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Entry Decision, the Option to Delay Entry, and Business Cycles

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Abstract

I show that firms' ability to postpone entry has important implications for our understanding of the observed business cycle behavior of start-ups. I use a model that closely replicates the main features of the US firm dynamics to explore and quantify the mechanism. I find that the option to wait endogenously generates a countercyclical opportunity cost of entry: during recessions, a higher risk of failure increases the value of waiting, hence the cost of entry. The mechanism increases the elasticity of entrants to aggregate shocks five times. It is responsible for three-fourths of the observed persistent differences in the recessionary and expansionary cohorts' productivity, survival, and employment. Without the channel, existing models require either large shocks that generate excessive aggregate fluctuations or exogenous mechanisms to reconcile the observed dynamics of entrants. Overlooking this channel may also result in misleading predictions about entrants' responses to different shocks or policies.

Keywords: Entry Decision, Delay, Option Value, Firm Dynamics, Business Cycles

JEL Codes: D25, E22, E23, E32, E37, L25

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1 Introduction

Figure 1 illustrates the business cycle dynamics of the number of entrants together with real GDP and aggregate employment. The number of entrants is three times as volatile as real GDP and four times as volatile as aggregate employment. The recent empirical evidence indicates that the composition of entrants also significantly varies with the initial aggregate conditions. Specifically, cohorts of firms that start operating during recessions employ fewer workers at entry and over time, although they are, on average, more productive and have higher survival rates than their expansionary counterparts.[2] Despite the importance of start-ups for aggregate job creation and economic growth, we lack a microfounded explanation of what drives the observed selection of entrants across initial conditions.

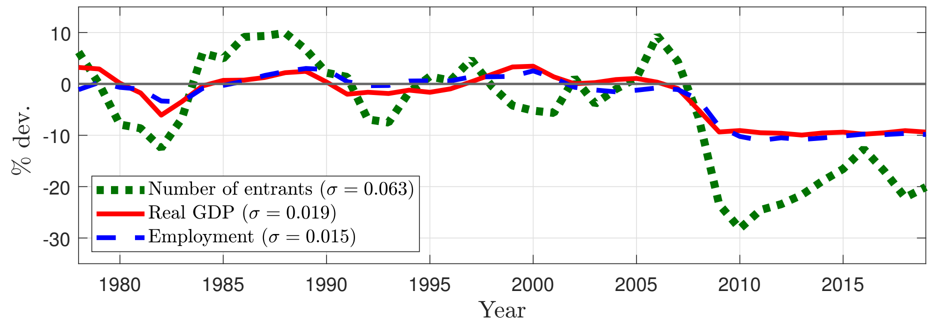
I show that firms' ability to delay entry has important implications for our understanding of start-ups' business cycle dynamics. The theory is motivated by a large body of microeconomics literature, which shows that an option to postpone an irreversible project makes investment especially sensitive to aggregate risks.[3] The neoclassical investment rule – invest in a project when its net present value (NPV) is non-negative – has been widely criticized for ignoring the option. Starting a business is a largely irreversible investment associated with high failure risks that vary with the aggregate states. Therefore, the option to choose initial conditions before committing resources could fundamentally alter firms' entry decisions. However, existing firm dynamics models that find it challenging to reconcile the observed dynamics of entrants have not considered the channel yet. In this paper, I develop a tractable framework to theoretically and quantitatively evaluate the role the option to delay plays in the documented business cycles dynamics of entrants and economic aggregates.

I begin by presenting empirical evidence supporting the option-to-delay channel. First, I briefly summarize recent empirical findings, which demonstrate that the composition of entrants significantly varies with the initial aggregate conditions. Next, I provide empirical evidence showing that entrants choose to wait for better aggregate conditions before committing their resources. I utilize the newly developed Business Formation Statistics (BFS) dataset that allows tracking the timing of the market entry decisions made by aspiring start-ups. I show that the share of firms that postpone starting a business is negatively correlated

[2] See Lee and Mukoyama (2015), Moreira (2016), Ates and Saffie (2021), Sedlacek and Sterk (2017). I use annual state-level Business Dynamics Statistics dataset over 1978-2019 to additionally document the persistent differences between the cohort-level employment, firms, and survivall, as shown in Table 6.

[3] For example, see Pindyck (1991), Bernanke (1983), and McDonald and Siegel (1986). See Dixit and Pindyck (1994) for a detailed discussion.

Figure 1



Note. The empirical time series represents the deviations of the log number of entrant establishments, log real GDP and log aggregate employment from their respective trends in the US over the period 1978-2019. To find the cyclical properties of these time series, I use a linear detrending method that allows a structural break in the trend (for details see Appendix D.2). *Source:* BDS, FRED.

with the aggregate conditions at entry.

To explore the implications of the option-value channel, I develop a heterogeneous firm dynamics model with endogenous firm entry and exit and aggregate demand volatility. Firms operate in monopolistically competitive markets and make decisions about production and exit. Potential entrants hold heterogeneous signals about their post-entry initial productivity. I deviate from the existing framework by allowing potential entrants to retain their signals over time if they choose to postpone entry after observing the aggregate state. The decision to enter today or postpone entry until tomorrow is mutually exclusive, creating a non-negative option value of delay that varies depending on the signal and the level of aggregate demand.

I find that the option to wait leads to an endogenous countercyclical opportunity cost of starting a business, which increases the elasticity of entrants with respect to the initial aggregate conditions. The mechanism works through the procyclical variation in survival rates: during recessions, in addition to lower profits, potential entrants expect to lose part of their long-run benefits due to the increased risk of post-entry failure. The higher the expected long-run value, the higher the expected cost of prematurely exiting the market. With the intertemporal choice, the latter value increases the threshold cost of entry, generating a new group of firms that choose to stay outside the market even if the net expected lifetime profits are more than zero.

To evaluate the quantitative implications of the option-value channel, I parameterize the model to match the main features of the US entrants' average life-cycle dynamics. The calibrated model closely replicates the average size, survival, and exit hazard rates of firms for up to the age of thirty. It also successfully matches the share of firms by cohort age in the total number of firms and the share of employment by cohort age in aggregate employment. The key parameters that shape the business cycle firm dynamics are those that drive the aggregate demand shock process. These exogenous shocks affect incumbent firms' production and exit decisions and determine entrants' expected lifetime profits. At the same time, the shock process shapes the endogenous countercyclical entry cost function, hence the option-value effect. Therefore, I discipline the channel by jointly matching the business cycle dynamics of the total number of firms and entrants in the model and the data.

I show that the calibrated model successfully accounts for the documented persistent and significant differences in the life cycle characteristics of cohorts born at different stages of business cycles. Specifically, due to the increased cost of entry, groups of firms that enter the market during recessions are, on average, more productive than their expansionary counterparts. At the same time, the recessionary cohorts consist of around 12% fewer firms, employ 8% fewer workers and have a 2.1 percentage point higher survival rates at entry. These differences persist over the cohorts' life cycles, with the recessionary cohorts consisting of around 8% fewer firms, employing 7% fewer workers, and having a 1.8 percentage point higher survival rate than their expansionary counterparts at age five. Using the annual state-level BDS dataset, I demonstrate that the model's predicted differences are very close in magnitude to the data.

I find that the selection of entrants across aggregate conditions has an important role in shaping the cohort-level and aggregate dynamics. First, I show that more than two-thirds of the differences between the recessionary and expansionary cohorts are due to the variation in the number and composition of firms at entry rather than the shocks they face over their life cycle. Next, I quantify the role of the persistent cohort dynamics in aggregate fluctuations. Toward the end, I study baseline economy's response to a shock series that matches the variation in the number of entrants from 1978 to 2019 in the data – illustrated in Figure (1), and the model. I find that the simulated dynamics of the economic aggregates closely track the data counterpart. That is, the correlation between the cyclical component of aggregate employment in the model and the data is around 0.93. The variation in the types of firms at entry is responsible for roughly 20% of the total variance in aggregate employment, which is a considerable contribution compared with a small share of entrants' employment.

The option-value channel is quantitatively important in accounting for the observed business cycle dynamics of entrants. In the model, firms do not start businesses during recessions because the NPV of entry falls (direct effect), and the cost of entry increases due to the option to wait (indirect effect). To isolate and quantify the indirect effect, I evaluate the model's performance without the intertemporal choice. I find that the endogenous countercyclical opportunity cost of entry increases the elasticity of entrants to aggregate shocks by a factor of five and reduces the differences in the productivity composition of entrants by a factor of ten. Furthermore, the direct effect is only responsible for approximately 20% and 25% of the persistent differences in the number of firms and employment across cohorts, respectively. More importantly, the countercyclical survival rates are completely driven by the medium-productivity entrants who choose to delay business formations. In terms of aggregate fluctuations, the selection through the option-value channel is responsible for 25% of the volatility in the model-simulated aggregate employment, which corresponds roughly to 12% of the volatility in the data counterpart.

Next, I compare the performance of the baseline model to a workhorse firm dynamics model, parameterized to match the same set of empirical facts. I find that a model without delay relies on large shocks to account for the observed elasticity of entrants to initial conditions, as the NPV of entry is otherwise insensitive to aggregate shocks. The response of incumbent firms to this calibrated shock process leads to excessive aggregate fluctuations that, in turn, significantly underestimate the relative importance of entry margin. Existing literature uses various approaches to reconcile the observed selection of entrants for a reasonable aggregate demand shock process. One option is to use exogenous entry cost shock or a cost function that varies with the business cycles, as in Lee and Mukoyama (2018), and Clementi and Palazzo (2016), or introduce entry function, which allows choosing the elasticity of entrants to aggregate shocks, as in Sedlaćek and Sterk (2017). In that respect, the option-value channel provides a microfoundation for these exogenous mechanisms by endogenously generating a countercyclical cost of entry.

Furthermore, I argue that overlooking the option-to-delay channel may lead to misleading predictions about potential entrants' responses to different shocks or policies. The reason is the following. With the intertemporal choice, the dynamics of entrants depend on how the changes in the aggregate environment affect the relative benefits of entry today versus tomorrow. Whereas the standard frameworks only account for the shock's direct effect. I show that the option-value channel qualitatively and quantitatively alters the existing model's predictions about the responses of entrants to shocks, depending on the magnitude, timing, and duration of the shocks.

Relation to the Literature The paper contributes to the existing business cycle firm dynamics literature along three dimensions. First, accounting for the option to delay entry, which leads to an endogenous countercyclical opportunity cost of entry, allows theoretical firm dynamics models to endogenously generate the observed substantial variation in the number and composition of entrants. Samaniego (2008) demonstrates that in a standard model, entry and exit are insensitive to productivity shocks of a reasonable magnitude. Lee and Mukoyama (2018) show that generating the substantial selection of entrants in Hopenhayn and Rogerson (1993) framework is a puzzle that can be solved by introducing an entry cost that varies over the cycles in a specific way. Others use exogenous entry cost shocks (e.g., Clementi and Palazzo, 2016), or introduce an entry function, which allows for choosing the elasticity of entrants to aggregate shocks (e.g., Sterk, Sedla'cek, and Pugsley, 2021). The observed difficulty of existing frameworks in accounting for the dynamics of entrants can be attributed to the fact that expected life cycle profits from entry do not vary much with a mean-reverting aggregate shock process. This finding is supported by the empirical microeconomics literature, which documents that expected lifetime profits do not vary much over time. Consequently, the standard entry decision rule also fails empirically to predict the dynamics of entrants, highlighting the need to account for additional factors, such as the option to delay entry, in order to better understand firm entry (e.g., O'Brien, Folta, and Johnson (2003), Geroski, 1995). Using the newly developed BFS dataset, I am able to provide empirical evidence showing that a part of the business cycle variation in start-ups can be attributed to potential entrants' option to delay entry.

Second, the selection of entrants through the option-to-delay channel complements the forces identified in existing literature as drivers of the observed persistent and significant differences between recessionary and expansionary cohorts. Sedlaćek and Sterk (2017) reconcile these differences through the variation in the share of niche and mass product firms, while Smirnyagin (2022) emphasizes the importance of the share of high-target size firms across cohorts. Moreira (2016) highlights the role of persistent customer capital accumulation processes in driving the wedge between these cohorts. In Ates and Saffie (2021), selection during financial crisis generates entrants that are fewer but better in terms of idiosyncratic productivity. Gourio, Messer and Siemer (2015) emphasize the role of the 'missing generation' in driving the cohort-level differences. In my paper, the procyclical variation in the medium-productivity entrants who choose to wait for better aggregate conditions provides an additional channel that drives the differences in post-entry dynamics of cohorts. This mechanism is in line with Pugsley, Sedlaćek, and Sterk (2016), who document that the differences in cohorts' life cycle dynamics are mainly due to variations in the types of firms within a cohort, rather than the shocks they face after entry.

Third, the paper contributes to the firm dynamics literature that evaluates the role of entry margin in shaping aggregate fluctuations. Lee and Mukoyama (2008), Bilbiie, Ghironi, and Melitz (2012), Clementi et al. (2014), and Clementi and Palazzo (2016) find that endogenous dynamics in the entry and exit margins significantly propagate aggregate shocks. Haltiwanger et al. (2013) emphasize the importance of accounting for the life-cycle demographics of entrants in measuring and understanding the total contribution of the entry margin to economic growth. Using a model that closely replicates the life cycle characteristics of cohorts of firms in the US, both on average, and over the business cycles, I show that the documented persistent differences in cohorts' characteristics significantly amplify and propagate aggregate shocks. In that regard, this paper also relates to the literature that studies the role of persistent drop in firm entry in propagating the slow recovery following the Great Recession (e.g., Gourio, Messer and Siemer (2016), Siemer (2016), Khan, Senga, and Thomas (2016), Sedlaćek, 2020) and the literature that investigates the propagation mechanism of standard business cycle models (e.g., Cogley and Nason (1995), King and Rebelo, 1999).

This paper is closely related to a considerable theoretical and empirical microeconomics literature that study investment under uncertainty (e.g., Abel (1983), and Abel and Eberly, 1994). Notably, the paper shares a strong connection to the subset of this literature that emphasizes the importance of the option to time an irreversible project in explaining investment behavior under aggregate uncertainty (e.g., Bernanke (1983), McDonald and Siegel (1986), Abel et al. (1996), and Pindyck, 1991). For detailed review see Dixit and Pindyck, 1994. Pindyck (2009) shows that various risks to post-entry profits magnify the cost of entry. I extend the workhorse Hopenhayn (1992) firm dynamics model to account for the timing of firm entry. Consistent with this literature, I also find that this channel, combined with the procyclical variation in the risk of failure, increases the cost of entry and has a substantial impact on firm entry decisions. That said, the paper also relates to the macroeconomics literature that studies the role of real options in shaping aggregate dynamics (e.g., Jovanovich (1993), Veracierto (2002), and Bloom, 2009). Fajgelbaum, Schaal and Taschereau-Dumouche (2017) show that in a framework where agents learn from the actions of others, high uncertainty about fundamentals discourages investment through this channel.

This paper is also closely related with a body of research that links business cycles to firms' or entrepreneurs' decisions to optimally time growth-enhancing activities, such as innovation and invention. Notable examples include Shleifer (1986), who demonstrates that business cycles can be implemented endogenously in a framework where entrepreneurs strategically time the introduction of new technologies with a limited-time return during booms, in order to maximize their profits. Barlevy (2007) demonstrates that when innovators can only appropriate the spillovers from their research for a limited number of periods, they choose to invest more in R&D during expansions, when high profits are expected to last for a longer period. In line with this literature, in my paper, entrants receive profits for a limited duration due to a combination of endogenous procyclical survival rates and exogenous exit. As a result, entrants have incentives to strategically time their entry decisions, which in turn contributes to the amplification of business cycle fluctuations.

The trade literature has long been interested in the optimal timing of entry into foreign markets. A few examples among many include Alessandria and Choi (2007) and Fitzgerald et al. (2023). Fitzgerald and Haller (2018) connects customer capital mechanisms with firm selection patterns in export markets. Finally, this paper is part of a larger body of literature that examines the relationship between business cycles and the opportunity cost of different activities (e.g., Aghion and Saint-Paul (1998), and Chodorow-Reich and Karabarbounis, 2016).

The rest of the paper is organized as follows. Section 2 provides empirical evidence for the option to delay entry channel. Section 3 presents the model, and Section 4 examines how the option to delay entry affects firm entry decisions at the micro and macro levels. The model calibration procedure and a strategy to discipline the option-value channel are outlined in Section 5. Section 6 evaluates the quantitative importance of the option to delay entry. Section 7 presents a range of extensions of the baseline model to verify the robustness of the result. Finally, Section 8 concludes.

2 Empirical Evidence

This section presents empirical evidence that supports the option-to-delay channel. First, I summarize relevant findings, suggesting that initial aggregate conditions play a significant role in determining the types of firms that choose to enter the market under various aggregate conditions. Next, I document that part of the business cycle variation in the number of start-ups is due to firms' decisions to delay entry.

2.1 Entry Conditions and Start-ups' Life Cycle Dynamics

Below is a brief summary of recent empirical findings showing that the composition of entrants significantly varies with the initial aggregate conditions.

Fact 1. *Cohorts of firms that start operating during recessions are, on average, more productive at entry and over time compared to their expansionary counterparts.*

Ates and Saffie (2021) use data from the Chilean manufacturing census (ENIA) to document that firms born during a crisis are, on average, more productive (measured by revenue total factor productivity) at both entry and over time compared to firms born during normal times. Using the US Annual Survey of Manufacturers, Lee and Mukoyama (2015) show that the average productivity (measured by total factor productivity) of plants born during recessions is 10%-20% higher compared to those established during booms. Moreira (2016) supports the evidence using detailed micro-level data from the Longitudinal Business Database (LBD) covering the universe of non-farm establishments in the US.

The prior literature (Syverson, 2011) suggest that higher productivity firms are more likely to survive compared to their less efficient industry competitors. Next fact supports the claim.

Fact 2. *Cohorts of firms that start operating during recessions exhibit, on average, higher survival rates at entry and over time compared to their expansionary counterparts.*

Using the annual Business Dynamics Statistics (BDS) dataset over the period 1978-2019, I provide a robust finding that cohorts of firms that start operating during recessions consist of fewer firms that, on average, survive longer than their expansionary counterparts.[4] Appendix A.1 provides an extensive documentation of this fact. Ates and Saffie (2021) also document that firms born during a crisis are less likely to exit during their life cycle compared to firms established during normal times. Fact 2 also emphasizes that the documented cohort-level productivity differences are not due to ex-post selection of firms.

Fact 3. *Cohorts of firms that start operating during recessions, on average, employ fewer workers in total, both at entry and over time, compared to their expansionary counterparts.*

Lee and Mukoyama (2015) found that recessionary plants have a 31% lower job creation rate compared to their expansionary counterparts. According to Sedla'cek and Sterk (2017),

[4] The BDS dataset covers the universe of employer businesses in the US and provides yearly measures of business dynamics aggregated by the establishment and firm characteristics. An establishment is defined as a fixed physical location where economic activity is conducted. A firm might span multiple physical locations and consist of one establishment or many establishments.

cohorts of firms that start operating during recessions employ significantly fewer workers in total compared to their expansionary counterparts, and these differences persist as the cohorts age. Using detailed micro-level data from the Longitudinal Business Database (LBD), Moreira (2016) and Smirnyagin (2022) show that firms that start operating during recessions start on a smaller scale and remain smaller compared to expansionary firms.

Next fact highlights the strength of the selection mechanism by assessing the impact of aggregate conditions at inception on overall size of cohorts upon entry. I use the BDS dataset that covers the universe of employer businesses in the US and provides yearly measures of business dynamics aggregated by the establishment and firm characteristics.[5] After controlling for year-fixed effects, I find that better initial conditions are associated with a smaller average size of cohorts of establishments (firms).[6] However, as the cohort ages, the effect of initial conditions tends to dissipate. Appendix A.2 provides an extensive documentation of this fact. Lee and Mukoyama (2015) also finds that compared to plants that enter in booms, recessionary plants, on average, start with about 30% more workers.

In summary, initial aggregate conditions significantly affect both the number and composition of firms, leading to significant and persistent differences in cohorts' post-entry dynamics.[7] Consequently, identifying the factors that drive the observed business cycle dynamics of entrants is crucial for accurately quantifying their contributions to aggregate fluctuations.

[5]An establishment is defined as a fixed physical location where economic activity is conducted. A firm might span multiple physical locations and consist of one establishment or many establishments.

[6]In this analysis, an average size of a cohort of age g at year t is measured as $\bar{L}_{g,t} = L_{g,t}/N_{g,t}$ where $L_{g,t}$ and $N_{g,t}$ measure the total employment and total number of establishments (firms) in a cohort of age g at time t. Moreira (2016) and Smirnyagin (2022) base their findings on unique longitudinal micro-level data, where the unit of analysis is the employment of an establishment (firm). Their main findings reveal how aggregate conditions at inception shape the life cycle size of an average business within an entering cohort. Note that the term $\bar{L}_{g,t}$ also accounts for the variation in the composition and size of entering cohorts. Additionally, although the aggregate statistics in the BDS are based on the LBD dataset, the authors' choice of business birth definitions, data cleaning procedures, and final sample selections could potentially result in discrepancies between the LBD and the publicly available BDS dataset, especially concerning the dynamics of aggregate averages.

[7]In Appendix A.4, I provide additional support for the *selection* hypothesis using information about the dynamics of entrants across industries. As per the existing literature, we can expect industries with more procyclical entry to exhibit a higher selection of entrants. Using two-digit US sector-level data from the BDS dataset, I show that industries with more procyclical entry have more countercyclical survival rates (Figure 19). Furthermore, the following two findings also support the selection hypothesis: (1) A positive relationship between the industry-level cyclicality of entry and the relative size of recessionary cohorts compared to expansionary cohorts (Figure 20). (2) Industries exhibiting higher countercyclical survival rates also tend to have larger relative size of recessionary cohorts compared to expansionary cohorts (Figure 21). These findings align with Moreira (2016), which finds that the selection effect dampens the procyclicality of firm average size across industries.

2.2 Evidence of Entry Timing

Next, I document that part of the business cycle variation in the number of start-ups comes from the firms' option to delay entry. Identifying the latter requires information about the dynamics and decisions made by aspiring start-ups before they enter the market. The newly developed Business Formation Statistics (BFS) dataset provides a subset of the information.

The BFS dataset is based on applications for Employer Identification Numbers (EINs) submitted in the US, known as IRS Form SS-4 filings.[8] Information provided in the EIN application is used to identify a subset of applications associated with the start of new businesses, referred to as business applications (BA).[9] The BAs are matched to the set of firms in the BDS dataset identified as new employer businesses based on payroll information. The matching process is straightforward because both of the datasets contain Information about EINs. The publicly available part of the BFS dataset provides the US- and state-level time series about the number of employer start-ups that form businesses within the first eight quarters from the date of the EIN application (***F**8Q*). This group of businesses covers more than 80% of the total number of entrants each year in the US.[10]

In the analysis, I consider the time series of the number of applications that form businesses within the *first* four (***F**4Q*) and *second* four (***S**4Q*) quarters from the date of the application. To identify the business cycle dynamics of start-ups due to the option to delay entry, I construct a times series about the share of the applications that form businesses with one year delay, $\mathbf{S}4Q/F8Q$. I refer to this variable as the *share of late start-ups*.[11] I use the latter time series to test the following hypothesis. Suppose the aggregate state has a significant effect on the number of start-ups through the option-to-delay channel. Then, the share of the applications that form businesses with one year delay should increase if the aggregate

[8]The EIN is a unique number assigned to most of the business entities. The EIN is required when the business is providing tax information to the Internal Revenue Service (IRS).

[9]The EIN application contains information about reasons for applying, type of entity, business start date, the expected maximum number of employees, the first wage pay date, the principal activity of a business, and etc.

[10]For more details see Appendix A.5, Figure 22.

[11]Information about the raw number of EIN applications alone does not help identify delays in business formation due to the following reasons. On the one hand, potential entrants who delay entry might not apply for the EIN applications. Thus, they are not included in the BFS dataset. On the other hand, some parts of the EIN applications might not be for employer business start-ups. In fact, the data about the raw applications is quite noisy about the business formation. For example, out of the total number of business applications, we see that only 14% become employer businesses within two years from the date of the application. Even after considering the subset of the applications with higher rates of employer business births (Business Applications with Planned Wages, Business Applications from Corporations, High-propensity Business applications), the transition rate does not exceed 36%. Bayard et al. (2018) argue that a significant share of the business applications ends up becoming non-employer businesses.

Table 1: Summary statistics

	Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A. State-level	*Share of late start-ups*	2,142	0.13	0.03	0.02	0.26
	$Dur\boldsymbol{F}4Q$	2,142	1.02	0.16	0.55	1.99
	$Dur\boldsymbol{S}4Q$	2,142	5.43	0.20	4.83	6.21
	$Dur\boldsymbol{F}8Q$	2,142	1.58	0.27	0.81	2.62
Panel B. US-level	*Share of late start-ups*	42	0.14	0.02	0.11	0.18
	$Dur\boldsymbol{F}8Q$	42	1.66	0.17	1.37	1.96
	$Dur\boldsymbol{S}4Q$	42	5.46	0.26	4.95	5.75
	$Dur\boldsymbol{F}4Q$	42	1.06	0.09	0.88	1.21

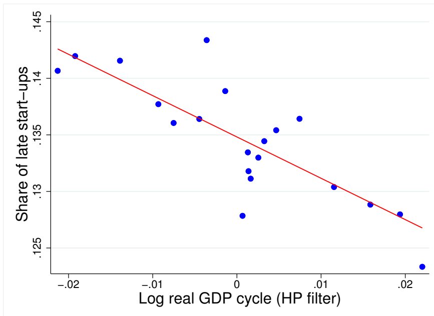
conditions at the time of the applications are unfavorable.

Table 1 reports the summary statistics of the share of late start-ups. At the state level (Panel A), the average share of late start-ups equals 13%. That is, out of the total applications that form businesses in the first eight quarters, 13% start businesses with one-year delay. This variable varies from 2% to 26% across time and states, with the overall standard deviation around 3 percentage point. At the US level, the average share of late start-ups equals 14% and varies from 11% to 18% across time. The table also includes variables that describe average duration (in quarters) from a business application to formation conditional on business formation within the first four quarters ($Dur\boldsymbol{F}4Q$), eight quarters ($Dur\boldsymbol{F}8Q$), and the second four quarters ($Dur\boldsymbol{S}4Q$). These time series are quarterly and span the period 2004Q3-2015Q4. Business formation among $\boldsymbol{F}4Q$ happens within the first two quarters. Similarly, business formation among the applications that become start-ups within the *second* four quarters happens between the fifth and sixth quarters from the quarter of the application. Panel B of Table 1 reports the same statistics for the aggregate data. Appendix A.5 provides a detailed description of the dataset.

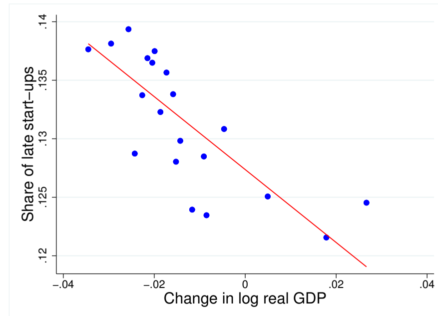
To assess economic conditions at the time of the application, I use the following business cycle indicators: (1) The cyclical component of the quarterly log real GDP. To find the cyclical component of the yearly log real GDP I apply the HP filter with a smoothing parameter of *1600*. (2) Change in the log annual real GDP between t and $t+1$. I measure the latter as a change in the rolling sum of the consecutive four quarters starting from the quarter of the application.[12] The positive value of this variable indicates that the economic condition today is expected to be better compared to tomorrow. I construct both of the indicators at

[12]For example, if the applications date is 2010Q3, I calculate annual GDP as $Y_{2010Q3}+Y_{2010Q4}+Y_{2011Q1}+Y_{2011Q2}$ and then calculate the difference as $log(Y_{2010Q3}+Y_{2010Q4}+Y_{2011Q1}+Y_{2011Q2})-log(Y_{2011Q3}+Y_{2011Q4}+Y_{2012Q1}+Y_{2012Q2})$.

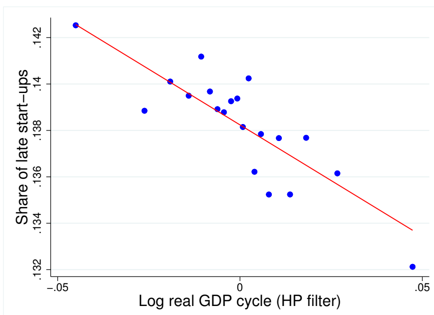
Figure 2: The share of late start-ups against the aggregate economic conditions at the date of the application



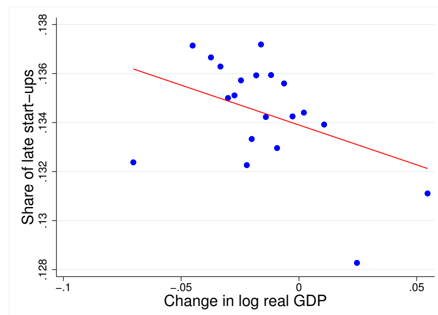
(a) US-level



(b) US-level



(c) State-level



(d) State-level

Note: Each panel illustrates a binned scatterplot of the share of late start-ups against the aggregate conditions at the time of the application. Panels (a) and (b) display correlations at the US level. Panels (c) and (d) illustrate correlations at the state level. All of the plots control for linear and quadratic time trends and include quarter-fixed effects. In Panels (c) and (d), I also control for the state-level fixed effects.

the state- and country-level.

Figure 2 illustrates the binned scatter plots of the share of late start-ups against the business cycle indicators at the time of applications. Panels (a) and (b) illustrate correlations at the US level, while Panels (c) and (d) display this relationship at the state level. The figures show that the share of late start-ups increases if the aggregate conditions at the time of the applications are below trend, measured by the HP-filtered real GDP. And, the share of late start-ups increases if the outlook for tomorrow is better, measured by the change in real GDP. These relationships hold at the country as well as state level. Based on this analysis, we can conclude that the share of the applications that form businesses with one year delay is negatively correlated with the economic conditions at the time of the application.

Next, I use the state-level variation in the share of late start-ups to further investigate the mechanism behind the relationship. I estimate the following regression

$$y_{s,t} = \alpha_0 + \beta Z_{s,t} + \alpha_1 Dur\mathbf{F}4Q + \alpha_2 Dur\mathbf{S}4Q + \alpha_3\mathbf{F}8Q + \alpha_4 WBA + \gamma_s + \eta_q + \varepsilon_{s,t},$$

where $y_{s,t}$ describes the share of late start-ups in state s at time t. $Z_{s,t}$ describes business cycle conditions in state s at time t. Additionally, I include variables that could lead to the variation in the share of late start-ups that are not due to the waiting for better aggregate conditions. For example, obtaining credit to finance start-up activity might take more time during recessions, which could automatically increase the share of late start-ups. To account for the latter effect, I control the variation in the average duration from a business application to formation within the first ($Dur\boldsymbol{F}4Q$) and second ($Dur\boldsymbol{S}4Q$) four quarters. To control for the variation in the total number of business formation and applications, I include the total number of applications that become employer businesses within the first eight quarters (**F**8Q). I also include the total number of wage-based business applications (WBA) to control for the variation in the composition of applications. The latter is a subset of business applications that indicate the intention of paying wages. Finally, γ_s and η_q control for the state- and quarter-fixed effects, respectively. That said, the coefficient β measures a percentage point change in the share of late start-ups due to the variation in the business cycle conditions at the time of the application, that are not due to changes in the average duration of the application and the variation in the total number of business applications.[13]

Table 2 reports the results of the regression equation (1). Panel A considers state-level variation in the share of late start-ups. Column (1) uses the state-level HP-filtered log real GDP as a business cycle indicator. The result shows that improving aggregate conditions at the date of the application decreases the share of late start-ups. Specifically, a 1 percentage point increase in the real GDP above the trend decreases the share of late start-ups by 0.063 percentage points. Column (2) considers the state-level change in the log real GDP as a business cycle indicator. The estimate implies that the improving aggregate economic conditions tomorrow relative to today has a statistically significant and positive effect on the share of late start-ups. Overall, Columns (1) and (2) support the original hypothesis that part of the business cycle variation in the start-ups is due to entrants' option to delay entry.

