility of productivity
σ_z	Standard deviation of idiosyncratic shock	0.02	Cyclical volatility of unemployment rate
A	Matching efficiency	0.36	Job finding rate
L	Size of labor force	15	Average firm size
λ^w	Entrepreneurial opportunity rate	0.008	Monthly entry rate from employment
λ^u	Entrepreneurial opportunity rate	0.007	Monthly entry rate from unemployment
s	Exogenous firm destruction rate	0.016	Unemployment rate
ξ	Aggregate TFP	2.1	Average labor productivity = 1

Hence, the dynamic 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 6 shows how the cutoff productivity from unemployment is changing with the aggregate unemployment. 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 6. 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 7 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 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

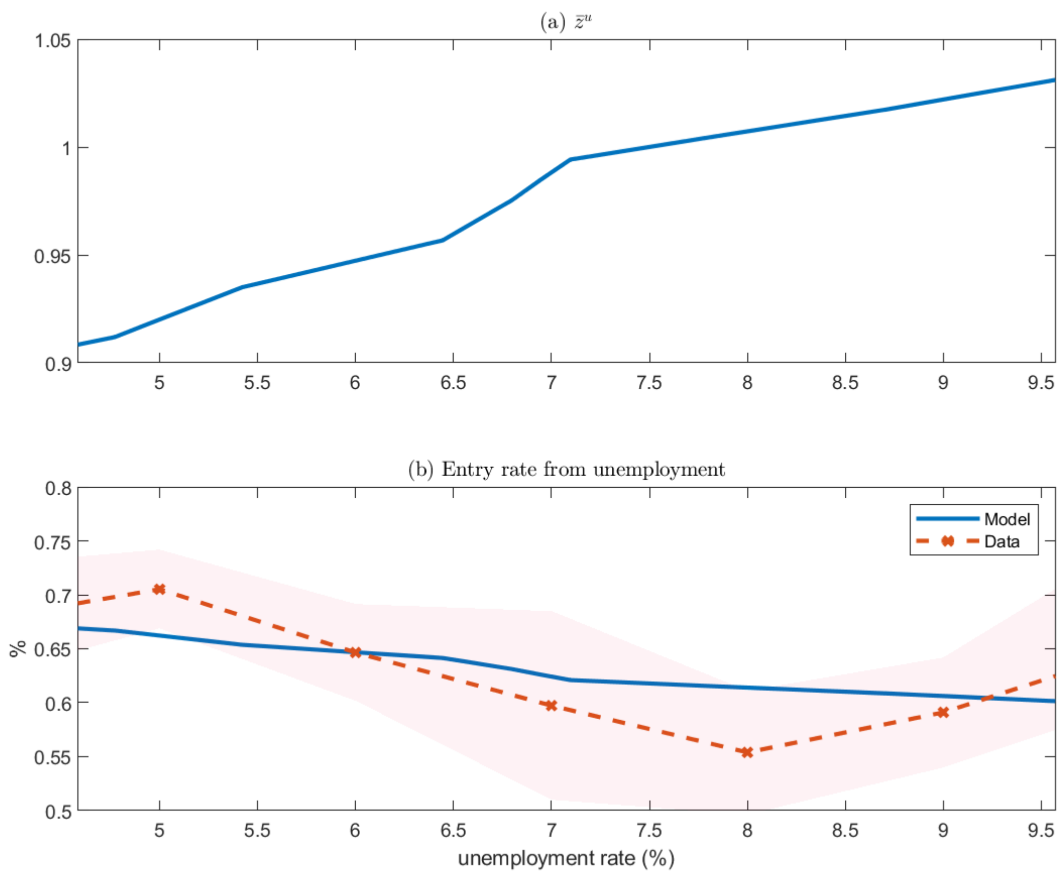

Figure 6: Entry Rate from Unemployment

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.

consistent with the increasing trend in the data and is 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 0.125% to 0.150% as the unemployment rate increases from 5.5% 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 0.11% 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 18. The matching of the unemployment rate from 2007 to 2011 is given in Figure 8, 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 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

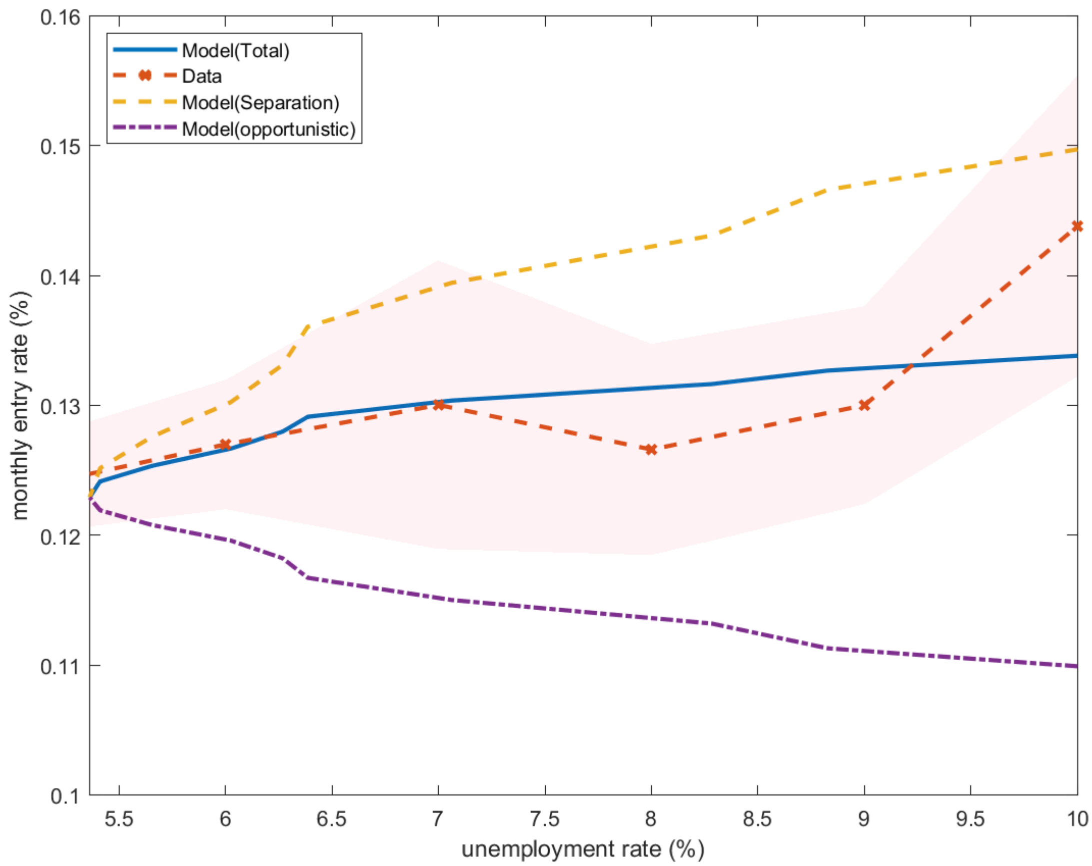

Figure 7: Entry Rate from Employment

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.

of separation-induced entry, becomes larger and eventually reaches two percentage points at the peak of 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 peak of the unemployment rate during the Great Recession would have been two percentage points (or 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.

