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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 delay entry generates a countercyclical opportunity cost of entry and significantly amplifies the effect of the initial aggregate conditions on the selection of entrants. This mechanism enables existing firm dynamics models to reconcile the documented business cycle dynamics of US entrant establishments without leading to an excessive variation in economic aggregates. I find the observed variation of firms at entry is responsible for around three-fourths of the business cycle fluctuations. Finally, I argue that not accounting for the option to delay entry may result in misleading predictions about entrants' responses to different shocks or policies.

Keywords: Option value, entry, firm dynamics, business cycles, propagation, Great Recession.

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

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1 Introduction

Aggregate economic conditions at inception have a significant and persistent effect on the US entrant establishments' life-cycle characteristics. Specifically, cohorts of establishments that start operating during recessions employ fewer workers at entry and over time, although they are, on average, more productive than expansionary cohorts.[2] The number of entrants is procyclical and four times as volatile as aggregate employment.[3] The variation in the entry margin, which leads to the observed significant and persistent differences in cohorts' life-cycle characteristics, provides an important propagation mechanism of aggregate shocks. Yet, the theoretical models used to quantify the role of entry are not able to rationalize or/and account for the documented life-cycle dynamics of entrants without generating excessive variation in aggregate variables.

What accounts for the observed significant effect of the initial economic conditions on the selection of entrants? In firm dynamics models, the expected lifetime value of entry is relatively insensitive to aggregate shocks of reasonable magnitudes and could explain only a modest part of the variation in the entry rate. In this paper, I show potential entrants' ability to delay entry, missing in existing frameworks, significantly amplifies the role of the initial aggregate conditions. With the intertemporal choice, even a small change in the relative benefits of entry today versus tomorrow has a substantial effect on firms' selection at entry. This mechanism enables standard models to reconcile and fully quantify the documented life-cycle dynamics of entrants in shaping the aggregate fluctuations. Finally, I argue that missing the option to delay entry may result in misleading predictions about the response of potential entrants to different shocks or policies.

I build a firm dynamics model with endogenous firm entry and exit and aggregate demand volatility. Heterogeneous firms operate in monopolistically competitive markets and make decisions about production and exit. Potential entrants hold heterogeneous signals about their post-entry initial productivity and make entry decisions. Upon entry, potential entrants pay the fixed entry cost and behave like incumbents. I deviate from the existing framework

[2] Moreira (2015) and Sedlacek and Sterk (2017) document that cohort-level employment is significantly and persistently procyclical. Lee and Mukoyama (2015) and Moreira (2015) find that entrants that are born during recessionary periods are, on average, more productive at entry and over time.

[3] Author's calculation using the establishment-level data from the Business Dynamic Statistics (BDS) dataset over 1977-2015.

and allow entrants to keep their signals over time if they decide to postpone entry after observing the aggregate demand level. Entering today or entering tomorrow are mutually exclusive alternatives, leading to a non-negative option value of delay, which varies with the signal and with the aggregate demand level.

I find that the option to delay entry generates a countercyclical opportunity cost of entry, which endogenously increases the elasticity of entry with respect to the aggregate demand. Procyclical variation in the expected survival rates moderates the relationship: during recessions, potential entrants expect low profits and 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 expected profits are more than the fixed entry cost.

A considerable body of theoretical and empirical microeconomics literature finds that the option to wait profoundly affects entry decisions.[4] To provide additional evidence, I study pre-entry and post-entry decisions made by firms in the US. Using the Business Formation Statistics (BFS), I document that the aggregate conditions at entry have a significant effect on the business formation through the option to delay entry channel. Employing the Business Dynamics Statistics (BDS) dataset, I find that recessionary cohorts, on average, have higher survival rates, than their expansionary counterparts. In the model, the latter is a direct implication of the option to delay entry: firms wait until the expected survival rates are high enough to compensate the lower expected post-entry profits. Without the option to wait, the model leads to acyclical survival rates.

I parameterize the model using the establishment-level data over the period 1977-2015 from the BDS dataset. The calibrated model generates a close match to the US cohorts' average size, exit, and survival for up to 30 years of operation, and the share of cohorts' employment in aggregate employment for up to 5 years of operation. I parameterize the exogenous aggregate demand shock process to match the dynamics of the entry rate in the model and the data. Finally, I show that the calibrated model generates the documented persistent and

[4]For example, see Bernanke (1993), McDonald and Siegel (1986), and Pindyck (1991). See Dixit and Pindyck (1994) for a detailed review. The empirical literature also points out that without the mechanism, the conventional measure of entry decision does not explain much of the variation in the entry rate. For example, see O'Brien, Folta, and Johnson (2003). See Geroski (1995) for detailed discussion.

significant differences in the life-cycle characteristics of cohorts that entered the market at different stages of the business cycle.

The option-to-delay channel is quantitatively important to account for the observed dynamics of entrants over the business cycles. The endogenous countercyclical opportunity cost of entry increases the variance of the number of entrants for a given aggregate demand shock process by seven times. The mechanism also leads to a significant variation in the composition of entrants. Specifically, due to the increased cost of entry, the group of firms that enter the market during recessions is, on average, more productive; however, the share of the high-survival, high-growth firms is lower in these cohorts due to the medium-productivity entrants who choose to postpone starting a business. The latter channel persistently decreases the recessionary cohorts' employment. I show that without the option to delay entry, the productivity composition of entrants, and the cohort-level employment vary little over the business cycles.[5]

Utilizing the good fit of the model, I quantify the role of the observed demographics of entrants in shaping aggregate fluctuations. I find a model that accounts for the US establishments' life-cycle demographics explains more than three-fourths of the observed persistence and variance of the aggregate employment. I show the variation in the number and the composition of firms at entry, which leads to the persistent procyclical variation in cohort-level employment, is responsible for shaping the aggregate fluctuations.[6]

The result seems surprising when compared with a small share of entrant cohorts' employment in aggregate employment. To support the finding and validate the model, I study the Great Recession, which is notorious for the historical drop in entry and the unprecedented slow recovery. I show 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.[7] Next, I study the response of the base-

[5]This mechanism speaks for the empirical findings by Pugsley, Sedlaćek, and Sterk (2016), who show that ex-ante variation in the types of entrants explains most of the differences in cohorts' post-entry performance; Haltiwanger et al. (2013), Decker et al. (2014), and Haltiwanger et al. (2016) stress the importance of the share of the high-growth firms in a cohort for aggregate job creation.

[6]The implications are consistent with the empirical findings by Sedlaćek, and Sterk (2017), who show that the selection of firms at the entry stage, rather than the post-entry choices made by the firms, drive the cohorts' contribution to aggregate fluctuations.

[7]Gourio, Messer, and Siemer(2016) and Sedlaćek (2019) use data over 2008-2012 and study how the persistent drop in the number of entrants contributes to the aggregate dynamics. In my exercise, I concentrate

line economy to a shock process that matches entrants' dynamics over 2008-2016. I find the model closely predicts the contribution and explains the drop in cohort-level employment through the variation in the number and composition of firms at entry.

Firm dynamics models that employ a traditional entry decision rule are not able to account for the observed dynamics of entrants without generating excessive aggregate fluctuations. I consider a version of the baseline model without the option to delay entry, parameterized to account for the same set of facts. For the calibrated aggregate demand shock process, the model leads to the variance of the aggregate employment that is 1.7 times larger than the data counterpart. To put the number into perspective, I illustrate that a shock series that matches the dynamics of entrants over 2008-2016 leads to a decline in aggregate employment that is twice as large as that observed during the Great Recession.

Finally, I show that potential entrants' ability to postpone entry also qualitatively alters existing models' implications about the response of entrants to different shocks or policies. With the intertemporal choice, the dynamics of entrants depend on the changes in the relative benefits of entry today versus tomorrow, whereas in standard frameworks the entry decisions depend only on the expected post-entry profit today. Indicating that not accounting for the option to wait may lead to imprecise predictions about the response of potential entrants to various shocks, depending on their magnitude, timing, and duration. I illustrate the point by contrasting the response of entrants to a permanent, temporary, and future reduction in entry cost with and without the option to postpone entry.

Relation to the Literature This paper mainly contributes to three strands of literature.

First, it contributes to the firm dynamics literature that studies the significant and persistent effect of the aggregate economic conditions on the selection of entrants. Samaniego (2008) finds that entry and exit are insensitive to productivity shocks of a reasonable magnitude. Lee and Mukoyama (2018) show that generating the documented significant selection of entrants in Hopenhayn and Rogerson's (1993) framework is a puzzle that can be solved by introducing an entry cost that varies over the cycles in a particular way. Sedlaćek and Sterk (2019) introduce entry function, which enables the model to account for the elasticity of entrants with respect to the aggregate shocks. Others rely on exogenous entry-specific

on changes in cohort-level employment, rather than the number of entrants.

shock processes (e.g., Clementi and Palazzo (2016), Sedlaćek and Sterk (2017)). I show that these models can be reconciled with the data by allowing potential entrants to postpone starting a business. The additional selection generated through the option to delay entry also complements the literature that use "missing generation" mechanism (e.g.,Gourio, Messer and Siemer (2015), Clementi and Palazzo (2016)) and demand-side factors (Sedlacek and Sterk (2017), and Moreira (2015)) to explain the persistent procyclical variation in cohorts' employment.

Second, the paper contributes to a large body of theoretical literature that studies the role of endogenous entry and exit in the amplification and propagation of aggregate shocks. Samaniego (2008) finds that aggregate fluctuations are insensitive to entry and exit, whereas Lee and Mukoyama (2008), Bilbiie, Ghironi, and Melitz (2012), Clementi, Khan, Palazzo, and Thomas (2014), and Clementi and Palazzo (2016) find that endogenous dynamics in the entry and exit significantly shapes the dynamics of the aggregate variables. Recent empirical literature emphasizes the importance of the life-cycle demographics of entrants in measuring and understanding the contribution of the entry margin to aggregate fluctuations. Haltiwanger et al.'s (2013) findings show that young firms exhibit distinct life-cycle dynamics compared with their mature counterparts, and emphasize the importance of accounting for not only the entry process but also the subsequent post-entry dynamics (growth, survival, job creation). In this paper, I propose a model that closely accounts for the US establishments' life-cycle dynamics on average and over the business cycles. Using the framework, I revisit and fully quantify the role of the observed variation in the entry margin in shaping aggregate fluctuations.