Finally, to check the robustness of these estimates, I consider the following exercises. Columns (3) and (4) of Panel A use business cycle conditions at the US level rather than the state

[13] In the appendix, I also consider a regression specification that includes interactions of the control variables with the business cycle indicators. The results of the coefficients are highly robust to the latter specification.

Table 2: The option to delay entry and business cycles

	Panel A. State-level share of late start-ups				Panel B. US-level share of late start-ups	
$Z =$	$Y_{HP\ s,t}$ (1)	$\Delta Y_{s,t}$ (2)	$Y_{HP\ t}$ (3)	ΔY_t (4)	$Y_{HP\ t}$ (1)	ΔY_t (2)
β	-0.062***	-0.068***	-0.187***	-0.154***	-0.326***	-0.165***
	(0.017)	(0.017)	(0.026)	(0.036)	(0.084)	(0.037)
DurF4Q	0.042***	0.042***	0.037***	0.027***	0.087***	0.071**
	(0.006)	(0.005)	(0.006)	(0.006)	(0.025)	(0.027)
DurS4Q	-0.062***	-0.020	-0.062***	-0.010	-0.201**	-0.086
	(0.008)	(0.016)	(0.007)	(0.016)	(0.096)	(0.125)
F8Q	0.006*	0.016***	0.004	0.001	0.017	0.013
	(0.003)	(0.003)	(0.004)	(0.001)	(0.013)	(0.009)
WBA	-0.021***	-0.011***	-0.014***	-0.014***	-0.013	-0.021***
	(0.001)	(0.005)	(0.003)	(0.004)	(0.010)	(0.007)
State FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Observations	2,040	2,040	2 040	2,040	39	35
R-squared	0.815	0.699	0.818	0.720	0.967	0.757

Note. Robust standard errors are in parenthesis. In Panel A the robust standard errors are clustered at state-level. The table reports results from a linear regression with a dependent variable the *share of late start-ups*. *** significance at 0.01 level, ** significance at 0.05 level, * significance at 0.10 level.

level. Panel B of Table 2 runs the same regression using the US-level time series of the share of late start-ups. Again, we see that deteriorating aggregate conditions have a statistically significant and positive effect on the share of late start-ups. To conclude, the results show that part of the variation in the new business formation as a response to the changes in the aggregate conditions at entry is due to firms' option to delay entry.

It is important to note that due to data limitations, the empirical result provides only partial evidence and does not fully capture the quantitative significance of the option value channel. The rationale behind this is as follows: A considerable portion of entrants that potentially decide to delay entry do not appear in the BFS. This includes entrants who postpone both entry and EIN application, as well as those who apply for EINs but ultimately decide to delay entry and never re-enter the market.[14] In the subsequent sections, I employ a theoretical model to quantify the role of the option to delay entry in the observed business cycle variation of entrants.

[14] In Appendix A.5.3, I discuss the relevance of the information provided by the BFS for identifying the option-to-delay channel. Figure 23 presents a diagram that illustrates the relationship between the BFS, the BDS, and potential entrants in the model.

3 The Model

The model builds on Moreira (2016), which features endogenous firm entry and exit in the style of Hopenhayn (1992). The exogenous aggregate demand shock that affects firms' profitability and selection of entrants is the model's only source of business cycles. The economy consists of incumbent firms and potential entrants. Incumbent firms produce differentiated products and are heterogeneous over idiosyncratic productivity and customer capital. They make decisions about production and exit. Potential entrants hold heterogeneous signals about their initial post-entry productivity. I deviate from the original framework and allow potential entrants to keep the signals over time until they enter the market. The modification gives potential entrants the option to delay entry after observing the aggregate state. The following section provides a detailed description of the framework.

3.1 Firms

Technology At the beginning of each period, a positive measure of heterogeneous firms produce differentiated products on a monopolistically competitive market using the following production function:

$$y_i = s_i n_i.$$

The production function is linear in labor n_i. Labor supply is infinitely elastic. Wage is exogenous and constant. s_i is a time-varying idiosyncratic productivity specific to a firm i and evolves according to a persistent $AR(1)$ process:

$$log(s_i') = \rho_s log(s_i) + \sigma_s \varepsilon_i,$$

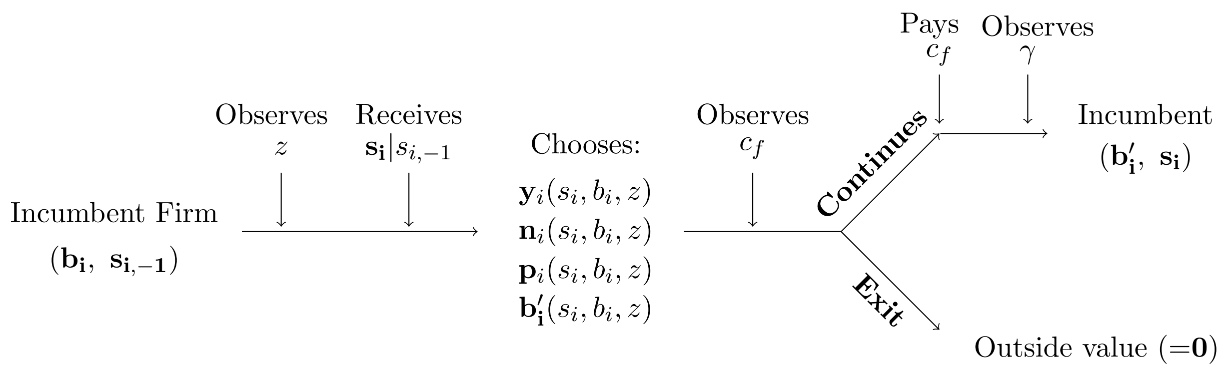
where $\varepsilon_i \sim i.i.d.\ N(0,1)$. Idiosyncratic productivity is distributed independently across firms. Every period, firms that are operating in the market incur fixed cost $c_f > 0$, drawn from a time-invariant log normal distribution $c_f \sim G(c_f)$ with mean μ_f and standard deviation σ_f. The fixed cost is distributed independently across firms.

Demand In each period, demand for firm i's differentiated good is determined according to the following demand function

$$y_i = p_i^{-\rho} b_i^{\eta} \alpha z,$$

where p_i is the price set by firm i, and $\rho > 1$ is the price elasticity of demand. $\eta \in (0,1)$ measures the elasticity of demand with respect to customer capital b_i, which evolves according

Figure 3: Incumbent firm's timing



to:

$$b'_i = \begin{cases} (1-\delta)b_i + (1-\delta)p_i y_i & \text{incumbent firm } i \\ b_0 & \text{entrant firm,} \end{cases}$$

where b_0 is the initial level of customer capital, common across all entrants. $\delta \in (0,1)$ is the depreciation rate of customer capital. The process of customer capital that is tied to past sales hinders firms' ability to freely adjust their demand over time, which creates persistence in the dynamics of production and employment.[15] z represents a common aggregate demand shock that evolves as a persistent $AR(1)$ process,

$$log(z') = \rho_z log(z) + \sigma_z \epsilon,$$

where $\epsilon \sim i.i.d.N(0,1)$. $\alpha > 0$ is a scale factor.

3.1.1 Incumbent Firms

At the beginning of each period, an incumbent firm i, with predetermined customer capital b_i, observes aggregate demand shock z, and idiosyncratic productivity s_i. Using the information, the incumbent firm makes decisions about the optimal production level, price, and the next period's customer capital. At the end of the period, the incumbent firm draws fixed cost c_f and makes the continuation decision. Even if the firm decides to stay in the market, it may be hit by a random exit shock with probability $\gamma \in (0,1)$. The outside value is normalized

[15]The channel is motivated by the growing literature that emphasizes the demand-side factors in understanding the firm-level and aggregate dynamics. For example, Foster et al. (2016) find that the differences between young and mature firms are due to individual demand dynamics rather than differences in productivity. Sedlacek and Sterk (2017), and Moreira (2016) emphasize the demand-side factors in accounting for thee persistent procyclical variation in cohorts-level employment.

to zero.[16] Firms discount future profits at the time-invariant factor β.

The incumbent firm solves the following functional equation:

$$V^I(b,s,z) = \max_{y,p,b'} \left(p - \frac{w}{s}\right) y + \int max\left\{0, -c_f + \beta(1-\gamma)E[V^I(b',s',z')|s,z]\right\} dG(c_f),$$

$$\text{s.t.} \quad b' = (1-\delta)(b+py),$$

$$y = \alpha p^{-\rho} b^{\eta} z.$$

The summary of the incumbent firm's timing is illustrated in Figure 3.

3.1.2 Potential Entrants

At the beginning of every period, there is a constant mass of potential entrants M. Potential entrants are endowed with heterogeneous signals q about their first-period idiosyncratic productivity. For a given signal, the idiosyncratic shock in the first period of operation is normally distributed and follows the process $log(s) = \rho_s\ log(q) + \sigma_s\ \epsilon$, where $\epsilon \sim N(0,1)$.[17]

The aggregate distribution of potential entrants over signals is time invariant and is given by the Pareto distribution $W(q)$ with location parameter $\underline{q}$ and Pareto exponent $\xi > 0$.[18] The potential entrant's timing is described below and is summarized in Figure 41.

At the beginning of every period, each potential entrant with a signal q observes an aggregate state of the economy z and makes an entry decision. A firm can either enter the market today or wait until tomorrow. Entry into the market is subject to a fixed entry cost c_e. Entrant solves the following Bellman equation

$$V^e(q,z) = \max\left\{\ V^w(q,z),\quad -c_e + V^{gross}(q,z)\right\}, \tag{1}$$

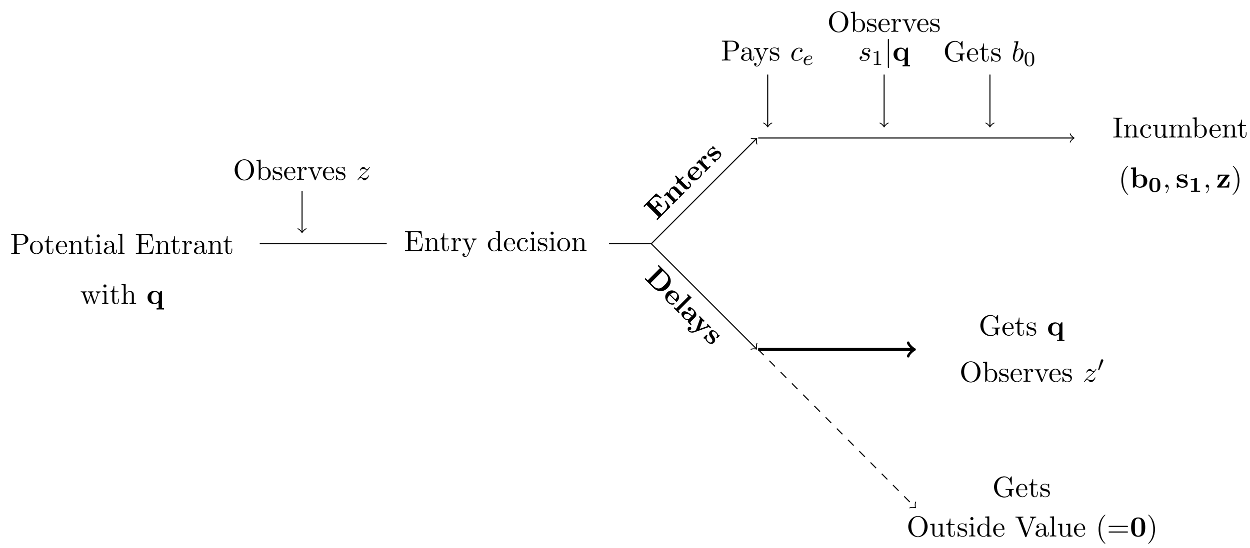
where V^{gross} is the value of entering after paying the entry cost c_e and $V^w(q,z)$ is the value

[16] I assume that if the incumbent firm decides to exit, the probability that the firm receives an initial productivity signal and becomes a potential entrant again is zero.

[17] The ex-ante heterogeneity of potential entrants is crucial for the option-value channel. With ex-ante homogeneous potential entrants, the interior entry solution requires the option value of delay to equal zero. For example, see paper Bilbiie, Ghironi, and Melitz (2012).

[18] Underling the restriction is an assumption that the number of business ideas that can be implemented in the market in each period is limited. This assumption is used throughout the literature (e.g, see Sedlacek and Sterk (2017), Sedláček (2020), Lee and Mukoyama (2018)). Fajgelbaum, Schaal, and Taschereau-Dumouche (2017) assume a constant mass of entrants in a model where firms make decisions between entry and waiting. In Appendix B.1, I extend the entry phase that justifies the constant mass of potential in this framework. In Appendix B.2, I show that the main results of the paper are robust if I extend the model and allow the accumulation of potential entrants over time.

Figure 4: Potential entrant's timing



of waiting.

If a firm decides to enter the market today, the firm observes actual idiosyncratic productivity (s), receives the initial customer capital stock (b_0), and behaves like an incumbent with state variables (b_0, s, z). Therefore, the gross value of entry today is

$$V^{gross}(q, z) = \int_s V^I(b_0, s, z) dH_e(s|q).$$

If the firm waits, it starts the next period with the same signal q, but observes a new aggregate demand level z'. Therefore, the value of waiting is

$$V^w(q, z) = \beta \int_{z'} V^e(q, z') dF_z(z'|z).$$

3.2 Recursive Competitive Equilibrium

Denote the distribution of incumbent firms across productivity and customer capital by $\Omega(s, b)$. Then, at the beginning of every period, the vector of the aggregate state variables is given by $\Gamma = \{\ z,\ \Omega(b, s),\ W(q)\}$. For a given Γ_0, a recursive equilibrium consists of the following: (i) value functions $V^I(b, s, z)$, $V^e(q, z)$; (ii) policy functions $y(b, s, z)$, $p(b, s, z)$, $n(b, s, z)$, and $b'(b, s, z)$; and (iii) distribution of operating firms $\{\Omega_t\}_{t=1}^{\infty}$, such that

1. $V^I(b,s,z)$, $y(b,s,z)$, $p(b,s,z)$, $n(b,s,z)$ and $b'(b,s,z)$ solves incumbent's problem; and

2. $V^e(q,z)$ solves the entrant's problem.

4 Inspecting the Mechanism

The goal of the section is twofold. First, in Section 4.1, I study the optimal timing of market entry decisions made by heterogeneous potential entrants. Then, in Section 4.2 I illustrate how the option modifies the selection of entrants across different aggregate conditions.

4.1 Entry Timing and the Value of Waiting

To illustrate how the option to wait alters firms' entry decisions, consider the following modification of equation (1)

$$V^e(q,z) = \max\left\{\, dV^w(q,z), \quad -c_e + V^{gross}\left(z,q\right)\,\right\}, \tag{2}$$

where the variable d indicates whether an entrant can keep its signal over time. If $d=0$, the initial productivity signals are of the "use it or lose it" type, resulting in an option value of zero. In this case, as in a standard framework, firms enter the market if the net expected value of entry is nonnegative. If $d=1$, entrants problem coincides with the baseline model. Result 4.1 uses the numerical methods to summarize the properties of the option value of delay, $V^w(z,q)$.

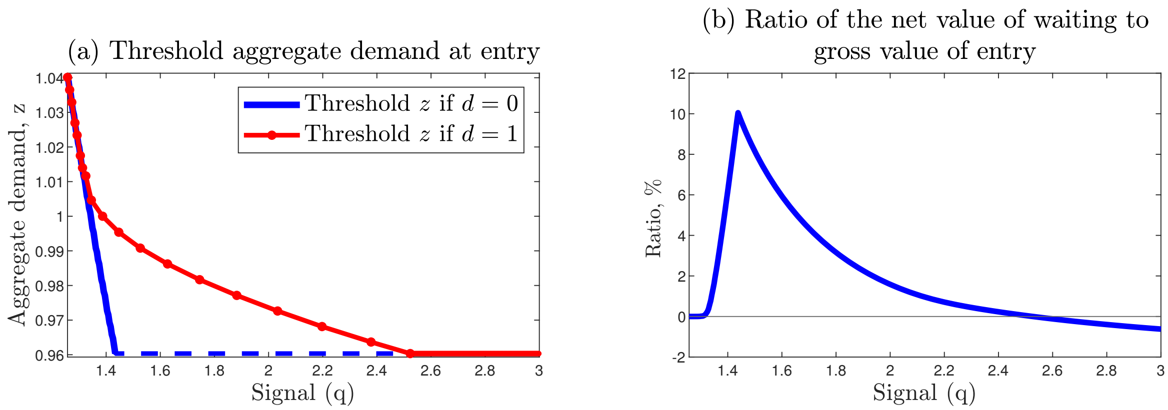
Result 4.1. *(i) $V^w(q,z)$ is non-negative for all q and z; (ii) For a given aggregate demand level z, $V^w(q,z)$ is a weakly increasing function of the signal q; and (iii) For a given signal q, $V^w(q,z)$ weakly increases with the aggregate demand level z.*

Result 4.1 implies that the ability to keep signals weakly increases the total cost of entry for all potential entrants. Result 4.2 provides a formal characterization of the entry timing problem for a potential firm with signal q, for both $d=0$ and $d=1$. This problem involves identifying a 'trigger' or threshold aggregate demand level $\underline{z}^d(q)$, at which the firm enters the market if $z \geq \underline{z}^d(q)$.

Result 4.2. *Suppose for a signal level q, exists an aggregate demand level $\underline{z}^d(q)$ such that*

$$V^{gross}\left(\underline{z}^d(q), q\right) - c_e = dV^w(\underline{z}^d(q), q);$$

Figure 5: Entry decision and the value of waiting



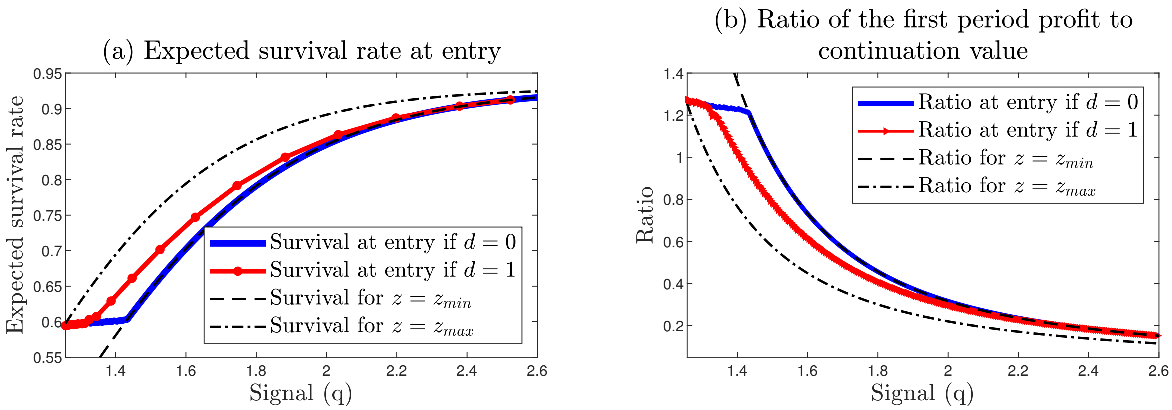
Then, a potential entrant with signal q decides to enter the market for all $z > \underline{z}^d(q)$, otherwise chooses to stay outside the market.

Figure 5(a) illustrates the threshold aggregate demand levels $\underline{z}^d(q)$, for both $d = 1$ (red-circled line) and $d = 0$ (solid-blue line). The blue-dash line indicates scenarios for which $\underline{z}^{d=0}(q) < z_{min}$, where z_{min} represents the minimum grid point for the aggregate demand level identified by the numerical solution. The figure shows that if $d = 1$, the threshold aggregate demand is weakly higher for each signal level. In particular, while the decision of high- and low-productivity entrants to enter the market does not change with the option to delay entry, firms with medium-range productivity signals find it strictly more profitable to wait for higher aggregate demand levels. Importantly, even firms with a nonnegative net present value of entry, as illustrated by the blue-dashed line in Figure 5(a), choose to wait if the option is available. Figure 5(b) shows that firms that ignore the option and follow the traditional investment decision rule may lose up to 10% of the present value of lifetime benefits.[19]

The procyclical variation in the expected survival rates is responsible for the option-value effect among medium-productivity entrants. In Equation (3), the gross value of entry is decomposed into the expected first-period profit and the continuation value. The latter value depends on the probability of a potential entrant remaining in the market after the first period, given by the expression $(1 - \gamma)G(c_f^*)$. The expected survival rate increases with the aggregate demand level, which means that during recessions, firms not only expect lower first-period profits but also lose part of their long-run benefits due to the increased

[19] I define the *net value of waiting* as the difference between the net present value of entering the market today and the net present value of keeping the option to enter 'alive'. That is, Net value of waiting$(q, z) = V^w(q, z) - [V^{gross}(q, z) - c_e]$.

Figure 6: The risk of post-entry failure and the option to wait



probability of irreversible exit. Therefore, the flexibility to choose the timing of entry enables potential entrants to internalize the latter cost, allowing them to delay business formation until the expected survival rates are sufficient to offset the initial low demand levels.

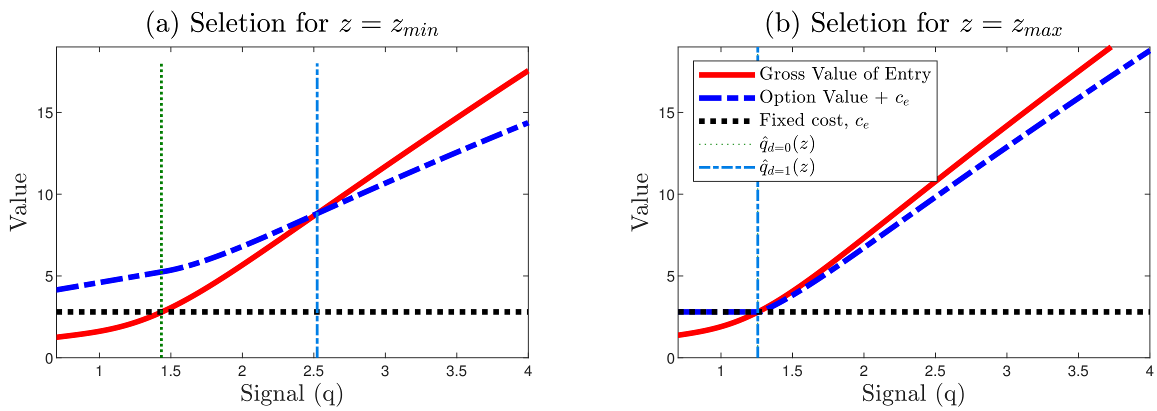
$$V^{\text{gross}}(b_o, q, z) = \underbrace{\int_s \Pi(b_o, s, z) \quad dH_e(s|q)}_{\textit{Expected first period profit}} + \tag{3}$$

$$+ \underbrace{\int_s \beta \underbrace{(1-\gamma)G\left(c_f^*\right)}_{\textit{Survival rate}} \left[E(V^I(b', s', z')|s, z) - \frac{1}{(1-\gamma)\beta} E(c_f \mid c_f \leq c_f^*)\right] \; dH_e(s|q)}_{\textit{Expected continuation value}},$$

where $c_f^* = \beta(1-\gamma)E[V^I(b', s', z')|s, z]$.

Figure 6 illustrates the expected survival rates and the ratio of the expected first-period profit to the continuation value at the threshold aggregate demand levels for both $d = 0$ (blue-solid line) and $d = 1$ (red-circled line). Note that the weight of the continuation value, and therefore the cost of premature market exit, increases with the signal level. However, at the same time, the benefits of waiting, represented by the procyclical variation in expected survival rates, decrease with the signal level. This trade-off between the first-period profit and long-run value, which depends on the signal level, results in a positive value of waiting for some potential entrants but not all. Specifically, for medium-productivity entrants, the expected survival rate is more procyclical, and hence the benefits of waiting are higher, making it optimal to delay entry until conditions improve. In contrast, for low-productivity entrants, the expected survival rate is less procyclical, and the first-period profits represent

Figure 7: Mechanism: selection of entrants



a more significant share of their entry value, making it optimal to enter only during high-demand periods. Finally, for high-productivity entrants, delaying entry leads to a negative net present value as their survival does not vary with the aggregate state.

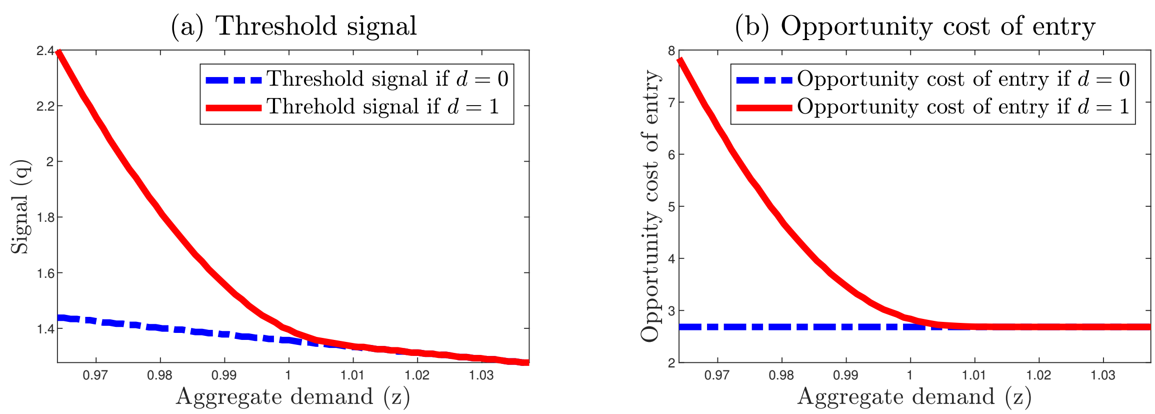
Keeping the mechanism in mind, in Section 5.3, I show that the option to wait is a qualitatively important channel to generate the selection of entrants over the business cycles with the countercyclical survival rates – an empirical fact presented in Section 2.

4.2 Aggregate Selection of Entrants

Next, I investigate how the option to delay entry affects macro-level elasticities and the selection of entrants across various aggregate demand levels. The model assumes that all potential firms receive the same level of customer capital b_0 and observe the same aggregate demand level z at entry. Hence, we can determine the selection of firms for each aggregate demand level based solely on a signal level q. Consider Figure 7(a) that displays the gross value of entry, the fixed entry cost, and the option value of delay across the signal for an aggregate demand level z. In the baseline scenario ($d = 1$), firms decide to enter today if the expected benefits cover the total cost of entry – sum of the fixed cost and the option value of delay. Thus, in Figure 7(a), the firms that hold signals $q \geq \hat{q}_{d=1}(z)$ decide to enter the market, while the rest stay outside. I refer to $\hat{q}_{d=1}(z)$ as the threshold signal for the aggregate demand level z. If firms are unable to keep the signal over time ($d = 0$), they will enter the market as soon as the expected post-entry benefits are sufficient to cover the fixed cost of entry. Accordingly, in Figure 7(a), only firms that hold signals $q \geq \hat{q}_{d=0}(z)$ enter the market, while the rest remain outside.

Comparing the threshold signal levels across these cases isolates the selection that occurs

Figure 8: Selection of entrants across different aggregate conditions



solely through the option-to-delay channel. Specifically, for a given aggregate demand level z, this channel creates a new group of firms with signals $q \in [\hat{q}_{d=0}(z),\ \hat{q}_{d=1}(z)]$ who choose to stay outside the market despite having positive net expected benefits from entry. Figure 7(b) shows that for the highest aggregate demand levels, the group of potential entrants that decide to enter the market is same with or without the option to delay entry: during the peak, nobody finds it optimal to delay entry. Result 4.3 formally summarizes the threshold signal levels for the rest of the aggregate states:

Result 4.3. *Suppose for an aggregate demand level z, exists a signal $\hat{q}_d(z)$ such that*

$$V^{gross}\left(z,\ \hat{q}_d(z)\right) - c_e = dV^w(z, \hat{q}_d(z));$$

Then, all potential entrants with $q \geq \hat{q}_d(z)$ decide to enter the market, whereas the rest stay outside the market.

Figure 8(a) shows that the threshold signal is countercyclical: the group of firms that enter the market during recessions hold a relatively higher range of signals than the group of firms that enter during expansions. As previously discussed, the option-value effect is captured by the group of firms whose signals fall within the range of $q \in [\hat{q}_{d=0}(z),\ \hat{q}_{d=1}(z)]$. Note that as the aggregate demand level decreases, the range of signals that leads to delay decisions widens, resulting in notable increase in the elasticity of entrants to aggregate demand compared to the case $d = 0$.[20]

The increased elasticity of the threshold signal in the baseline model is due to the endogenous variation in the threshold opportunity cost of entry. The latter is defined as the minimum

[20] In Appendix G.1, I investigate how the value of delay changes if $d \in (0, 1)$. Figure 42 shows that the total opportunity cost of entry, as well as, the threshold signal level significantly increases with d.

level of benefits required by potential firms to enter the market given the aggregate state. In the $d = 0$ case, the value is constant and equals c_e. However, in the baseline model the value is endogenous and varies with the option value. Particularly, Figure 8(b) shows that the opportunity cost of entry is countercyclical, significantly increasing above the fixed entry cost during recessions.[21] In fact, for reasonable parameter values, firms that enter the market during recessions are the ones that expect the present value of entry up to twice the fixed entry cost.

The latter result is the core finding of the paper: the option to delay endogenously generates a countercyclical cost of entry in equilibrium, which amplifies the elasticity of entrants with respect to the aggregate conditions compared to a model with a fixed entry cost. The higher elasticity, in turn, leads to greater variation in the number and composition of entrants over business cycles. Later, we will see, that this feature enables the model to account for the observed dynamics of entrants for a reasonable aggregate shock process.

5 Calibration and Model Performance

In this section, I describe the calibration procedure for the model and explain the strategy I use to discipline the option-value channel. Once I demonstrate that the model closely replicates the main features of US firm dynamics at entry and over time, I examine the business cycle dynamics of cohorts in the model and compare them to the data. Consistent with the empirical facts, I find that aggregate conditions have a significant and persistent effect on firms' life cycle dynamics. These differences, in turn, result in significant persistence and variance in aggregate variables.

5.1 Calibration

A period in the model corresponds to one year, consistent with the timing of the BDS dataset. The unit of analysis is an establishment. Estimating the model requires calibrating 17 parameters. First, I describe the parameters that I choose based on the estimations in the literature. Then, I jointly calibrate the rest of the parameters to match the cohorts' average life cycle characteristics. The summary of the parameters, identification strategy, and the final values of the parameters are given in Table 3.