5.4 The Impact of Unemployment Benefits

The model developed in this paper provides us with a perfect laboratory to evaluate the impact of public policies on entrepreneurial entry and the aggregate economy. Here I investigate the effects of increasing unemployment benefits. I first consider the case when the unemployment benefits are constant over time, and uniformly increases.

Figure 9 shows the impact of different b on entrepreneurship and the aggregate economy. The blue curve in the each panel (labeled 'baseline') shows the effects in the baseline model, while the red dotted line shows the impact when the layoff separation rate is fixed. First, as the flow utility of unemployment increases from 0.71 to 0.75, the entry rate from unemployment decreases from 0.65% to 0.638%. 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

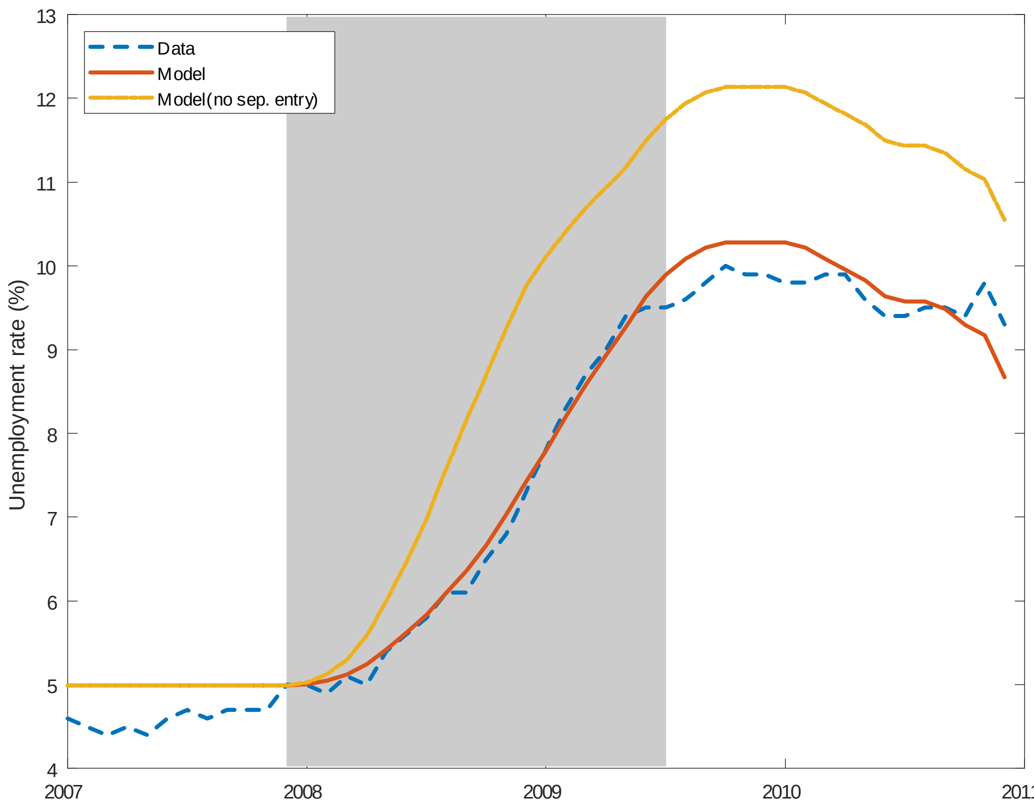

Figure 8: Unemployment Rate During the Great Recession

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 $\lambda^w = 0$. The Great Recession defined by NBER is in the shaded area.

of being 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 6.2% to 6.5%. This is due to the increasing number of unemployed workers who have a higher entry rate into entrepreneurship. Finally, the aggregate output in the economy, or the GDP, also displays a U-shaped relationship with respect to increasing unemployment benefits. This is due to the two opposing effects on employment. First, as in the standard model (when the layoff separation rate is fixed), the larger unemployment benefits discourage unemployed workers from working and boost the unemployment rate. Also, as the number of entrepreneurs increases with the hiring activities, employment eventually picks up and contributes to higher aggregate output. The second effect is absent in the standard search model, where there are often detrimental effects of unemployment benefits. This shows the inclusion of entrepreneurial entry is important in analyzing the impact of unemployment benefits on the aggregate economy. By comparing the effects in the baseline with those when the separation is fixed, we can see that the separation effect in fact has a great impact for policy implications.

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 10 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 0.78 in bad times and as low as 0.68 during expansions. The resulting aggregate unemployment is shown in (b). We can see that with the countercyclical benefits, unemployment becomes much more volatile. In fact, the unemployment rate now goes up to 14% in bad times, while the reduction of unemployment is more muted.

How would the countercyclical benefits affect entrepreneurship over the business cycle?