Third, the paper relates to a considerable amount of theoretical and empirical microeconomic literature that finds the ability to delay entry could profoundly affect entry decision under aggregate volatility.[8] Pindyck (2009) shows that various risks to post-entry profits could magnify the cost of entry, and have a profound effect on firm dynamics. I additionally find endogenous variation in the risk of post-entry failure increases the entry threshold. This paper also relates to the theoretical macroeconomics literature that studies the role of real options in shaping aggregate dynamics (e.g., Jovanovich (1993), Veracierto (2002), Bloom (2009)). I contribute to the literature by extending the analysis on an entry margin. I find

[8]For example, see Bernanke (1993), McDonald and Siegel (1986), and Pindyck (1991). See Dixit and Pindyck (1994) for a detailed review.

that the option to delay entry significantly amplifies and propagates aggregate shocks by affecting the number and composition of entrants. In that respect, the paper also relates to the literature that points out the weak internal propagation mechanism of standard business cycle models (e.g., Cogley and Nason (1995), King and Rebelo (1999)).

Finally, this paper is also related to the theoretical and empirical literature that studies the causal relationship between the significant and persistent drop in the entry rate and the slow recovery in aggregate employment observed after the Great Recession (e.g., Gourio, Messer and Siemer(2016), Sedlaćek and Sterk (2019), Siemer (2016), Clementi and Palazzo (2016), Khan, Senga, and Thomas (2016)).

2 The model

2.1 Setup

The model builds on Moreira (2015), and 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 only source of business cycles.

Time is discrete. Agents face an infinite horizon. 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 in the future after observing the aggregate state. A detailed description of the framework is given below.

2.2 Incumbent 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 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 to:

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

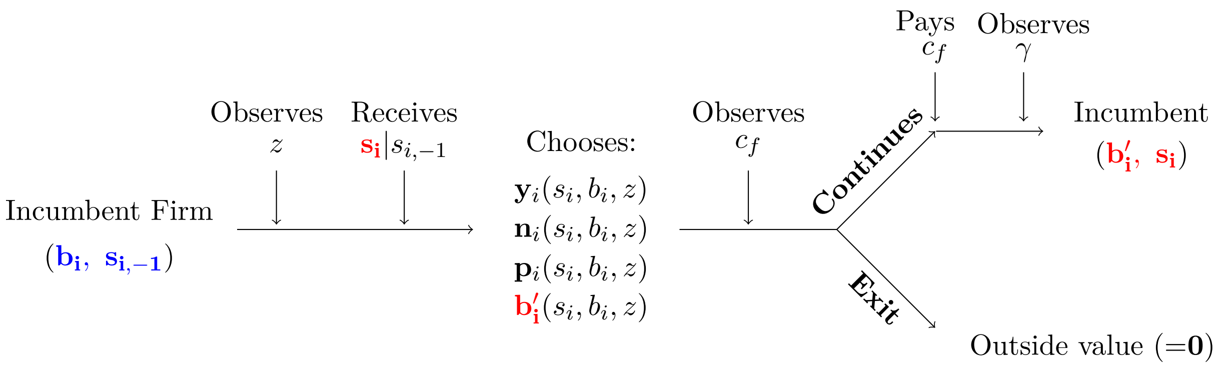
where b_0 is the initial level of customer capital, common across all entrants. $\delta \in (0,1)$ is the depreciation rate of customer capital. The process of customer capital that is tied to past sales hinders firms' ability to freely adjust their demand over time, which creates persistence in the dynamics of production and employment.[9] 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.

[9] Foster et al.'s (2016) findings motivate incorporating the persistent customer-capital-accumulation process in the model. Specifically, they find the differences between young and mature firms are due to individual demand dynamics rather than differences in productivity. Sedlacek and Sterk (2017), and Moreira (2015) explain the persistent procyclical variation in cohorts' employment using the demand-side factors. This framework enables me to quantify the role of the demand-side factors versus the option value of delay in explaining the post-entry cohorts' performance.

Figure 1: **Incumbent Firm's Timing**



Incumbent Firm's Timing 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 to zero.[10] Firms discount future profits at the time-invariant factor β.

The incumbent firm solves the following functional equation:

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

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

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

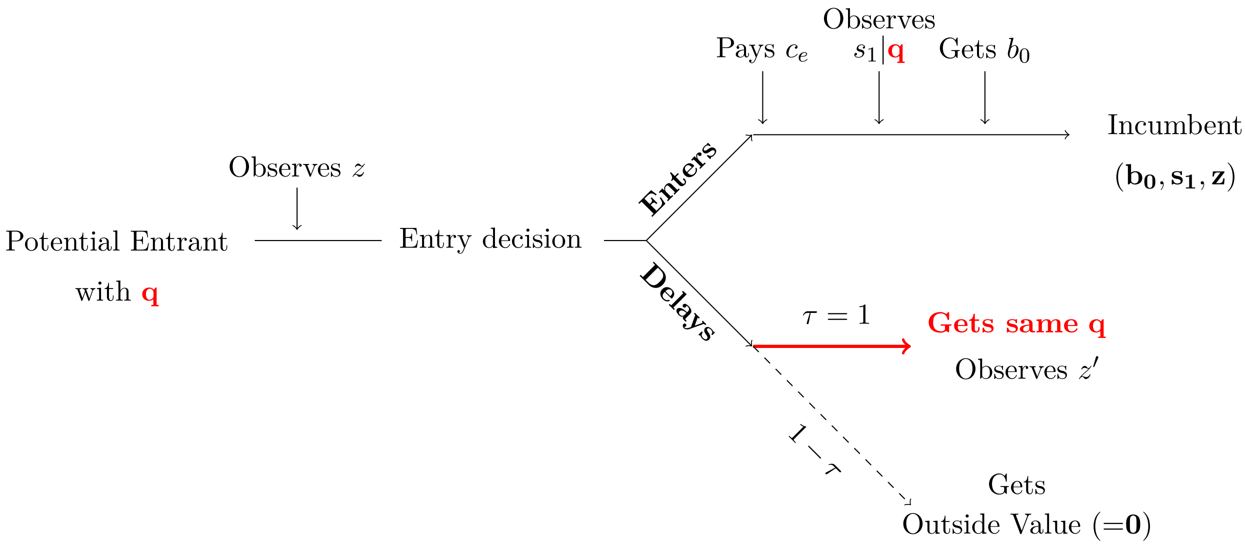
The summary of the incumbent firm's timing is illustrated in Figure 1.

2.3 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 q, the distribution of the initial period productivity is given

[10] Assume that if the incumbent firm decides to exit from the market, the probability that the firm receives an initial productivity signal and becomes a potential entrant again is zero.

Figure 2: **Potential Entrants' Timing**



by $H_e(s|q)$, and the distribution decreases with the signal q.[11] The aggregate distribution of potential entrants over signals is time invariant and is given by $W(q)$.[12] The potential entrant's timing is described below and is summarized in Figure 29.

Potential Entrants' Timing 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. Entering the market today or entering tomorrow are mutually exclusive alternatives. By entering today, the potential entrant gives up the value associated with exercising the signal in the future. Entry into the

[11]The ex-ante heterogeneity of potential entrants is crucial to study the role of the option value of delay. In particular, if one decides to delay entry, other entrants want to defer entry if potential entrants are ex-ante homogeneous. For the interior solution of the entry rate, the option value of delay has to equal to zero. For example, see paper Bilbiie, Ghironi, and Melitz (2012). The distribution of the potential entrants across the signal does not vary with the business cycles; thus, the feature does not contribute to the cyclical variation of entrants.

[12]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), Sterk (2019), 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 wait. In Appendix A.1, I extend the entry phase that justifies the constant mass of potential in this framework. In Appendix A.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. In fact, I find that allowing the accumulation of potential entrants amplifies the differences between the characteristics of entrants over the business cycle.

market is subject to a fixed entry cost c_e. Entrant solves the following Bellman equation

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

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

If a 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

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

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 value of entry today is

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

2.4 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 problem.

3 The Option to Delay Entry

The goal of the following section is threefold. First, I describe the model mechanism that generates the variation in the number and composition of entrants across aggregate states.

Second, I illustrate how the option to wait amplifies the effect of the initial aggregate conditions on the selection of firms at entry. Third, I provide empirical evidence that supports the mechanism developed in the paper.

3.1 Selection of Entrants

To compare the selection of entrants with and without the option to delay entry, I consider the following modification of equation (1)

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

where τ describes the probability that a potential entrant with a signal q can keep the signal until tomorrow if it decides to wait. With probability $1-\tau$, the potential entrant loses the signal tomorrow and obtains the outside option value. Note that if $\tau = 0$, firms cannot keep the signal over time, and the value of the option to wait equals 0. In this case, the baseline model reduces to a standard framework where potential entrants enter the market if the net lifetime benefits of entry are non-negative.[13] If $\tau = 1$, the entry decision coincides with the baseline model. Comparing the case $\tau = 1$ to $\tau = 0$ allows me to isolate the selection of firms at entry through the option-to-delay channel.

If $\tau = 1$, firms enter the market if the value of entry is greater than the total opportunity cost of entry. The latter equals the fixed entry cost plus the option value of delay. The following result summarizes the properties of the option value of delay $V^w(z,q)$.

Result 3.1. *(The properties of the option value of delay)*

(a) $V^w(q,z)$ is non-negative for all q and z.

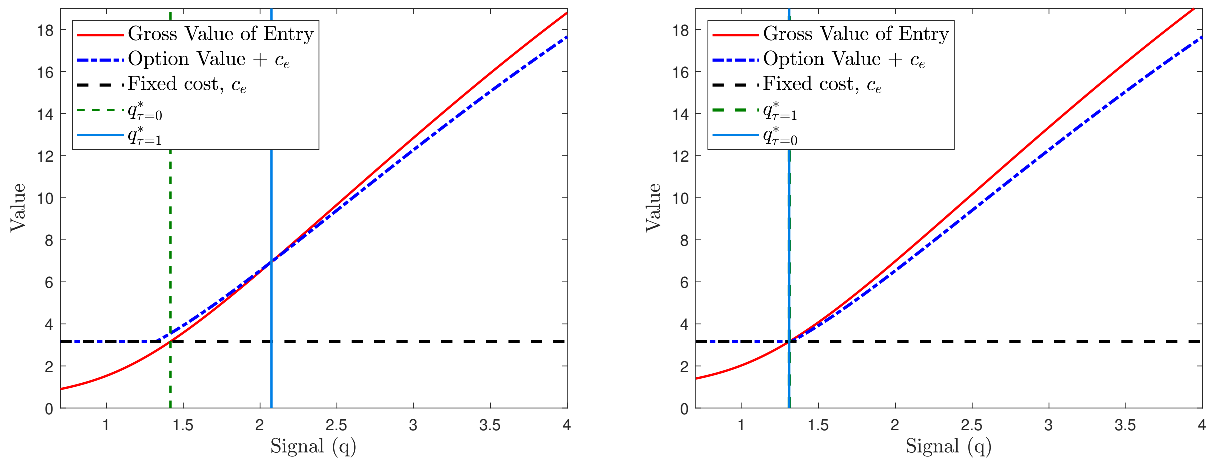
(b) For a given aggregate demand level z, $V^w(q,z)$ is a weakly increasing function of the signal q.