[21] The value coincides with the threshold signal's $\hat{q}_{d=1}(z)$ opportunity cost of entry. *Proof:* $V^{gross}(q, z)$ strictly increases with the signal. For an aggregate demand level z, firms with $q > \hat{q}_{d=1}(z)$ enter the market. The following inequality holds: $V^{gross}(z, q) > V^{gross}(z, \hat{q}_{d=1}(z)) = c_e + V^w(z, \hat{q}_{d=1}(z))$.

Table 3: Calibration

Symbol	Description	Value	Targets/Source
β	Discount rate	0.960	Riskless interest rate
ρ	Price elasticity of demand	1.622	Foster et al. (2016)
η	Elasticity of demand to capital	0.919	Foster et al. (2016)
δ	Depreciation rate of reputation	0.188	Foster et al. (2016)
ρ_s	Idiosyncratic shock – persistence parameter	0.814	Foster et al. (2008)
σ_s	Idiosyncratic shock – SD parameter	0.161	Firm size by age
α	Demand shifter	0.261	Firm size by age
b_o	Initial customer capital level	12.00	Firm size
μ_f	Operating cost – SD parameter	0.621	Firm survival by age
σ_f	Operating cost – SD parameter	0.410	Firm survival by age
γ	Exogenous exit shock	0.071	Firm exit hazard by age
$\underline{q}$	Pareto location	0.700	Firm size at entry
ξ	Pareto exponent	2.478	Employment share at entry
c_e	Fixed entry cost	2.684	Entry rate – mean
ρ_z	Aggregate shock – persistence parameter	0.750	Entry rate – persistence
σ_z	Aggregate shock – SD parameter	0.003	Entry rate – SD

I set the time-preference parameter $\beta = 0.96$ to match a 4% percent annualized average riskless interest rate. In the baseline model, the production function, demand function, and the process of the customer capital accumulation follows the specification developed and estimated in Foster et al. (2008), and Foster et al. (2016). Using the establishment-level data from the Census of Manufactures, Foster et al. (2008) estimates that the autocorrelation of the establishments' idiosyncratic productivity process equals $\rho_s = 0.814$.[22] Foster et al. (2016) identifies parameters that drive the demand function and the customer-capital-accumulation process by jointly estimating the demand and the Euler equation, using the dataset from Foster et al. (2008). Based on their estimates, I set the price elasticity of demand (ρ) equal to 1.622, the elasticity of demand to customer capital (η) equal to 0.919, and the depreciation rate (δ) equal to 0.188.

I formally calibrate the rest of the parameters $\sigma_s, b_o, \alpha, \mu_f, \sigma_f, \gamma, \underline{q}, \xi, c_e, \rho_z, \sigma_z$ using the minimum distance estimation procedure proposed by Chamberline (1994). That is, I minimize

[22]Technology in Foster et al. (2008) is linear in inputs and productivity: $q_i = s_i x_i$ where x_i is the input and s_i is producer-specific productivity. Foster et al. (2008) uses establishment-level data of eleven manufacturing products. The data provide detailed information about producer-level quantities and prices for the following census years: 1977, 1982, 1987, 1992, and 1997. Using the dataset, they are able to directly measure total physical factor productivity, defined as $TFPQ_i = \frac{s_i x_i}{x_i} = s_i$. Autoregressive properties of the measured TFPQ imply persistence rate $\rho_s = 0.814$. Foster et al. (2008) finds that persistence of TFPQ is very close to the persistence parameters generated from other measures of total factor productivity (TFP) (e.g., traditional measure of TFP and revenue TFP).

Table 4: Calibration targets and the model-implied counterparts

Statistics	Data	Model
Firm size	17.0	17.0
Firm size at entry	8.73	9.95
Firm size at age 5	13.9	14.5
Firm size at age 23	21.2	22.1
Employment share at entry	0.56	0.58
Firm exit hazard at age 5	0.10	0.09
Firm survival rate up to age 5	0.49	0.49
Firm survival rate up to age 23	0.15	0.12
Entry rate (%)	9.90	10.0

Note: The moments are calculated using the US-level cohorts of establishments from the BDS dataset covering the the period 1978-2019.

Table 5: Calibration targets for the aggregate demand shock process

Statistics	Data	Model
Autocorrelation of the cyclical component of establishments	0.70	0.72
SD of the cyclical component of establishments	0.01	0.01
SD of the cyclical component of entry	0.06	0.06

Note: The time series about the entry rate comes from the BDS and covers the period 1978-2019. The cyclical component of the log entry rate is calculated using the HP filter with smoothing parameter 100.

the sum of squared deviations of the eleven moments that characterize firms' life cycle dynamics in the model from its data counterpart. To compute the relevant statistics, I use annual time series about the US-level cohorts of establishments from the BDS dataset covering the period 1977-2015. I choose the following moments to capture cohorts' average characteristics at entry: entry rate, the employment share of entrants', the average size at entry, the average size at entry relative to the size of all active establishments.[23] To capture cohorts' post-entry growth, survival, and exit, I target average cohorts' size and survival rate at age 5 and at age 23. Table 4 summarizes the targeted moments and their corresponding values in the data and the model. The model-simulated moments are calculated in the the stochastic steady state.

Although these parameters are jointly estimated, I describe below how the targeted sample moments help us infer about each of these parameters. The standard deviation of the idiosyncratic productivity shock (σ_s) shapes cohorts' growth rate, while the demand parameter (α) affects the scale of the economy. Therefore, in the calibration, these two parameters

[23]size is defined as the total employment number by entrants/incumbents/all establishments over the total number of entrants/incumbents/all establishments.

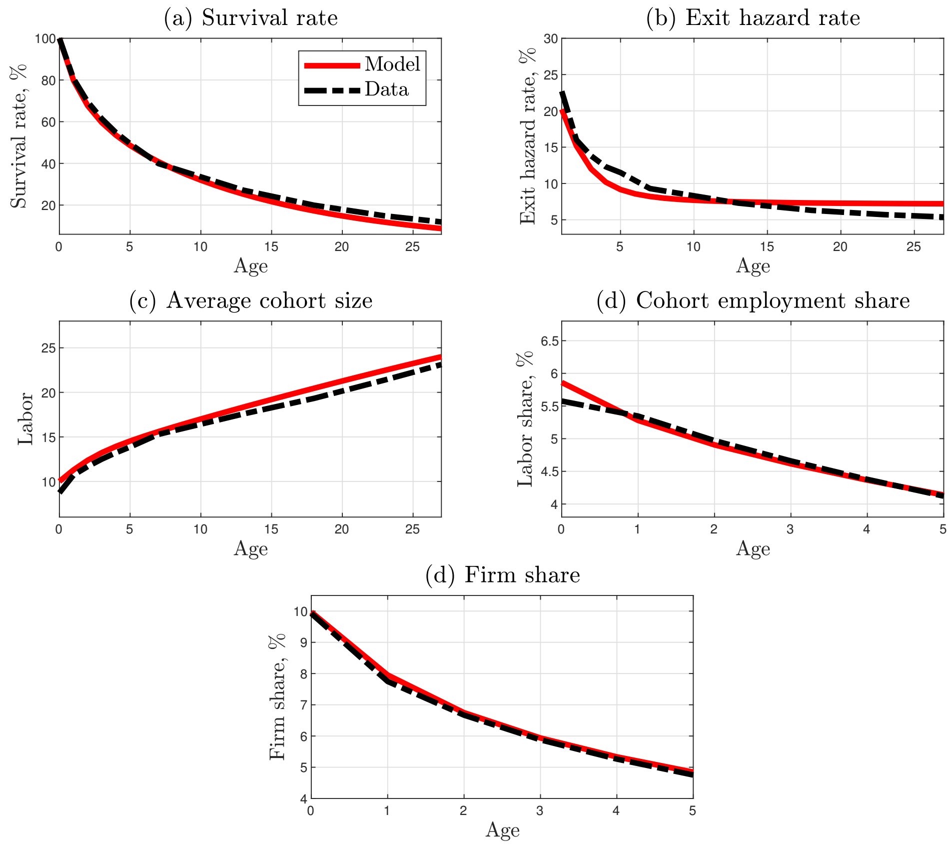
mainly target cohorts' average size at ages 5 and 23. Finally, the exogenous exit probability (γ), alongside the mean (μ_f) and standard deviation (σ_f) of the fixed operating cost, shapes cohorts' life cycle survival and exit rates. Therefore, these parameters are estimated using average cohorts' survival rates at ages 5 and 23 and the exit hazard rate at age 5.

The entry cost (c_e) determines the steady-state mass of entrants, while parameters $\underline{q}$ and ξ shape the potential entrants' distribution over the productivity. I estimate these parameters by targeting the average entry rate, the share of entrants' employment in total employment, and the average size of entrants. The initial level of customer capital (b_0) is calibrated to match the relative size of entrants compared to the average size of all active firms. Note that the parameters $\underline{q}$ and ξ also affect the variation in the number of entrants across aggregate demand levels, as they shape the distribution of entrants across signals. That said, I will partially use these parameters to discipline the business cycle variation in the number of entrants, which I will explain next.

The baseline case assumes that potential entrants can keep signals indefinitely, which implies $d = 1$.[24] Consequently, the key parameters driving business cycle firm dynamics are the persistence (ρ_z) and standard deviation (σ_z) of the aggregate demand shock process. The exogenous shock affects incumbent firms' production and exit decisions, and at the same time, determines the business cycle variation in the number and composition of entrants. First, it directly determines the NPV of entry through its effect on incumbent firms. Second, as discussed in Section 4.2, the shock endogenously alters the cost of entry through the option-value channel. The latter mechanism partially breaks the link between the dynamics of entrants and the aggregate demand shock process, allowing me to discipline the option-value channel. That is, I jointly calibrate these parameters to match the autocovariance and the variance of the total number of firms and the variance of the entry rate in the model and the data. To construct the cyclical component of the entry rate and total number of establishments, I apply the HP filter with a smoothing parameter of *100*. To calculate the same moments in the model, I simulate the economy over many periods and apply the same detrending method to the model-simulated total number of firms and entry rate. The autocovariance and standard deviation of the time series are reported in the second and third columns of Table 5. The final values of the parameters that generate the match are $\rho_z = 0.75$, and $\sigma_z = 0.003$.

[24] In Section 7 and Appendix G.1, I introduce a methodology to estimate the probability of keeping signal d. Applying this approach, I set $d = 0.965$, and find that the dynamics of both the number of entrants and the aggregate economy with $d = 0.965$ are comparable to those in the baseline scenario with $d = 1$.

Figure 9: Cohorts' average characteristics: Data, model



Note. The data moments are calculated from the US-level annual Business Dynamics Statistics dataset over the period 1978-2019. The unit of analysis is a cohort of establishments by age. The model-simulated moments are calculated at the stochastic steady state.

5.2 Cohorts' Average Life Cycle Characteristics

Columns (2) and (3) of Table 4 lists the data moments and their model-implied counterparts, respectively. The model successfully replicates the main features of the US firm dynamics. The average firm employs 17 workers in the data and 16.9 workers in the model. Entrants contribute only around 5.6 percent to total employment in the model and the data. The model does a good job in reproducing the well-known 'up or out' dynamics of firms. About 50% of the entrants fail within the first five years, and by age 23, only around 10% out of original start-ups survive. At the same time, cohorts of firms grow from 9.6 workers at entry to 22 workers by age 23.

Figure 9 goes beyond the moments reported in Table 4 and illustrates the full life cycle profile of firms – moments and statistics not directly targeted in the calibration. Panel (a) show that the model closely replicates the survival rates of firms up to age 30. Panel (b) shows that the model also successfully matches the dynamics of the exit hazard for up to

Table 6: Differences in cohorts' characteristics based on the initial conditions: Data

	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5
Firms	2.38***	2.24***	2.01***	1.80***	1.81***	1.87***
	(0.17)	(0.15)	(0.13)	(0.11)	(0.10)	(0.09)
Survival rate		-0.22***	-0.41***	-0.49***	-0.44***	-0.39***
		(0.02)	(0.04)	(0.05)	(0.05)	(0.06)
Employment	3.01***	3.01***	2.23***	1.64***	1.66***	1.95***
	(0.23)	(0.18)	(0.16)	(0.14)	(0.13)	(0.14)
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Note. The estimates use the state-level annual BDS dataset over the period 1978-2015. To be consistent with the model calibration, I consider a cohort of establishments as a unit of analysis. I use the cyclical component of the HP-filtered log real GDP to measure the aggregate economic conditions at entry.

age 30. Panels (c) and (d) further describe growth of cohorts measured by average size and the share of cohorts' employment in total employment. Finally, Panel (e) describes the share of firms by age in the total number of firms. Overall, Figure 9 shows that the model quite closely reproduces average cohorts of establishments life cycle dynamics in the US.

5.3 Entry conditions and Persistent Cohort Dynamics

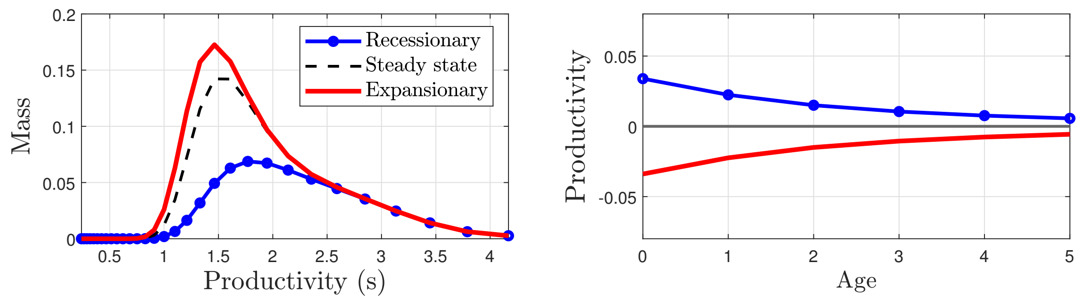
Next, I show that the calibrated model successfully accounts for the documented persistent and significant differences in the average life cycle characteristics of cohorts born at different stages of business cycles. To investigate the effect of the initial aggregate conditions on cohorts' life cycle characteristics, I estimate the following regression equation in the data and the model:

$$X_{c,g,t} = \alpha + \sum_{g=0}^{T} \beta_g D_g Z_c + \eta_g + \varepsilon_{g,t}, \tag{4}$$

where $X_{c,g,t}$ is a cohort-level outcome variable that varies with cohort age (g) and time (t); Z_c represents the economic conditions at the time when the cohort entered the market. D_g is an indicator variable that take the value of one if a group of firms is g years of age. η_g represents age-fixed effects. To study the effect of the initial aggregate conditions over the cohorts' life-cycle, I consider the interaction of the business cycle conditions at entry with the cohort age. The coefficient β_g measures the average change in the variable of interest at age g with the variation in the business cycle conditions at entry.

To empirically estimate the regression, I use the state-level annual BDS dataset over the period 1978-2015. To be consistent with the model calibration, I consider a cohort of estab-

Figure 10: Productivity at entry and over time



lishments as a unit of analysis. The aggregate economic conditions at entry are measured using the cyclical component of the HP-filtered log real GDP, and state-fixed effects are included in the regression equation. The results in Table 6 indicate that cohorts born during recessions have fewer firms, employ fewer workers, and have higher survival rates compared to their expansionary counterparts. These effects persist over the cohorts' life cycles.

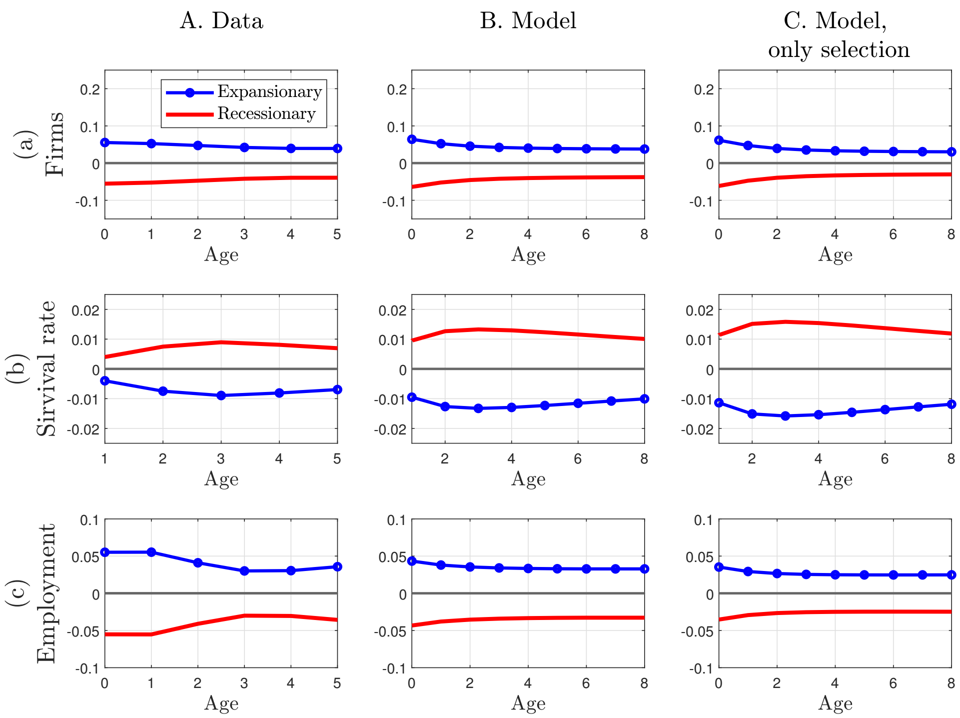
To estimate the regression using model economy, I simulate the model over 500 periods and follow each cohort of firms for up to 15 years of operation. I measure Z_c using the log aggregate demand level firms observe at entry.[25] For comparability, I use the estimated coefficients of the model and the data to construct the simulated life cycle characteristics of cohorts born across different aggregate states. That is, I calculate $\hat{X}_{c,g} = \hat{\alpha} + \sum_{g=0}^{T} D_g \hat{\eta}_g + \sum_{g=0}^{T} D_g \hat{\beta}_g Z_c$. Based on the expression, cohorts' average life cycle characteristics vary across the aggregate conditions at entry Z_c. I assign Z_c the following three values $\{-\sigma_z, 0, \sigma_z\}$, where σ_z is a standard deviation of the respective business cycle variable. I refer to cohorts of firms as recessionary (expansionary) if they are born when the aggregate conditions are one standard deviation below (above) the mean. Figures 10 and 11 illustrate recessionary (blue-circled line) and expansionary (red-solid line) cohorts life cycle characteristics relative to the mean cohort ($Z_c = 0$).

Consistent with the empirical findings, Figure 10 shows that the average productivity of the recessionary cohorts is higher than their expansionary counterparts. The difference persists in later years due to the persistent idiosyncratic productivity process. The result is a direct implication of the countercyclical variation in the threshold signal discussed in Section 5.3.

The model predicts that the cohort of firms that begin operating during recessions have

[25] The results are robust if I define business cycles using the deviations from the average log employment (output) or the cycle component of the HP-filtered log employment (output).

Figure 11: Entry conditions and persistent cohort dynamics



Note. The figure illustrates the deviations of the recessionary and expansionary cohorts' characteristics from the mean (steady state) cohorts. Recessionary cohorts refer to groups of firms that start operating when the aggregate conditions are one standard deviation below (above) the mean. Panel A ('Data') uses the state-level annual Business Dynamics Statistics dataset. The unit of analysis is a cohort of establishments. Panel B ('Model') describes the same statistics using simulated model data. Panel C ('Model, only selection') considers a counterfactual version of the model where the shocks affect the selection of firms at entry and not post entry shocks.

approximately 12% fewer firms at entry compared to expansionary cohorts. This difference persists over time and is very close to the data counterpart. Specifically, in the US, recessionary cohorts have approximately 11% and 8% fewer establishments at age 0 and age 5, respectively. These dynamics are illustrated in Figures 11A(a) and 11B(a).

In the data and the model, the firms that start operating during recessions have, on average, higher survival rates compared to their expansionary counterparts. In the model, the difference equals 1.8% at entry and 2.0% at age 5. In the data, the corresponding statistics equal 0.8% and 1.5%, respectively. These statistics are illustrated in figures 11A(b) and 11B(b).

In the model, the recessionary cohorts employ around 8.6% fewer workers at entry and 6.4% at age five. In the data, the estimates are statistically significant and equal to 11% and 7%, respectively. These statistics are illustrated in figures 11A(c) and 11B(c). Note that while the model matches the differences between the expansionary and recessionary cohorts' employment starting from age 3, it underestimates the effect of the initial aggregate conditions on cohort-level employment at age 0. That is, in the model, the difference between the recessionary and expansionary cohorts' employment is three percent less than the data counterpart. The latter suggest that other channels, such as the variation in the niche and mass product firms (Sedlaćek and Sterk, 2017), and variation in the share of the high-target size firms (Smirnyagin, 2021) over the business cycles might be needed to fully account for the effect of the initial conditions on the cohorts' employment.[26]

The Role of Selection Finally, I confirm that the model's selection mechanism is consistent with recent findings in the firm dynamics literature, which show that a significant portion of the life-cycle differences across cohorts can be attributed to pre-entry selection rather than post-entry shocks (Sterk, Sedlaćek, and Pugsley, 2021).[27] Toward this end, I consider the dynamics of the counterfactual economy where the shocks only affect selection of firms. The demography of cohorts in the counterfactual scenario is illustrated in Panel C of Figure 11. Comparing Panel C to Panel B reveals that the vast majority (more than 80%) of the differences in the characteristics of cohorts across aggregate conditions are due to the selection of firms rather than post-entry shocks.

5.4 Aggregate Fluctuations

Before proceeding to quantify the effect of the option value channel, I use the good fit of the model to the life cycle firm dynamics to evaluate how the persistent and significant differences in cohorts' business cycle characteristics shape the aggregate fluctuations.

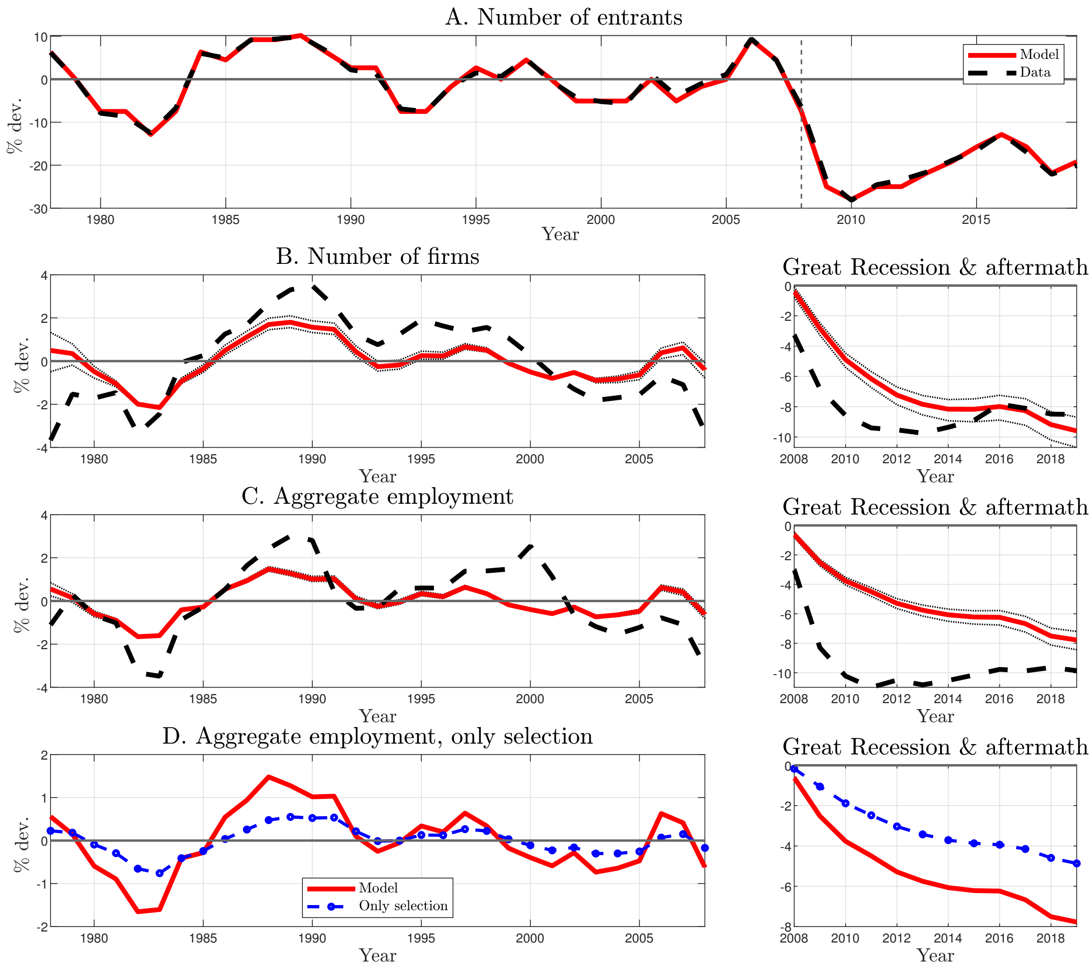
To find the cyclical properties of the log number of entrant establishments, log total number of establishments, and log aggregate employment over the period 1978-2019, I follow Fajgelbaum, Schaal, and Taschereau-Dumouche (2017) and use a linear detrending method that allows a structural break in the trend.[28] To study the model's implications for the aggregate

[26]In line with Moreira (2016) and Smirnyagin (2022), in the model, an average size of a firm that belongs to a recessionary cohort is persistently smaller compared to its expansionary counterpart. The model attributes this difference to the persistent customer capital accumulation and persistent aggregate demand shock process. Simultaneously, the model generates an average size that is higher for recessionary cohorts compared to expansionary cohorts, with the difference diminishing as the cohort ages. This observation is consistent with the findings documented in Appendix A.2 and discussed in Section 2.

[27]In Appendix A (Table 12), I also document that after controlling for the time fixed effects in regression equation (4), the role of the initial aggregate conditions on the persistent differences in cohorts' characteristics (reported in Table 6) stays statistically significant. Moreover, the magnitude of the effect increases over the cohorts life cycle.

[28]In Appendix D.2, Figure 37 compares the trend and cyclical component of aggregate variables after applying the HP-filter with smoothing parameter 100, a linear trend and a linear trend that allows a break point in trend. The HP-filters predicts that the Great Recession was a strong downturn after which the economy recovered quickly. On the other hand, the linear trend exaggerates the severity of the recession. I show that the predictions of the model is robust across these filters.

Figure 12: Aggregate fluctuations



Note. The empirical time series represents the deviations of the log number of entrant establishments, log number of establishments, and log aggregate employment from their respective trends in the US over the period 1978-2019. To find the cyclical properties of these time series, I use a linear detrending method that allows a structural break in the trend. In Panel D, 'only selection' describes a counterfactual economy where aggregate shocks only affect the selection of firms at entry and not decisions made by firms after entry.

fluctuations, I construct an aggregate demand shock series that matches the deviations of the log number of entrants from the trend over the period 1978-2019 in the model and the data. I use the shock process to generate 1000 simulations of the economy over 300 periods. In each simulation, the economy faces the same constructed shock process in the last 42 periods (1978-2019). First, I apply a linear trend to find the cyclical component of each variable, then I average each time series across simulations. The results are illustrated in Figure 12. For improved visual clarity, I have split the time series into two periods: the pre-Great Recession period (1978-2008) and the Great Recession and its aftermath (2008-2019).

I find a correlation of 0.93 between the cyclical component of the total number of establishments in the model and the data. For aggregate employment, this correlation is 0.94.

Table 7: Business cycle moments: Data, baseline, and alternative scenarios

	Entry	**Firms**	**Employment**
Panel A: Standard deviation			
Data	0.062	0.019	0.016
Baseline	0.063	0.010	0.008
Baseline, only selection	0.063	0.009	0.004
Baseline, $d = 0$	0.014	0.003	0.006
Baseline $d = 0$, only selection	0.014	0.002	0.001
Model w/o delay	0.064	0.012	0.027
Model w/o delay, only selection	0.064	0.009	0.003
Panel B: Autocorrelation (1st lag)			
Data	0.624	0.850	0.809
Baseline	0.624	0.815	0.755
Baseline, only selection	0.624	0.784	0.818
Baseline, $d = 0$	0.587	0.880	0.726
Baseline $d = 0$, only selection	0.587	0.490	0.139
Model w/o delay	0.636	0.850	0.713
Model w/o delay, only selection	0.636	0.801	0.951

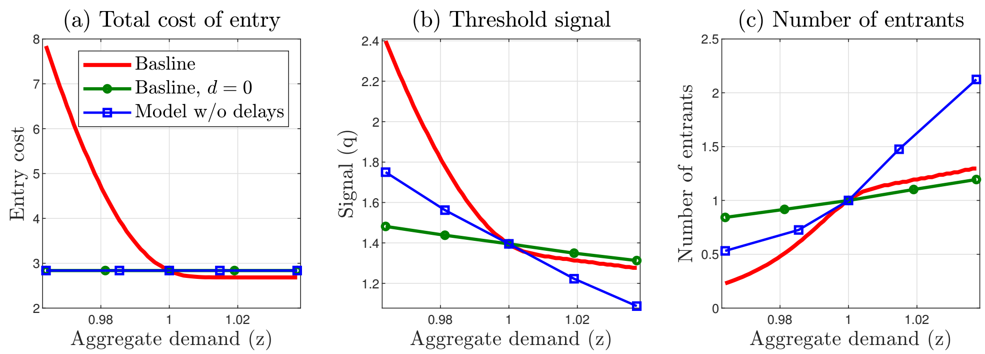
Note. These empirical time series describe the deviations of the log number of entrant establishments, log number of establishments, and log aggregate employment from their respective trends in the US over the period 1978-2008. To find the cyclical properties of these tune series, I use a linear detrending method in the data and the model. 'Only selection' describes a counterfactual economy where the aggregate shock process only affect the selection of firms and not their post-entry decisions.

These high correlations between the model-simulated time series and the data demonstrate that the model closely captures the observed aggregate fluctuations. Table 7 compares the properties (standard deviations and autocorrelations) of these time series in the data and the model. The variance of aggregate employment in the baseline model is 0.008, 50% of what is observed in the data. the autocovariance of aggregate employment is 0.76 in the model, compared to 0.91 in the data.

To evaluate the role of the variation in the number and composition of entrants, I construct a counterfactual scenario ('Only selection') in which the exogenous shock affects only the selection of entrants. Panel C of Figure 12 compares the dynamics of the counterfactual employment to the baseline model. The correlation of the counterfactual aggregate employment with the baseline and the data equals 0.99 and 0.92, respectively. According to Row 'Baseline, only selection' of Table 7, around 50% of the variation in aggregate employment in the model, or roughly 20% of the volatility observed in the data, is attributable to the variation in the types of firms at entry and the resulting persistent differences in cohort-level employment. The latter is a large number when compared with a small share of entrants' employment in aggregate employment (see Figure 9).

The entire model accounts for around 45% of the depth and more than 85% of the slow recovery in aggregate employment during and aftermath of the Great Recession (Panel C).

Figure 13: The option-to-delay channel



Panel D shows that while the changes at the entry margin do not explain much of the depth of the recession, the cumulative contribution of the persistent drop in the new cohorts' employment accounts for around half of the slow recovery in aggregate employment by 2019.[29]

6 The Option–Value Channel

Thus far, I have established that the model closely captures the life cycle characteristics of cohorts of firms in the US, on average, and over the business cycles. Moreover, the persistent differences in cohorts' characteristics significantly amplify and propagate aggregate shocks. In the remainder of the paper, I demonstrate that the option-value channel plays a crucial role, both quantitatively and qualitatively, in explaining the observed dynamics of variables at the micro- and macro-levels.