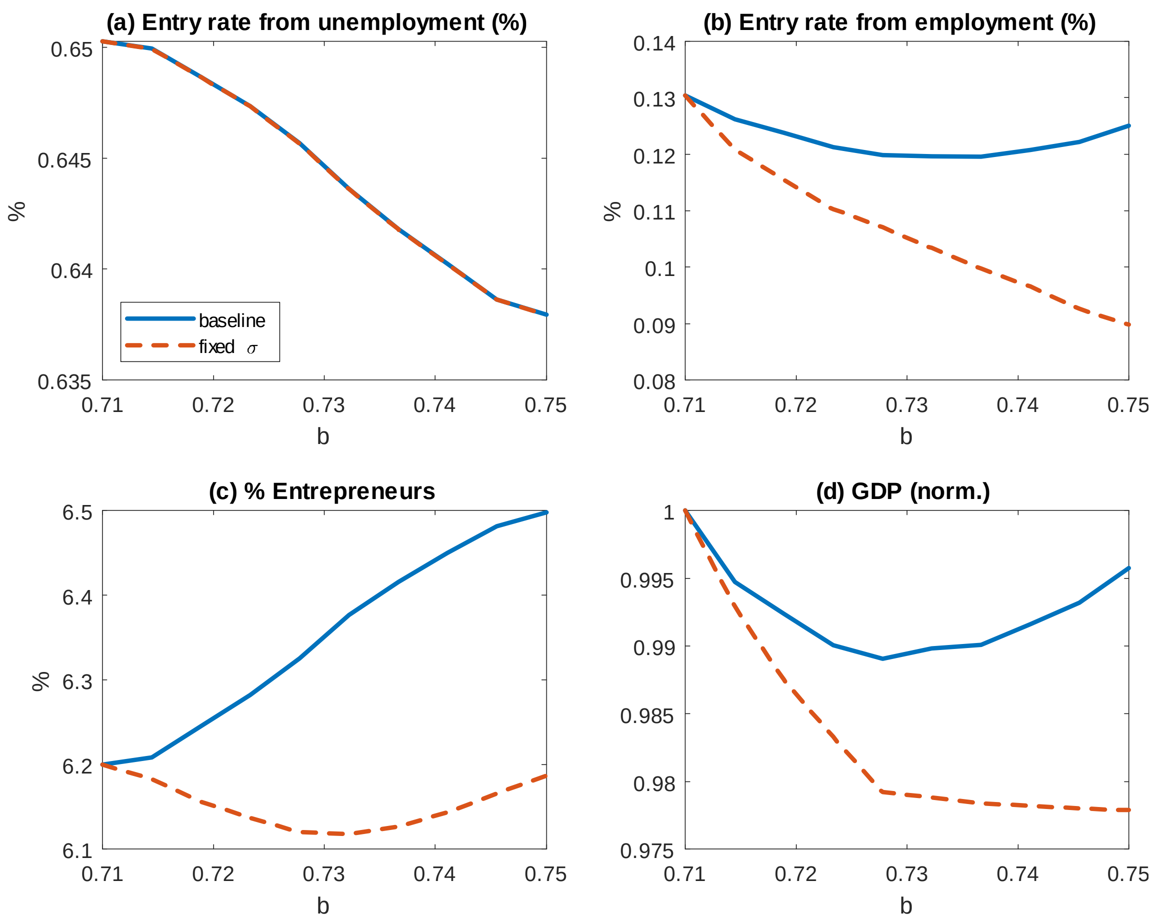

Figure 9: Effects of Unemployment Benefits

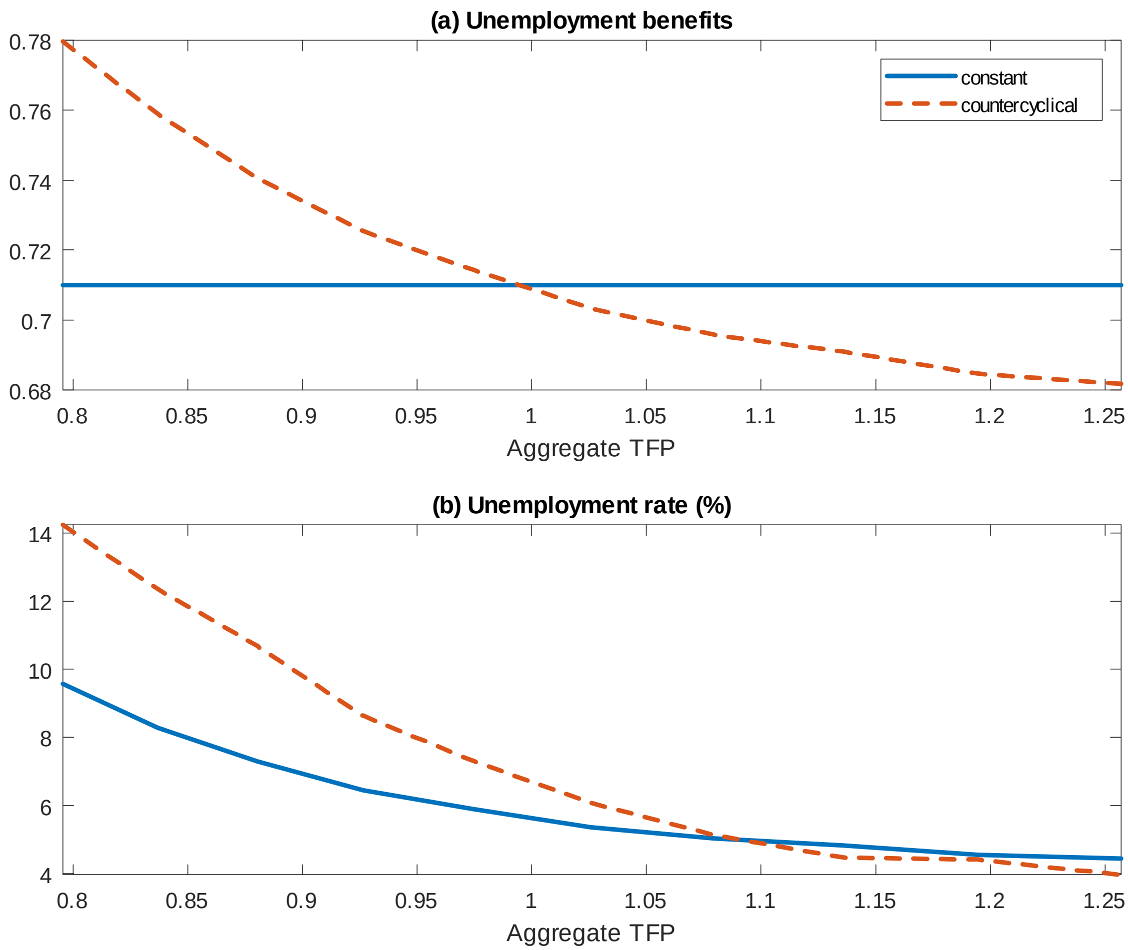

Figure 10: Countercyclical Unemployment Benefits and Unemployment Rate

Figure 11 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 (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 to a rise in the entry rate despite the fall in entry rate from individual status (see Figure 10). As a result, the entry rate becomes more volatile over the business cycle. Also, due to the increase in the separation rate from employment and hence the overall entry rate, the share of entrepreneurs also increases during recessions (panel b). In fact, we see an overall rise in the percentage over most of the business cycle. Finally, the average firm size decreases as well over the business cycle. This is likely due to the selection effect: while there is an increase in the entry into entrepreneurship in the labor market in bad times when profitability is low, there is less selection in the entrepreneurial entry, and hence the average quality of entrepreneurs becomes lower. Therefore, the firm size, which is increasing in the productivity of the firm, becomes smaller as well. Note that the model predicts a countercyclical average firm size which is consistent with the empirical data as well[15].

5.5 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. Note that κ affects the cutoff productivities directly as follows.

$$\Pi_t\left(\bar{z}_t^u\left(\kappa\right), 0\right) + \kappa = U_t \tag{20}$$

$$\Pi_t\left(\bar{z}_t^w\left(z_t, n_t; \kappa\right), 0\right) + \kappa = W_t\left(z_t, n_t; \kappa\right) \tag{21}$$

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

[15] See, e.g., Moreira (2017) and Lee and Mukoyama (2015).