(c) For a given signal q, $V^w(q,z)$ weakly increases with the aggregate demand level z.

All potential entrants expect the same level of customer capital b_0 and observe the same aggregate demand level z. Thus, we can characterize the selection of firms at entry based

[13] For example, see Moreira (2015), and Clementi and Palazzo (2016).

Figure 3: Aggregate Selection of Entrants



(a) Selection for an aggregate demand $z = z_{min}$ (b) Selection for an aggregate demand $z = z_{max}$

only on a signal level q. The following results summarize the numerical solution findings for the $\tau = 0$ and $\tau = 1$ cases:

Result 3.2. *Suppose for an aggregate demand level z, exists a signal $q^*_\tau(z)$ such that*

$$V^{gross}\left(z,\ q^*_\tau(z)\right) - c_e = \tau V^w(z, q^*_\tau(z));$$

then, all potential entrants with $q \geq q^*_\tau(z)$ decide to enter the market, whereas the rest stays outside the market.

Figure 3(a) 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. If $\tau = 0$, firms enter the market if the gross value of entry is greater than the fixed entry cost; these firms are the ones that hold signals $q \geq q^*_{\tau=0}(z)$. The rest stay outside the market. I refer to $q^*_{\tau=0}(z)$ as a threshold signal for an aggregate demand level z when $\tau = 0$. A signal with similar characteristics exist in the case $\tau = 1$. In particular, $q \geq q^*_{\tau=1}(z)$ characterizes a group of firms that enter the market because their expected post-entry profits are greater than the total opportunity cost of entry. Again, the rest stay outside the market. Comparing these two cases helps us isolate the selection through the option to delay entry. In particular, for an aggregate demand level z, the option generates an additional group of firms with $q \in [q^*_{\tau=0}(z),\ q^*_{\tau=1}(z)]$ that, despite the positive net expected benefits of entry, decide to stay outside the market. Figure 3(b) shows that during the "highest" aggregate demand periods, 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 3.3. *The threshold signal $q^*_\tau(z)$ is countercyclical.*

Figure 4(a) shows the threshold signal $q^*_\tau(z)$ is countercyclical for a given τ: 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. The mechanism leads to an endogenous variation in the number and the productivity composition of entrants over the cycles. Specifically, during recessions, an increased threshold signal leads to a fewer but higher-productivity entrants compared with expansionary cohorts. That said, reconciling the documented variation in the number and composition of entrants requires high elasticity of the threshold signal with respect to aggregate demand level.

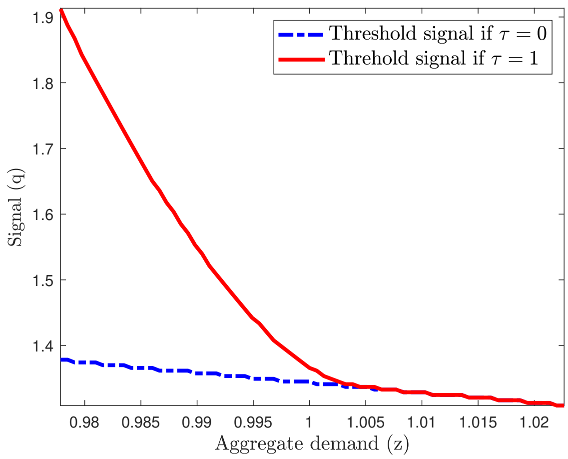
Note that without the option to delay entry, the threshold signal hardly varies with the aggregate demand level. In this case, the entry decision follows a traditional, neoclassical investment-decision rule: a firm starts a business if the net life-time benefits of entry are non-negative. The latter value is relatively insensitive to aggregate shocks of reasonable magnitudes. As a result, models that rely on conventional entry decisions could explain only a modest part of the observed variation in the entry margin.

Figure 4(a) illustrates that the option to delay entry significantly increases the elasticity of the threshold signal with respect to the aggregate demand level compared with the case $\tau = 0$. The latter is due to the medium-productivity firms with $q \in [q^*_{\tau=0}(z),\ q^*_{\tau=1}(z)]$ that choose to postpone entry despite the positive expected post-entry benefits. Note the lower the aggregate demand level, the wider the range of signals that leads to the delay decision.

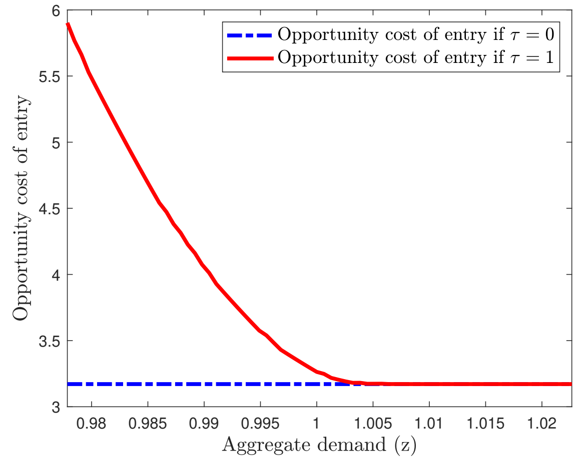
To understand how the option to delay entry amplifies the effect of the aggregate conditions on the selection of entrants I compare the threshold cost of entry across these scenarios. I define the latter as follows: all potential entrants with the gross value of entry higher than the threshold cost enter the market, while the rest decide to stay outside the market. In a model with the option to delay entry, the threshold cost coincides with the threshold signal's $q^*_{\tau=1}(z)$ opportunity cost of entry.[14] Figure 4(b) illustrates that the latter value is

[14]Potential entrants with signal $q > q^*_{\tau=1}(z)$ enter the market and expect returns that are higher than the threshold signal's $q^*_{\tau=1}(z)$ total opportunity cost of entry. *Proof:* $V^{gross}(q, z)$ strictly increases with the signal. For an aggregate demand level z, firms with $q > q^*_{\tau=1}(z)$ enter the market. The following inequality holds: $V^{gross}(z, q) > V^{gross}(z, q^*_{\tau=1}(z)) = c_e + V^w(z, q^*_{\tau=1}(z))$.

Figure 4: Selection of Entrants at Entry Conditions



(a) Equilibrium threshold signal



(b) Equilibrium opportunity cost of entry

countercyclical: the cost of entry significantly increases above the fixed entry cost during the recessions. In fact, for reasonable parameter values, potential entrants postpone exercising the signal until the present value of entry is up to twice the fixed entry cost. Comparing the threshold cost of entry across cases elucidates the mechanism of how the option to delay entry increases the affect of the aggregate conditions on the selection of entrants.

I find that the results 3.1 and 3.2 hold for all $\tau \in [0, 1]$. In Appendix F.1, Figure 30 illustrates the equilibrium threshold signal and the equilibrium opportunity cost of entry for different values of τ. For the given aggregate demand shock process, the elasticity of the threshold signal with respect to the aggregate demand level significantly increases with τ.

3.2 The Net Value of Waiting

In this section, I investigate the rationale behind a firm's choice to delay entry. With the intertemporal choice, a firm's decision to start a business depends on the *net value of waiting*:

$$\textit{Net value of waiting(q,z)} = V^w(q, z) - (V^{gross}(q, z) - c_e)\,.$$

The positive net value of waiting represents the part of the present value of benefits that the firm gives up by entering the market today instead of tomorrow. Potential entrants optimally decide to stay outside the market until the net value of waiting is non-negative.

To understand what contributes to the variation in the value of waiting, consider equation (2), which decomposes the gross value of entry into the expected first-period profit and the expected continuation value. Note that, the aggregate demand level at entry affects not only the post-entry profits but also firms' expected post-entry survival rates. In particular, in the equation, $(1-\gamma)G(c_f^*)$ describes the probability that a potential entrant is going to stay in the market after the first period. The expected survival rate is procyclical: the lower the aggregate demand at entry, the lower the expected long-run value, and the higher the risk of post-entry failure. This variation in the survival rates leads to a procyclical discount factor that increases the value of entry during expansions compared with recessionary periods.