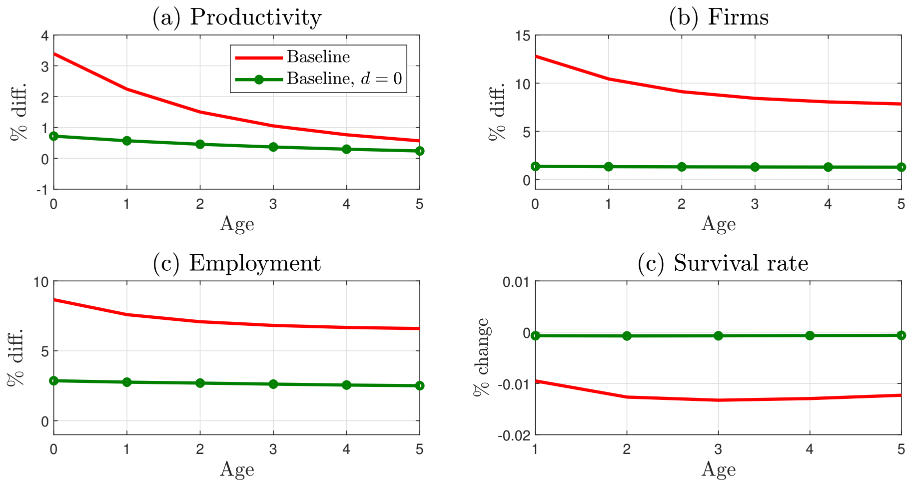
6.1 Quantitative Evaluation

To examine the contribution of the option to delay entry on cohorts dynamics and aggregate fluctuations, I compare the baseline model to an alternative scenario where I set $d = 0$. I refer to this case as the "baseline, $d = 0$". This scenario is identically parameterized except for the fixed entry cost, which is adjusted to ensure that the "baseline, $d = 0$" coincides with the baseline model in the stochastic steady state.[30] Figure 13 illustrates that the opportunity

[29]To externally validate the result, in Appendix A.7, I use a simple accounting exercise to estimate the contribution of cohorts born over 2008-2016 to the data counterpart. Interestingly, I find that cohorts of firms that started operating over 2008-2016 persistently employed fewer workers, which cumulatively accounts for 45% of the depth and more than 85% of the slow recovery in aggregate employment.

[30]To achieve the goal, the fixed entry cost in the baseline with $d = 0$ case should equal to the steady state total opportunity cost of entry in the baseline model. That is, $c_{d=0} = c_{d=1} + V^w(q^*_{d=1}(z_{ss}), z_{ss})$. The Column (b) of Table 16 summarizes the parameter values used in the "baseline, $d = 0$".

Figure 14: Entry conditions and persistent cohort dynamics: The option-value effect



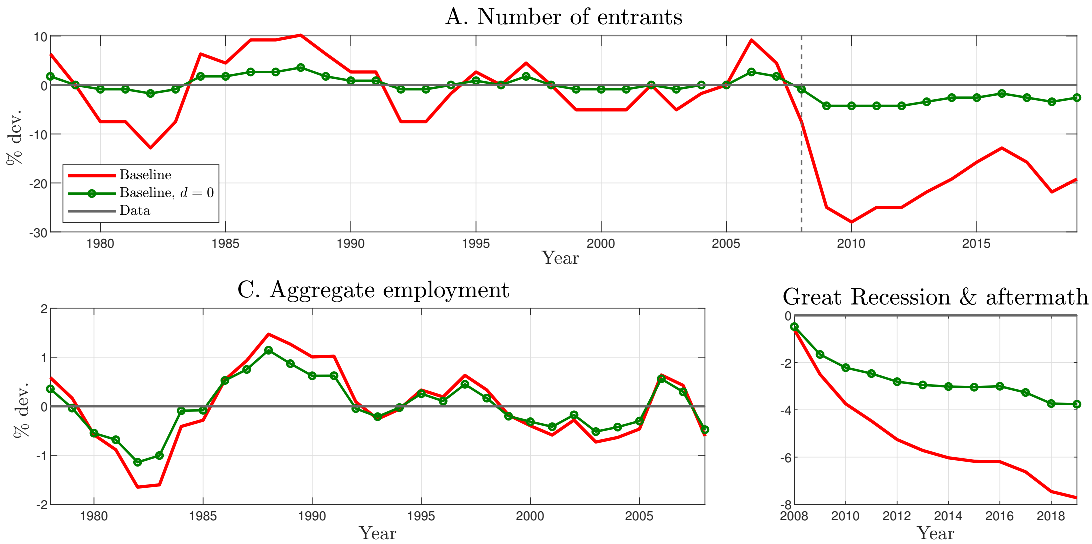
cost of entry, the threshold signal, and the number of entrants are equivalent across the baseline and "baseline, $d = 0$" case in the steady state, but the differences arise beyond the steady state due to the endogenous opportunity cost of entry.[31] As the entry cost only affects selection (the number and composition of entrants), and has no effect on the post-entry decisions of firms, comparing these scenarios completely isolates the option-to-delay channel in the selection and post-entry dynamics of firms.

I re-estimate the regression equation (4) using simulated data from the "baseline, $d = 0$". Figure 14 illustrates the percentage differences between expansionary and recessionary cohorts characteristics. Panel 14(a) shows that in the absence of the option to delay entry, the elasticity of the threshold signal decreases significantly, causing the differences in average productivity to fall from 3% to 0.5%. Panel 14(b) shows that 80% of the drop in the number of firms during recessions is due to the firms that decide to delay entry, while Panel 14(c) shows that the option-value channel is responsible for around 70% of the persistent drop in employment of the recessionary cohorts. Finally, as a direct implication of the option-to-delay entry channel, Figure 14(c) shows that without the option to wait, the differences in the survival rates become economically negligible. For a more detailed discussion on the mechanism, refer to Section 4.

Next, I compare the response of the "baseline, $d = 0$" to the shock process considered in Figure 12 to evaluate the aggregate implications of the option-value channel. Figure 15 illustrates the results and the properties of these time series are summarized in Table 7. I

[31]Note that the range of signals between the green-circle line and the red-solid line describes an additional group of firms that decide not to enter the market if they have the option to wait.

Figure 15: Aggregate fluctuations: The option-value channel



find that the endogenous countercyclical opportunity cost of entry is responsible for around 80% of the variance in the number of entrants and 60% of the variance in the total number of firms. Without the option-value channel, the volatility of the aggregate employment drops by 25% in the model, which corresponds to 12% of the volatility in the data. Additionally, the removal of the option-value channel in the "baseline, $d = 0$" scenario results in lower auto-correlations in the aggregate time series, as the persistent differences across cohorts are no longer present.

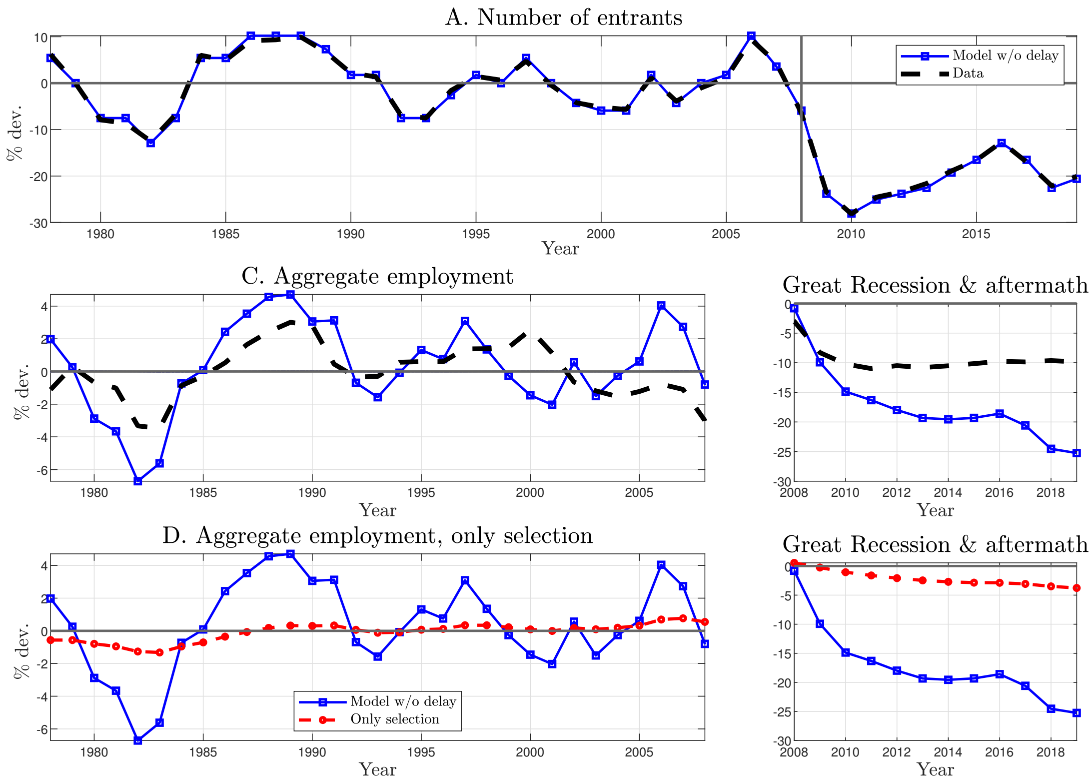
Note that the option-value channel is particularly relevant during episodes with prolonged adverse aggregate shocks accompanied by the persistent drop in the number of entrants, as seen in the years 1980-1983 and 1978-1993. That said, the channel plays a notably important role during the Great Recession, accounting for around 40% of the drop in aggregate employment by 2019 over the period 2009-2019.[32]

6.2 Standard Case: A Model without Delay

In this section, I show that without the delay channel, existing models require either large shocks that generate excessive aggregate fluctuations or exogenous mechanisms to reconcile the observed dynamics of entrants. Specifically, I consider a modified version of the baseline model with $d = 0$, referred to as the "Model w/o delay," that is calibrated to replicate the

[32]In Appendix A.6, Figure 24 provides evidence that there was an increase in the share of late startups during and after the Great Recession. Specifically, the share of startups that formed businesses with a one-year delay increased from 12% in 2007 to 17% in 2014.

Figure 16: Aggregate fluctuations: Model without delay



same empirical facts presented in Section 5.1. Figure 13 provides a useful comparison of entrant dynamics in three different versions of the model: the baseline model, the "Baseline, $d = 0$", and the "Model w/o delay".

In "Model w/o delay," the aggregate shock can only affect the selection of entrants through its direct effect on potential firms' lifetime profits. Producing the observed variation in the number and composition of entrants requires the standard deviation and the autocorrelation of the aggregate demand shock to be 0.016 and 0.64, respectively.[33] In the baseline model, the numbers are 0.003 and 0.75, respectively. In terms of the unconditional variance, the "model w/o delay" requires shocks with 5-times higher magnitudes to produce the observed variation in entry than the baseline model. To put it differently, the endogenous countercyclical variation in the cost of entry amplifies the elasticity of entrants to aggregate shocks 5-times.

The exogenous shock process affects not only the selection of entrants, but incumbent firms' production and continuation decisions. Thus, the different exogenous shock processe in

[33] Appendix E provides a detailed description of the model w/o delay's calibration procedure. In Appendix E, Table 16 summarizes the parameter values, and tables 17, and 18 summarize how the moments targeted in the Standard model compare with the data counterpart and the baseline model.

the baseline and the "model w/o delay" have different implications about the role of entry margin in aggregate fluctuations. In light of the aggregate dynamics illustrated in Figure 16, as well as the summary statistics described in Table 7, two main conclusions emerge. First, the "model w/o delay" leads to excessive aggregate fluctuations: the variance of the aggregate employment is around *1.7* times higher than the data counterpart. To put the number into perspective, Panel C of Figure 16 shows that a shock process that matches the dynamics of entrants would predict a drop in aggregate employment more than twice as large as the one observed in the data. The second key finding is that the "model w/o delay" significantly underestimates the role of the entry margin in shaping aggregate fluctuations. This is because, unlike the baseline model, in the "model w/o delay" post-entry shocks account for around 90% of the volatility in aggregate variables.

Existing literature uses various approaches to reconcile the observed variation in the number and composition of entrants for a reasonable aggregate demand shock process. One possibility is to use exogenous entry cost shock or a function that varies over the cycles as in Lee and Mukoyama (2018) and Clementi and Palazzo (2016), or introduce entry function, which allows choosing the elasticity of the number of entrants with respect to aggregate shocks as in Sedlaćek and Sterk (2017). In that respect, one could also think about the option-to-delay channel as a microfoundation for these exogenous mechanisms – it endogenously generates the countercyclical cost of entry that increases the elasticity of entrants with respect to aggregate demand.

6.3 Policy Implications

Finally, I argue that failing to account for the entry timing may lead to misleading predictions about the response of potential entrants to different shocks or policies. This is because, with the option to delay entry, entrants' dynamics depend on how changes in the aggregate environment affect the relative benefits of entering the market today versus tomorrow. In contrast, standard models only consider the direct effect of the shock. Thus, depending on the nature, size, timing, and duration of the shocks, the standard framework may lead to imprecise predictions regarding potential entrants' responses. To illustrate the point, Appendix F shows that the behavior of entrants in response to permanent, temporary, or future reductions in entry costs varies significantly depending on the presence or absence of the option to wait.

7 Robustness and Extensions

In summary, the key contribution of this paper is to demonstrate that the option to delay entry, coupled with aggregate risk, induces a countercyclical cost of entry that amplifies the selection of entrants over business cycles. The subsequent section presents a range of extensions of the baseline model to verify the robustness of this result across different modeling environments. For brevity, I defer the details of each extension to their respective appendices.

7.1 Customer Capital Accumulation

The decision to study and quantify the option-to-delay channel in a model with customer capital accumulation is motivated solely by the growing literature that emphasizes the significance of demand-side factors (as opposed to differences in productivity or capital accumulation) in understanding both firm-level and aggregate fluctuations (Foster et al. (2016), Sedlacek and Sterk (2017), and Moreira, 2016).[34] In this section, I evaluate the role that the customer capital accumulation plays in quantitative importance of the option value channel.[35] Toward the end, in the baseline model, I shut down the customer capital accumulation process ($\delta = 0$), and at the same time, fix each firm's customer base at $\tilde{b}$. I choose the latter value to ensure that the average entry rate in the counterfactual scenario matches that of the baseline model. Note that, in this "No customer capital accumulation" case, any changes in firms' period demand and lifetime profits over the business cycles are entirely due to aggregate demand shocks.

I find that the customer capital accumulation plays a minor role in the quantitative importance of the option-value channel. In Figure 45, we observe that the option to delay entry still results in countercyclical variation in the opportunity cost of entry, even when the customer capital accumulation process is not present. In fact, based on the figure, the option to delay entry more than doubles the fixed entry cost during recessions. In Figure 46, I compare the dynamics of entrants with and without the option to delay entry in the absence of customer capital accumulation. I find that the option value channel amplifies the variation in entrants by a factor of 5.2, which is slightly higher than the baseline model prediction.

[34] Fitzgerald et al. (2018) demonstrate that in successful cases of export market entry, a firm's customer base is insensitive to lagged sales. Instead, customer capital growth is driven by marketing and advertising efforts, which are argued to act as customer-base adjustment costs.

[35] For a detailed discussion, including all supporting tables and figures, please refer to Appendix G.2.

7.2 Probability of Keeping Signal

In this subsection, I study a version of the baseline model that allows potential entrants to keep signals over time with some non-zero probability, $d \in (0, 1)$. Importantly, I estimate d within the model and reexamine the quantitative importance of the option to delay entry. For a detailed description of the discussion that follows, including all supporting tables and figures, please refer to Appendix G.1.

Figure 42 demonstrates that as the value of d decreases, the value of waiting decreases disproportionately, leading to a decrease in both the total opportunity cost of entry and the threshold signal level. The following features of the option value of delay are used to design an estimation strategy for d. First, the value of d does not affect the steady-state characteristics of the economy, as it has no impact on the steady-state threshold signal (Figure 42). Second, the value of d directly affects the equilibrium opportunity cost of entry for a given aggregate demand shock process, which entirely shapes the elasticity of entrants to aggregate shocks. Therefore, d is used to target the business cycle variation of the number of firms for any given aggregate demand shock process.

Next, by estimating parameter d endogenously, the model can additionally capture the effects of the shock on incumbent firms' production and hiring decisions. That is, the parameters that govern the aggregate demand shock process can also be used to target the standard deviation of aggregate employment in addition to the business cycle variation of the number of firms. Following the estimation strategy, the values of the parameters d, ρ_z, and σ_z that match the targeted moments are $d = 0.965$, $\rho_z = 0.72$, and $\sigma_z = 0.0054$.

In "Baseline ($d = 0.965$)", the endogenous countercyclical opportunity cost of entry accounts for approximately 70% of the variance in the number of entrants in contrast to 80% in "Baseline ($d = 1$)". Nevertheless, the option value of delay continues to play the same role in the variation of aggregate employment. In particular, the absence of the option-value channel results in a 25% drop in the volatility of aggregate employment in the "Baseline ($d = 0.965$)", which corresponds to 12% of the volatility observed in the data. Overall, while the introduction of parameter d in "Baseline ($d = 0.965$)" slightly reduces the quantitative importance of the observed dynamics of firms, the option value of delay is a major channel that accounts for the dynamics of entrants over the business cycle.

7.2.1 Industry-level Value of Waiting

Following the discussion in the previous section, the model predicts that the elasticity of the number and composition of entrants to aggregate entry conditions is higher in the economy with a higher value of d. It is reasonable to anticipate that the ability of firms to maintain signal d varies across industries. Therefore, the evidence presented in Section A.4, which indicates that industries with more procyclical entry tend to have more countercyclical survival rates, lends support to the model's framework.

The result on Figure 19 can also be used to roughly rank industries based on their estimated value of d. This ranking can serve as a rough validation of the model framework and its compatibility with our prior knowledge of the importance of the option value of waiting across different sectors. For example, Figure 19 indicates that industries such as Construction, Real Estate and Rental and Leasing, Transportation, and Manufacturing tend to have higher predicted values of d, while industries such as Accommodation and Food Services, Finance and Insurance, and Wholesale Trade tend to have lower predicted values of d.

7.3 General Equilibrium

Next, I evaluate how does the general equilibrum framework modifies the quantitative and qualitative implications of the option-value channel. Appendix B.3 provides a description of the general equilibrium version of the model.[36] In general equilibrium, both wages and the stochastic discount factor become procyclical.[37] The procyclical discount factor makes delay favorable, since potential entrants give more weight to periods with high aggregate demand. However, the procyclical variation in wages makes delay less favorable during recessions. In the following section, I investigate the extent to which the procyclical variation in wages dampens the option-value channel. For a detailed discussion, including all supporting tables and figures, please refer to Appendix B.3.4.

Towards this end, in the baseline model, I allow wage to vary with the aggregate demand shock process in a particular way: $w_t = \bar{w} z_t^{\zeta}$, where $\zeta > 0$. Figure 32 shows variation in the opportunity cost of entry for different values of ζ. As expected, given an aggregate shock process, the procyclical variation in wages reduces the effect of initial conditions on the

[36] It should be noted that the model presented in the main body of the paper is a reduced form of the general equilibrium model with infinitely elastic labor supply $\chi(L_t) = \psi L_t$ and demand for the aggregate consumption basket $P_t = C_t^{\rho}$.

[37] Hong (2018) extends the model to general equilibrium framework and shows that the stochastic discount factor is procyclical.

selection of entrants by dampening both the direct and option-value effects. However, recall that the calibration approach presented in Section 5.1 mandates that the model matches the observed dynamics of entrants. To restore the dampening effect of procyclical wages on the opportunity cost of entry, which is necessary to ensure that the variation in the number of entrants remains consistent with the data, the general equilibrium version of the model requires a higher magnitude aggregate demand shocks.

To put the discussion into perspective, I calibrate the model with exogenous procyclical wage process to match the same set of facts as the baseline model (see Section 5.1 for details). The two key parameters that discipline the wage process are ζ, and ρ_z. I set $\zeta = 0.69$ that ensures that the relationship between the cyclical component of wages and real GDP in the model matches to the data counterpart. I set $\rho_z = 0.704$ to match the autocorrelation of the wage process in the model and the data. Finally, to match the variation in the entry rate in both the model and the data, I set the variance of the aggregate demand shock process $\sigma_z = 0.0053$. In terms of the unconditional variance, the model with procylcial wage requires shocks with 1.56-times higher magnitudes than the baseline model.

I find that allowing procyclical wages in the model does not alter the quantitative or qualitative effects of the option value of delay. Figure 33 shows that, in the recalibrated model, similar to the baseline case, the option to delay entry more than doubles the fixed entry cost during recessions. In Figure 34, I find that the option value channel amplifies the variation in entrants by a factor of 6.2, which is higher in magnitude compared to the baseline model. Motivated by the similar predictions of the GE version of the model, it is possible to view the exogenous demand shock process in the baseline version of the model as a reduced-form effect of both aggregate shocks and wages.

7.4 Time Varying Distribution of Potential Entrants

In the baseline model, the distribution of potential entrants across signals are fixed and does not vary with time. This assumption is based on the idea that the number of viable business ideas that can be implemented in the market each period is limited.[38] In Appendix B.1, I provide an extended description of the entry phase within the baseline framework that justifies the assumption of a time-invariant mass of business opportunities. Specifically, I divide the entry decision into two stages. In the first stage, aspiring start-ups compete for the

[38] This assumption is used throughout the literature (e.g, see Sedlacek and Sterk (2017), Sedlaćek (2020), Lee and Mukoyama (2018)). Fajgelbaum, Schaal, and Taschereau-Dumouche (2017) assume a constant mass of entrants in a model where firms make decisions between entry and waiting.

limited mass of business ideas. In the second stage, which is similar to the baseline model, potential entrants with signals about their business ideas make decisions about entry. This framework incorporates a time-varying distribution of aspiring start-ups while preserving the time-invariant distribution of potential entrants across different signals. This extension could also be interesting in its own right, as it helps explain why we may observe low transition rates from EIN applications (aspiring start-ups) to actual business formation (entrants) in the BFS dataset.

In Appendix B.2, I investigate how the baseline model results change by explicitly incorporating the law of motion of potential entrants across signals over time. That is, I track all potential entrants over time until they enter the market (Figure 29). I find that allowing endogenous variation in the distribution of potential entrants in the baseline model amplifies the differences between expansionary and recessionary cohort (Figure 30). As for the aggregate dynamics, I find that a model with signal accumulation exhibits higher variance and lower persistence in the dynamics of entrants and employment compared to the same baseline model without signal accumulation (Figure 31). The results show that allowing endogenous distribution of entrants over time increases the role the option to delay entry plays in the observed aggregate dynamics.[39] To establish this case as the baseline model, it is essential to properly discipline the data generating process for potential entrants, which would entail determining a functional form for the distribution of entrants, $W(q)$, that reconciles the observed dynamics of entrants within the model of delay. While this task is interesting in its own right, it is complex and pursuing it would make comparisons between the model and existing literature more challenging. As such, I leave this aspect for future research.

7.5 Other Costs of Entry/Waiting and Their Implications

In this section, I demonstrate that the model's predictions remain robust even after incorporating various other costs of entry and waiting.

In Appendix G.3.1, I extend the baseline model to allow countercyclical fluctuations in the direct cost of entry, which captures other potential factors leading to variations in entry costs during recessions, such as financial frictions and higher capital costs. In the model, I

[39]The modification is closely related to Shleifer's (1986) study of implementation cycles. Specifically, the distribution of new signals (innovations, ideas) does not vary over the cycle, and every idea is implemented at some point. However, due to exogenous aggregate demand volatility, optimal timing leads most firms to implement their ideas during booms. These strategic timing decisions from the firms increase the variation in the business cycle twofold.

exogenously allow the fixed entry cost to vary with the aggregate demand level, represented by $z_t^{\zeta_c}$ in Equation (13). I discipline the parameter ζ_c such that, in the absence of the option value of delay ($d = 0$), the model matches the observed variation in entrants. The main findings of this exercise are as follows: First, allowing the cost of entry to vary countercyclically across aggregate states significantly increases the benefits of waiting, leading to greater amplification of the option-value channel in the dynamics of entrants (Figure 47). Second, the direct cost of entry required to match the observed dynamics of entrants in the absence of the option value effect implies a counterfactual 30000 basis point increase in the cost of financing during recessions.

Finally, in Appendix G.3.2, I demonstrate that incorporating the cost of waiting in addition to forgone profits and discounting has no impact on the quantitative implications of the option-value channel. The reason for this is that, in the baseline calibration, the option-value effect is restricted to match the observed dynamics of entrants and firms. Therefore, c_e can be interpreted as the fixed cost of entry net of the cost of waiting. Similarly, the potential impact of the procyclical cost of waiting can be analyzed through the framework of the countercyclical cost of entry discussed in Appendix G.3.1. This is because the exogenous cost of entry can be redefined, once again, as the cost of entry net of the cost of waiting.

8 Conclusions

In this paper, I show that firms' option to delay entry, missing in existing frameworks, has important implications for our understanding of entrants' business cycle dynamics. I provide a firm dynamics model with endogenous entry and exit, which allows firms to postpone business formation after observing the initial aggregate conditions. I find that the option to wait endogenously generates a countercyclical opportunity cost of entry: During recessions, a higher risk of failure increases the value of waiting, hence the cost of entry. The calibrated model successfully accounts for the life cycle dynamics of cohorts in the US on average and over the business cycles.

The option-value channel is quantitatively important in accounting for the observed business cycle dynamics of entrants. I find that the endogenous countercyclical entry cost increases the variation of entrants over the business cycles five times. This channel accounts for around 80% of the observed differences in the recessionary and expansionary cohorts' number of firms, employment, and productivity. The variation in the medium productivity firms who choose to postpone entry produce cohorts with countercyclical survival rates. The option-value channel also builds significant persistence in the dynamics of economic aggregates and contributes to 10% of the volatility in aggregate employment observed in the data.

The option-to-delay channel provides a microfoundation for endogenously reconciling the observed significant effect of the initial aggregate conditions on the selection of entrants. Without the mechanism, existing models require either large shocks that generate excessive aggregate fluctuations or exogenous mechanisms to reconcile the observed dynamics of entrants. I also argue that overlooking this channel may also result in misleading predictions about entrants' responses to different shocks or policies.

Further Applications The framework provides an interesting avenue for future research. For example, using the framework, one can study how the changes in the ability to delay entry over time could explain the decreasing business dynamism in the US. Another possibility is to explore how the heterogeneity in the ability to postpone entry explains the variation in the entry rates across sectors. Additionally, one can re-examine, study and quantify the effect of different policies (e.g., labor adjustment tax, entry subsidies, R&D subsidies) on the response of entrants and the dynamics of the aggregate variables or investigate stabilization policies. While in the paper, I examined how the option to wait alters entry decisions, explaining the dynamics of potential entrants after they use the option (e.g., whether they actually come back to start a business) is also left for future research. I believe that with the development of the Business Formation Statistics dataset, the framework can be very useful to uncover further details about the dynamics of entrants over time.

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Appendix (For Online Publication)

Table of Contents

A Appendix for Empirical Findings

A.1 Aggregate Conditions at Entry and Cohorts' Survival Rates

To study how firms' survival rates vary with the aggregate conditions at entry, I use the US- and state-level annual time series about the number of establishments/firms by age from the Business Dynamics Statistics (BDS) dataset.[40] I measure a survival rate of a cohort of age g at year t as

$$S_{g,t} = \frac{N_{g,t}}{N_{0,t-g}},$$

where $N_{g,t}$ measures the number of establishments (firms) in a cohort of establishments (firms) of age g at year t; $N_{0,t-g}$ measures the number of establishments (firms) in the same cohort at the time of entry (age 0).[41] In this analysis, I consider cohorts' survival rates for up to age 5.[42] I measure the aggregate conditions at entry using the cyclical component of log annual real GDP.[43] I find the latter using the HP filter with a smoothing parameter of *100*.

Figure 17 provides binned scatter plots of pooled cohorts' life cycle survival rates at the US-level against the business cycle indicators at the time of entry. The binned scatter plots include age-specific and year-specific fixed effects. The latter controls for the sequence of aggregate shocks cohorts face after entry. Panel (a) of Figure 17 shows that the business cycle conditions at entry is negatively associated with cohorts' survival rates. Panel (b) of Figure 17 shows that the negative relationship is robust if we consider cohorts of firms rather than establishments.

Next, I use the state-level variation in the life cycle dynamics of new businesses to further investigate the relationship. I estimate the following regression:

$$S_{c,g,s,t} = \alpha + \beta Z_c + \eta_g + \theta_t + \gamma_s + \varepsilon_{g,s,t}, \tag{5}$$

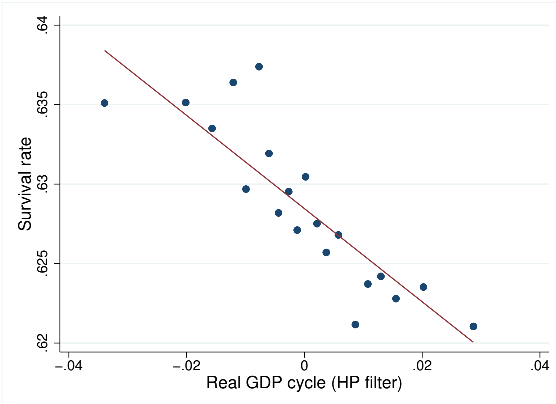
[40] The BDS dataset covers the universe of employer businesses in the US and provides yearly measures of business dynamics aggregated by the establishment and firm characteristics. An establishment is defined as a fixed physical location where economic activity is conducted. A firm might span multiple physical locations and consist of one establishment or many establishments.

[41] Employer businesses are identified as start-ups (age 0) based on their first payroll information in the Longitudinal Business Database.

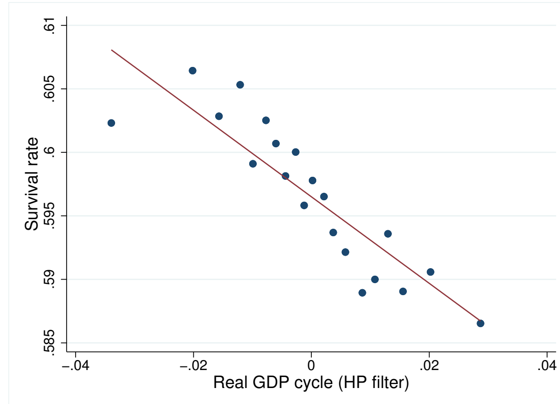
[42] The publicly available part of the BDS dataset only provides information about cohorts from age 0 to age 5. Information about cohorts above age 5 is binned into 5-year age groups.

[43] I annualize the quarterly real GDP data so that it's consistent with BDS timing. The source and the construction of the annual real GDP data are described in Appendix D. For more information see the link.

Figure 17: Correlation between the survival rates and aggregate economic conditions at entry



(a) Cohort of establishments



(b) Cohort of firms

Note: Each panel plots a binned scatterplot of the survival rates up to age five against the aggregate conditions at entry. I measure the latter using the cyclical component of HP-filtered log real GDP. The time series is at the US level. Bin scatter controls for year-fixed effects and age-fixed effects.

where $S_{c,s,t}$ is a survival rate of a cohort c of age g, in state s, at time t; Z_c represents the economic conditions at the time when the cohort first entered the market.[44] η_g, θ_t, γ_s represent age-, year-, and state-fixed effects, respectively. That said, β measures a percentage point change in the cohorts' average survival rates due to the variation in the business cycle conditions at entry. The coefficient should capture the effect of the initial economic conditions on the cohorts' average survival rates after controlling for the age, year and state fixed effects.