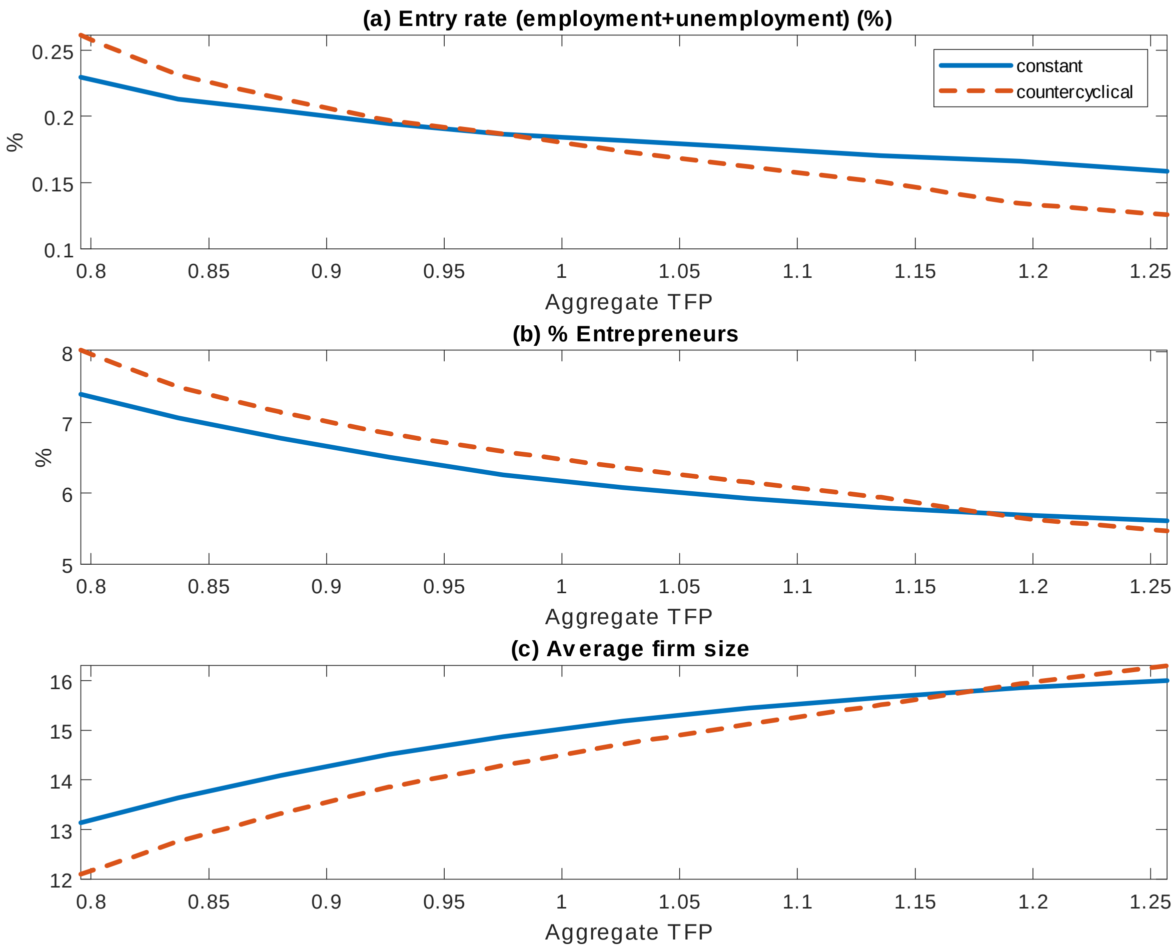

Figure 11: Effects of Countercyclical Unemployment Benefits on Entrepreneurship

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 that on the separation probability as well.

Figure 12 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 0.65% to about 0.73% due to purely the direct incentive to open a business. However, the entry rate from employment decreases to 0.11%. This shows that the drop in the separation rate dominates the incentive to become an entrepreneur. As a result of the decrease in separations among employed workers, the overall entry from employment is lower. 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 drop in the entry from employment, along with 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 increase in the percentage of entrepreneurs from 6.2% to about 6.5%. 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 1% when κ is close to 1. This shows that the self-employment subsidy has a quantitatively important impact on the aggregate economy.

One can 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:

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

where u_t and e_t are the fraction of unemployed and employed workers respectively. From the model, the average multiplier associated with the policy over the business cycle is about 1.6 when $\kappa = 1$. This shows that there is a multiplier effect from the self-employment subsidy,

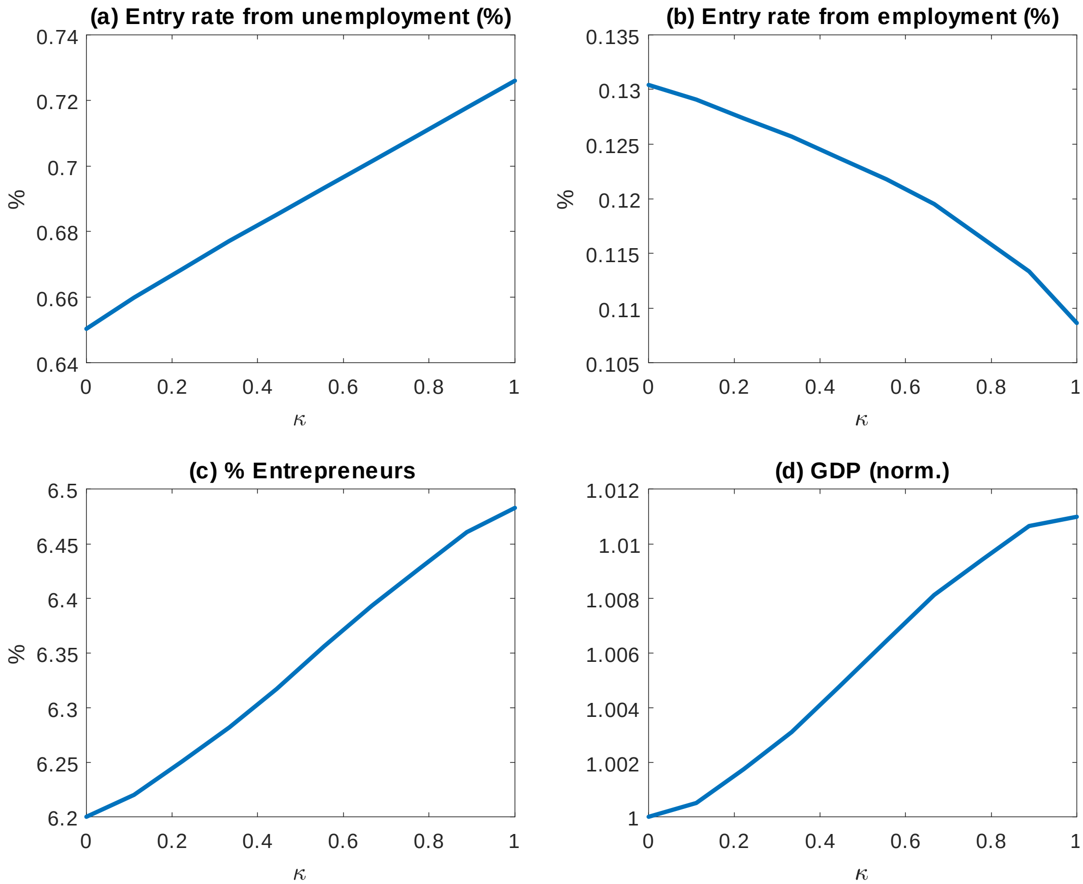

Figure 12: Effects of Self-employment Subsidy

which is unseen in a standard search model.