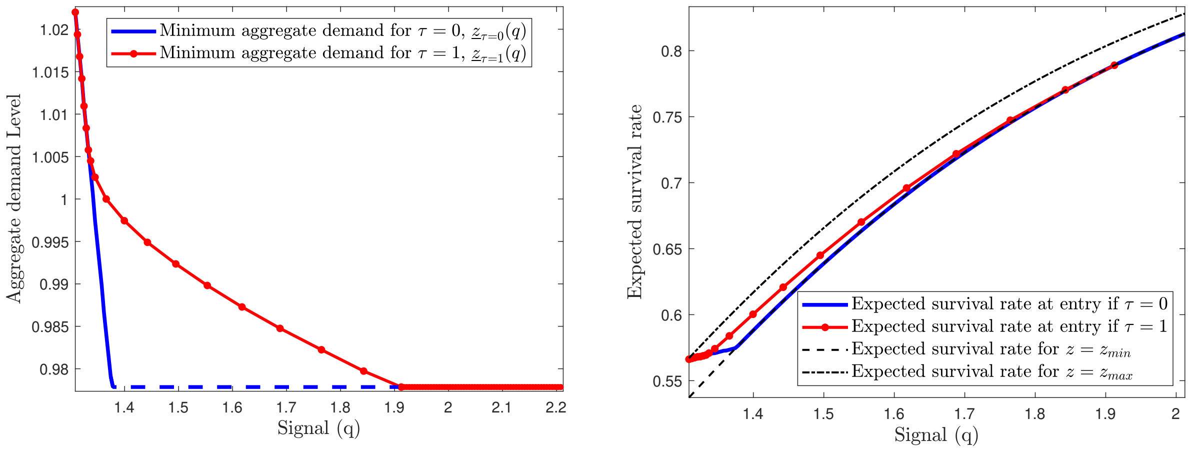
$$
\begin{aligned}
V^{\text{gross}}(b_o, q, z) &= \int\limits_s \left(\Pi(b_o, s, z) + \int\limits_{c_f} max\left\{0, -c_f + \beta(1-\gamma)E[V^I(b', s', z')|s, z]\right\} dG(c_f) \right) dH_e(s|q) \\
&= \underbrace{\int\limits_s \Pi(b_o, s, z) \;\; dH_e(s|q)}_{\textit{Expected first period profit}} + \qquad\qquad (2) \\
&+ \int\limits_s \beta \underbrace{(1-\gamma)G\left(c_f^{\ *}\right)}_{\textit{Survival rate}} \left[\underbrace{E(V^I(b', s', z')|s, z)}_{\textit{Long run value}} - \frac{1}{(1-\gamma)\beta} E(c_f \mid c_f \leq c_f^{\ *}) \right] \; dH_e(s|q),
\end{aligned}
$$

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

The option to delay entry allows potential entrants to endogenize the pro-cyclical variation in the discount factor. Postponing entry incurs period profits for potential entrants. However, entering at suboptimal time may reduce potential entrants' lifetime profits through the increased risk of post-entry failure. The trade-off leads to a positive value of waiting for some potential entrants. They choose to stay outside the market until the expected survival rate is high enough to compensate for lower demand levels in the first several years of operation. Note that without the irreversible and endogenous exit, the benefits of waiting would always be negative.

Figure 5(a) compares the minimum aggregate demand levels $\underline{z}_\tau(q)$ for which a potential entrant with signal q is ready to enter the market, with and without the option to delay entry. The figure shows that the option has no effect on high- and low-productivity entrants, whereas firms with medium-range signals find it profitable to wait for better aggregate demand conditions. To quantify the differences in threshold aggregate states, I calculate the

Figure 5: Entry Decision with and without the Option to Delay Entry



(a) Minimum aggregate demand level, $\underline{z}^{\tau}(q)$

(b) Expected survival rate

expected number of periods from $\underline{z}_{\tau=0}(q)$ to $z \geq \underline{z}_{\tau=1}(q)$. I find that the expected duration of delays varies, on average, from zero to six periods, and the number is negatively correlated with the signal level.[15] Figure 5(b) shows that by postponing entry, these group of firms are able to increase the expected survival rates.

3.3 Empirical Evidence

A considerable body of theoretical and empirical microeconomics literature supports the mechanism developed in the paper. Specifically, the literature finds that under aggregate state volatility, the option to postpone entry profoundly affects the decision to start a business.[16] The empirical microeconomics literature points out that the conventional measure of entry decision does not explain much of the variation in the entry rate, because the variation in the expected stream of profits over time is minor.[17] Pindyck (2009) also shows that various risks to post-entry profits could magnify the cost of entry and have a profound effect on firms' entry decisions. In this section, I use a newly developed Business Formation Statistics (BFS) to provide additional support for the mechanism developed in the paper. Specifically, I show that the aggregate conditions at entry have a significant effect on the

[15] The aggregate demand process is calibrated to match the business cycle dynamics of the entry rate in the model and in the data. The period in the calibration is defined as a year, indicating the option to delay entry could have a quantitatively significant effect on potential entrants' decisions.

[16] For example, see Bernanke (1993), McDonald and Siegel (1986), and Pindyck (1991). See Dixit and Pindyck (1994) for a detailed review.

[17] For example, see O'Brien, Folta, and Johnson (2003). See Geroski (1995) for a detailed discussion.

number of business formation, through the option-value-delay mechanism.

The BFS dataset is based on applications for Employer Identification Numbers (EINs) submitted in the US, known as IRS Form SS-4 filings.[18] 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, the principal activity of a business, and so on. This information is used to identify a subset of applications associated with the start of new businesses, referred to as business applications. The business applications are matched to the set of firms in the BDS dataset identified as new employer businesses based on payroll information.[19] The match process is straightforward because both of the datasets contain information about EINs.

The publicly available part of the BFS dataset allows me to track the subset of the employer business start-ups that applied for the EINs within eight quarters before entry. this group of businesses comprises more than 80% of start-ups in the BDS dataset each year.[20] Using the data, I first study how the business formation varies over the cycles conditional on application age. That is, I separately consider EIN applications that form business within the first four quarters (*First 4Q*) and within the second four quarters (*Second 4Q*) from the date of the application. Next, I use the variation in business formation across these groups to identify the "wait-and-see" channel in the entry decision. In particular, I investigate the share of the applications that form businesses in the second four quarters relative to the total number of applications ($\frac{Second\ 4Q}{First\ 4Q\ +\ Second\ 8Q}$). I refer to the ratio as the *share of late start-ups.* These time series are at a quarterly frequency and span the period 2004Q3-2016Q4. Appendix C.1 provides a detailed description of the dataset.[21]

To assess economic conditions at the date of the application, I use the following business cycle indicators: the cyclical component of the quarterly log real GDP after applying the Hodrick and Prescott (1997) (HP) filter with a smoothing parameter of 1600 (Y_{hp}), the deviations

[18] EIN is a unique number assigned to most of the business entities. An 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 new EIN.

[19] The BDS dataset covers the universe of employer businesses in the US and provides annual measures of business dynamics for the economy aggregated by the establishment and firm characteristics. Employer businesses are identified as start-ups based on their first payroll information by the Longitudinal Business Database.

[20] See Appendix C.1, Figure 21.

[21] In Appendix C, I also discuss in detail the information provided in the BFS dataset and its relevance for the mechanism developed in the paper.

Table 1: Correlations Between the Business Formation with the Business Cycle Conditions

	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	First 4Q (p_val)	0.63 (0.00)	0.72 (0.00)	0.60 (0.00)	-0.48 (0.01)
	Second 4Q (p_val)	0.48 (0.00)	0.79 (0.00)	0.56 (0.00)	-0.39 (0.01)
Panel B	Share (p_val)	-0.62 (0.00)	-0.62 (0.00)	-0.60 (0.00)	0.37 (0.02)

Notes. The numbers in the table describe the raw correlations between cyclical variation in the time series of X with business cycle indicators Y. First 4Q (Second 4Q) describes businesses formation within the four-quarter (between the fifth and the eighth quarter) window from the date of the application. *Share* describes the share of business applications that form business after a year from the date of the application. Source: The BFS, frequency: quarter, covers the period from $2004Q3$ to $2016Q4$. Y describes seasonally adjusted, quarterly time series for log real GDP. $X_{hp,t}(Y_{hp,t})$ and $X_{linear,t}(Y_{linear,t})$ describe HP-filtered and linearly detrended time series for the respective variables, $\Delta X_t(\Delta Y_t)$ represents year-over-year changes in the quarterly time series of the respective variables. Δu_t refers to the deviations of unemployment rates from the average unemployment rate.

of quarterly log real GDP from the linear trend (Y_{linear}), the year-over-year growth in the quarterly log real GDP (ΔY_{linear}), and the deviations of unemployment rates from the average unemployment rate (Δu_t).[22] I use the same detrending methods to find the cyclical variation in the application time series. The following facts emerge:

Fact 1 *Aggregate conditions at entry have a significant effect on the number of start-ups. The worsening of the aggregate conditions at entry is associated with fewer employer business birth regardless of the application age.*

Panel A of Table 1 reports the correlations between the cyclical variation in the number of applications with different age groups with the business cycle conditions at the beginning of the year of entry.[23] The table shows that the number of business formation is significantly procyclical even at a quarterly frequency. The better the aggregate conditions at entry, the higher the number of start-ups, regardless of the application age. Further investigating the table shows that the finding is robust across alternative definitions of the cycles.[24]

Fact 2 *The share of the business applications that lead to business formation after a year is negatively correlated with the economic conditions at the time of the application.*

Panel B of Table 1 describes correlations between cyclical variation in the *share of late start-ups* with the business cycle conditions at the date of the application. The table shows that

[22]Figure 23 in Appendix **??** illustrates the time series for these business cycle indicators.

[23]The business cycle condition for First 4Q describes the aggregate state at the quarter of an application. For Second 4Q aggregate state at entry characterizes economic conditions at the begining of Q5.

[24]This finding is also robust for the annualized application time series. Refer to Appendix **??**.

Table 2: "Wait-and-see" Channel of Entry Decision

Dependent variable: *the share of late start-ups*	Panel A			Panel B		
Real GDP cycle (HP)	-0.304***	-0.263***	-0.258***			
	(0.061)	(0.066)	(0.082)			
Δ Real GDP				0.207***	0.171***	0.156***
				(0.052)	(0.067)	(0.052)
Av. duration, first 4Q		0.048	0.049		0.069**	0.064*
		(0.032)	(0.033)		(0.033)	(0.032)
BF within 8Q			-0.002			-0.035*
			(0.022)			(0.018)
No. of Observations	42	42	42	42	42	42
R-squared	0.383	0.416	0.416	0.282	0.351	0.405
F-Statistics	24.8	14.0	9.04	15.7	10.6	8.61

Notes. 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.

the time series is significantly countercyclical, and the results are robust across alternative definitions of the cycles.[25]

The countercyclical variation in the *share of late start-ups* could be due to the following reasons: First, bad aggregate state at entry might generate a group of entrants that decide to wait for the better aggregate economic conditions. This channel corresponds to the mechanism developed in the paper. I refer to it as "wait-and-see" channel. Second, aggregate conditions at entry could affect the time required to build a business, which could lead to the variation in the number of employer business start-ups across the different application age groups. For example, during recessions, obtaining credit to finance start-up activity could take more time. To control for the second channel, I use the information about the average duration of business formation within the first four quarters from the date of the application.