Panel A of Table 8 reports the results of the regression equation (5) when the unit of analysis is a cohort of establishments. Column (1) indicates that cohorts born during good economic conditions are characterized by lower survival rates over their life cycle. Specifically, a 1-percentage point increase in real GDP above the trend decreases cohorts' average survival rates by 0.28 percentage point. For robustness, I additionally consider the following business cycle indicators. Column (2) uses a business cycle indicator that refers to a year as a recession if the cyclical component of the log real GDP is below trend ($Y_{HP,I}$). Column (3) uses the NBER-based indicator of a recession that spans the period following the peak through the trough ($NBER$).[45] The indicator equals -1 if the year is indicated as recession, 0 otherwise. Columns (2) and (3) show that cohorts born during recessions, on average, have

[44] The specification is also similar to the age-period-cohort model where cohort effects are a proxy for economic conditions at birth. See Moreira (2005) for more details.

[45] The latter indicator specifies the peak and trough dates on a monthly frequency. Using the monthly data, I define a year t as a recession if at least four months from April in year $t-1$ to April t are indicated as recessionary periods. Based on the definition, the recessionary years are $1981, 1982, 1983, 1991, 2002,$ and 2009. All other years are defined as expansionary.

Table 8: The survival rates and aggregate economic conditions at the time of entry.

	Panel A. Establishment			**Panel B. Firm**		
	Y_{HP}	$Y_{HP,I}$	$NBER$	Y_{HP}	$Y_{HP,I}$	$NBER$
	(1)	(2)	(3)	(1)	(2)	(3)
β	-0.28***	-0.013***	-0.015***	-0.33***	-0.014***	-0.010***
	(0.03)	(0.001)	(0.001)	(0.03)	(0.001)	(0.001)
Age FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	9,945	9,945	9,945	9,945	9,945	1,989
R^2	0.603	0.959	0.959	0.955	0.956	0.596

Note: Robust standard errors clustered at the state-level are in parentheses. The dependent variable represents cohorts' survival rates up to five years of operation. Panel A uses cohorts of establishments and Panel B uses cohorts of firms as a unit of analysis. Columns (1)-(3) use different business cycle indicators at entry. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

higher survival rates compared to their expansionary counterparts. Panel B of Table 8 shows that the results hold if I use cohort of firms as a unit of analysis rather than establishments.

To additionally investigate whether the effects of the initial aggregate conditions disappear over cohort's life cycle, I consider the regression specification where I interact business cycle conditions at entry with cohort age:

$$S_{c,g,s,t} = \alpha + \sum_{g=1}^{5} \beta_g D_g Z_c + \eta_g + \theta_t + \gamma_s + \varepsilon_{g,s,t}, \tag{6}$$

where D_g is an indicator variable that takes the value of one if the business establishments/firms are g years of age. The coefficient β_g measures the change in the survival rates of a cohort at age g with the variation in the business cycle conditions at entry.

Panel A of Table 9 reports the regression results. $1_{\{age=g\}} \times Z$ describes the interaction of the business cycle indicators with the cohort of age g. Column (1) of Panel A shows that the aggregate conditions at entry have a statistically significant and persistent effect on cohorts' survival rates: cohorts of establishments that start operating during recessions are characterized by higher survival rates at entry and over time. Moreover, the results are robust to alternative business cycle indicators. The results also hold if we use a firm as the unit of analysis rather than an establishment.

To interpret the results, note that the initial economic conditions have two counteracting effects on new cohorts' survival rates. On the one hand, unfavorable economic conditions

Table 9: Survival rates by age and aggregate economic conditions at entry

	Panel A. Establishment			Panel B. Firm		
$Z =$	Y_{HP}	$Y_{HP,I}$	$NBER$	Y_{HP}	$Y_{HP,I}$	$NBER$
	(1)	(2)	(3)	(1)	(2)	(3)
$1_{\{age=1\}} \times Z$	-0.20***	-0.007***	-0.024***	-0.35***	-0.010***	-0.023***
	(0.04)	(0.001)	(0.001)	(0.04)	(0.001)	(0.001)
$1_{\{age=2\}} \times Z$	-0.25***	-0.011***	-0.016***	-0.33***	-0.013***	-0.013***
	(0.04)	(0.001)	(0.001)	(0.04)	(0.001)	(0.001)
$1_{\{age=3\}} \times Z$	-0.31***	-0.016***	-0.013***	-0.33***	-0.015***	-0.008***
	(0.03)	(0.001)	(0.001)	(0.03)	(0.001)	(0.001)
$1_{\{age=4\}} \times Z$	-0.33***	-0.017***	-0.010***	-0.34***	-0.016***	-0.002***
	(0.03)	(0.001)	(0.001)	(0.03)	(0.001)	(0.001)
$1_{\{age=5\}} \times Z$	-0.33***	-0.016***	-0.008***	-0.32***	-0.015***	-0.002**
	(0.02)	(0.001)	(0.001)	(0.03)	(0.001)	(0.001)
Age FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	9,945	9,945	9,945	9,945	9,945	9,945
R^2	0.959	0.956	0.959	0.955	0.956	0.955

Note: Robust standard errors clustered at the state-level are in parentheses. The dependent variable represents cohorts' survival rates by age. Panel A uses a cohort of establishments, and Panel B uses a cohort of firms as a unit of analysis. Columns (1)-(3) use different indicators for characterizing the business cycle conditions at entry. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

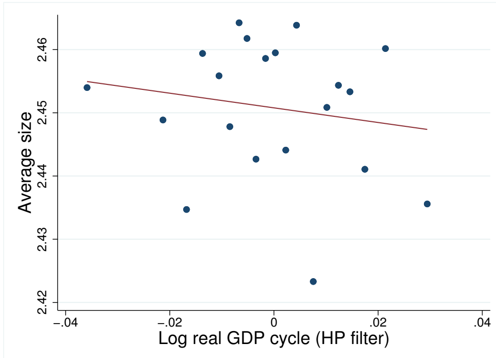
directly decrease cohorts' survival rates due to higher failure rates. On the other hand, cohorts' survival rates could go up due to the selection of better firms at entry during bad aggregate conditions. The finding that cohorts' average survival rates are countercyclical supports the hypothesis that the initial aggregate conditions significantly affect the selection of firms at entry.

A.2 Aggregate Conditions at Entry and Cohorts' Average Size

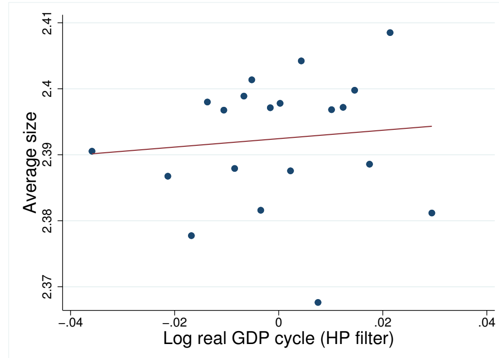
I use the US- and state-level annual time series about cohorts of establishments/firms by age from the BDS. The BDS dataset covers the universe of employer businesses in the US and provides yearly measures of business dynamics aggregated by the establishment and firm characteristics. An establishment is defined as a fixed physical location where economic activity is conducted. A firm may consist of one establishment or many establishments and often spans multiple physical locations. The dataset covers the period $1978-2019$. I measure an average size of a cohort of age g at year t as

$$\bar{L}_{g,t} = \frac{L_{g,t}}{N_{g,t}},$$

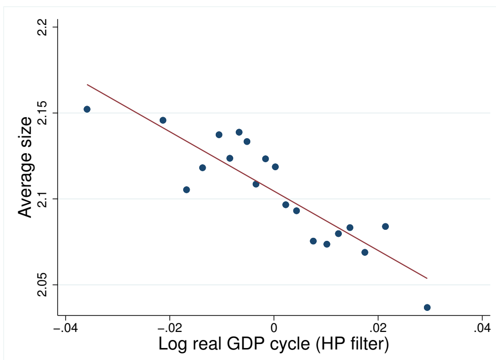
Figure 18: Cohorts' average size against the aggregate economic conditions at the entry



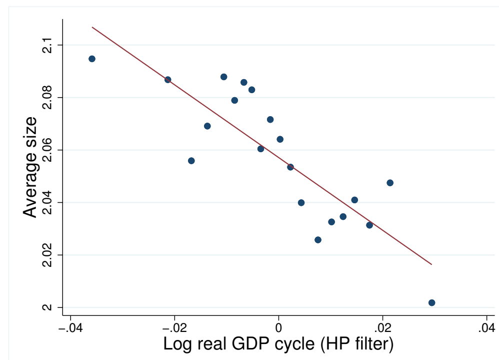
(a) Cohort of establishments (US-level)



(b) Cohort of establishments (state-level)



(c) Cohort of firms (US-level)



(d) Cohort of firms (state-level)

Note: Each panel displays a binned scatterplot of cohorts' average sizes against the aggregate conditions at the time of entry. I measure the latter using the cyclical component of the HP-filtered log real GDP with a smoothing parameter of 100. The bin scatterplots control for year- and age-fixed effects. Panels (b) and (d) also control state-fixed effects.

where $L_{g,t}$ and $N_{g,t}$ measure the total employment and total number of establishments (firms) in a cohort of establishments (firms) of age g at time t. $\bar{L}_{g,t}$ measures the average size of a cohort of establishments (firms) of age g at year t. In this analysis, I consider cohorts' for up to age 5.[46] I measure the aggregate conditions at entry using the cyclical component of log annual real GDP. I find the latter using the HP filter with a smoothing parameter of *100*.

Figure 18 provides binned scatter plots of pooled cohorts' life cycle averages sizes at the US level and state level against the business cycle indicators at the time of entry. Panel (a) of Figure 18 shows that the business cycle conditions at entry are positively associated with average sizes of cohorts of establishments at the US level. However, Panel (b) shows

[46]The publicly available part of the BDS dataset only provides information about cohorts from age 0 to age 5. Information about cohorts above age 5 is binned into 5-year age groups.

Table 10: Cohorts' average size and aggregate economic conditions at the time of entry

	Panel A. Establishment			**Panel B. Firm**		
	Y_{HP}	$Y_{HP,I}$	$NBER$	Y_{HP}	$Y_{HP,I}$	$NBER$
	(1)	(2)	(3)	(1)	(2)	(3)
β	0.064	-0.006	-0.032***	-1.38***	-0.040***	-0.045***
	(0.106)	(0.004)	(0.007)	(0.135)	(0.005)	(0.007)
State FE	✓	✓	✓	✓	✓	✓
Age FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	12,087	12,087	12,087	12,087	12,087	12,087
R^2	0.807	0.807	0.808	0.786	0.783	0.782

Note: Robust standard errors clustered at the state-level are in parentheses. Panel A uses a cohort of establishments, and Panel B uses a cohort of firms as a unit of analysis. Columns (1)-(3) use different indicators for characterizing the business cycle conditions at entry. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

that the correlation becomes negative at the state level. Panels (c) and (d) consider average size of cohorts of firms rather than cohorts of establishments. In both cases, the aggregate conditions at entry are negatively correlated with cohorts' average size. That is, better aggregate conditions at entry are associated with groups of firms with smaller average size.

Next, I use the state-level variation in the life cycle dynamics of new businesses to further investigate the relationship. I estimate the following regression:

$$log(\bar{L}_{c,g,s,t}) = \alpha + \beta Z_c + \eta_a + \theta_t + \gamma_s + \varepsilon_{g,s,t}, \tag{7}$$

where $log(\bar{L}_{c,g,s,t})$ is a log average size of a cohort c of age g, in state s, at time t; Z_{t-g} represents the economic conditions at the time when the cohort first entered the market.[47] η_a, θ_t, γ_s represent age-, year-, and state-fixed effects, respectively. The year-fixed effects controls for the sequence of aggregate shocks cohorts face after entry. That said, β measures a percentage point change in cohorts' average size due to the variation in the business cycle conditions at entry. The coefficient should capture the effect of the initial economic conditions on cohorts' average size after controlling for the age, year and state fixed effects.

Panel A of Table 10 summarizes the estimates of regression equation (7) with a unit of analysis of a cohort of establishments. Column (1) indicates that cohorts born during good economic conditions are characterized by a larger average size over the life cycle, but the coefficient is not statistically significant. For robustness, I additionally consider the following

[47] The specification is also similar to the age-period-cohort model where cohort effects are a proxy for economic conditions at birth. See Moreira (2005) for more details.

Table 11: Cohorts average size by age and aggregate economic conditions at entry

	Panel A. Establishment			**Panel B. Firm**		
$Z =$	Y_{HP}	$Y_{HP,I}$	$NBER$	Y_{HP}	$Y_{HP,I}$	$NBER$
	(1)	(2)	(3)	(1)	(2)	(3)
$1_{\{age=0\}} \times Z$	-0.982***	-0.027***	-0.072***	-2.24***	-0.043***	-0.115***
	(0.160)	(0.005)	(0.007)	(0.16)	(0.005)	(0.008)
$1_{\{age=1\}} \times Z$	-0.447**	-0.013**	-0.034***	-1.76***	-0.034***	-0.074***
	(0.156)	(0.006)	(0.006)	(0.15)	(0.006)	(0.007)
$1_{\{age=2\}} \times Z$	-0.254*	-0.013***	-0.026***	-1.71***	-0.044***	-0.058***
	(0.144)	(0.005)	(0.006)	(0.16)	(0.005)	(0.008)
$1_{\{age=3\}} \times Z$	0.151	-0.011**	-0.023***	-1.33***	-0.048***	-0.032***
	(0.145)	(0.005)	(0.008)	(0.20)	(0.006)	(0.010)
$1_{\{age=4\}} \times Z$	0.706***	0.006	-0.018***	-0.87***	-0.041***	-0.004
	(0.134)	(0.005)	(0.007)	(0.20)	(0.007)	(0.009)
$1_{\{age=5\}} \times Z$	1.116***	0.021	-0.014*	-0.49***	-0.033***	0.012
	(0.134)	(0.005)	(0.007)	(0.22)	(0.008)	(0.010)
Age FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	12,087	12,087	12,087	12,087	12,087	12,087
R^2	0.808	0.807	0.809	0.787	0.783	0.785

Note: Robust standard errors clustered at the state level are in parentheses. Panel A uses a cohort of establishments, and Panel B uses a cohort of firms as a unit of analysis. Columns (1)-(3) use different indicators for characterizing the business cycle conditions at entry. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

business cycle indicators. Column (2) uses a business cycle indicator that refers to a year as a recession if the cyclical component of the log real GDP is below trend ($Y_{HP,I}$). Column (3) uses the NBER-based indicator of a recession that spans the period following the peak through the trough ($NBER$).[48] The indicator equals -1 if the year is indicated as recession, 0 otherwise. Columns (2) and (3) show that cohorts born during recessions, on average, have larger average size compared to their expansionary counterparts. Panel B of Table 10 shows that the results hold if I use a cohort of firms as a unit of analysis rather than establishments.

I additionally I consider a regression specification where I interact business cycle conditions at entry with the cohort age:

$$log(\bar{L}_{g,t}) = \alpha + \sum_{g=1}^{5} \beta_g D_g Z_{t-g} + \eta_g + \theta_t + \gamma_s + \varepsilon_{g,s,t}, \tag{8}$$

[48]The latter indicator specifies the peak and trough dates on a monthly frequency. Using the monthly data, I define a year t as a recession if at least four months from April in year $t-1$ to April t are indicated as recessionary periods. Based on the definition, the recessionary years are $1981, 1982, 1983, 1991, 2002,$ and 2009. All other years are defined as expansionary.

where D_g is an indicator variables that take the value of one if the business establishments/firms are g years of age. The coefficient β_g measures a change in average cohort size at age g with the variation in the business cycle conditions at entry.

Panel A of Table 11 reports the regression results. $1_{\{age=g\}} \times Z$ describes the interaction of the business cycle indicators with the cohort of age g. Panel A uses a cohort of establishments as a unit of analysis. Analyzing Columns (1)-(3) show no statistically robust relationship between cohorts' size over the life cycle and aggregate conditions at entry. Panel B considers the same regression if the unit of analysis is a cohort of firms rather than a cohort of establishments. Panel B shows a statistically negative relationship between the aggregate conditions at entry and cohorts' size. That is, cohorts of firms that start operating during recessions are larger at entry and over time than their expansionary counterparts. However, one can see that the effect dissipates over time when the cohort age.

A.3 Aggregate Conditions at Entry and Cohorts' Characteristics

In this section, I investigate differences between cohorts born at different stages of business cycles after controlling the sequence of aggregate conditions they face after entry. Toward the end, in the regression equation (4), I include year-fixed effects.

Table 12: Differences in cohorts' characteristics based on the initial conditions: Data

	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5
Firms	0.14	0.37***	0.99***	1.83***	2.60***	2.93***
	(0.10)	(0.09)	(0.07)	(0.09)	(0.13)	(0.15)
Survival rate		-0.20***	-0.25***	-0.30***	-0.33***	-0.33***
		(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Employment	-0.84***	-0.08	0.74***	1.98***	3.31***	4.05***
	(0.18)	(0.17)	(0.17)	(0.15)	(0.14)	(0.16)
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The estimates use a state-level annual BDS dataset over the period 1978-2015. To be consistent with the model calibration, I consider a cohort of establishments as a unit of analysis. I use the cyclical component of the HP-filtered log real GDP to measure the aggregate economic conditions at entry.

A.4 Selection of Firms at Entry Across Industries

In this section, I use information about the dynamics of entrants across industries to provide additional support for the hypothesis that the composition of entrants significantly varies with the initial aggregate conditions.

As suggested by the existing literature, including this paper, the aggregate conditions at entry impact not only the number but also the composition of entrants. Consequently, it is reasonable to expect that industries with more procyclical entry exhibit a higher selection of entrants. Specifically, the differences in characteristics between the recessionary and expansionary cohorts are expected to increase with the level of procyclicality of entry. I utilize two-digit US sector-level data from the BDS dataset spanning the period 1978-2019 to test the following three hypotheses: (1) Industries with more procyclical entry have more countercyclical survival rates. (2) There is a positive relationship between the industry-level cyclicality of entry and the relative size of recessionary cohorts compared to expansionary cohort. (3) Industries exhibiting higher countercyclical survival rates also tend to have larger relative size of recessionary cohorts compared to expansionary cohorts.

First, I construct measures of the cyclicality of entry for each industry i. Toward this end, I extract the cyclical component of the HP-filtered log number of entrant establishments for each sector i from 1978 to 2019. I use the following two measures to evaluate the cyclicality of sector-level entry: (1) I regress the time series of the cyclical dynamics of the number of entrants in each industry i on the cyclical component of real GDP at the time of entry, and denote the coefficient on real GDP as $\boldsymbol{\beta_{entry}}$. (2) I calculate the correlation between the cyclical component of entry rate and the cyclical component of real GDP, denoting the correlation coefficient as $\boldsymbol{r_{entry}}$.

Next, To evaluate the cyclicality of cohorts' survival rates with the aggregate condition at entry across sectors, I use the regression equation from the previous section:

$$S_{c,g,i,t} = \alpha + \boldsymbol{\beta_{S,i}} Z_c + \eta_g + \theta_t + \varepsilon_{g,i,t},$$

where $S_{c,g,i,t}$ is a survival rate of a cohort c at age g, in industry i, at time t, defined as in the Section A.1. Z_c represents the economic conditions at the time when the cohort first entered the market, that I measure using the cyclical component of the HP filtered log real GDP. η_g, and θ_t represent age-, and year-fixed effects, respectively. That said, $\boldsymbol{\beta_{S,i}}$ measures a percentage point change in cohorts' average survival rates in industry i due to the variation in the business cycle conditions at entry.

I employ a similar approach to evaluate the cyclicality of cohorts' average size with the aggregate condition at entry across sectors. Again, I use the regression equation from the previous section:

$$log(\bar{L}_{c,g,i,t}) = \alpha + \boldsymbol{\beta_{L,i}} Z_c + \eta_g + \theta_t + \varepsilon_{g,i,t},$$

where $\bar{L}_{c,g,i,t}$ is a n average size of a cohort c at age g, in industry i, at time t, defined as in the Section A.2. The rest of the variables are defined as before. The coefficient $\boldsymbol{\beta_{L,i}}$ represents the percentage change in cohorts' average size in industry i due to the variation in business cycle conditions at entry. It can also be interpreted as the relative difference between the size of expansionary and recessionary cohorts.

Figure 19: Relationship between the cyclicality of entry and the cyclicality of cohorts' survival rates across industries

(a) (b)

Hypothesis 1: *Industries with more procyclical entry have more countercyclical survival rates.*

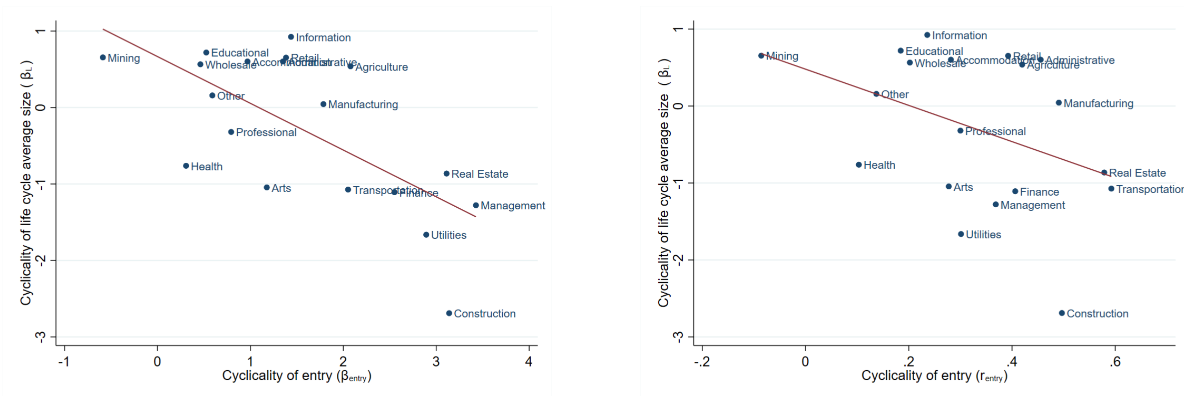
Figure 19 displays a scatter plot of the cyclicality of cohorts' survival rates ($\boldsymbol{\beta_{S,i}}$) and the cyclicality of entry rate ($\boldsymbol{\beta_{entry}}$) across industries, along with the fitted line. The figure shows that higher procyclicality of entry is associated with more countercyclical cohorts' survival rates, indicating that the selection of entrants is stronger in sectors with higher procyclicality of entry. Figure 19(b) replicates the analysis, using $\boldsymbol{r_{entry}}$ as a measure of entry cyclicality across industries.

Hypothesis 2: *There is a positive relationship between the level of cyclicality of entry and the relative size of recessionary cohorts compared to expansionary cohort.*

Figure 20(a) displays a scatter plot of the cyclicality of cohorts' average sizes ($\boldsymbol{\beta_{L,i}}$) and the cyclicality of entry rate ($\boldsymbol{\beta_{entry}}$) across industries, along with the fitted line. Note that some sectors exhibit procyclical average size, such as the Information, Education, Retail, and Wholesale industries, while others, such as Utilities and Construction, are countercyclical.

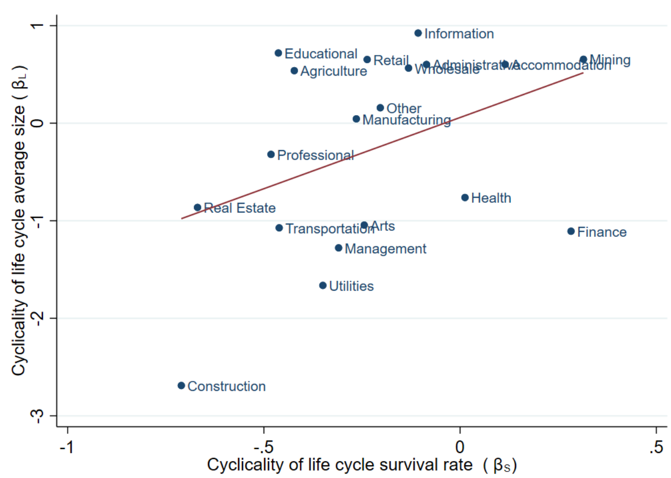
However, the crucial point is that the level of cyclicality of entry is positively associated with the size of recessionary cohorts relative to expansionary cohorts, as illustrated in the figure, lending support to the *selection* hypothesis. This finding is consistent with Moreira's (2016) research, which suggests that the selection effect decreases the procyclicality of firm average size. Figure 20(b) replicates the analysis, using $\boldsymbol{r_{entry}}$ as a measure of entry cyclicality across industries.

Figure 20: Relationship between the cyclicality of entry and the cyclicality of cohorts' average sizes across industries



(a) (b)

Figure 21: Relationship between the cyclicality of cohorts' survival rates and the cyclicality of cohorts' average sizes across industries



Hypothesis 3: *Industries exhibiting higher countercyclical survival rates also tend to have larger relative size of recessionary cohorts compared to expansionary cohorts.*

Figure 20 presents a scatter plot with a fitted line depicting the relationship between the cyclicality of cohorts' average sizes ($\boldsymbol{\beta_{L,i}}$) and the cyclicality of cohorts' survival rates ($\boldsymbol{\beta_{S,i}}$) across industries. The figure reveals that idustries exhibiting higher countercyclical survival rates also tend to have larger relative size of recessionary cohorts compared to expansionary cohorts. The finding is consistent with Moreira (2016), who observes that the procyclicality of firm average size is dampened by the selection effect.

A.5 Evidence of Entry Timing

A.5.1 Data Description

The BFS dataset is based on applications for Employer Identification Numbers (EINs) submitted in the United States, known as IRS Form SS-4 filings.[49] EIN application responses include information about reasons for applying, type of entity, business start date, the expected maximum number of employees, the first wage pay date, principal activity of a business, etc. This information is used to identify a subset of applications associated with new businesses, referred to as business applications. Then, the business applications are matched to the set of firms in the BDS identified as new employer businesses based on payroll information. The matching process is straightforward since both datasets contain information about EINs.

In the analysis, I use the following publicly available seasonally adjusted time series at quarterly frequency:

1. *Business formations within 4 quarters (**F**4Q)* - the number of employer businesses that originate from the business applications within four quarters from the quarter of the applications. Time period: 2004Q3-2015Q4. In the analysis, I refer to this time series as **F**4Q.

2. *Business formations within 8 quarters (B8Q)* - the number of employer businesses that originate from the business applications (BA) within eight quarters from the quarter of the applications. Time period: 2004Q3-2014Q4.

3. *Average duration (in quarters) from business application to formation within 4 Quarters (Dur**F**4Q)* - a measure of delay between business application and formation, conditional on business formation within four quarters. Time period: 2004Q3-2015Q4.

[49] EIN is a unique number assigned to most of the business entities. The EIN is required when the business is providing tax information to the Internal Revenue Service (IRS). Note that EIN applications describe start-up and not establishment-level activities since opening a new establishment does not require a new EIN.

4. *Average duration (in quarters) from business application for formation within eight quarters (Dur$\boldsymbol{F}$8Q)* - a measure of delay between business application and formation, conditional on business formation within eight quarters. Time period: 2004Q3-2014Q4.

   I use these time series to construct the following three variables:

5. *Business formations within the fifth and eighth quarters ($\boldsymbol{S}$4Q):* The number of employer businesses that take between four and eight weeks to transition into employer business from the date of the application. I construct the time series as the difference of $BF8Q - BF4Q$.

6. *Share of late start-ups :* a time series that describes the share of the applications that become employer businesses with one year delay from the date of the application:

$$\textit{Share of late start-ups} = \frac{\mathbf{F}8Q - \mathbf{F}4Q}{\mathbf{F}8Q}$$

7. *Average Duration (in Quarters) from Business Application to Formation from 5 to 8 Quarters (Dur$\boldsymbol{S}$8Q):* a measure of delay between business application and formation, conditional on business formation between the fifth and eighth quarters. I construct the variable using the following formula:

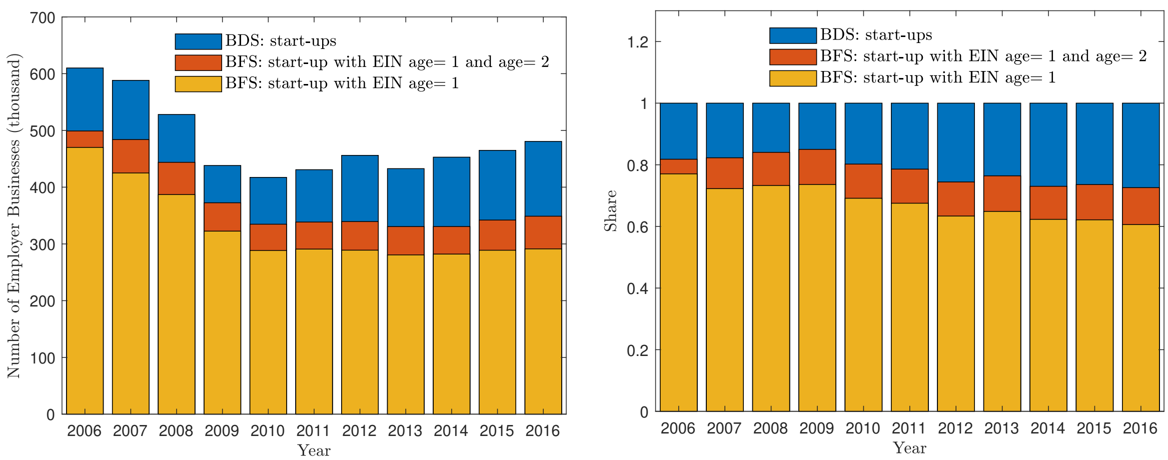
$$Dur\mathbf{S}8Q = \frac{Dur\mathbf{F}8Q\ \mathbf{F}8Q - Dur\mathbf{S}4Q\ \mathbf{F}4Q}{\mathbf{F}8Q - \mathbf{F}4Q}$$

A.5.2 Coverage of the BFS

All firms that show up in the BDS have EINs. Thus, they show up in the BFS dataset before entry.[50] The publicly available part of the BFS dataset allows tracking only the subset of the employer businesses that applied for the EINs within eight quarters before entry. To evaluate the coverage of the publicly available BFS, I compare the information about employer business formation provided by the BFS to the BDS. Since the BDS dataset is annual, I convert the quarterly data from the BFS into a yearly time series. Figure 22 shows that the information about the employer businesses provided in the BFS covers more than 80% of the total start-ups in the BDS.

[50] There is a small group of employer businesses that get EINs after submitting the first payroll information.

Figure 22: The BDS vs the BFS



(a) Number of business formation

(b) Share of business formation

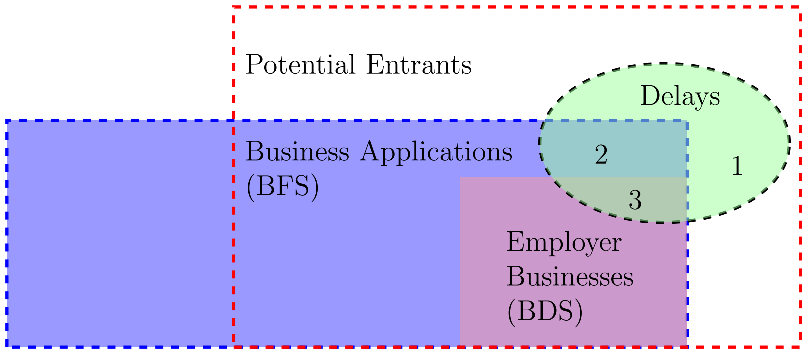
Note: The figure compares the annual total number of new employer businesses in the BDS and the BFS.