5.6 Labor Share Decline and Entrepreneurship

Recently, there is evidence that the U.S. is experiencing a significant decline in the labor share[16]. How would a labor share decline affect entrepreneurship? In the model, the labor share is captured by the parameter α^f in the production function. Here I consider the decline of α^f from 0.72 (baseline) to 0.648, which is a 10% decline. The aggregate statistics of the economy for different values of α^f are given in Table 5. The measure of welfare is the

[16] See,e.g., the evidence in Karabarbounis and Neiman (2014) and, more recently, Koh, Santaeulàlia-Llopis and Zheng (2020).

weighted sum of all the value functions as follows.

$$welfare_t = \int W_t(z_t, n_t)\, n_t dH(z_t, n_t) + U_t \cdot u_t + \int \Pi_t(z_t, n_{t-1})\, dH(z_t, n_{t-1}) \tag{22}$$

A few observations are in order. First, the entry rate from unemployment is relatively constant with respect to the labor share. Intuitively, there are two opposing effects on the entry decisions of the unemployed workers. On the one hand, a lower labor share entails that firms are employing fewer workers on average. This leads to a decrease in job finding rate and hence the value of being unemployed. As a result, there is more incentive for unemployed workers to open a new business. On the other hand, firms are now less profitable since they are hiring fewer workers. This reduces the opportunistic entry. Therefore, the overall change in the entry rate from unemployment is minimal. This is not the case for the entry rate from employment, which drops significantly from 0.13% to 0.07%, an over 40% decline. This is because of the decrease in opportunistic entry leading to a significant overall decline in the entry rate. Surprisingly, the share of entrepreneurs in the labor market increases from 6.2% to 7.4%. This is primarily due to compositional changes between employment statuses. Since there are more unemployed workers, who have a much higher entry rate, the overall flow of entry into entrepreneurship is actually higher, leading to a surge in the share of entrepreneurs. In addition, the average firm size is about 18% lower under a smaller labor share. This is natural since firms are now hiring fewer workers due to lower concavity in the production function. The income inequality, measured by the Gini coefficient, is also significantly lower when the labor share is smaller. Note that the aggregate output, or GDP, is also lower since there is less employment in the labor market. Finally, the welfare of the economy is relatively stable. This is because while the values of being unemployed and entrepreneurship are both lower, the value of being employed is actually higher since the workers are bargaining their wages at a higher marginal product due to smaller firm size.

Table 5: Effects of Labor Share Decline

	α_f										
Variable	0.72 (baseline)	0.712		0.696		0.68		0.664		0.648	
$entry\_u$	0.65%	0.65%	(0.00%)	0.65%	(0.00%)	0.65%	(0.00%)	0.65%	(0.00%)	0.65%	(0.00%)
$entry\_w$	0.13%	0.11%	(-0.02%)	0.08%	(-0.05%)	0.07%	(-0.05%)	0.07%	(-0.05%)	0.07%	(-0.05%)
% $entre$	6.20%	6.28%	(0.08%)	6.41%	(0.21%)	6.72%	(0.52%)	7.06%	(0.86%)	7.42%	(1.22%)
$firm\ size$	15.0	14.6	(-2.48%)	14.2	(-5.38%)	13.6	(-9.64%)	12.9	(-13.76%)	12.3	(-17.80%)
u	5.68%	7.23%	(1.55%)	8.85%	(3.17%)	10.09%	(4.41%)	11.34%	(5.66%)	12.71%	(7.03%)
v	3.14%	3.02%	(-0.12%)	2.63%	(-0.51%)	2.41%	(-0.73%)	2.22%	(-0.91%)	2.04%	(-1.10%)
$theta$	0.552	0.417	(-24.48%)	0.297	(-46.27%)	0.239	(-56.73%)	0.196	(-64.52%)	0.160	(-70.94%)
$gini$	0.0195	0.0188	(-3.67%)	0.0175	(-10.41%)	0.0169	(-13.14%)	0.0164	(-15.65%)	0.0160	(-17.77%)
GDP	13.2	12.8	(-2.96%)	12.2	(-7.51%)	11.8	(-10.86%)	11.4	(-13.93%)	11.0	(-16.82%)
$welfare$	235	235	(-0.00%)	235	(-0.01%)	235	(0.02%)	235	(0.03%)	235	(0.04%)

6 Conclusion

The contribution of this paper is threefold. First, I show empirically that in times when the labor market condition is bad, employed workers are more likely to become entrepreneurs, while the opposite is true for the unemployed. Second, I build an equilibrium search model of entrepreneurship and unemployment with endogenous job destruction to explain these empirical findings. I show that increasing unemployment risk in recessions leads to an increase in the entry rate from employment, which is due to a combination of opportunistic effect and separation effect. The separation-induced entry, which is often ignored in the literature, is quantitatively important. I show that, absent the separation-induced entry, the unemployment rate during the Great Recession would have been two percentage points higher. Finally, I conduct policy experiments in the model and find results that are unseen in the standard model. For example, increasing unemployment benefits can potentially be beneficial to the economy by inducing more nascent entrepreneurs. A self-employment subsidy can boost the aggregate output as well. Moreover, a decline in labor share would discourage entry from employment with a smaller average firm size.

There are a few promising extensions of the model. First, I abstract from on-the-job search, which can be interesting as an alternative option to entrepreneurship. Also, since the focus is on the entry decision, the firm's exit probability is assumed to be exogenous. Modeling exit decisions could have important implications regarding the business cycle dynamics of entrepreneurship.

Finally, further empirical evidence is necessary to show that the existence of separation-induced entry. Therefore, a more detailed identification of the separation-induced entry using employer-employee matched data is a worthwhile undertaking for future investigation, which is currently an ongoing work of my research agenda. I believe the framework developed in this paper can be useful to investigate the entry decisions into entrepreneurship and to conduct further policy analysis.

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Appendix

A Additional Empirical Results

A.1 Average Marginal Effects

Table A.1 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, the entry rate from employment would increase by 0.015 percentage point, which corresponds to a 12% increase from the mean level. On the other hand, the entry rate from unemployment would drop by 0.084 percentage point, which corresponds to a 13% decrease from the mean level. This shows that the business cycle effects on the entry rates are different and quantitatively significant.

A.2 Robustness

Table A.2 shows various robustness checks. For example, the results are similar when I use OLS and probit models, though in the OLS model the coefficient associated with the cross term between employed and unemployment rate loses significance. Also, when I define entrepreneurs as self-employed workers. I get similar but strong 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 positive 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 business owners are actually employed in different firm owning some business on the side.

Table A.1: Average Marginal Effects (CPS)

Logit model	$entre_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
$unemployed_t$	0.00282***		0.00282***	0.00337***	0.00398***	0.00595***
	(3.51e-05)		(3.55e-05)	(3.91e-05)	(0.000106)	(0.000151)
u_t^{agg}		0.00593***	0.000308	-0.00139*		
		(0.000705)	(0.000713)	(0.000719)		
$employed \times u_t^{agg}$					0.00148*	0.00273**
					(0.000838)	(0.00122)
$unemployed \times u_t^{agg}$					-0.00843***	-0.0116***
					(0.00135)	(0.00197)
$nilf$						0.00446***
						(0.000104)
$nilf \times u_t^{agg}$						-0.0111***
						(0.00113)
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 average marginal effects on $entre_{t+1}$ corresponding to the models (1) to (6) in Table 2. See Table 2 for the logit regression coefficients. See Section 3 for the data construction and definitions.