Fact 3 *A significant part of the countercyclical variation in the share of late start-ups is due to the "wait-and-see" channel in the entry decision.*

Panel A of Table 2 shows that the aggregate state at the time of the application has a significant and negative effect on the cyclical variation in the *share of late start-ups*, even after controlling for the total number of business formations within eight quarters, and the average duration of delays within the first four quarters. Panel B of Table 2 describes

[25] This finding is also robust for the annualized application time series. Refer to Appendix **??**

aggregate conditions using a change in real GDP between the second and the first year from the date of the application. The results indicate that better aggregate conditions tomorrow lead to increased *share of late start-ups*, even after including the controls. The results indicate that the variation in the aggregate state at entry (and the relative variation in the aggregate conditions today versus tomorrow) significantly affects the number of employer business formations through the "wait-and-see" channel.

To sum up, during recessions, fewer applications become employer businesses, out of which the share of the applications that starts business with one year delay is higher. Moreover, a significant share of the late start-ups can be attributed to the 'wait-and-see' channel in entry decision, supporting the mechanism developed in the paper. Unfortunately, I am not able to evaluate the economic significance of the "wait-and-see" channel from the data as the substantial share of entrants that potentially choose to delay entry are not observed, for example, entrants that postpone entry and also postpone applying for EINs, and entrants that apply for EINs but decide to delay entry and never come back the market.[26] In what follows, I use the theoretical model to quantify the role of the option to delay entry in the observed variation of entrants over the cycles.

4 Quantitative Evaluation

In this section, I calibrate the model to match the stylized facts about the average life-cycle dynamics of entrants. Then, I evaluate the model's performance in accounting for the observed dynamics of entrants over the cycles and quantify the role of the option to wait, by comparing it with an alternative scenario without the channel. Utilizing the good fit of the model, I evaluate the role of entrants' demographics in shaping the business cycle dynamics of the aggregate variables.

4.1 Functional Forms

The fixed operating cost is distributed log normally with parameters μ_f and σ_f. Aggregate distribution of the signal $W(q)$ is set to be Pareto with location parameter $\underline{q}$ and Pareto

[26] In Appendix C, I discuss in details on information provided in the BFS dataset and its relevance for the mechanism developed in the paper.

Table 3: Calibration

Symbol	Description	Value	Calibration Targets/Source
τ	Probability of recalling signal	1.0	
β	Discount rate	0.960	Annual riskless interest rate. $R = 1.04$
ρ_z	Persistence of aggregate shock	0.570	Persistence of entry rate
σ_z	Std. dev. aggregate shock	0.002	Standard deviation of entry rate
ρ_s	Persistence of idiosync. prod. shock	0.814	Foster et al. (2008)
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)
b_o	Initial customer capital	12.0	Establishment-level moments
σ_s	Std. dev. idiosyncratic shock	0.16	Establishment-level moments
σ_s^e	Std. dev. Initial productivity	0.26	Establishment-level moments
α	Demand shifter	0.26	Establishment-level moments
$\underline{q}$	Pareto location	0.70	Establishment-level moments
ξ	Pareto exponent	3.98	Establishment-level moments
μ_f	Mean log operational cost	0.62	Establishment-level moments
σ_f	Std. dev. log operational cost	0.41	Establishment-level moments
γ	Exit shock	0.07	Establishment-level moments
c_e	Entry cost	3.98	Establishment-level moments

exponent $\xi > 0$. For a given signal, the idiosyncratic shock in the first period of operation is normally distributed and follows the process $log(s) = \rho_s \; log(q) + \sigma_s^e \; \epsilon$, where $\epsilon \sim N(0, 1)$.

4.2 Calibration

Estimating the model requires calibrating the following 17 parameters: $\beta, \rho_s, \rho, \eta, \delta, b_o, \sigma_s, \sigma_s^e$, $\underline{q}, \xi, \mu_f, \sigma_f, \gamma, c_e, \alpha, \rho_z$, and σ_z. In this section, I describe the calibration procedure. The summary of the identification strategy and the final values of the parameters are given in Table 3.

To be consistent with the BDS dataset timing, I assume a period corresponds to a year. The unit of analysis is an establishment. 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 establishment-level data from the Census of Manufactures, Foster et al. (2008)

Table 4: Calibration Targets for the Establishment-level Characteristics

Statistics	**Data**	**Baseline Model**
Average entry rate (1991-2006) (%)	12.1	12.1
Average size of all establishments	17.0	16.3
Entrant employment share in total employment (%)	5.9	6.4
Cohort employment share in total employment at age 5 (%)	4.2	4.2
Average size of entrants (age 0)	8.7	8.5
Average size of cohort at age 5	13.9	14.1
Average size of cohort between 21 and 25 years	21.4	22.4
Survival until 5 years old	0.48	0.41
Survival between 21 and 25 years	0.15	0.10
Establishments' exit rate at age 5	0.12	0.09

Notes. The moments are calculated from the BDS dataset covering the economy-wide establishment level data over the period 1977-2015.

Table 5: Calibration Targets for the Aggregate Demand Shock Process

Statistics	**Data**	**Baseline Model**
Autocorrelation of the cycle component of entry rate	0.25	0.25
Standard deviation of the cycle component of entry rate	0.06	0.06

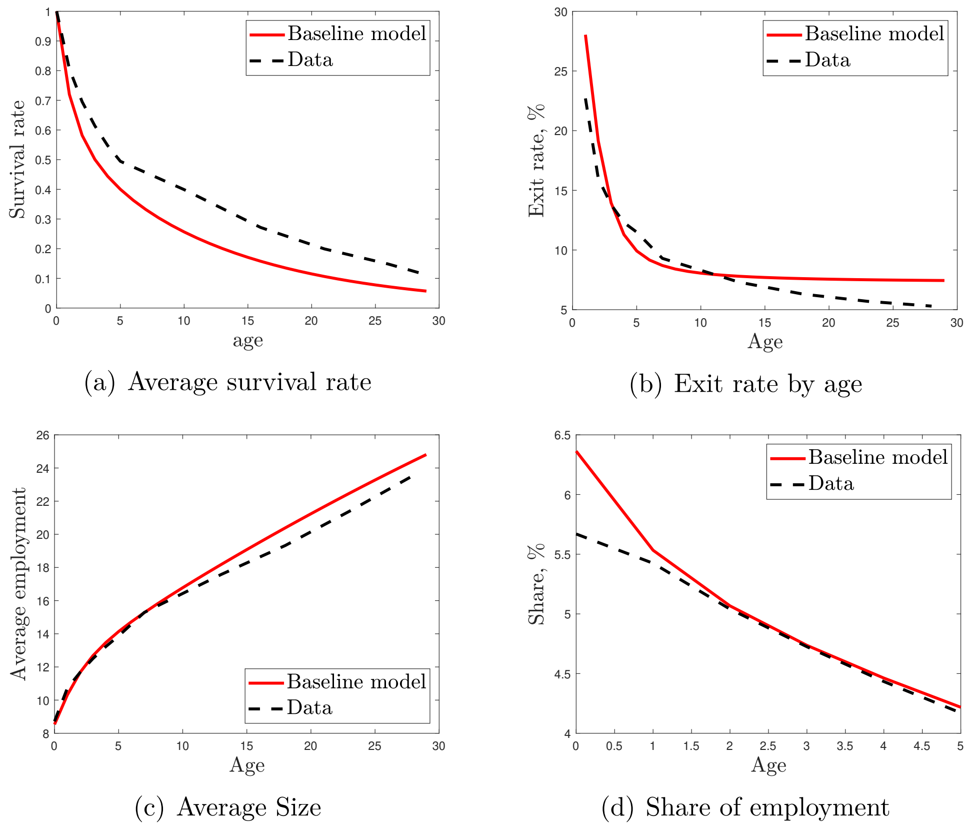
Notes. The time series about the entry rate comes from the BDS and covers the period from 1977 to 2015. The cyclical component of the log entry rate is calculated using the HP filter with smoothing parameter 100.

estimates that the autocorrelation of the establishments' idiosyncratic productivity process equals $\rho_s = 0.814$.[27] Foster et al. (2016) identify parameters that drive the demand function and the customer-capital-accumulation process by jointly estimating demand and the Euler equation, using the dataset from Foster et al. (2008).[28] Based on their estimation results, 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.

[27] 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).

[28] In Foster et al. (2016), firms need to pay a constant fixed cost of operation, whereas in my model, the fixed operational cost is drawn each period randomly. However, because they estimate the Euler equation conditional on survival, the final estimated parameters represent a good fit to the model parameters.

Figure 6: Average Cohorts Characteristics: Data, Baseline Model



(a) Average survival rate

(b) Exit rate by age

(c) Average Size

(d) Share of employment

The parameters that drive potential entrants' distribution ($\underline{q}$, ξ), selection at entry (c_e), survival function (μ_f, σ_f, γ), average size of entrants (b_0, σ_s^e), growth of entrants (σ_s), and average size of all active establishments (α) are jointly calibrated to match the simulated average characteristics of cohorts' at entry and over time to the data counterparts. I calculate data moments using the economy-wide establishment-level data from the BDS dataset over 1977-2015. I capture cohorts' characteristics at entry (age zero) by the following moments: average entry rate, the share of entrants' employment in total employment, the average size of active establishments, and the average size of entrant establishments.[29] To capture cohorts' post-entry characteristics, I target the following moments: the average cohort's size at age 5 and between 21 and 25 years old, average survival rate until 5 years old, survival between 21 and 25 years old, establishment exit rate, and cohort employment share in total employment at age 5. I calculate the model-simulated moments in the stochastic steady state, when $z = 1$ ($\sigma_z \neq 0$).

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

The first and the second columns of Table 4 reports the values of the calibration targets and the model simulated counterparts. Figure 6 additionally illustrates the evolution of the steady state cohorts' average size, average survival rates, and average exit rates in the model and the data for up to 30 years of operation. It also displays the share of the cohorts' employment in the aggregate employment for up to 5 years of operation.[30] Investigating the figures shows that the average cohorts' characteristics at entry and over time closely mimic the data counterpart.

I calibrate the parameters that drive the aggregate demand shock process (ρ_z, σ_z) to match the autoregressive properties of the cycle component of the entry rate in the model and the data. The entry rate data comes from the BDS dataset and cover 1977-2015. To calculate the cycle component of the entry rate, I apply the HP filter with a smoothing parameter of 100. To generate the model counterparts of the data moments, I simulate the economy over many periods and apply the same detrending method to the model-simulated 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 $\rho_z = 0.57$, and $\sigma_z = 0.0022$.