A.5.3 Discussion

The potential entrants that delay entry could belong to the following three groups. First is the group of potential entrants that delay entry and also delay applying for the EIN. Second, the group of potential entrants that apply for the EIN delay starting a business at least for the first eight quarters from the date of the application. Third, the group of potential entrants who apply for the EINs, delay entry in the first year and start businesses in later years. Figure 23 illustrates the potential links between the BFS, the BDS, and potential entrants in the model.

I cannot identify the first and the second groups of entrants using the BFS dataset. On the one hand, potential entrants who choose to delay entry might not apply for the EIN applications. Thus, they are not included in the BFS dataset. On the other hand, some parts of the EIN applications might not be for employer business start-ups. In fact, the data about the raw applications is quite noisy about the business formation. For example, out of the total number of business applications, we see that only 14% become employer businesses within two years from the date of the applications. In particular, 12% become employer businesses in the first four quarters, and an additional 2% become employer businesses after a year. Even after considering the subset of the applications with higher rates of employer business births – business applications with planned wages, business applications from corporations, high-propensity business applications, their transition rate does not exceed 36%. Bayard et al. (2018) claim that a significant share of the business applications ends up becoming

Figure 23: The potential links between the Business Formation Statistics Dataset (BFS), the Business Dynamics Statistics Dataset (BDS), and potential entrants in the model.



Note: The figure illustrates potential links between the BDS, the BFS datasets, and the potential entrants that could potentially choose to delay entry. Segment 1 corresponds to potential entrants who decide to delay entry and do not apply for the EIN. Segment 2 characterizes potential entrants who apply for the EIN, decide to delay entry, and never start a business. Finally, segment 3 represents a group of potential entrants that apply for the EIN and choose to wait for a year and enter the market with one year delay.

non-employer businesses.

Finally, note that by combining information in the BFS and BDS dataset, I can follow the pre-entry and post-entry decisions made by the third group of entrants. Specifically, I can use the variation in the time it takes to become employer businesses for the third group of entrants to identify delays in potential entrants' entry decisions.

A.5.4 Robustness: Annual Data

In this section, I conduct the same analysis using an annualized time series about business formation. I construct the following time series: The annual number of applications that form businesses within a year ($BF1Y$); The annual number of applications that form businesses within two years ($BF2Y$); The annual number of applications that form businesses with one year delay ($BF2Y$); The share of the business applications that form businesses with one year delay ($Share$).

To be consistent with the BDS, I construct annual data by summing up $BF4Q$ and $BF8Q$ time series from the second quarter of the year $t-1$ to the first quarter of the year t. $BF1Y$ covers the period $2006-2016$, and the time series for $BF2Y$ covers the period $2006-2015$.[51] The summary statistics for the annual time series are given in Table 13. For comparison, the table also reports summary statistics for the employer business start-ups from the BDS

[51] $BF4Q$ and $BF8Q$ data starts the year $2004Q4$. Since I do not have the complete number of applications for the year 2005, I had to drop them from the analysis.

Table 13: Summary statistics (in thousands)

	Mean	SD	Min	Max
Firms (BDS)	491.5	70.8	417.2	610.0
BF in 2 years	376.0	62.5	330.8	505.9
First year	326.3	59.7	281.6	462.2
Second year	51.2	4.80	43.70	59.40

Table 14: Correlations between the business applications and aggregate conditions at entry

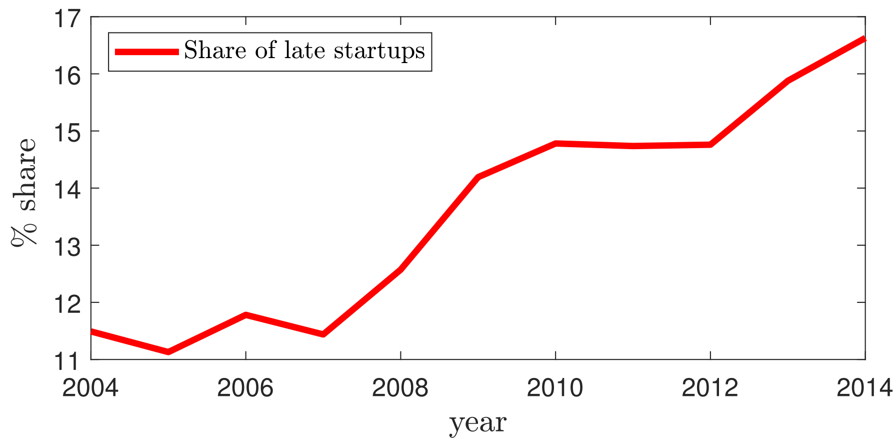
	X / Corr()	$(X_{hp,t}, Y_{hp,t})$	$(X_{lin,t}, Y_{lin,t})$	$(\Delta X_t, \Delta Y_t)$	$(X_{hp,t}, \Delta u_t)$
Panel A	BF within 2 years (p_val)	0.69 (0.03)	0.75 (0.01)	0.63 (0.07)	-0.71 (0.02)
Panel B	First year (p_val)	0.78 (0.01)	0.84 (0.00)	0.67 (0.03)	-0.83 (0.01)
	Second year (p_val)	0.94 (0.00)	0.95 (0.00)	0.77 (0.02)	-0.98 (0.01)
Panel C	Share (p_val)	-0.83 (0.00)	-0.84 (0.00)	-0.74 (0.02)	0.70 (0.03)

dataset.

Cyclicality of the business formation at annual frequency Next, I study the cycle properties of the annual business formation data. Table 14 reports the results. The results imply that the number of applications that form business within a year decreases during the recessionary periods. The subset of the applications that form businesses a year to form a business also decreases during recessions. The share of the applications that form a business with one-year delay increases.

A.6 The Great Recession and the Share of Late Start-ups

Figure 24: Share of late startups



A.7 The Great Recession: A Simple Accounting Exercise

In this section, I use a simple accounting exercise to directly measure the extent to which changes in employment for cohorts that began operating between 2008 and 2016 contributed to the slow recovery of aggregate employment.[52]

Aggregate employment at time t (denoted as N_t) can be expressed as the sum of the total employment of cohorts of establishments at different ages:

$$N_t = n_{0,t} + n_{1,t-1} + n_{2,t-2} + n_{3,t-3} + n_{4,t-4} + n_{5,t-5} + Res_t, \tag{9}$$

where $n_{g,t-g}$ represents the total employment of a cohort of age g that began operating at time $t-g$. The ages considered are $g = 0, 1, 2, 3, 4, 5$. Due to data limitations, only cohorts up to age five are included in the analysis.[53] The term Res_t encompasses the portion of aggregate employment attributed to establishments aged six or older, as well as the employment segment not included in the BDS dataset.

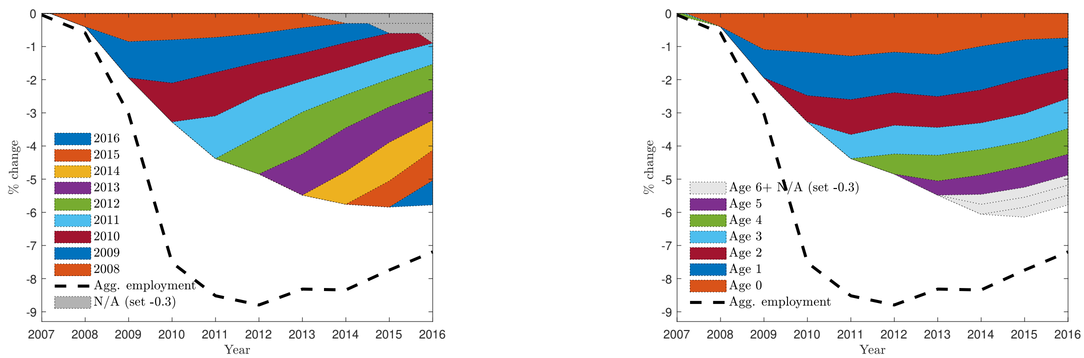
I consider the beginning of the recession to be year 2008.[54]

[52] Gourio, Messer, and Siemer(2016) and Sedlaćek (2019) use data over the period $2008-2012$ and study how the persistent drop in the number of entrants contributes to the aggregate dynamics. In my exercise, I concentrate on changes in cohort-level employment, rather than the number of entrants.

[53] The publicly available part of the BDS dataset only allows me to separately track cohorts from age zero up to age five.

[54] The National Bureau of Economic Research (NBER) dates the beginning of the Great Recession as December 2007. In the BDS, the year 2007 characterizes establishment-level activity from March 2006 to March 2007. To be consistent with the NBER, I choose year 2008 as the beginning of the Great Recession.

Figure 25: New Cohorts' Contribution to the Slow Recovery of Aggregate Employment after the Great Recession



(a) By cohort

(b) By age

Consider $\hat{N}_t$ as the hypothetical level of aggregate employment at time $t \geq 2008$, assuming the Great Recession had not occurred. $\hat{N}_t$ can be formulated as follows:

$$\hat{N}_t = \hat{n}_{0,t} + \hat{n}_{1,t-1} + \hat{n}_{2,t-2} + \hat{n}_{3,t-3} + \hat{n}_{4,t-4} + \hat{n}_{5,t-5} + \hat{Res}_t, \tag{10}$$

where $\hat{n}_{g,t-g}$ represents the employment of a cohort of age g that entered the market at time t, under the assumption that the Great Recession did not take place. $\hat{Res}_t$ is defined similarly. By using equation (9) and equation (10), the changes in aggregate employment can be decomposed as a sum of changes in cohort-level employment by age:

$$\Delta\hat{N}_t = \Delta\hat{n}_{0,t} + \Delta\hat{n}_{1,t-1} + \Delta\hat{n}_{2,t-2} + ... + \Delta\hat{Res}_t, \tag{11}$$

where $\Delta\hat{N}_t = \dfrac{N_t - \hat{N}_t}{\hat{N}_t}$ and $\Delta\hat{n}_{g,t-g} = \dfrac{n_{g,t-g} - \hat{n}_{g,t-g}}{\hat{N}_t}$ for $g = 0, 1, 2, 3, 4, 5$. The term $\Delta\hat{n}g, t-g$ illustrates the extent to which changes in the employment of a cohort of age g contribute to the changes in aggregate employment at time t.[55]

Using the equation, I examine the dynamics of aggregate employment attributable to cohorts that entered the market from $t \geq 2008$. To this end, consider the following counterfactual: for each year $t \geq 2008$, I focus solely on the deviations in aggregate employment, denoted as $\Delta\hat{N}t$, *counter*, which can be attributed to the cohorts that entered the market starting

[55]Note that the term can also be interpreted as a percentage deviation of actual cohort-level employment from the predicted cohort-level employment, weighted by the share of the cohort employment in aggregate employment:

$$\frac{N_t - \hat{N}_t}{\hat{N}_t} = \left(\frac{n_{0,t} - \hat{n}_{0,t}}{\hat{n}_{0,t}}\right)\frac{\hat{n}_{0,t}}{\hat{N}_t} + \left(\frac{n_{1,t-1} - \hat{n}_{1,t-1}}{\hat{n}_{1,t-1}}\right)\frac{\hat{n}_{1,t-1}}{\hat{N}_t} + .. + \Delta\hat{Res}_t.$$

from $t \geq 2008$. In the year 2007, $\Delta\hat{N}2007,\ counter = 0$. From the year 2008 onwards,

$$\Delta N_{2008,\ counter} = \Delta\hat{n}_{0,2008},$$

$$\Delta N_{2009,\ counter} = \Delta\hat{n}_{0,2009} + \Delta\hat{n}_{1,2008},$$

$$. \quad . \quad .$$

$$\Delta N_{2016,\ counter} = \Delta\hat{n}_{0,2016} + \Delta\hat{n}_{1,2015} + \Delta\hat{n}_{2,2014} + ... + \Delta\hat{n}_{6,2013} + \Delta\hat{n}_{7,2012} + \Delta\hat{n}_{8,2011}.$$

I estimate the evolution of aggregate employment from the year 2008 onward, as if the Great Recession had not occurred, by applying a linear trend over the period 1979-2007 to predict aggregate employment.[56] I set $\hat{n}_{g,t-g}$ equal to the average employment of cohorts of age g over the period 2003-2007.

This approach enables me to examine how aggregate employment would have evolved during the Great Recession if the new cohorts of establishments had behaved similarly to the representative pre-crisis cohorts of establishments.[57]

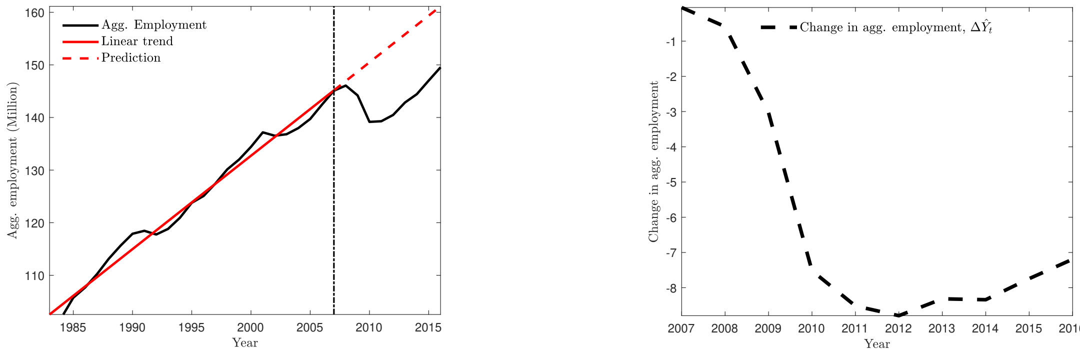
Figure 25(a) illustrates the result of this exercise. The dashed black line represents the total deviation of the aggregate employment from the pre-crisis trend. The dashed black line represents the overall deviation of aggregate employment from the pre-crisis trend, while the shaded areas depict the contribution of cohorts born between 2008 and 2016 to the decline in aggregate employment. Notably, cohorts that joined the labor market after 2008 have consistently employed fewer workers compared to their pre-crisis counterparts. These cohorts contributed roughly 45% to the total 8.9% decline in aggregate employment in 2012. By 2016, aggregate employment remained 7% below the trend, with 85% of the drop being attributable to the cohorts that commenced operations between 2008 and 2016. Therefore, while incumbent firms were responsible for the recession's severity, the dynamics of new cohorts have contributed significantly to the persistence of aggregate employment dynamics. The robustness of these results to alternative specifications, including the ten-year pre-crisis average of cohort-level employment, is demonstrated in Appendix A.7.1. Figure 25(b) presents the same analysis by establishment age instead of cohort year and confirms that the persistent decline in cohort-level employment across various age groups contributed to the decline in aggregate employment.

[56] Figure 26 demonstrates the evolution, pre-crisis trend, and prediction for aggregate employment.

[57] Figure 27(a) illustrates that cohort-level employment by age experienced an upward trend during the period 1983-2007. In contrast, Figure 27(b) shows that the share of cohorts' employment in aggregate employment declined over the same period. Therefore, creating a representative cohort using the average pre-crisis cohort-level employment provides a conservative estimate of recent cohorts' contribution.

A.7.1 Robustness

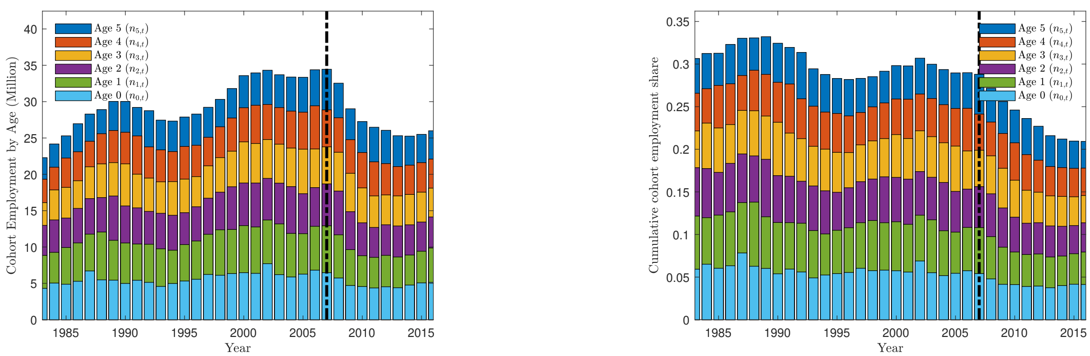
Figure 26: Dynamics of the aggregate employment



(a) Linear trend

(b) Change in agg. employment

Figure 27: Employment dynamics by cohort age



(a) Employment by cohort age

(b) Employment share by cohort age

B Model Appendix

In Section B.1, I present an extended description of the entry phase that justifies the assumption about the constant mass of potential entrants. In Section B.2, I describe results from a model that allows the accumulation of potential entrants who delayed entry. In Section B.3, I present a general equilibrium version of the model.

B.1 Extension: Two-Stage Entry Phase

Every period, there is a limited mass of heterogeneous business opportunities that potential entrants can use to enter the market. These business opportunities are characterized by signal q. The signal describes the productivity of a business opportunity after it is implemented in the market. For a given signal q the distribution of the initial period productivity is given by $H_e(s|q)$. The higher the signal, the higher the expected first-period productivity of a business opportunity. The distribution of business opportunities over the signal is time-invariant and is given by $q \sim W(q)$.[58]

Analyzing the Business Formation Statistics dataset shows that, on average, only 14% of the business applications end up becoming employer start-ups. Using this information, I extend the entry phase and model an additional stage that decomposes entrants between aspiring start-ups – those that wish to be entrepreneurs and potential entrants who hold business ideas and enter the market.

The entry phase consists of two stages. During the first stage, an infinite mass of individuals makes decisions about whether to compete or not for the available business opportunities. Individuals need to pay a fixed cost, c_q, to participate in the competition. After which they are free to direct their search for a particular group of business opportunities characterized by a signal q. Since there are a limited number of business opportunities within each signal category, not all aspiring startups receive a signal. During the second stage, those aspiring startups that receive a signal about business opportunities become potential entrants and make entry decisions. The signal is persistent over time, which gives a potential entrant the ability to exercise the business opportunity in the future instead of today.

In what follows, I describe each phase in detail.

[58]The distribution is such that the mass of business opportunities with signal q decreases with q.

Stage 1. The expected value of attempting to seize a business opportunity with a signal q equals to

$$V^o(q,z) = \frac{B_t(q)}{n_t(q)} V^e(q, z_t) - c_q,$$

where $B_t(q)$ is a mass of available business opportunities with quality q at time t.[59] The total mass of available business opportunities equal to the total number of business opportunities within each signal category minus the mass of ideas that is already in the hands of entrants that delayed entry in the previous periods. $n_t(q)$ refers to a number of aspiring startups competing for the business opportunities with the signal q. The ratio in the equation represents a probability by which an individual receives a signal q and becomes a potential entrant.[60] $V^e(q, z_t)$ is a value of a potential entrant with signal q at time t.

If $V^e(q, z_t) < c_q$, individuals do not compete for the business opportunities with signal q. A positive mass of individuals decide to pay fixed cost c_q and compete for a business opportunity with signal q if $V^e(q, z_t) > c_q$. Due to the free entry, the number of individuals $n_t(q)$ competing for each signal q is such that $\frac{B_t(q)}{n_t(q)} V^o(q, z_t) = c_q$.

Denote $\underline{q_t}$ a signal at time t that satisfies $V^e(\underline{q_t}, z_t) = c_q$. Since the value of entry increases with a signal level, aspiring startups choose to compete for the business opportunities with signal level $q > \underline{q_t}$. The total number of individuals attempting to get the business opportunities equals

$$N_{t,\text{aspiring startups}} = \int_{\underline{q_t}} n_t(q) dq.$$

Note that while $\underline{q_t}$ is weakly countercyclical (the higher the aggregate demand level, the higher the expected value of entry for all q), the cyclical variation of $N_{t,\text{aspiring startups}}$ depends on the available business opportunities at time t that is determined by the states in the past period.

Stage 2. Stage 2, in which potential entrants make entry decisions, follows the same process as described in the 3.1.2.

Calibration To parameterize the entry phase, I use the Business Formation Statistics dataset. As I have noted before, the transition rate from application to business formation is

[59] $0 < B_t(q) < W(q)$

[60] $0 \leq \frac{B_t(q)}{n_t(q)} \leq 1.$

around 12% and 14% within one and two years from the date of the application, respectively. In terms of the model, I consider the number of applications as the number of aspiring start-ups. I choose c_q, the fixed cost that individuals need to pay to become aspiring start-ups so that the share of the actual entrants in the total number of aspiring start-ups is 13%. The value corresponds to $c_q = 0.022$.

The data also shows that only an additional 2% of applications transition into employer businesses with one year delay. In terms of the model, the fact implies that $B(q)$ is close to $W(q)$; only a few potential entrants who choose to delay entry come back to the market next period. The ability to delay entry is an option for a potential entrant and does not require the potential entrant to enter the market in the future. Explaining the reasons behind what makes potential entrants actually come back or not come back in the market after delaying entry is beyond the scope of this paper and is left for future research.

Interestingly, the two-stage entry phase can also be used to reconcile the low transition rates from the business applications to employer businesses observed in the BFS data. In particular, the framework differentiates aspiring start-ups – those who want to start businesses and apply for the EIN, from those who actually hold business ideas and make entry decisions. According to the model, the restricted number of actual business ideas does not allow most aspiring start-ups to enter the market.

B.2 Extension: Model with Signal Accumulation

In this section, I relax the assumption that keeps the aggregate distribution of potential entrants constant in the baseline model. I investigate how the accumulation of potential firms modifies cohorts' characteristics over the cycles. I show that the recessionary cohorts have significantly and persistently different characteristics compared to their expansionary counterparts, even after allowing the accumulation of potential entrants over time.

In the baseline model, the aggregate distribution of potential entrants over the signal is time-invariant and is given by $W(q)$. In this section, I relax the assumption in the following way. At the beginning of every period, a constant mass of new potential entrants is born and make entry decisions. The distribution of new potential entrants over the signal is given by $W(q)$, see Figure 28(a). In addition to the new potential entrants, the aggregate distribution also consists of old potential firms. Old potential entrants are the ones who chose to delay entry in the previous periods even though their NPV of entry was non-negative. Figure 28 (b) displays the threshold signal, $\hat{q}_d(z)$ for each aggregate state when $d = 0$ (blue-dashed

Figure 28

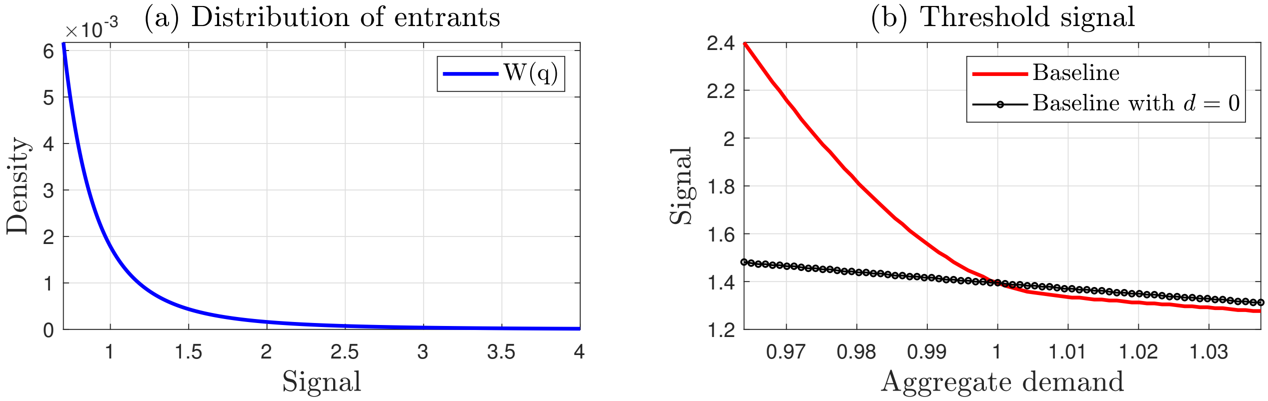
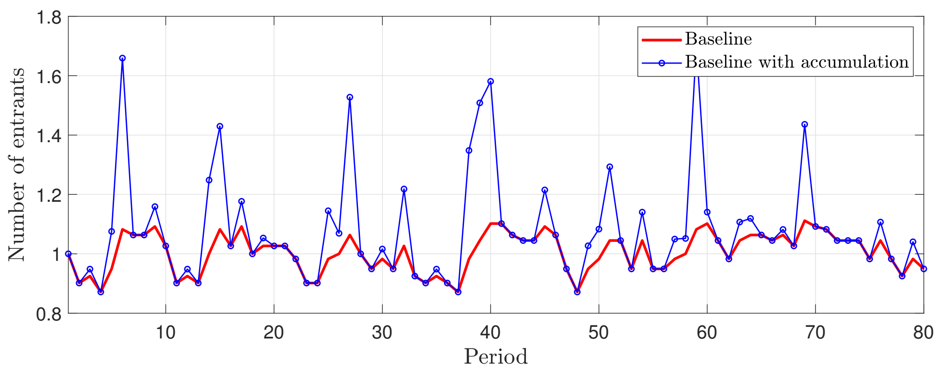


Figure 29: Dynamics of entrants with and without accumulation



line) and $d = 1$ (solid red line). For given z, potential entrants that decide to delay entry hold signals in between $[\hat{q}_{d=0}(z), \quad \hat{q}_{d=1}(z)]$.

The distribution of old potential entrants evolves endogenously and depends on the realization of the aggregate states in the previous periods. Denote the mass of old potential entrants with signal q at the beginning of period t with $\Lambda_t^{\text{old entrants}}(q)$.

$$\Lambda_{t-1}^{\text{old entrants}}(q) = \sum_{k=0}^{t} W(q)\ 1\left\{\hat{q}_{d=0}(z_k) \leq q < \hat{q}_{d=1}(z_k)\right\} + \Lambda_0^{\text{old entrants}}(q),$$

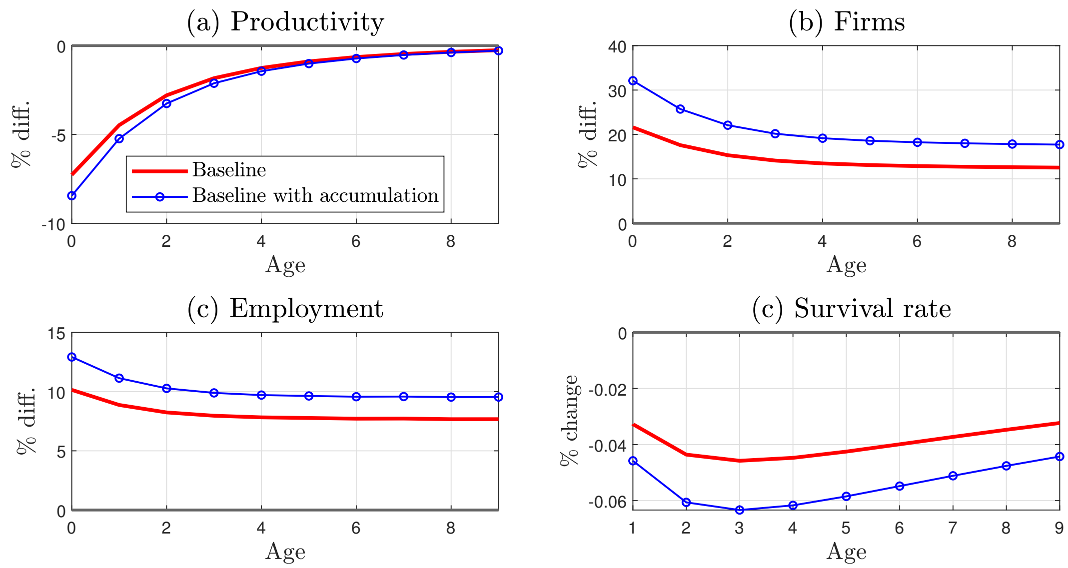
where $\Lambda_0^{\text{old entrants}}(q)$ denote the distribution of old potential entrants at time 0.

Then, the total mass of potential entrants with signal q at the beginning of period t, $\Psi_t(q)$ is given by

$$\Psi_t(q) = W(q) + \Lambda_t^{\text{old entrants}}(q).$$

Figure 29 compares the dynamics of entrants in the baseline and the alternative scenario with entrant accumulation. Note that when the aggregate demand decreases from z_{t-1} to z_t, these two scenarios coincide with each other. However, if the aggregate demand level increases from period $t-1$ to period t in addition to new potential entrants, some of the old potential entrants also decide to enter the market, resulting in a higher number of entrants to the model with signal accumulation compared to the baseline model.

Figure 30: Differences between the expansionary and recessionary cohorts' life cycle characteristics: Baseline with signal accumulation

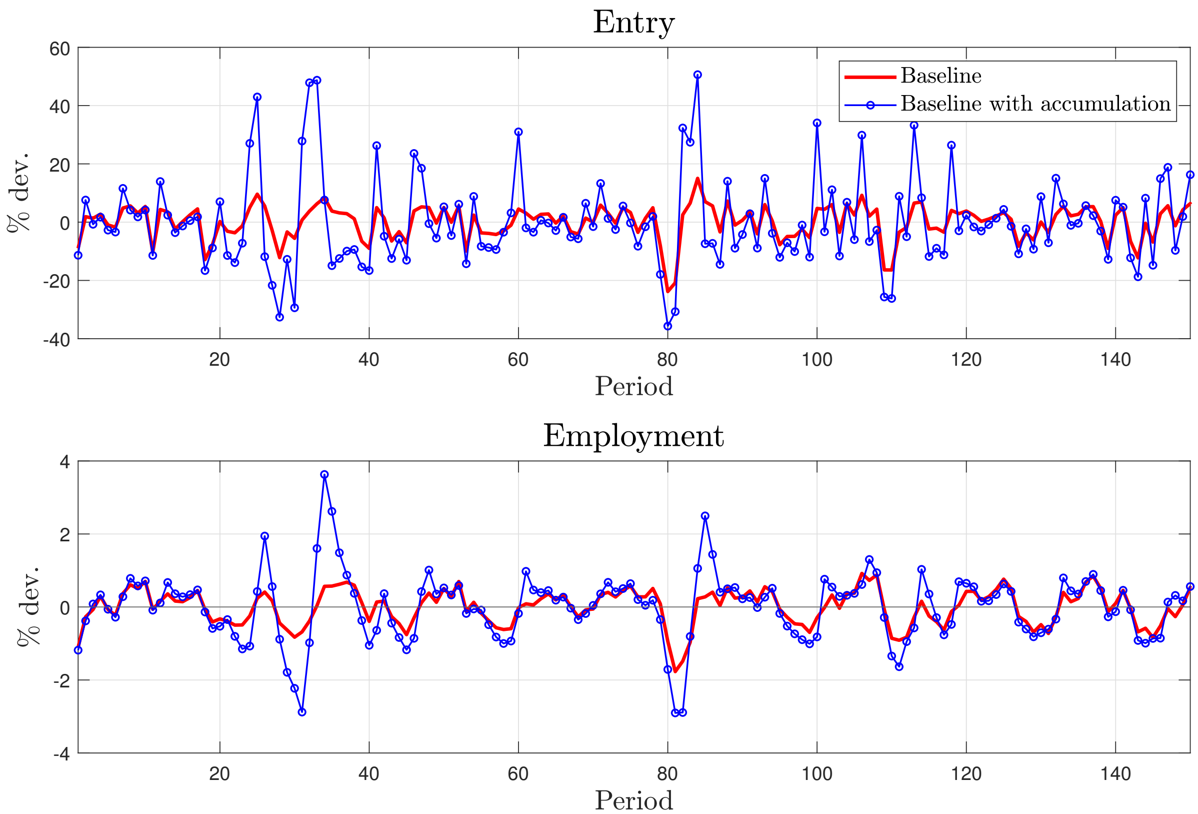


It turns out that the alternative model produces an entry rate that has a higher variance and is more procyclical. Moreover, Figure 30 describes the differences between the expansionary and recessionary cohorts life cycle characteristics. The figure shows that allowing accumulation of potential entrants over time leads to cohorts with significantly and persistently different characteristics based on the business cycle conditions at entry. That is, cohorts born during recessions are more productive and have higher survival rates. However, they consist of fewer firms and employ fewer workers at entry and over time. Interestingly, the differences are even larger compared to the baseline model, where I did not allow for the signal accumulation.