Table A.2: Regression Results (Robustness)

Logit model			$entre_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OLS	Probit	Selfemployed	Incorporated	Unincorporated	Bus. Owner
$unemployed_t$	0.00855***	0.821***	2.825***	2.118***	2.922***	-0.218***
	(0.000375)	(0.0216)	(0.0376)	(0.103)	(0.0410)	(0.0501)
$employed \times u_t^{agg}$	0.000742	0.307*	1.856***	3.754***	1.160***	-2.996***
	(0.000687)	(0.157)	(0.336)	(0.654)	(0.392)	(0.146)
$unemployed \times u_t^{agg}$	-0.0266***	-1.705***	-5.873***	-4.124***	-5.961***	-5.498***
	(0.00554)	(0.296)	(0.486)	(1.438)	(0.514)	(0.763)
$nilf$	0.00537***	0.605***	3.787***	3.487***	3.806***	-0.715***
	(0.000138)	(0.0138)	(0.0290)	(0.0629)	(0.0326)	(0.0249)
$nilf \times u_t^{agg}$	-0.0220***	-1.634***	-3.152***	-2.526***	-3.180***	-4.965***
	(0.00208)	(0.163)	(0.337)	(0.795)	(0.366)	(0.390)
Constant	-0.00370***	-3.843***	-6.849***	-9.351***	-6.898***	-6.471***
	(0.000161)	(0.0512)	(0.0704)	(0.209)	(0.0743)	(0.0749)
Observations	14,394,049	14,393,290	11,049,947	11,047,463	11,049,947	14,332,247
Controls	YES	YES	YES	YES	YES	YES
*** p<0.01, ** p<0.05, * p<0.1						

Notes: Robust standard errors in parentheses. This table shows the regression results using different specificiations. Columns (1) and (2) shows 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 a incorporated and unincorporated business respectively. Column (6) shows the logit regression results when entrepreneurs are defined as business owners. See Section 3 for the data construction and definitions.

Table A.3: 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 state. The logit regression coefficients show the effects on the log of odds ratio of $entre_{t+1}$. See Section A.3 for the data construction and definitions.

A.3 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 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 bi-annually 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[17]. 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.3 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 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 the 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 become insignificant. Finally, in column (7) I control also the individual fixed effects. The coefficients are almost the same as (6), thought the magnitudes of the effects are slightly smaller.

[17] 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.

A.4 Local Unemployment

In the previous section, I demonstrate the effects of changes in the aggregate unemployment rate on entrepreneurship entry. Some may argue that workers response more to the local labor market condition. Here instead of the unemployment rate at the aggregate 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 market. Here the 2000 definition of commuting zones defined by United States Department of Agriculture Economic Research Service is used[18]. The baseline regression 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.4 shows the regression results using local unemployment rate. Note that compared to Table 2, we have very similar effects of changing unemployment rate, both qualitatively and quantitatively. Again the unemployed workers have 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.5 State-level Cross-sectional Relationship

While Figure 1 and 2 looks 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

[18] The cross tab between countries and commuting zones can be obtained at: https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/

Table A.4: 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^{local}		2.567***	-0.867**	-1.163***		
		(0.413)	(0.427)	(0.422)		
$employed \times u_t^{local}$					0.638	0.925*
					(0.509)	(0.512)
$unemployed \times u_t^{local}$					-5.246***	-4.935***
					(0.766)	(0.760)
$nilf$						1.872***
						(0.0420)
$nilf \times u_t^{local}$						-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 state. 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.

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 there are much stronger correlations. 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 level tend to have higher entrepreneurial entry rate for the employed workers and lower for the unemployed.

A.6 Entry and Separation by Industry

Table A.5: 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.