Finally, I set $\tau = 1$. In Appendix F.1, I propose a strategy to identify τ using the time-series of the aggregate employment. I find that $\tau = 0.965$ and the dynamics of the economy are very close to the case $\tau = 1$.

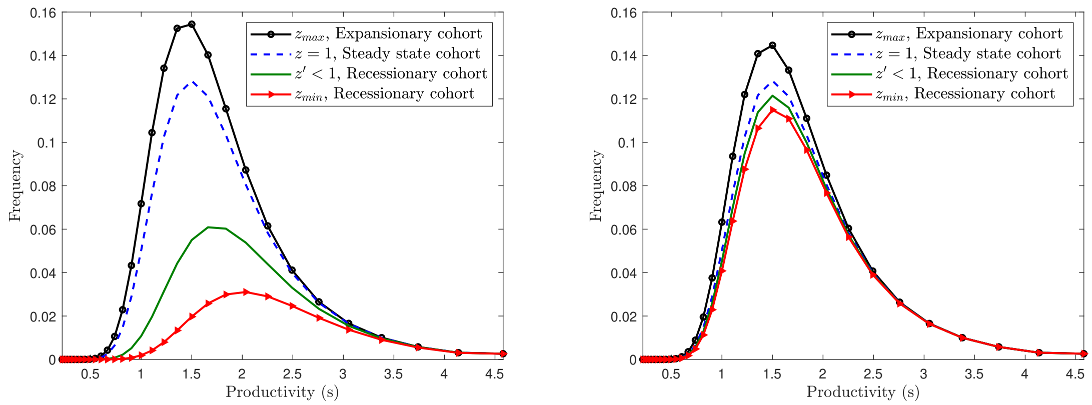
4.3 Cohort-level Dynamics

I start by evaluating the model performance in accounting for the significantly and persistently different life-cycle characteristics of cohorts that enter the market at different aggregate states of the economy. To describe the business cycle conditions at entry, I use the aggregate demand shock process. I refer to a period as a recession (expansion) when the aggregate demand level is below (above) the stochastic steady state level $z < 1$ $(z > 1)$. I define cohorts as recessionary (expansionary) if they start operating during the recessions (expansions).[31]

[30] The BDS dataset does not allow to identify individual cohort employment after five years of operation.

[31] The results are robust to the definition of the business cycles within the model. In particular, results are similar 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). The results are robust because the model generates more or less symmetric business cycles.

Figure 7: Cohorts over BC: Productivity



(a) Baseline model

(b) $\tau = 0$ case

To isolate the role of the option to delay entry, I consider a version of the baseline model in which potential entrants keep the signal with $\tau = 0$ probability ($\tau = 0$ *case*). The $\tau = 0$ case is identically parameterized except for the fixed entry cost. I set the latter equal to the steady state total opportunity cost of entry in the baseline model.[32] The choice of the fixed entry cost ensures the alternative scenario exhibits the same dynamics in the stochastic steady state as the baseline model.[33] Due to the differences in the implied entry-cost structure these scenarios exhibit different dynamics beyond the steady state, .[34] Hence, by comparing the business cycle dynamics in the baseline model against the $\tau = 0$ case allows me to quantify the role of the option to delay entry in accounting for the observed significant and persistent differences in the cohort post-entry characteristics.

Productivity Consistent with the empirical findings, I find that the aggregate economic conditions at entry have a significant and persistent effect on the productivity composition of entrants in the baseline model. Figure 8(a) depicts entrants' distribution over the initial productivity across different aggregate demand levels. The productivity distribution of entrants is positively skewed. The skewness decreases with the aggregate demand level, producing countercyclical average productivity. If $\tau = 1$, the average productivity of cohorts that start operating during recessions is around 3% higher than their expansionary counterparts. The

[32] $c_{\tau=0} = c_{\tau=1} + V^w(q^*_{\tau=1}(z_{ss}), z_{ss})$. The Column (b) of Table 17 summarizes the parameter values used in the $\tau = 0$ case.

[33] Equalizing the opportunity cost of entry ensures that the threshold signal coincides across these two scenarios, which in turn imply the same number and composition of entrants in these scenarios.

[34] For illustration see Figure 26.

Table 6: Cohort-level Employment in the Baseline and Counterfactual Scenarios

		Recessionary Cohorts			Expansionary Cohorts		
		Age 0 % dev.	Age 5 % dev.	Age 15 % dev.	Age 0 % dev.	Age 5 % dev.	Age 15 % dev.
(a)	Baseline	-5.7	-4.7	-4.8	5.0	4.0	4.1
(b)	The $\tau = 0$ case	-1.2	-1.0	-1.0	1.0	0.9	1.0
(c)	Baseline, adjust lowest s	-3.4	-1.4	-1.5	2.6	1.2	1.3
(d)	Baseline, adjust highest s	-12.5	-14.1	-13.3	10.0	11.2	10.6
(e)	Baseline, only selection	-5.3	-4.4	-4.5	5.4	4.3	4.4

Note: The numbers in the table describe percentage deviations (% dev.) of the recessionary (expansionary) cohorts' employment from the average cohort employment. Recessionary (Expansionary) cohorts refer to the group of firms that started operation when $z < 1$ ($z > 1$).

difference persists in later years, due to the persistent idiosyncratic productivity process. Figure 8(b) shows the same statistics for the $\tau = 0$ case. Shutting down the option to delay entry reduces the difference in average productivity to 0.4%. The result emphasizes the importance of the countercyclical opportunity cost of entry to account for the significant and persistent variation in the productivity composition of entrants over the cycles.

Employment Row (a) of Table 6 summarizes the dynamics of cohort-level employment at entry and over time for the baseline model. According to the results, the recessionary (expansionary) cohorts employ 5.7% less (5.0% more) workers than the average cohort and the differences do not disappear even after 15 years of operation. Row (b) of Table 6 summarizes the dynamics of cohort-level employment for the $\tau = 0$ case and shows that shutting down the option to delay entry reduces the difference to 1%, thus implying that the major share (80%) of the variation in cohort-level employment comes from the entrants that delay entry.[35]

I find that the persistent differences in cohort-level employment are due to variations in the composition rather than the number of firms at entry. Rows (c) and (d) of Table 8

[35] The model generates cohorts' with a countercyclical average size. The result is in line with Lee and Mukoyama (2015), who show that the average size of US manufacturing plants is countercyclical. However, the result is at odds with Sedlacek and Sterk's (2016) finding. Using the BDS dataset, they show entrants' average size is procyclical. I expect that extending the model to account for the procyclical average size at entry will increase the difference in cohort-level employment over the cycles. One potential extension to generate the procyclical average size of entrants is to assume the first-period level of customer capital is procyclical.

summarize the dynamics in two counterfactual scenarios that feature the same variation in the number of entrants as the baseline model, whereas I let the composition of entrants vary systematically across these scenarios. Specifically, "Baseline, adjust lowest s", and "Baseline, adjust highest s" refer to the scenarios in which the variation in the number of entrants are generated by adjusting, respectively, the lowest- and highest-productivity firms from the steady state distribution of entrants.[36] Comparing the dynamics of these two scenarios shows that the variation in the number of entrants has a persistent effect on cohort-level employment if it comes from the high-productivity entrants.[37] Note that the dynamics of the baseline economy are in between these two counterfactual scenarios. The medium-productivity firms that delay entry increase the pro-cyclical variation in the high-productivity entrants and lead to higher persistence in the dynamics of cohort-level employment. The mechanism corresponds to Decker et al.'s (2014) empirical findings that the entrant cohorts' contribution to the aggregate employment comes from the small share of the high-growth firms. Pugsley, Sedlaćek, and Sterk (2016) also find that the major share of the entrant cohorts' post-entry performance is due to ex-ante differences in the types of entrants.

Finally, consider row (e) in Table 8. "Baseline, only selection" refers to the baseline scenario in which the aggregate demand shocks affect only the selection of entrants and have no effect on the firms' post-entry demand structure. Contrasting the baseline model with the counterfactual scenario shows that the persistent customer-capital-accumulation process plays a minor role (less than *7*%) in generating persistence in the dynamics of cohort-level employment.

4.3.1 Survival Rate: The Model and Data

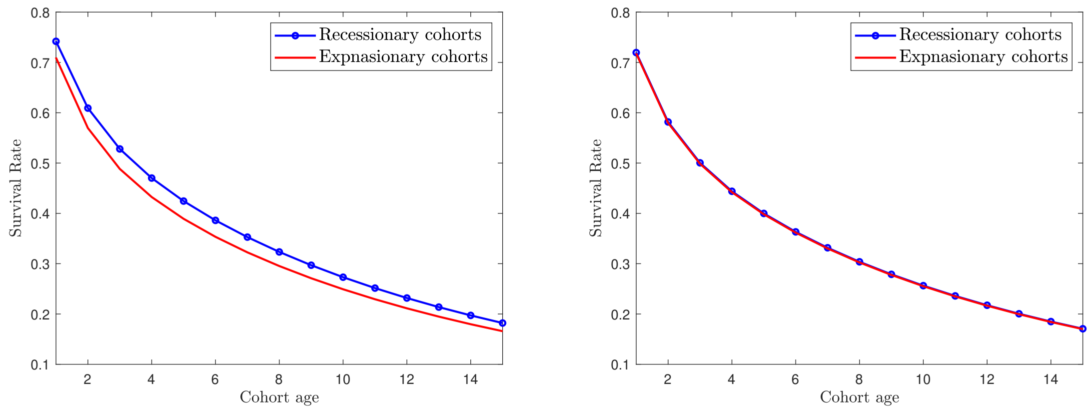
The Model Figure 9(a) shows that the average survival rates for the expansionary and recessionary cohorts are countercyclical in the baseline model.[38] The result is a direct im-

[36] For more details refer to Appendix E.3.3.

[37] The mechanism corresponds to the "missing generation" channel initially discussed in Gourio, Messer and Siemer (2015).

[38] To compare the average survival rate generated by the model with the data counterpart, I define recession (expansion) as the period when the aggregate demand is *1*% below (above) the steady state level. I define cohorts as recessionary (expansionary) if they started operation during the recessions (expansions). After simulating the economy for many periods, I calculate the average survival rates for the recessionary and expansionary cohorts for up to 15 years of operation.