B.2.1 Aggregate Fluctuations with Signal Accumulation

In this section, I analyze the effect of signal accumulation on the aggregate dynamics. Specifically, I compare the dynamics of the number of entrants and aggregate employment between a model with signal accumulation and the baseline case over a 150-period horizon. To ensure

Figure 31: Aggregate dynamics with and without signal accumulation



comparability, I apply the HP-filter with a smoothing parameter of 100 to both time series. Figure 31 displays these time series. The results indicate that the baseline model with signal accumulation exhibits higher variance and lower persistence in the dynamics of entrants and employment compared to the same model specification without signal accumulation. Keeping the result in mind, one can conclude that a model that allows for signal accumulation predicts the role of the option value in accounting for the dynamics of variables at micro and macro level that is greater in magnitude than the one predicted in the baseline model.

B.3 General Equilibrium Framework

In this section, I extend the model to the general equilibrium framework. Note that the model presented in the main body of the paper is a reduced form of a general equilibrium model with infinitely elastic labor supply $\chi(L_t) = \psi L_t$ and where the demand of aggregate consumption basket is given by $P_t = C_t^{\rho}$.

B.3.1 Consumers

The economy is populated by a unit mass of atomistic, identical households. At time t, the household consumes the basket of goods C_t, defined over a continuum of goods Ω. At any given time t, the only subset of goods $\Omega_t \subset \Omega$ is available. Let $p_t(\omega)$ denote the nominal price of a good $\omega \in \Omega_t$.

First layer maximization:

$$\max_{\left(C_t, L_t, (c_t(\omega))_{\omega\in\Omega_t}\right)_{t=0}^{\infty}} E_0\left[\sum_{t=0}^{\infty}\beta^t \frac{C_t^{1-\sigma}-1}{1-\sigma} - \chi(L_t)\right],$$

such that

$$P_t C_t = P_t w_t L_t + \Pi_t.$$

Second layer maximization:

$$\max_{(c_t(\omega))_{\omega\in\Omega_t}} C_t = \left(\int\limits_{\omega\in\Omega_t} (\alpha z_t)^{\frac{1}{\rho}} b_t(\omega)^{\frac{\gamma}{\rho}} c_t(\omega)^{\frac{\rho-1}{\rho}} d\omega\right)^{\frac{\rho}{\rho-1}},$$

such that

$$\int\limits_{\omega\in\Omega_t} p_t(\omega) c_t(\omega) d\omega \leq P_t C_t.$$

B.3.2 The Mutual Fund

The household owns shares in the mutual fund. The mutual fund consists of heterogeneous incumbent firms and new entrants. The mutual fund collects profits from all active firms at the end of the period and allocates dividends to households based on their shares. Description of the incumbent firms and potential entrants are similar to the baseline model. Except, I modify parts of the value functions to include aggregate prices and stochastic discount factors. The timing is shortly summarized below.

Incumbent Firms Incumbent firms are distributed over consumer capital (b) and productivity (s). The distribution given by $\Omega_t(s, b)$. At time t, for given aggregate demand level z, an incumbent firm characterized by (s, b) takes solves the following functional equation, while taking as given real wage w and the aggregate price index P.

$$V^I(b,s,z) = \max_{y,p,b} \quad py - Pwn + \int max\left\{0, -Pc_f + \tilde{\beta}(1-\gamma)E[V^I(b',s',z')|s,z]\right\} dG(f),$$

s.t.

$$y_t^s = s_t n_t;$$

$$y_t^d = \alpha z_t b_t^{\eta} \left(\frac{p_t}{P_t}\right)^{-\rho} Y_t;$$

$$b_{t+1} = (1-\delta)\left(\ b_t + y_t p_t\ \right);$$

$$c_f \sim G(f),\ c_f \text{ is in consumption units:};$$

$$log(s_{it}) = \rho_s log(s_{it-1}) + \sigma_s \varepsilon_{it};$$

$$log(z_t) = \rho_z log(z_{t-1}) + \sigma_z \epsilon_t.$$

Potential Entrants Potential entrants are endowed with signal, q that characterize their initial productivity. At any t, density of potential entrants over q is constant and is given by $W(q)$. To enter into the market the potential entrant needs to pay fixed entry cost in consumption units c_e (value $P_t c_e$). Upon entry the potential entrant observes actual idiosyncratic productivity (s), receives fixed initial capital stock (b_0) and behaves like an incumbent with (b_0, s).

At time t, for the given aggregate demand level z, aggregate price P and real wage w potential entrants solve the following problem:

$$V^e(b_0,q,z) = max\left\{\tau\ \tilde{\beta}E[V^e(b_0,q,z')|z],\quad -Pc_e + \int_s V^I(b_0,s,z)dH_e(s|q)\right\}.$$

Value of the Mutual Fund The value of mutual fund, Λ_t at the beginning of time t, after entry and exit has occurred:

$$\Lambda_t = \int_s \int_b V(s,b,z)\Omega(b,s,z)dsdb + \int_{q*}^{\infty} \int_s V(b_o,s,z)H(s|q)W(q)dq.$$

Denote $N_{e,t}$ be the number of entrants in period t, than: $N_{e,t} = \int\limits_{q_*}^{\infty} W(q)dq$. At the end of the period value of mutual fund is

$$\Lambda_t' = \Pi - N_{e,t}c_e + (\Lambda_t - \Pi).$$

Let $x_t \in [0, 1]$ was the share household decides to hold of the mutual fund in period t. Then, household budget constraint will be

$$\Lambda_t x_t + C_t \leq [\Pi - N_{e,t}c_e + (\Lambda_t - \Pi)]\, x_t + L_t P_t w_t.$$

The optimal solution implies that if $\Lambda_t \geq 0$ then $x_t = 1$. The latter reduces HH budget constraint to

$$P_t C_t + P_t N_e c_e = P_t w_t L_t + \Pi_t.$$

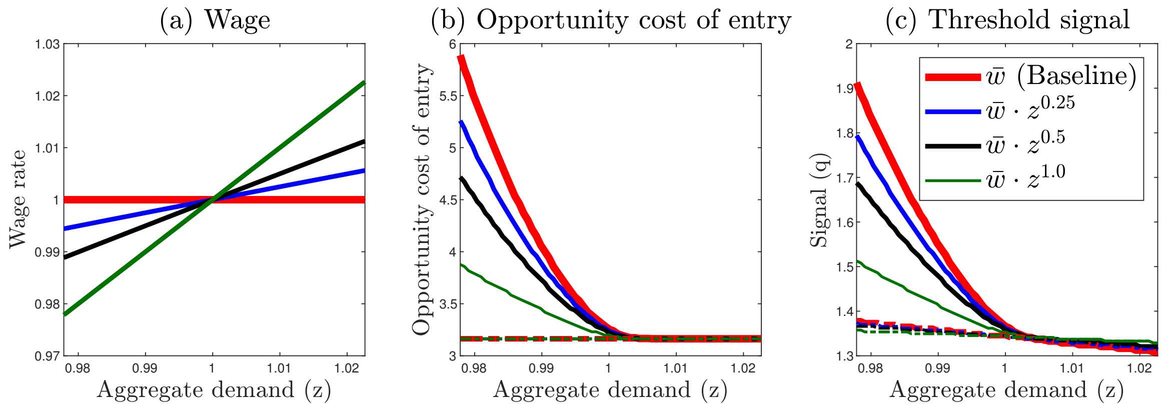
B.3.3 Discussion

In general equilibrium, both wages and the stochastic discount factor become procyclical (Hong, 2018). The procyclical discount factor makes delay favorable, since potential entrants give more weight to high aggregate demand conditions. The procyclical variation in wages makes delay less favorable during recessionary periods. However, the option value of delay is always non-negative due to entrants' ability to get an outside option by not entering the market. As a result, for any initial aggregate states the threshold value of the entry is weakly higher in the model with persistent signal compared to the models without persistent signals.

B.3.4 Exogenous Wage Process

In the following section, I investigate the extent to which the procyclical variation in wages dampens the option-value channel. Towards this end, in the baseline model, I allow wage to vary with the aggregate demand shock process in a particular way: $w_t = \bar{w} z_t^{\zeta}$, where $\zeta > 0$. Figure 32 of Appendix B.3.4 shows variation in the opportunity cost of entry for different values of ζ. As expected, given an aggregate shock process, the procyclical variation in wages reduces the effect of initial conditions on the selection of entrants by dampening both the direct and option-value effects. However, recall that the calibration approach presented in Section 5.1 mandates that the model matches the observed dynamics of entrants. To restore the dampening effect of procyclical wages on the opportunity cost of entry, which is necessary to ensure that the variation in the number of entrants remains consistent with the data, the general equilibrium version of the model requires a higher magnitude aggregate demand shocks.

Figure 32: Procyclical wage variation and the selection of entrants



To put the discussion into perspective, I calibrate the model with exogenous procyclical wage process to match the same set of facts as the baseline model (see Section 5.1 for details). The two key parameters that I use to discipline the wage process are ζ, and ρ_z. calibrate ζ so that the relationship between the cyclical component of wages and real GDP in the model matches to the data counterpart. I use ρ_z to match the autocorrelation of the wage process in the model and the data. Finally, I recalibrate σ_z to match the variation in the entry rate in the model and the data.

To estimate the statistical properties of the wage process in the data, I analyze annual time series data from FRED on the real hourly compensation for all employed persons in the non-farm business sector. To be consistent with the baseline calibration, I use the HP filter with smoothing parameter 100 to find the cyclical component for log wage process. To evaluate the cyclical properties of the wage process in the model and the data, I run the following regression:

$$wage_t = \beta_0 + \beta_1 X_t + \varepsilon_t$$

where X_t takes on either the time series for lagged wage or the HP filtered cyclical component of real GDP. The results from the data are reported in the second column of Table 15. Comparing the third and the second column of the table shows that the model does a good job in producing the realistic prociclycal wage dynamics. Parameter values that achieve the goal are $\zeta = 0.69$, and $\rho_z = 0.706$. Finally, to match the variation in the entry rate in both the model and the data, the variance of the aggregate demand shock process with the procyclical wage process should be set to $\sigma_z = 0.0053$, which is approximately 1.65-

Table 15: Calibration process of the procyclical wage process

X	Data β_1	Model β_1
Wage (Autocorrelation - 1st lag)	0.704***	0.704
Real GDP	0.311***	0.311
Entry	0.022	0.059

times higher than that of the baseline model. I find that allowing procyclical wages in the model does not alter the quantitative or qualitative effects of the option value of delay. In Figure 33, we see that in the recalibrated model that the option to delay entry still results in countercyclical variation in the opportunity cost of entry and in fact, similar to the baseline case the option to delay entry more than doubles the fixed entry cost during recessions. In Figure 34, I compare the dynamics of entrants with and without the option to delay entry. I find that the option value channel amplifies the variation in entrants by a factor of 6.2, which is slightly higher in magnitude compared to the baseline model.

Figure 33: Selection of entrants (with procyclical wage)

(a) Threshold signal (b) Opportunity cost of entry

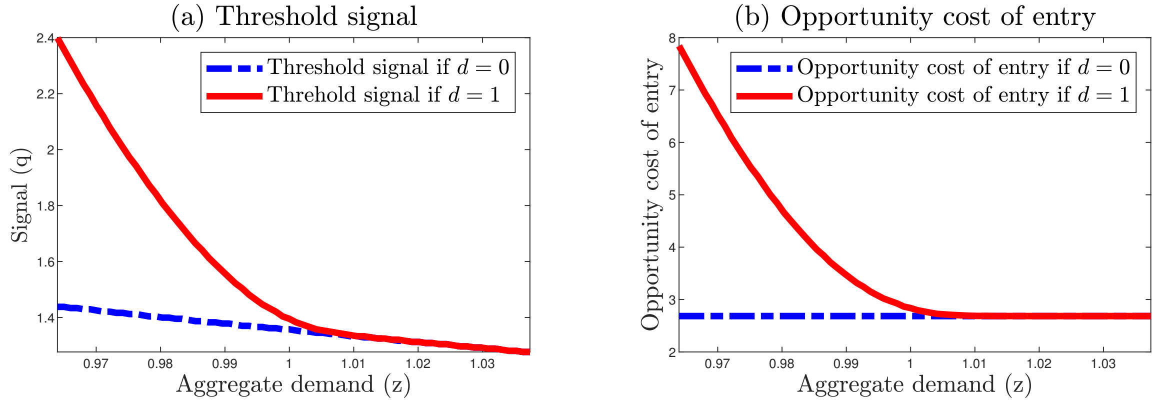
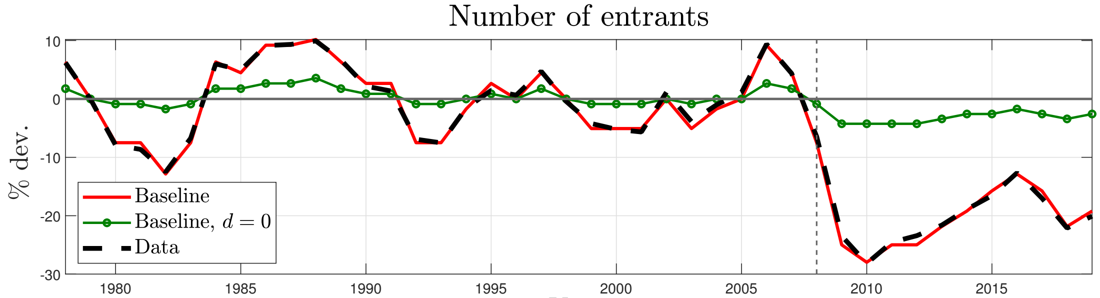


Figure 34: The option-value channel (with procyclical wage)



C Numerical Solution

The following section describes the numerical solution algorithm used to solve the model.

C.1 Incumbent's Value Function

1. Define grid points for the state variables s, z, and b.
   (a) The grids and the transition matrices for the idiosyncratic productivity shock s and the aggregate demand shock z are constructed following the Rouwenhorst (1995)'s method. Denote the number of grid points as I_s and I_z, and the probability transition matrices as $P^s(s'|s)$ and $P^z(z'|z)$, respectively.
   (b) To construct grid points for the customer capital I use equally distributed grid points on a logarithmic scale on the interval $[b_0, \quad b_{max}]$. I choose b_0 to match entrants' average size. I choose b_{max} so that employment by large firms is more than 1000+. The latter corresponds to the highest size bin in the BDS dataset. Denote the number of customer capital grid points as I_b.
2. For all the grid points (b, s, z), guess the incumbent firm's value function $V_0^I(b, s, z)$.
3. Construct a revised guess for the value function $V_1^I(b, s, z)$ by solving:

$$V_1^I(b,s,z) = \max_b \left\{ \Pi(b,s,z) + G(c_f^*) \left(\beta(1-\gamma) E[V_0^I(b',s',z')|s,z] - E[c_f|c_f < c_f^*] \right) \right\},$$

subject to

$$\Pi(b,s,z) = \left(\frac{b'}{1-\delta} - b \right) - \frac{w}{s} \left(\frac{b'}{1-\delta} - b \right)^{\frac{\rho}{\rho-1}} b^{\frac{-\eta}{\rho-1}} \ (\alpha z)^{\frac{-1}{\rho-1}},$$

$$E[V_0^I(b',s',z')|s,z] = \sum_i \sum_j V_0^I(b', s_i, z_j) P^z(z_j|z) P^s(s_j|s),$$

where $P^z(z_j|z)$ and $P^s(s_j|s)$ represents probabilities that next periods aggregate shock equals to z_j and idiosyncratic shock equals s_j. c_f^* is the value of the fixed cost which equals to incumbent's expected continuation value $\beta(1-\gamma)E[V^{I*}(b',s',z')|s,z]$. In other words, when an incumbent firm receives c_f^*, the incumbent firm is indifferent between staying or exiting from the market.
4. Stopping criteria: $|\dfrac{V_{n+1}^I(b,s,z) - V_n^I(b,s,z)}{V_n^I(b,s,z)}| \leq 10.0^{-8}$.

C.2 Potential Entrants' Distribution

Figure 35: $W(q)$

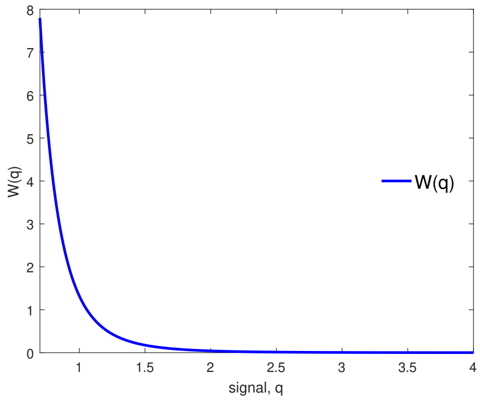
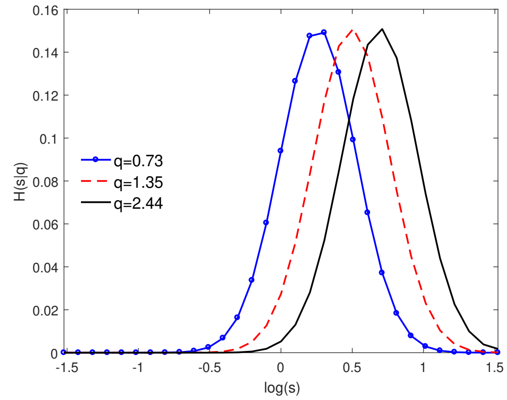


Figure 36: $H(s|q)$



1. Denote the number of grid points for the signal by I_q. I use Gauss-Legendre quadrature method over the interval $[\underline{q},\ q_{max}]$ to generate grid points q and weights w_q for the signal.

2. The aggregate signal distribution $W(q)$ has Pareto Distribution with a location Parameter of $\underline{q}$ and Pareto exponent ξ. I approximate the mass of potential entrants denoted by P_q, at each grid point of signal according to the following equation:

$$P_q(q) = w_q(q)\ \xi \frac{\underline{q}^{\xi}}{q^{\xi+1}}.$$

3. I construct the distribution for the initial idiosyncratic productivity $H(s|q)$ as follows:

   The idiosyncratic shock in the first period of operation follows the normal distribution. For each grid point $q_j \in I_q$ and $s_i \in I_s$, I calculate $F(s_i|q_j)$, the probability that the entrant with signal q_j gets the initial productivity lower than s_i as follows:

$$H(s_i|q_j) = \frac{1}{2}\left(F(s_i|q_j) - F(s_{i-1}|q_j)\right) + \frac{1}{2}\left(F(s_{i+1}|q_j) - F(s_i|q_j)\right).$$

   I construct the initial and the terminal grid points of the productivity based on the following function:

$$H(s_1|q_j) = F(s_1|q_j) + \frac{1}{2}\left(F(s_2|q_j) - F(s_1|q_j)\right),$$

$$H(s_{I_s}|q_j) = \max\left(0, 1 - F(s_{I_s}|q_j)\right) + \frac{1}{2}\left(F(s_{I_s}|q_j) - F(s_{I_s-1}|q_j)\right).$$

I denote the final value function by $V^I(b,s,z)$.

C.3 Entrant's Value Function

1. For all grid points (q_j, z_k) I calculate the gross value of entry as

$$V^{gross}(b_o, q_j, z_k) = \sum_{i \in I_s} \left[H(s_i|q_j) V^I(b_o, s_i, z_k) \right].$$

2. To approximate the entrant's value function and the option value of delay, I use the value function iteration algorithm described below:

   (a) Guess for the values of the entrant value function. $V_0^e(b_0, q, z)$

   (b) Given the guess find value of the option value of delay.

$$V^{Opt}(q,z) = \tau \ \beta E[V_0^e(b_0, q, z')|z] = \tau \ \beta \sum_{z_j \in I_z} V_0^e(b_0, q, z_j).$$

   (c) Update guess for value function of entry.

$$V_1^e(b_0, q, z) = \max\left\{ V^{Opt}(q,z), V^e(b_0, q, z) - c \ \right\}.$$

   (d) Stopping criteria: $|\dfrac{V_{n+1}^e(b,s,z) - V_n^e(b,s,z)}{V_n^e(b,s,z)}| \leq 10.0^{-8}$.

Denote the final entry value function by $V^e(b_0, q, z)$ and the final option value of delay function as $V^{Opt}(q,z)$.

D Calibration Appendix

D.1 The Sources of Data

The BDS dataset covers the universe of employer businesses in the US and provides yearly measures of business dynamics for the US economy aggregated by the establishment and firm characteristics. For more information see the link. The establishment is defined as a single physical location, whereas the firm is defined at an enterprise level. The data report establishment/firm-level activity based on the employment status on March 12. Specifically, at year t, establishment- and firm-level activity describes the period from the second quarter of year $t-1$ through the first quarter of year t. For more information see the link.

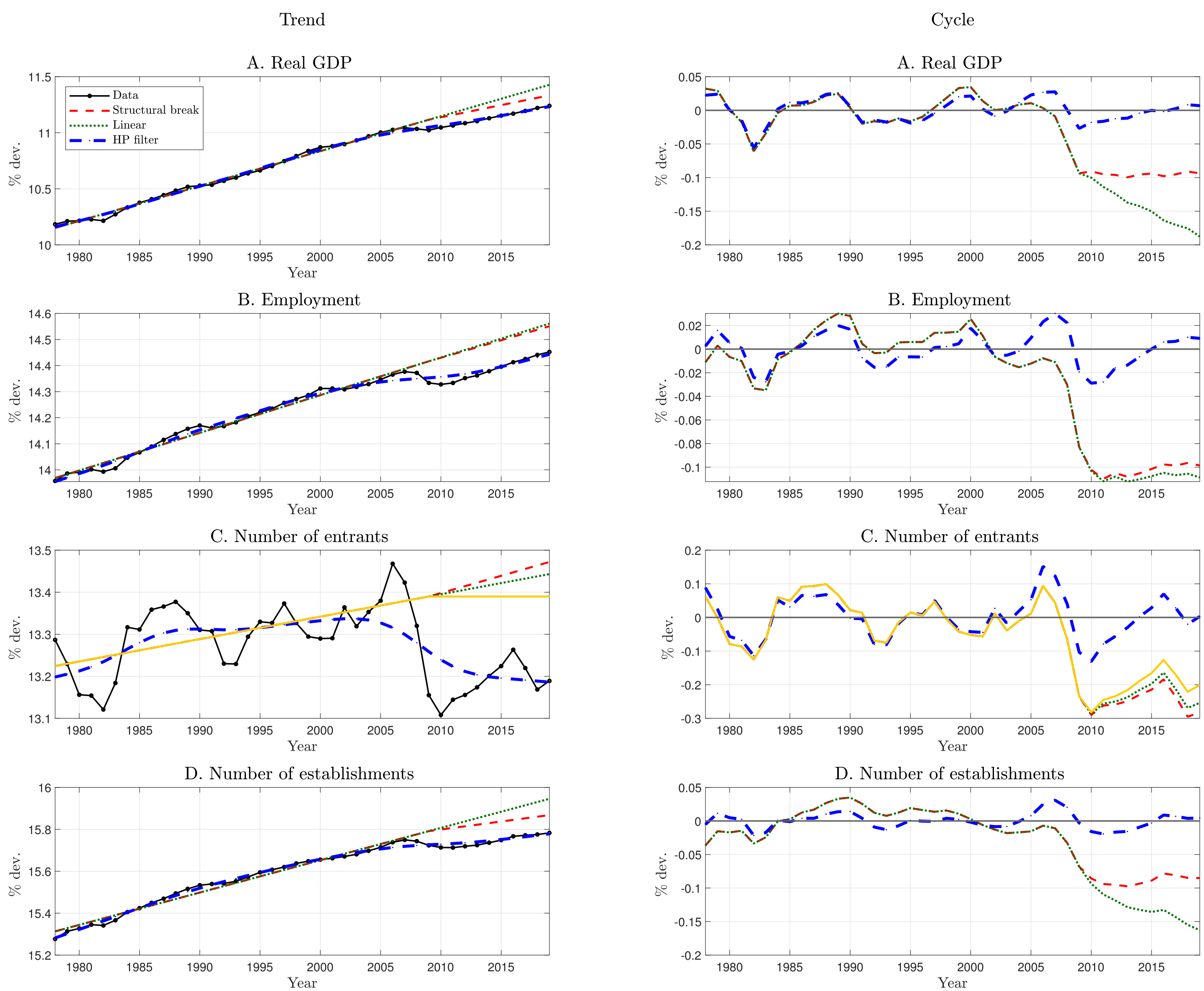
The BDS follows each cohort of establishments for up to 5 years. After five years, the dataset gives information in 5-year bins. More specifically, The data set characterizes cohorts within the following age groups [0, 1, 2, 3, 4, 5, 6-10, 11-15, 16-20, 21-25, 26+].

Aggregate Time Series To measure aggregate activity I use time series for real GDP, and aggregate employment from the Federal Reserve Economic Data (FRED). While studying the business cycle conditions at entry, I consider the modified versions of the time series that is consistent with the BDS timing. Specifically, in the BDS, establishment-level and firm-level activity at year t covers the establishment activity from March of year $t - 1$ to the March of year t. Thus, I construct the annual time series of the aggregate variables as March-to-March averages, to be consistent with the BDS dataset timing.

D.2 Detrending

Figure 37 illustrates the trend and cyclical component of aggregate variables after applying alternative detrending methods. Specifically, I compare the trend and cyclical component of log real GDP, aggregate employment, number of entrants, and number of establishments over the period 1978-2018 after applying (i) a linear trend (ii) a linear trend and a linear trend that allows a break point in trend (iii) the HP filter with smoothing parameter 100. Note that the HP-filters predicts that the Great Recession was a sharp downturn after which the economy recovered quickly. On the other hand, the linear trend exaggerates the severity of the recession.

Figure 37

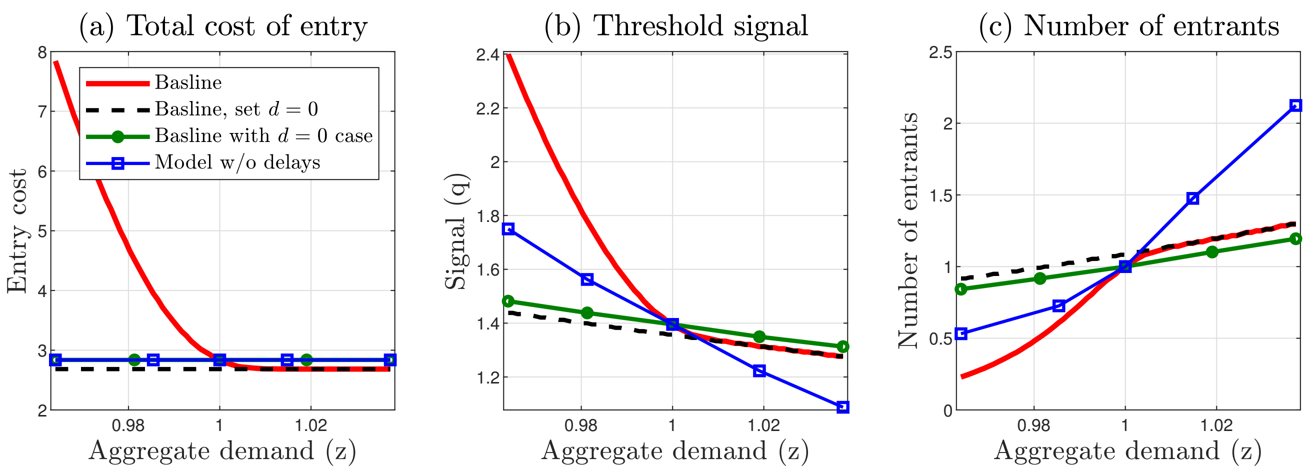


Trend
Cycle
A. Real GDP
B. Employment
C. Number of entrants
D. Number of establishments
Data
Structural break
Linear
HP filter
% dev.
Year

E Alternative Models

In this section, I describe in detail the construction of the alternative scenarios that I use to understand the role of the option to delay entry in driving the micro and macro level fluctuations. First, in Section E.1, I describe the baseline with $d = 0$ case that I use to study how much the option to delay entry amplifies and propagates aggregate shocks. Second, in Section E.2, I compare the performance of the baseline model to a workhorse firm dynamics model (model w/o delay), parameterized to account for the same set of facts.

Figure 38: Alternative scenarios



E.1 Baseline with $d = 0$

To isolate the role of the option to delay entry in the business cycle dynamics of the aggregate variable, I consider a version of the baseline model with $d = 0$ (*Baseline with* $d = 0$ *case*).

Setting $d = 0$ in the baseline model decreases the opportunity cost of entry by the amount of the option value of delay. As a result, compared to the baseline model, the threshold quality signal is lower in the baseline model with $d = 0$. In the steady state, the threshold signal uniquely determines the distribution of entrants over the initial productivity, which in turn can be mapped uniquely to the invariant firm distribution. Hence these two scenarios exhibit different dynamics in the steady state. To isolate the role of the option value of delay in the business cycle dynamics of entrants, I need to re-calibrate the baseline model with $d = 0$ to match the same set of facts in the steady state, as the baseline model.

$$V^{gross}(z_{ss}, \hat{q}_d) = c_e + dV^w(z_{ss}, \hat{q}_d) \tag{12}$$

Table 16: Calibration of alternative scenarios

Symbol	Description	Baseline	$d = 0$	Mode w/0 delay
β	Discount rate	0.960	0.960	0.960
ρ	Price elasticity of demand	1.622	1.622	1.622
η	Elasticity of demand to capital	0.919	0.919	0.919
δ	Depreciation rate of reputation	0.188	0.188	0.188
ρ_s	Idiosyncratic shock – persistence parameter	0.814	0.814	0.814
σ_s	Idiosyncratic shock – SD parameter	0.161	0.161	0.161
α	Demand shifter	0.261	0.261	0.261
b_o	Initial customer capital level	12.00	12.00	12.00
μ_f	Operating cost – SD parameter	0.621	0.621	0.621
σ_f	Operating cost – SD parameter	0.410	0.410	0.410
γ	Exogenous exit shock	0.071	0.071	0.071
$\underline{q}$	Pareto location	0.700	0.700	0.700
ξ	Pareto exponent	2.478	2.478	2.478
c_e	Fixed entry cost	2.684	2.837*	2.833*
ρ_z	Aggregate shock – persistence parameter	0.750	0.750	0.600*
σ_z	Aggregate shock – SD parameter	0.003	0.003	0.019*
d		1	0	0

The gross value of entry does not vary with d. The threshold signal depends on the total opportunity cost of entry $c_e^d + dV^w(z_{ss}, \hat{q}_d)$. For any d and d', equating the threshold signals in the stochastic steady state $\hat{q}_d(z_{ss}) = \hat{q}_{d'}(z_{ss})$ requires the opportunity cost of entry to equal each other across these scenarios. The value of the option is endogenously determined within the model, while the fixed cost of entry $c_{e,d}$ can be modified to generate the desired level of the threshold signal. Since the fixed entry cost only affects the selection of entrants at entry, equalizing the threshold signal implies that these scenarios will lead to the same dynamics in the stochastic steady state.