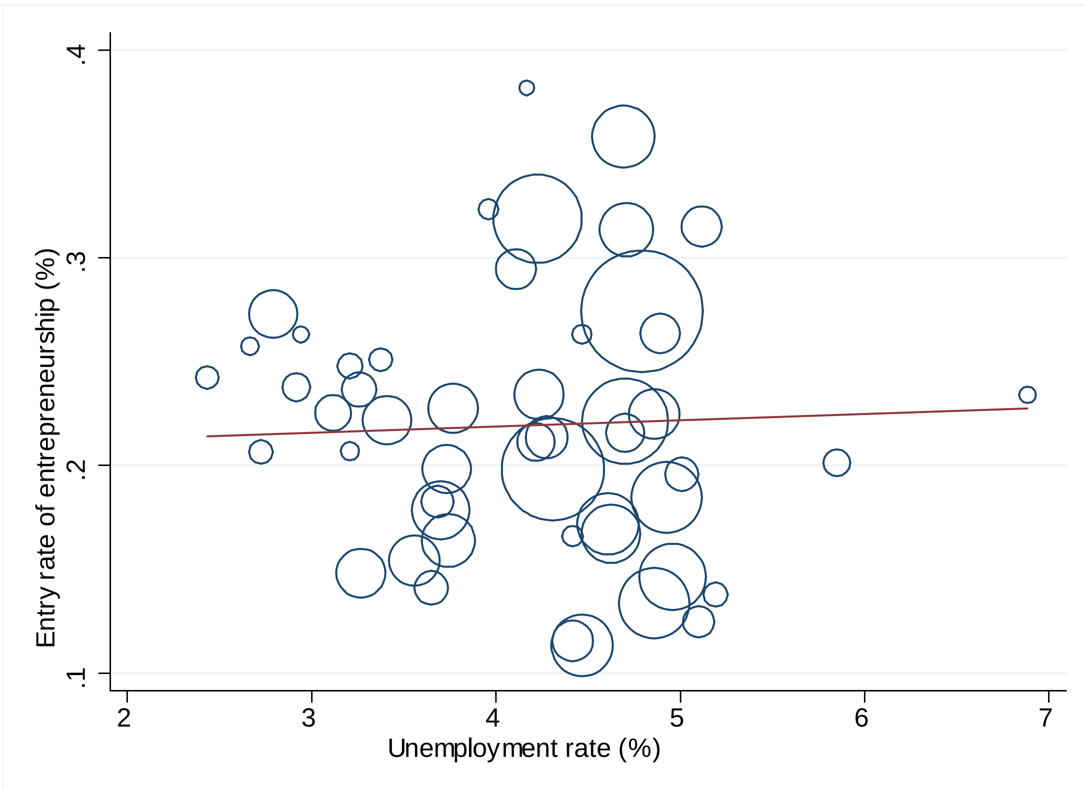

Figure A.1: Entry and Unemployment at the State Level

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

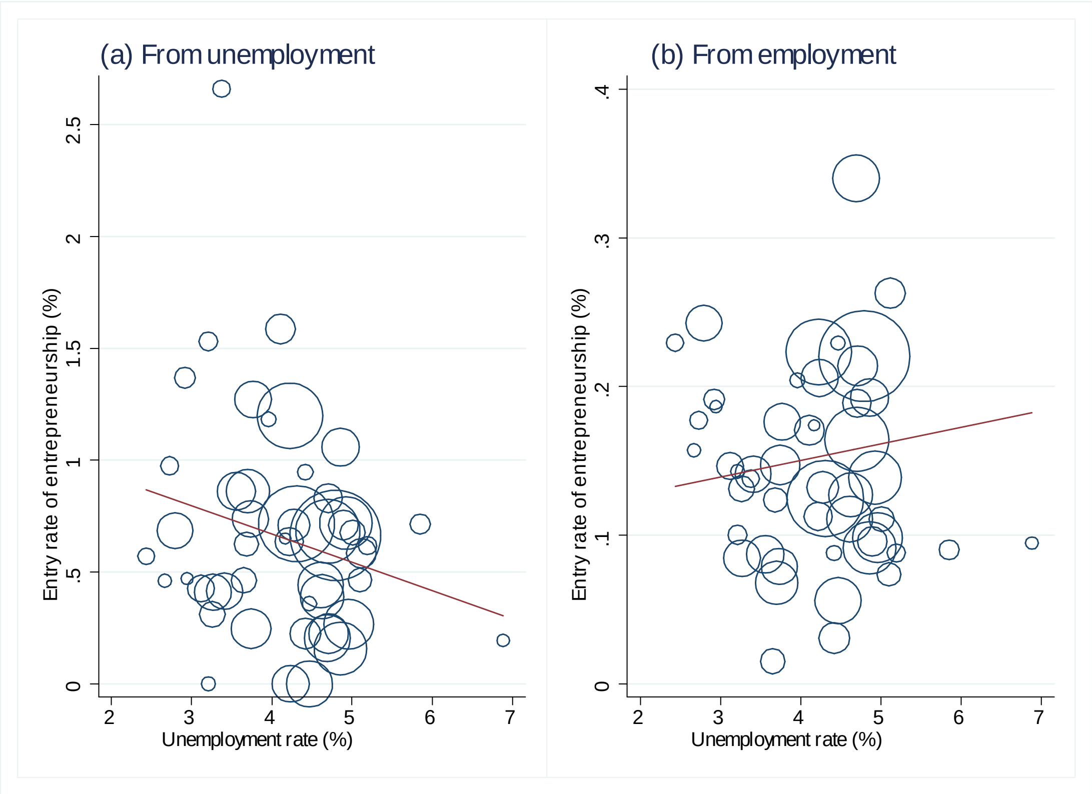

Figure A.2:
Entry and Unemployment at the State Level by Previous Employment Status

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.

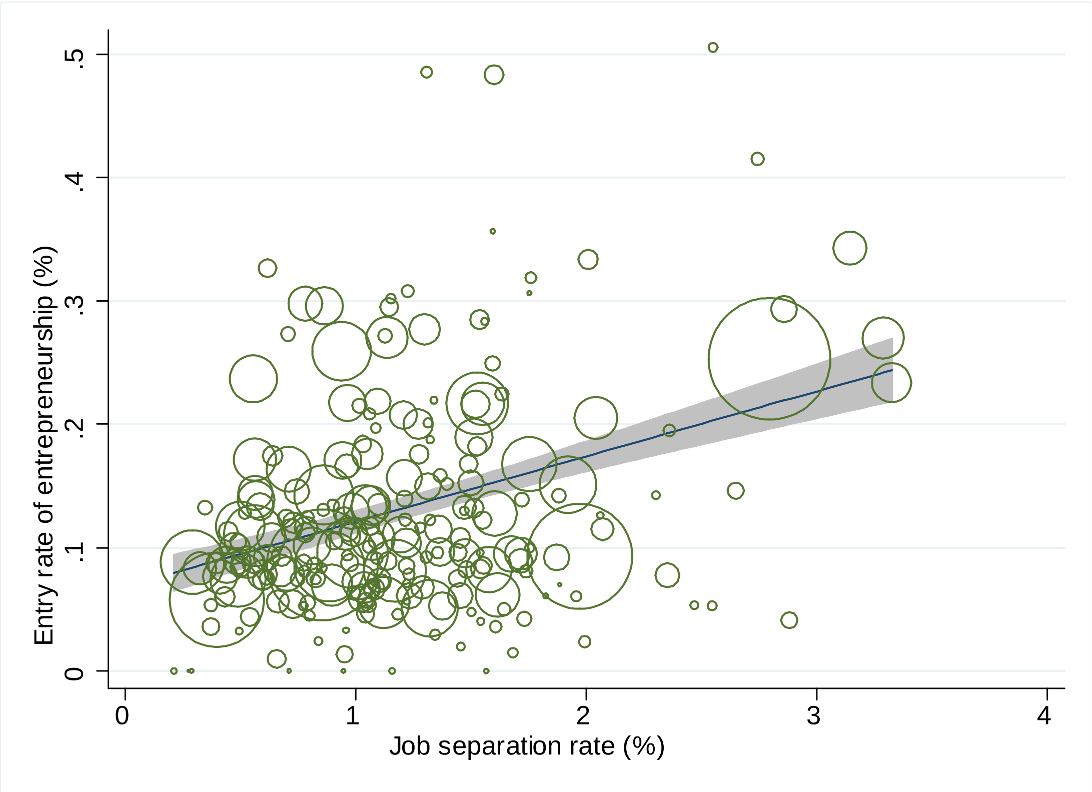

Figure A.3: Entry Rate and Job Separation Rate by Industry

Notes: This figure shows the relationship between the entry rate into entrepreneurship and the job separation rate across different industries using the CPS date. 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.

B Employment growth

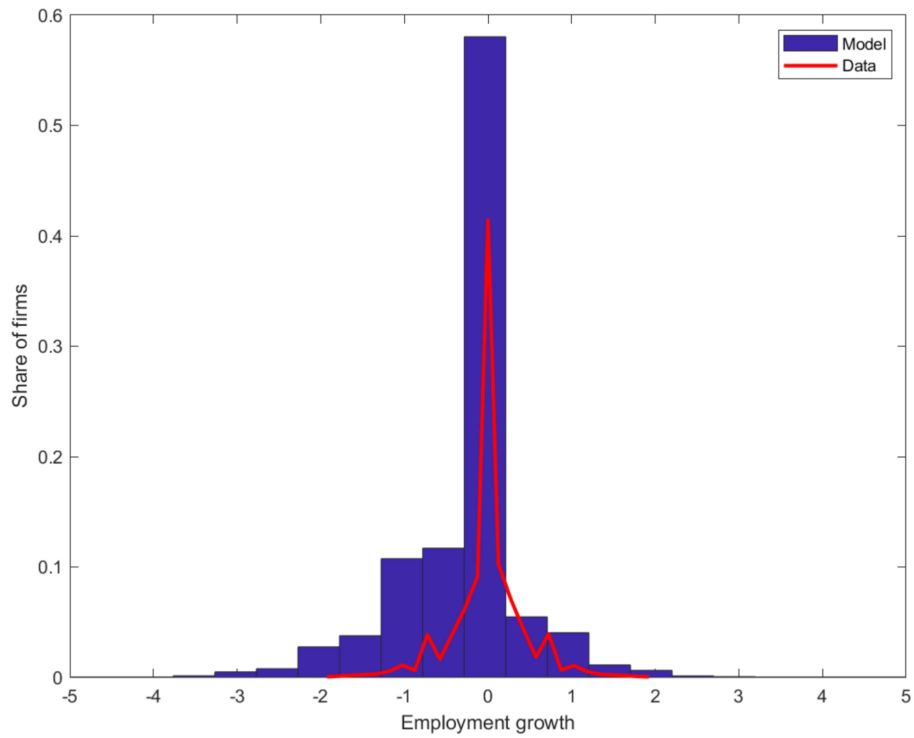

Figure B.1: Employment Growth Distribution

Notes: This figure shows the 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 **?**Elsby2013).