Figure 8: Cohorts over BC: Survival Rate



(a) Baseline model

(b) $\tau = 0$ case

plication of the selection through the option to delay entry. As discussed in section 3, firms decide to wait until the expected survival rate is high enough to compensate for lower demand levels in the first several years of operation. As a result, a cohort of firms that start operating during recessions has, on average, higher survival rates than their expansionary counterparts. Figure 9(b) shows that without the option to wait the model leads to acyclical average survival rates.[39] This result provides a potential testable implication for the mechanism.

The Data I use the BDS database over 1979 − 2015 to study how the average cohorts' long-run survival rates vary with the aggregate economic conditions. Let $N_{g,t}$ be the number of firms in a cohort of age g at year t. Employer businesses enter with age $g = 0$. I measure the survival rate of a cohort of age g at year t as

$$S_{g,t} = \frac{N_{g,t}}{N_{0,t-g}}, \quad where \quad g = 0, 1, 2, 3, 4, 5.$$

To characterize economic conditions at entry, I use the time series about the quarterly real GDP.[40] To find the cyclical component of the yearly log real GDP, I apply the HP filter with a smoothing parameter of 100. I also define an indicator that refers to a year as a

[39]For more details see section 3.

[40]In the BDS dataset, establishment-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. The source and the construction of the annual real GDP data are described in Appendix E.2.

Table 7: Correlations between the Survival Rates with the Business Cycle Conditions.

	Period *1979 − 2016*				
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t	NBER$(0,1)$
$corr(S_{1,t+1}, Y_t)$	-0.19 (0.25)	-0.24 (0.16)	-0.07 (0.68)	0.12 (0.48)	0.08 (0.63)
$corr(S_{2,t+2}, Y_t)$	-0.36 (0.03)	-0.41 (0.01)	-0.28 (0.10)	0.30 (0.09)	0.14 (0.41)
$corr(S_{3,t+3}, Y_t)$	-0.38 (0.02)	-0.46 (0.00)	-0.38 (0.02)	0.39 (0.02)	0.18 (0.30)
$corr(S_{4,t+4}, Y_t)$	-0.31 (0.08)	-0.41 (0.02)	-0.34 (0.05)	0.37 (0.03)	0.20 (0.26)
$corr(S_{5,t+5}, Y_t)$	-0.16 (0.36)	-0.24 (0.18)	-0.21 (0.24)	0.27 (0.13)	0.21 (0.24)

Notes. The table reports correlations (p-values) of the cohorts' survival rates at age g with the business cycle indicator at the time of entry. $Y_{hp,t}$ refers to the cycle of log real GDP after applying the HP filter with a smoothing parameter of 100. $I_{hp,t}$ refers to an indicator that defines an aggregate state as a recession (expansion) if the cycle component of log real GDP is more than 1% below(above) the trend. $Y_{linear,t}$ describes the aggregate state at entry using the cycle component of log real GDP after applying the linear trend. Δu_t refers to the deviations of annual unemployment rates from the average unemployment rate. NBER$(0,1)$ describes the NBER-based recession indicators for the US from the period following the peak through the trough. The unit of analysis is a cohort of establishments.

recession (expansion) if the cyclical component of the log real GDP is below (above) trend by 1% ($I_{hp,t}$). A cohort born in year t is referred to as recessionary (expansionary) cohort if t is indicated as a recessionary (expansionary) year based on the indicator.[41]

Columns (a) and (b) of Table 15 report correlations (p-values) between the cohorts' survival rates at age g with the business cycle indicator at the time of entry. The values indicate that economic conditions at entry have a persistently negative effect on cohorts' post-entry survival rates. To assess the robustness of these findings, I additionally consider the following business cycle indicators: the cyclical component of the log real GDP after applying linear trend ($Y_{linear,t}$), the deviations of annual unemployment rates from the average unemployment rate (Δu_t), and the NBER-based recession indicators for the US from the period following the peak through the trough.[42] Columns (c), (d), and (e) of Table 15 report correlations (p-values) of the survival rates with the new set of indicators. Again, we see that the aggregate state at entry has a persistent and negative effect on cohorts' post-entry survival rates. I also find that the results hold if we consider cohorts of firms rather than establishments as units of analysis. The results are also robust if one considers firms rather than

[41]The indicator takes a value 1 for expansions, -1 for recessions, and 0 for in-between scenarios. The choice of the magnitude of the deviation equally divides 39 observation into three groups.

[42]The latter indicator specifies peak and the 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 the April year t are indicated as recessionary periods. Based on the definition, the recessionary yearsare 1981, 1982, 1983, 1991, 2002, and 2009. All other years are defined as expansionary.

establishments; see Appendix C.2, Table 7.[43]

To interpret the results, note the aggregate economic conditions have two counteracting effects on new cohorts' survival rates. On the one hand, the lower aggregate demand directly decreases cohorts' survival rates by increasing firms' post-entry failure rates. On the other hand, the lower aggregate demand increases cohorts' survival rates by selecting firms at entry. The finding that cohorts' average survival rates are countercyclical supports the option-value-of-delay mechanism and emphasize that initial aggregate conditions have a significant effect on the selection of firms at entry.[44]

5 Implications of Entrant Demographics

5.1 Aggregate Fluctuations

In this section, using a model that closely mimics the life-cycle dynamics of the US establishments on average and over the cycles, I quantify the role of the entry margin in shaping aggregate fluctuations.

To compute the business cycle moments from the data, I use the time series of the natural logarithm of aggregate employment, real GDP, and the total number of establishments that covers the period 1977-2015.[45] I apply the HP-filter with a smoothing parameter of 100 to find the cycle component of these variables. I use the same methodology to compute the moments from the model-simulated time-series.[46] The statistics from the data and the model are described in columns (a) and (b) of Table 8, respectively.

Table 8 shows that the variance and the autocovariance of the simulated total number of firms are very close to the data counterpart. The variation in the exogenous aggregate demand shock affects firms' life-cycle demographics in the following two ways: First, the

[43]In the appendix I also study variation in the survival rates by sector.

[44]The variation in the survival rate itself does not explain much of a variation in the number of firms over the cycles (Sedlaćek (2019), Sedlaćek and Sterk (2017)).

[45]The time series of the aggregate employment and the real GDP are constructed to be consistent with the timing of the BDS dataset. Detailed information about the source and the construction of the aggregate variables are provided in Appendix E.2.

[46]In particular, I run the baseline economy over a large number of periods. I find the cyclical component of the natural logarithm of the simulated aggregate employment, output, and the total number of firms using the HP filter with a smoothing parameter of 100. I use the latter time series to compute the standard deviation and the autocorrelation of these variables.

Table 8: Business Cycle Moments: Data, the Baseline Model, and the Counterfactuals.

		Data (a)	Baseline (b)	Baseline, only selection (c)	The case $\tau = 0$ (d)
No. of firms	ρ	0.640	0.619	0.607	0.661
	σ	0.012	0.010	0.010	0.002
Employment	ρ	0.610	0.574	0.622	0.432
	σ	0.015	0.012	0.010	0.004
Entry Rate	ρ	0.250	**0.253**	0.252	0.222
	σ	0.062	**0.065**	0.065	0.010
No. of Entrants	ρ	0.311	0.278	0.278	0.245
	σ	0.066	0.073	0.073	0.011

Notes. All series are computed in log deviation from the HP trend. The numbers that are in bold refer to the targeted model statistics. All other values indicate untargeted model statistics and their empirical counterparts.

aggregate demand condition affects the composition/number of entrants at entry. Second, aggregate demand affects incumbent firms' decisions about production and continuation. Aggregation of these two effects by adding up cohorts at different stages of their life cycle creates dynamics of the total number of firms that are very close to the data counterpart. The result can also additionally be interpreted as an external validation of the exogenous aggregate demand shock process.

Table 8 shows that the model that is built to account for the life-cycle demographics of firms (selection at entry, growth, survival) accounts for more than three fourths of the business cycle fluctuations in aggregate variables. In particular, the autocorrelation of the aggregate employment in the model is 0.57, whereas in the data, it equals 0.61. The standard deviation in the model and the data is 0.012 and 0.015, respectively.

Further investigation of the results shows that the variation in the number and the composition of firms at entry is responsible for shaping the dynamics of the aggregate variables. In particular, I consider a counterfactual scenario in which the variation in the aggregate demand affects selection but does not have an effect on firms' post-entry decisions.[47] The dy-

[47] In particular, I construct a counterfactual economy in which the aggregate demand shock has the same impact on the selection (composition/number) of entrants as in the baseline model. However, I set aggregate demand shocks equal to zero for all the firms that operate in the market.

Table 9: Impulse-Response Analyses

		Panel A: One-time shock			Panel B: Persistent Shock		
		Full Model	Fixed entry		Full Model	Fixed entry	
				z_{high}			z_{high}
		(a)	(b)	(c)	(d)	(e)	(f)
Depth (%)	Employment	-1.83	-0.72	-1.90	-2.0	-0.72	-2.1
	No. of Firms	-2.93	-0.07	-0.18	-3.04	-0.14	-0.43
50% Recovery	Employment	3	2	2	16	7	6
	No. of Firms	3	15	14	9	17	18
75% Recovery	Employment	15	2	2	28	14	15
	No. of Firms	8	23	23	17	26	27

Note: Baseline refers to a model with baseline specification. Fixed entry refers to a case in which the shock affects cohorts' post-entry performance, whereas the entry rate is fixed at the steady state level. z_{high} refers to a case in which the magnitude of the shock is chosen to produce a drop in employment as in Baseline scenario. Depth refers to the highest deviation of the time series from trend. 50% Recovery (75% Recovery) describes the number of periods (years) starting from period 1, after which economy recovers 50% (75%) from the 'depth'.

namics of the economy are summarized in column (c) of Table 8. One can see the aggregate dynamics in the counterfactual and the baseline scenarios are quite similar, which means the observed significant and persistent differences in cohorts' characteristics over the cycles build up significant persistence and variance in aggregate variables. At the same time, the result also implies that the post-entry shocks that affect firms' post-entry decisions provide a relatively minor contribution to aggregate fluctuations. The latter result corresponds to the recent empirical findings by Sedlacek and Sterk (2017), who show the selection of firms at the entry stage, rather than the post-entry choices made by the firms, drive the cohorts' contribution to aggregate fluctuations.