Following the argument, I set $c_e^{d=0} = c_e + V^w(z_{ss}, \hat{q}_{d=1})$ in the baseline model with $d = 0$. Figure 38(a) summarizes the difference in the fixed entry cost. The Column (b) of Table 16 summarizes the parameter values used in the baseline with $d = 0$ case and shows that the $d = 0$ case is identically parameterized except the fixed entry cost. Table 17 reports the steady state moments for the $d = 0$ case. Comparing the business cycle dynamics in the baseline model against the $d = 0$ case allows quantifying the role of the option to delay entry in accounting for the observed dynamics of the cohorts over the business cycles.

Table 17: Calibration targets and the model-implied counterparts

Statistics	Data	Baseline	$d = 0$	model w/o delay
Firm size	17.0	17.0	17.0	17.0
Firm size at entry	8.73	10.0	10.0	10.0
Firm size at age 5	13.9	14.5	14.5	14.5
Firm size at age 23	21.2	22.1	22.1	22.1
Employment share at entry	0.56	0.58	0.58	0.58
Firm exit hazard at age 5	0.10	0.09	0.09	0.09
Firm survival rate up to age 5	0.49	0.49	0.49	0.49
Firm survival rate up to age 23	0.15	0.12	0.12	0.12
Entry rate (%)	9.90	10.0	10.0	10.0

Note: The moments are calculated using the US-level cohorts of establishments from the BDS dataset covering the the period 1978-2019.

Table 18: Calibration targets for the aggregate demand shock process

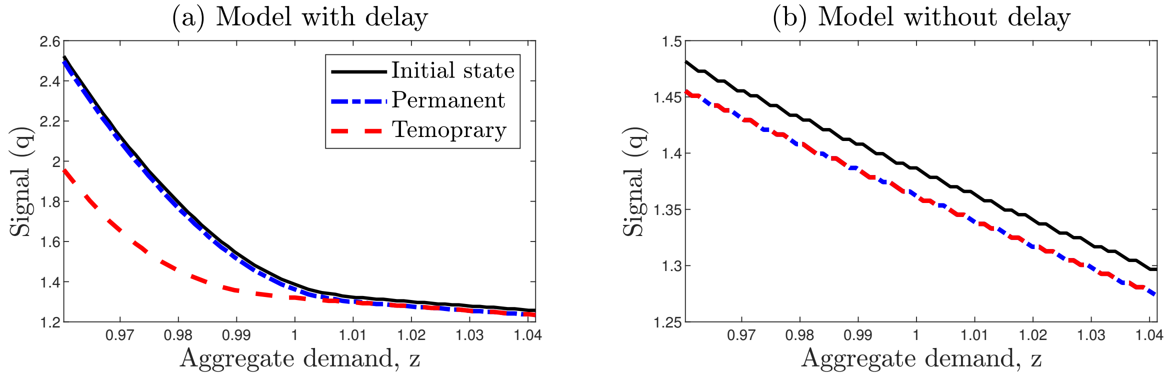
Statistics	Data	Baseline	Baseline with $d = 0$	model w/o delay
Autocorrelation of establishments	0.70	0.72	0.72	0.74
SD of establishments	0.01	0.01	0.01	0.01
SD of entry	0.06	0.06	0.01	0.06

Note: The time series about the entry rate comes from the BDS and covers the period 1978-2019. The cyclical component of the log entry rate is calculated using the HP filter with smoothing parameter 100.

E.2 Model without Delay

A model w/o delay is a version of the baseline model with $d = 0$, calibrated to match the same set of facts described in Section 5.1. In this model, the entry decision follows a traditional neoclassical investment rule: enter if the NPV is non-negative. The entry cost is fixed and does not vary over the cycles (Figure 13a). Thus, the aggregate shock can affect the selection of entrants only through its direct effect on potential firms' lifetime profits. I find that producing the observed variation in the number and composition of entrants without the option-value channel requires the standard deviation and the autocorrelation of the aggregate demand shock to be 0.016 and 0.64, respectively. In the baseline model, the numbers are 0.003 and 0.75, respectively. In terms of the unconditional variance, the model w/o delay requires shocks with 5-times higher magnitudes to produce the observed variation in entry than the baseline model. To put it differently, the endogenous countercyclical variation in the cost of entry amplifies the elasticity of entrants to aggregate shocks 5-times. Table 16 summarizes parameter values, Table 17, and Table 18 summarizes how the moments targeted in the model w/o delay compares to the data counterpart and other scenarios.

Figure 39: Permanent/temporary decline in the fixed entry cost



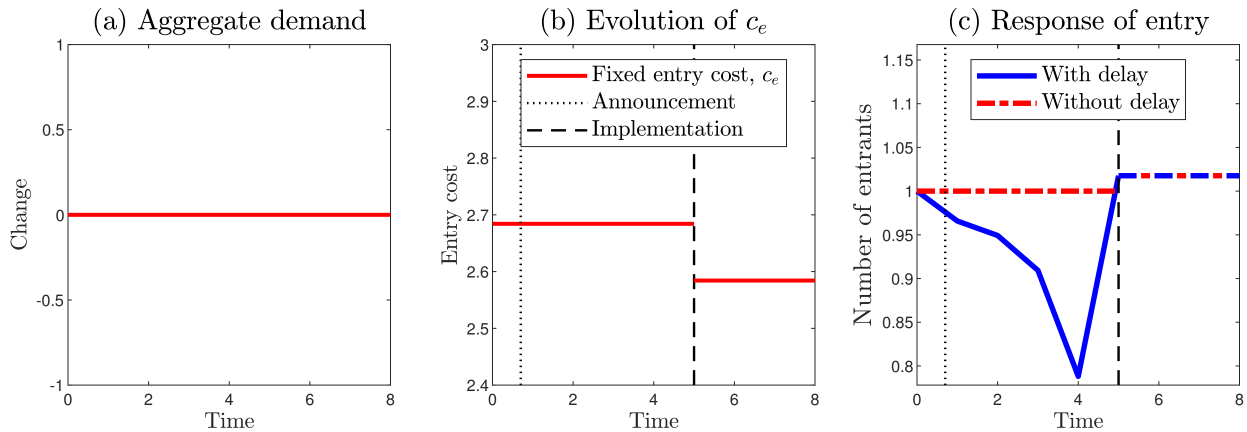
F Policy Implications

In this section, I show that not accounting for entry timing may lead to misleading predictions about potential entrants' responses to different shocks or policies. The reason is the following. With the option to delay entry, the dynamics of entrants depend on how the changes in the aggregate environment affect the relative benefits of entry today versus tomorrow. Whereas the standard frameworks only account for the shock's direct effect. Thus, depending on the type, magnitude, timing, and duration of the shocks, the standard framework may lead to imprecise predictions about the response of potential entrants. To illustrate the point, I demonstrate how the option to wait alters potential entrants' responses to the permanent, temporary, or future reductions in the entry cost.

F.1 Permanent versus Temporary Policy

Figures 39(a) and 39(b) contrast the changes in the threshold signal level as a response to a permanent and a temporary decrease in the fixed entry cost. First, consider a model with the option to delay entry. If the goal is to increase the number of entrants, the temporary decline in the fixed entry cost does a better job during recessions, and has the same effect during expansions compared with a permanent decline in the fixed entry cost. Moreover, marginal entrants who respond to the reduction of the fixed entry cost are mostly high-productivity firms during recessions and low-productivity firms during expansions. Without the option to delay entry, the responses of entrants do not vary across these policies.

Figure 40: News about the decline in the fixed entry cost



F.2 News Shock

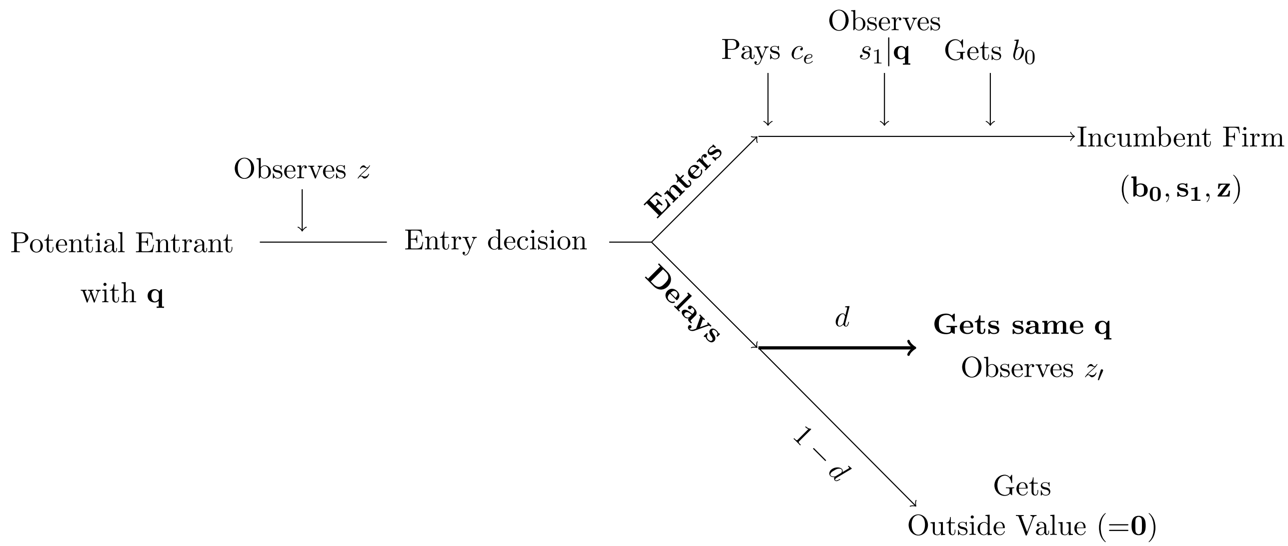
Consider the response of potential entrants to an anticipated decline in the fixed entry cost after five periods from today. Figures 40(a) and 40(b) show the actual change in the aggregate demand and the level of entry cost, respectively, over time. I find that the threshold signal in the news scenario is weakly higher than in the baseline (no-news) scenario. The magnitude of the change depends on the distance between today and the policy's actual time. Figure 40(c) describe the response of entrants to the news with and without the option to delay entry. If the time of the actual decrease in the entry cost is close enough (small T), the indirect effect of the news that decreases the number of entrants today is quantitatively more significant than the increase in the number of entrants at time T as a response to the lower fixed entry cost. In the standard firm dynamics models, the news would have altered the dynamics of entrants today only through general equilibrium effects.[61] However, as the exercise illustrates, the response of entrants to the policy announcement through the option-value-of-delay channel could be quantitatively more important.

[61] Constantini and Melitz (2008) also show that potential entrants respond differently to the news about trade liberalization depending on the timing and the implementation of the policy.

G Robustness and Extensions

G.1 The Probability of Keeping Signal

Figure 41: **Potential Entrants' Timing**



In the baseline model, potential entrants can keep their signals about initial productivity over time with probability one, i.e., $d = 1$ in Equation (2). In this section, I provide a calibration strategy to internally estimate d. After estimating d, I reexamine the quantitative and qualitative importance of the option-value channel. The timing of the modified entry process is illustrated in Figure 41.

First, I investigate how the value of delay changes as d varies between zero and one in the baseline model. Figure 42(a) shows that the value of waiting decreases with d as expected. Furthermore, Figures 42(b) and 42(c) demonstrate that the total opportunity cost of entry and the threshold signal decrease disproportionately as d decreases. The two crucial points to keep in mind when designing a calibration strategy for a model with an additional parameter, d, are: First, the value of d has a negligible effect on the steady-state threshold signal, and therefore, the characteristics and dynamics of the economy in the steady state. Second, for a given aggregate demand shock process, the value of d entirely shapes the elasticity of entrants to aggregate shocks through its direct effect on the equilibrium opportunity cost of entry.

Figure 42: Selection of entrants across different aggregate conditions at entry

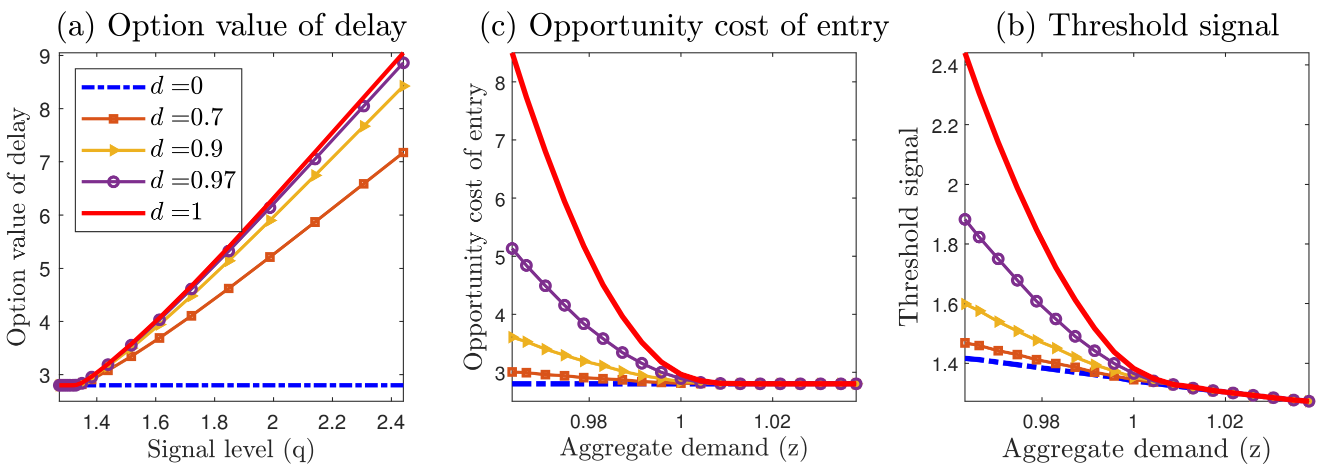


Table 19: Calibration: Aggregate demand shock process and probability of keeping signal

Statistics	**Data**	**Baseline** ($d = 1$)	**Baseline** ($d = 0.965$)
Autocorrelation of the cyclical component of establishments	0.720	0.710	0.720
SD of the cyclical component of establishments	0.012	0.009	0.010
SD of the cyclical component of entry	0.062	0.064	0.067
SD of the cycle component of employment	0.015	0.012	0.015

Note: The time series about the entry rate comes from the BDS and covers the period 1978-2019. The cyclical components of the log entry rate and employment are calculated using the HP filter with smoothing parameter 100.

Building on the above argument, one can use d instead of the parameters that govern the aggregate demand shock process to target the business cycle variation of the number of entrants for any given aggregate shock process. In turn, the parameters that govern the aggregate demand shock process can be used to target both the business cycle variation of the number of firms and the standard deviation of aggregate employment. Thus, by estimating parameter d endogenously, the model can additionally capture the effects of the shock on incumbent firms' production and hiring decisions.

Following the calibration strategy, the value of parameters d, ρ_z, σ_z that matches the targeted moments are $d = 0.965$, $\rho = 0.72$ and $\sigma = 0.0054$. Table 20 provides a comparison of the parameter values for the baseline model and the model with an additional parameter, d, referred to as "Baseline ($d = 0.965$)." The targeted moments and their model counterparts are described in Table 19. Overall, the "Baseline ($d = 0.965$)" in addition to moments captured by "Baseline ($d = 1$)", also captures the variation in the aggregate employment.

Table 20: Calibration

Symbol	Description	Baseline	Baseline ($d = 0.965$)
β	Discount rate	0.960	0.960
ρ	Price elasticity of demand	1.622	1.622
η	Elasticity of demand to capital	0.919	0.919
δ	Depreciation rate of reputation	0.188	0.188
ρ_s	Idiosyncratic shock – persistence parameter	0.814	0.814
σ_s	Idiosyncratic shock – SD parameter	0.161	0.161
α	Demand shifter	0.261	0.261
b_o	Initial customer capital level	12.00	12.00
μ_f	Operating cost – SD parameter	0.621	0.621
σ_f	Operating cost – SD parameter	0.410	0.410
γ	Exogenous exit shock	0.071	0.071
$\underline{q}$	Pareto location	0.700	0.700
ξ	Pareto exponent	2.478	2.478
c_e	Fixed entry cost	2.684	2.837
$\boldsymbol{\rho_z}$	Aggregate shock – persistence parameter	0.750	**0.720**
$\boldsymbol{\sigma_z}$	Aggregate shock – SD parameter	0.003	**0.0054**
$\boldsymbol{d}$	Probability of keeping signal	1	**0.965**

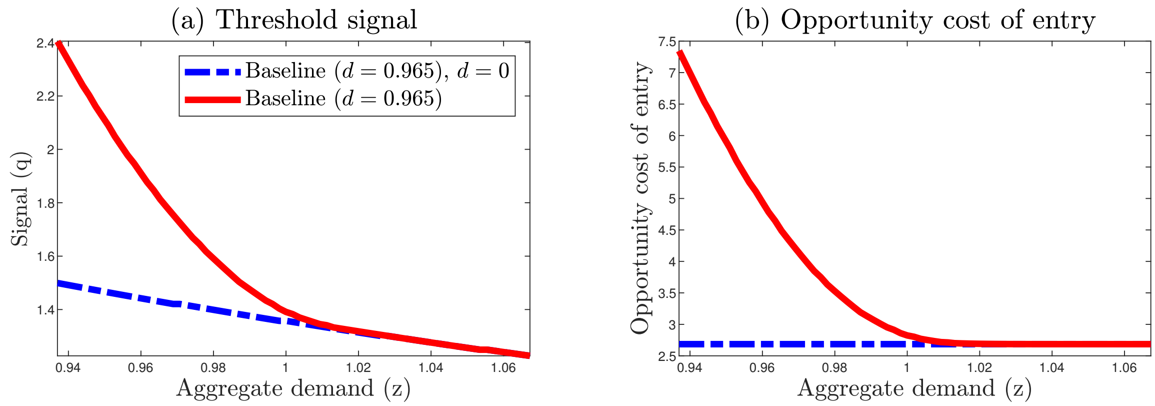
However, it should be noted that not targeted variance of the aggregate employment in "Baseline ($d = 1$)" is not too far from the data counterpart.

G.1.1 Quantitative Evaluation

I use Baseline ($d = 0.965$) to reexamine the quantitative role the option to delay entry plays in the dynamics of entrants, in a world where entrants can keep their signals with probability $d = 0.965$. Figure 45 displays the threshold signal and the opportunity cost of entry across aggregate demand levels. In Figure 46, I consider a response of an economy to a shock process that matches the dynamics of entrants over the period 1978-2019 in "Baseline ($d = 0.965$)" to the data counterpart. To reevaluate the quantitative role of the option value of delay, in "Baseline ($d = 0.965$)" model I shut down the option value channel, $d = 0$ ("Baseline ($d = 0.965$), $d = 0$"). The properties of the time series across these scenarios are summarized in Table 21.

In "Baseline ($d = 0.965$)", the endogenous countercyclical opportunity cost of entry accounts for approximately 70% of the variance in the number of entrants in contrast to 80% in "Baseline ($d = 1$)". Nevertheless, the option value of delay continues to play the same role in the variation of aggregate employment. In particular, the absence of the option-value channel results in a 25% drop in the volatility of aggregate employment in the model, which

Figure 43: Selection of entrants in Baseline ($d = 0.965$)



corresponds to 12% of the volatility observed in the data. The latter value is consistent with "Baseline ($d = 1$)" model. Overall, while the introduction of parameter d in "Baseline ($d = 0.965$)" slightly reduces the quantitative importance of the observed dynamics of firms, the option value of delay still remains a major channel that accounts for the dynamics of entrants over the business cycle and their contribution to aggregate employment.

Figure 44: The option-value channel ($d = 0.965$)

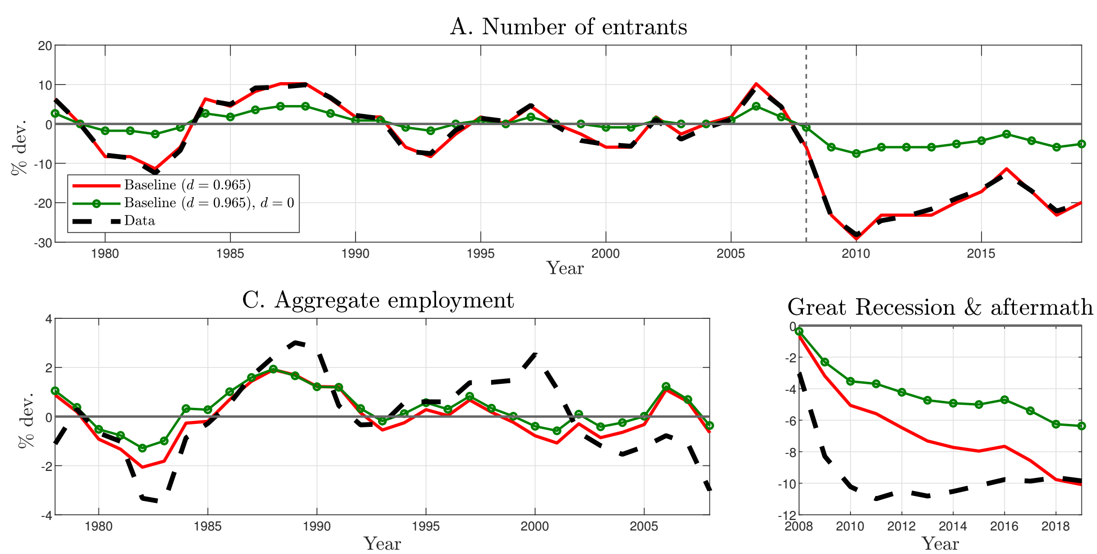


Table 21: Business cycle moments: Data, baseline, and alternative scenarios

	Entry	Firms	Employment
Panel A: Standard deviation			
Data	0.062	0.019	0.016
Baseline ($d = 1$)	0.063	0.010	0.008
Baseline ($d = 1$), $d = 0$	0.014	0.003	0.006
Baseline ($d = 0.965$)	0.061	0.010	0.010
Baseline ($d = 0.965$), $d = 0$	0.019	0.004	0.008

Note. These empirical time series describe the deviations of the log number of entrant establishments, log number of establishments, and log aggregate employment from their respective trends in the US over the period 1978-2008. To find the cyclical properties of these tune series, I use a linear detrending method in the data and the model.

G.2 Customer Capital Accumulation Process

The decision to study and quantify the option-to-delay channel in a model with customer capital accumulation is motivated solely by the growing literature that emphasizes the significance of demand-side factors (as opposed to differences in productivity or capital accumulation) in understanding both firm-level and aggregate fluctuations (Foster et al. (2016), Sedlacek and Sterk (2017), and Moreira (2016)).[62] In this section, I evaluate the role that the customer capital accumulation plays in quantitative importance of the option value channel. Toward the end, in the baseline model, I shut down the customer capital accumulation process ($\delta = 0$), and at the same time, fix each firm's customer base at $\tilde{b}$. I choose the latter value to ensure that the average entry rate in the counterfactual scenario matches that of the baseline model. Note that, in this "No customer capital accumulation" case, any changes in firms' period demand and lifetime profits over the business cycles are entirely due to aggregate demand shocks.

I find that the customer capital accumulation plays a minor role in the quantitative importance of the option-value channel. In Figure 45, we observe that the option to delay entry still results in countercyclical variation in the opportunity cost of entry, even when the customer capital accumulation process is not present. In fact, based on the figure, the option to delay entry more than doubles the fixed entry cost during recessions. In Figure 46, I compare the dynamics of entrants with and without the option to delay entry in the absence of customer capital accumulation. I find that the option value channel amplifies the variation in entrants by a factor of 5.2, similar to the magnitude predicted in the baseline

[62] Also, the parameters that drive demand dynamics and productivity are estimated in Foster et al. (2016) and Foster et al. (2008) using micr-level data

case.

Figure 45: Selection of entrants (No customer capital accumulation)

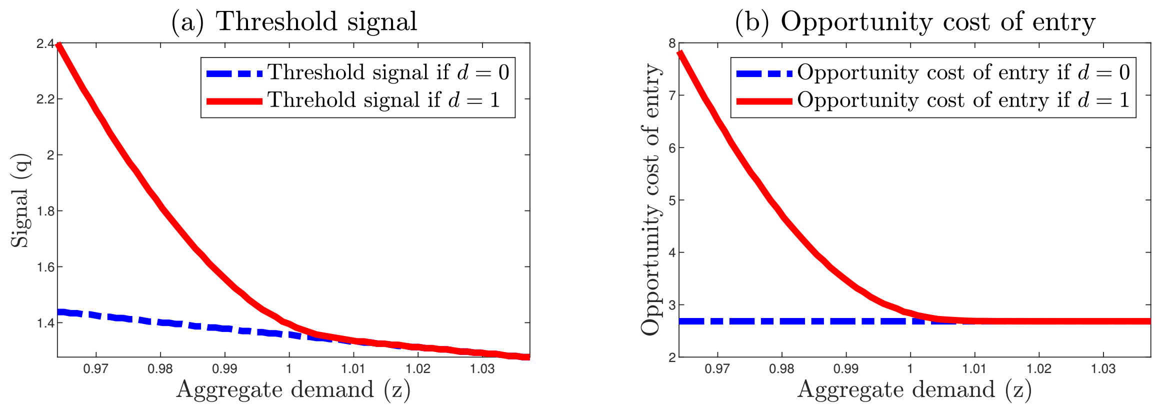
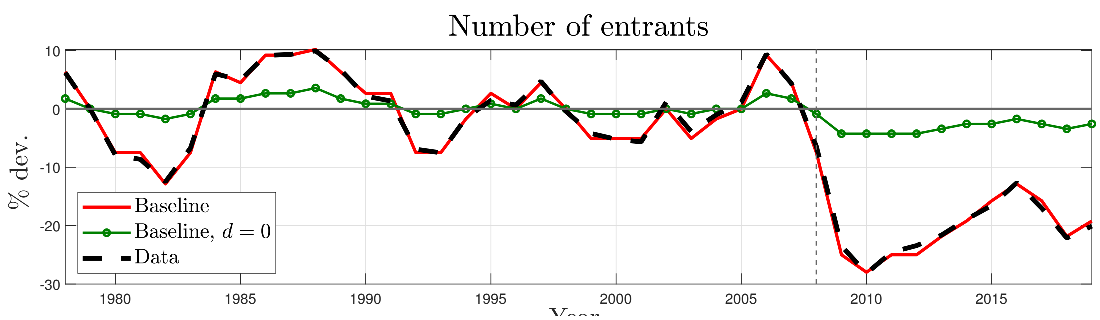


Figure 46: The option-value channel (No customer capital accumulation)



G.3 Other Costs of Entry/Waiting and Their Implications

In this section, I demonstrate that the model's predictions remain robust even after incorporating various other costs of entry.

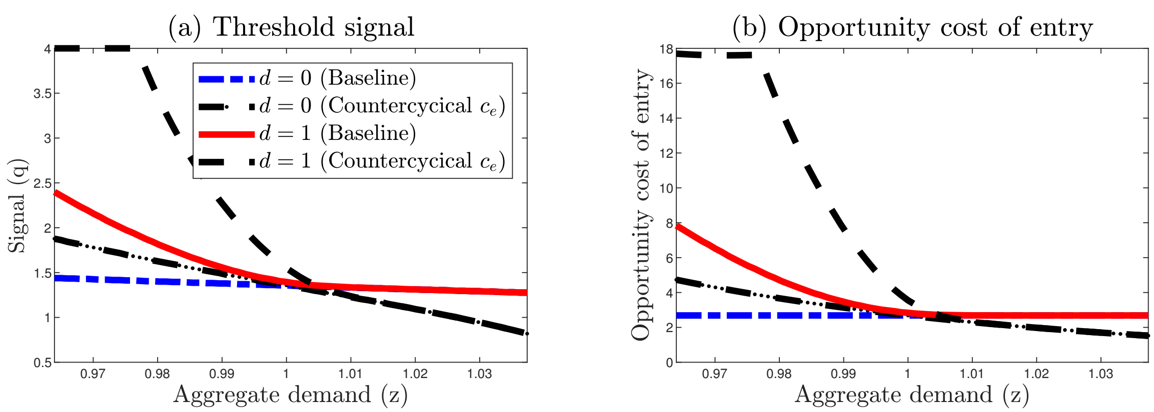
G.3.1 Other Costs of Entry

In this section, I extend the baseline model to allow countercyclical fluctuations in the direct cost of entry, which captures other potential factors leading to variations in entry costs during recessions, such as financial frictions and higher capital costs. In the model, I exogenously allow the fixed entry cost to vary with the aggregate demand level, represented by $z_t^{\zeta_c}$ in Equation (13). I discipline the parameter ζ_c such that, in the absence of the option value of delay ($d = 0$), the model matches the observed variation in entrants.

$$V^e(\mathbf{q}, z) = max \left\{ d\ \beta E[V^e(\mathbf{q}, z')|z], \qquad \underbrace{-c_e z_t^{\zeta_c}}_{\text{Countercyclical entry cost}} \quad + \underbrace{E[V^I(b_0, s, z)|\mathbf{q}])}_{\text{Gross value of entry}} \right\}$$

Figure 47 depicts the threshold signal and the opportunity cost of entry. Two key observations emerge. Firstly, allowing the cost of entry to vary countercyclically across aggregate states significantly amplifies the option to delay entry channel. This is because, with this modification, the benefits of waiting increase significantly during recessions. Secondly, the direct cost of entry required to match the observed dynamics of entrants in the absence of the option value effect implies a 300-basis point increase in the cost of financing during recessions.

Figure 47: Selection of entrants (Exogenous countercyclical cost of entry)



G.3.2 Direct Costs of Waiting

In the section, I extend the model to allow cost of waiting on top of forgone profits and discounting. Toward the end, consider Equation 13, where C_d represents direct cost of delay. First, note that this modification has no effect on the quantitative implications of the option to delay entry. The reason for this is that the baseline calibration procedure involves setting the cost of waiting to zero ($C_d = 0$) since the option value of delay is constrained to match the observed dynamics of entrants and firms. Therefore, the cost of waiting is already taken into account in the fixed entry cost c_e, which can be redefined as the cost of entry net of the cost of waiting.

Similarly, the potential impact of the procyclical cost of waiting can be examined through the lens of the countercyclical cost of entry discussed in the previous section (see Appendix

G.3.1). This is because one can redefine the exogenous cost of entry as the cost of entry net of the value of waiting.

For the sake of exploration, I utilize the baseline model specification with Equation 13 to evaluate the level of cost C_d that renders delay unprofitable for all potential entrants. Figure 48 depicts the variation in the threshold signal and opportunity cost of entry for different levels of $\frac{C_d}{c_e}100$, where c_e is obtained from the baseline calibration. As expected, the option value effect declines with an increase in C_d. I find that in the baseline specification if the cost of waiting surpasses 3.5% of the fixed entry cost, potential entrants would not want to delay entry.

$$V^e(\mathbf{q}, z) = max \left\{ \beta E[V^e(\mathbf{q}, z')|z] - \underbrace{C_d}_{\textbf{Cost of delay}} \quad , \quad -c_e + \underbrace{E[V^I(b_0, s, z)|\mathbf{q}])}_{\text{Gross value of entry}} \right\}$$

Figure 48: The cost of waiting