C Business Cycle Statistics

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

	p_t	u_t	jfr_t	jsr_t	$entry_t^u$	$entry_t^w$	v_t	θ_t
σ_x^c	0.105	0.215	0.215	0.101	0.116	0.079	0.186	0.368
$\epsilon_{x,p}$	1.000	0.530	-1.258	-0.611	-0.981	0.625	-0.787	-1.833
Correlation matrix								
	p_t	u_t	jfr_t	jsr_t	$entry_t^u$	$entry_t^w$	v_t	θ_t
p_t	1	0.258	-0.612	-0.633	-0.886	0.827	-0.479	-0.562
u_t		1	-0.918	0.525	-0.418	0.202	-0.812	-0.955
jfr_t			1	-0.156	0.715	-0.538	0.751	0.903
jsr_t				1	0.533	-0.666	-0.507	-0.428
$entry_t^u$					1	-0.903	0.204	0.323
$entry_t^w$						1	-0.117	-0.233
v_t							1	0.949
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 repectively 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	$entry_t^u$	$entry_t^w$	v_t	θ_t
σ_x^c	0.087	0.220	0.241	0.212	0.079	0.065	0.265	0.483
$\epsilon_{x,p}$	1.000	-2.476	2.681	-2.372	0.593	0.342	2.909	5.372
Correlation matrix								
	p_t	u_t	FR_t	SR_t	$entry_t^u$	$entry_t^w$	v_t	θ_t
p_t	1	-0.944	0.998	-0.979	-0.983	0.958	0.995	0.962
u_t		1	-0.959	0.916	-0.985	0.890	-0.966	-0.993
jfr_t			1	-0.979	0.992	-0.957	0.997	0.973
jsr_t				1	-0.969	0.996	-0.963	-0.922
$entry_t^u$					1	-0.949	0.990	0.987
$entry_t^w$						1	-0.936	-0.892
v_t							1	0.983
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 repectively. 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 Wage Equation

The bargaining equation is given by

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

Let

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

From (2) and using the fact that $J_{t+1}(z_{t+1}, n_{t+1}) = \frac{c}{q(\theta_{t+1})}$ for expanding firms, we have

$$\begin{aligned}
U_t - \beta \mathbb{E}_t U_{t+1} &= b + \beta \mathbb{E}_t \left[\begin{array}{c} \lambda^U \int \max\{\Pi_{t+1}(\tilde{z}, 0) - U_{t+1}, 0\}\, dG(\tilde{z}) \\ + \left(1-\lambda^U\right) f(\theta_t)\left(W_{t+1}(z_{t+1}, n_{t+1}) - U_{t+1}\right) \end{array} \right] \\
&= b + \lambda^U \beta \mathbb{E}_t \Gamma_{t+1}\left(\bar{z}^U_{t+1}\right) + \left(1-\lambda^U\right) f(\theta_t)\left(\frac{\eta}{1-\eta}\right) \beta \mathbb{E}_t \frac{c}{q(\theta_{t+1})}
\end{aligned}$$

Also, from (4) and (5), we have

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

$$\begin{aligned}
&\hat{W}_{t+1}(z_{t+1}, n_{t+1}) - U_{t+1} \\
= \;& \lambda^W \int \max\{\Pi_{t+1}(\tilde{z}, 0) - U_{t+1}, W_{t+1}(z, n) - U_{t+1}\}\, dG(\tilde{z}) + \left(1-\lambda^W\right)\left(W_{t+1}(z, n) - U_{t+1}\right) \\
= \;& \lambda^W \left(\Gamma_{t+1}\left(\bar{z}^W_{t+1}(z_{t+1}, n_{t+1})\right) + \int_{z_{\min}}^{\bar{z}^W_{t+1}(z_{t+1}, n_{t+1})} \left(W_{t+1}(z_{t+1}, n_{t+1}) - U_{t+1}\right) dG(\tilde{z}) \right) \\
& + \left(1-\lambda^W\right)\left(W_{t+1}(z_{t+1}, n_{t+1}) - U_{t+1}\right) \\
= \;& \lambda^W \Gamma_{t+1}\left(\bar{z}^W_{t+1}(z_{t+1}, n_{t+1})\right) + \left(1-\pi^W_{t+1}\right)\left(W_{t+1}(z_{t+1}, n_{t+1}) - U_{t+1}\right)
\end{aligned}$$

where

$$\pi^W_{t+1} = \lambda^W \left(1 - G\left(\bar{z}^W_{t+1}(z_{t+1}, n_{t+1})\right)\right)$$

Hence, from (3), we have

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

Therefore,

$$\begin{aligned}
W_t(z_t, n_t) - U_t = \; & w_t(z_t, n_t) - b - \Lambda_t(z_t, n_t) - \left(1 - \lambda^U\right) f(\theta_t) \left(\frac{\eta}{1-\eta} \right) \beta \mathbb{E}_t \frac{c}{q(\theta_{t+1})} \\
& + \beta \mathbb{E}_t (1-s)(1-\sigma_{t+1}) \left[1 - \lambda^W \left(1 - G\left(\bar{z}^W_{t+1}(z_{t+1}, n_{t+1}) \right) \right) \right] (W_{t+1}(z_{t+1}, n_{t+1}) - U_{t+1})
\end{aligned}$$

By the envelope theorem,

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

Finally, combining the bargaining equation (D.1) and (9), and rearranging, we obtain

$$w_t(z_t, n_t) = (1-\eta)(b + \Lambda_t(z_t, n_t)) + \eta \left[p_t z_t f'(n_t) - \frac{\partial w_t(z_t, n_t)}{\partial n_t} n_t + \left(1 - \lambda^U\right) f(\theta_t) \beta \mathbb{E}_t \frac{c}{q(\theta_{t+1})} \right]$$

Following standard procedure, we can solve the ordinary differential equation for the wage equation

$$\begin{aligned}
w_t(z_t, n_t) = \; & \left(\frac{\eta}{1 - \eta(1-\alpha)} \right) \alpha p_t z_t n_t^{\alpha - 1} + (1-\eta) b + \eta \left(1 - \lambda^U\right) \beta f(\theta_t) \mathbb{E}_t \left(\frac{c}{q(\theta_{t+1})} \right) \\
& + n_t^{-\frac{1}{\eta}} \left(\frac{1-\eta}{\eta} \right) \int_0^{n_t} n'^{\frac{1}{\eta} - 1} \Lambda_t(z_t, n') \, dn'
\end{aligned}$$

E Computational Appendix

First, the stochastic processes of the aggregate and idiosyncratic productivity are discretized as follows. The AR(1) stochastic processes (18) and (19) 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 $G(z_Z) = 1$. In the computation exercise, I set $Y = 10$ and $Z = 100$.

The model is then solved recusively 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 (11) and (12).
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 (6) and (15).
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 (9).
   (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 (18) and (19). 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 (7).
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 (3).
8. Update the value of a productive firm $\Pi_t(z_t, n_{t-1})$ using (6).
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 variables. I choose the sample size to be $6,000$ months, which is equivalent to 2000 quarters. The monthly series to 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.