5.2 Impulse-Response Analyses

The results of the previous exercise appear surprising compared with the employment share of each cohort that accounts for 5.5% at entry. To illustrate how the variation in cohorts' characteristics can build up persistence and variance in the aggregate dynamics, I study the response of the baseline economy to a one-time negative aggregate demand shock, summarized in Panel A of Table 9. The magnitude of the shock is chosen to yield a 25% decline in the number of entrant establishments.[48] One can see that after the shock, the baseline economy takes three years to recover half-life and another *12* years to recover an additional 25% of the decline. By contrast, an economy in which the shock does not affect the entry margin takes only *2* years to recover the full, three fourths of the decline, even after increasing the magnitude of the shock to be equal to the initial drop in employment in the baseline and the counterfactual scenarios. Thus, changes in the number and composition of firms at entry that leads to a persistent decline in entrant cohorts' employment plays a significant role in the propagation of aggregate shocks. Panel B of Table 9 shows that if the change in the entry margin is persistent, the effect accumulates and has a substantial impact on the depth and the long-run recovery of the economic aggregates.[49]

5.3 The Great Recession

To additionally support the findings and validate the model, I study the Great Recession, which is notorious with the historical drop in the number of entrants and the unprecedented slow recovery of the aggregate employment that followed.[50] I use the episode to illustrate that the persistent drop in entrant cohorts' employment over the period 2008-2016 had a substantial effect on the slow recovery of the aggregate employment. Then, I use the model to investigate how much of the effect is due to the variation of entrants at the entry margin. I find that the persistently low aggregate demand shock series that leads to the persistent changes in the number and the composition of firms at entry quite account for the contribution of cohorts born over the period 2008-2016.

5.3.1 The Data

Initially, I use an accounting exercise to directly quantify how much of the changes in the employment of cohorts that started operating over the period $2008-2016$ contributed to the slow recovery of aggregate employment.[51]

[48] The number corresponds to the decline in the number of entrants observed during the Great Recession.

[49] The mechanism is consistent with empirical findings by Gourio, Messer and Siemer (2016). Using an annual panel of US states over the period 1982-2014, they show that changes in the number of entrant firms have a persistent effect on the dynamics of the aggregate variables.

[50] Figure 32(a) plots the cyclical variation in the number of entrant establishments and the aggregate employment in the US over the period $1977-2016$.

[51] 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.

The aggregate employment at time t can be expressed as a sum of the total employment of the cohorts of establishments at different ages:

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

where N_t denotes aggregate employment and $n_{g,t-g}$ refers to total employment of a cohort of age g who started operating at time t, $g = 0, 1, 2, 3, 4, 5$. Due to the data limitations, I only consider cohorts up to age five.[52] Res_t combines part of the aggregate employment that belongs to establishments with ages 6+ and the segment of employment that is not part of the BDS dataset.

I consider the beginning of the recession to be year 2008.[53] Consider $\hat{N}_t$ to be the level of aggregate employment at time $t \geq 2008$ had the Great Recession not happened. $\hat{N}_t$ can be expressed as follows:

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

where $\hat{n}_{g,t-g}$ refers to the employment of a cohort of age g that entered the market at time t, had the Great Recession not happened. I define $\hat{Res}_t$ similarly. I use equation (3) and equation (4) to decompose changes in the aggregate employment as a sum of the changes in the cohort-level employment by age:

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

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 $g = 0, 1, 2, 3, 4, 5$. $\Delta\hat{n}_{g,t-g}$ shows how much of the changes in the cohort employment of age g contributes to the changes in the aggregate employment at time t.[54]

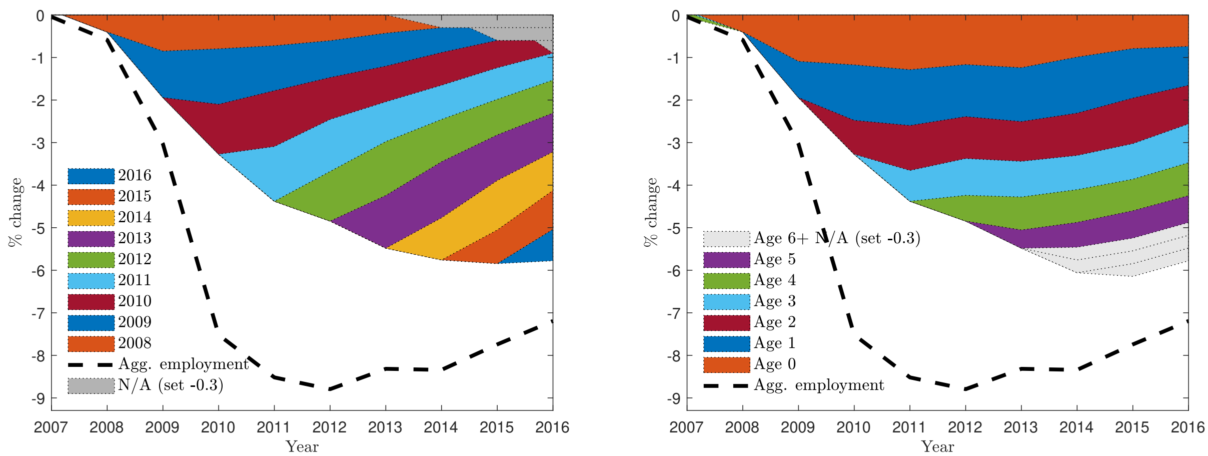
[52] The publicly available part of the BDS dataset only allows me to separately track cohorts from age zero up to age five.

[53] 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.

[54] One can also think about it as a percentage deviation of the actual cohort-level employment from the predicted cohort-level employment, weighted by the share of the cohort employment in aggregate employment:

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

Figure 9: New Cohorts' Contribution to the Slow Recovery of Aggregate Employment after the Great Recession



(a) By cohort

(b) By age

Using the equation, I isolate the dynamics of the aggregate employment accounted for by cohorts that entered the market starting from $t \geq 2008$. Toward the end, consider the following counterfactual: for each year $t \geq 2008$, I only consider the deviations of the aggregate employment, $\Delta\hat{N}_{t,\ counter}$, that is accounted for by the cohorts that entered the market from $t \geq 2008$. At year 2007, $\Delta\hat{N}_{2007,\ counter} = 0$. Starting from the year 2008,

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

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

$$. \quad . \quad .$$

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

I apply a linear trend over the period 1979-2007 to predict the evolution of aggregate employment from the year 2008 as if the Great Recession had not happened.[55] I set $\hat{n}_{g,t-g}$ equal to the average employment of cohorts of age g over the period $2003-2007$. The latter allows me to study how the aggregate employment would have evolved during the Great Recession had the new cohorts of establishments behaved as the representative pre-crisis cohorts of establishments.[56]

[55]In Appendix G.2, Figure 34 displays the evolution, pre-crisis trend and the prediction for the aggregate employment.

[56]The cohort-level employment by age over the period $1983-2007$ shows that the times series exhibits an increasing trend; see Figure 35(a) in the Appendix G.2. The share of cohorts' employment in aggregate employment have a decreasing trend; see Figure 35(b). Thus, constructing a representative cohort based on

Figure 9(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 shaded areas represent the contribution of each cohort born over the period $2008-2016$ to the drop in aggregate employment. Several observations stand out. The cohorts that entered the market after the year 2008 employ persistently fewer workers, compared with their pre-crisis counterparts. These cohorts' dynamics contribute around 45% of a total 8.9% drop in aggregate employment in the year 2012. By the year 2016, the aggregate employment is 7% below the trend, and now 85% of the drop is due to cohorts that started operating over the period $2008-2016$. Thus, whereas the incumbent firms drive the depth of the recession, the dynamics of the new cohorts build up significant persistence in the dynamics of aggregate employment.[57] Figure 9(b) shows the same exercise by establishment age rather than the cohort year. The figure once again illustrates how much the persistent drop in cohort-level employment across different age groups contributed to the drop in aggregate employment.

5.3.2 The Model

Next, I investigate how much a model that accounts for the US establishments' life-cycle demographics could explain the documented contribution of 2008-2016 cohorts. I also use the model to quantify the role of variation in the number and the composition of entrants in this contribution. Toward the goal, I construct an aggregate demand shock series that matches the changes in the simulated number of entrant establishments to the data counterpart over the period 2008-2016. Figure 40(b) illustrates the evolution of the number of entrant establishments in the model and in the data. Figure 40(a) displays the series of the aggregate demand shocks that generate the match. As in the empirical part, I used a linear trend over the period $1979-2007$ to predict the evolution of the number of entrant establishments starting from the year 2008, as if the Great Recession had not happened.[58]

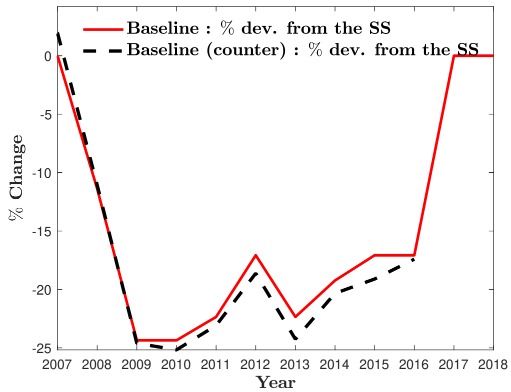
The model predicts that changes in the number and the composition of entrants over the period 2008-2016 account for around 39% of the depth of the aggregate employment reached in 2012. By 2016, the persistent drop in the new cohorts' employment level accumulate, and it explains around 75% of the drop in aggregate employment. Figure 40(c) contrasts the

pre-crisis average cohort-level employment captures a lower bound of the recent cohorts' contribution.

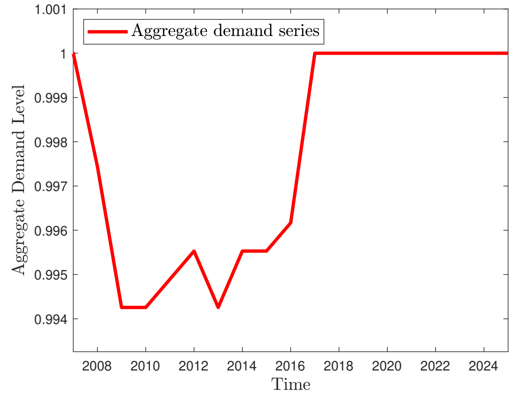
[57] In Appendix G.2, I show that the results are robust if I consider ten-year pre-crisis average of cohort-level employment.

[58] Figure 39 displays the evolutions, pre-crisis trends and predictions for these time series.

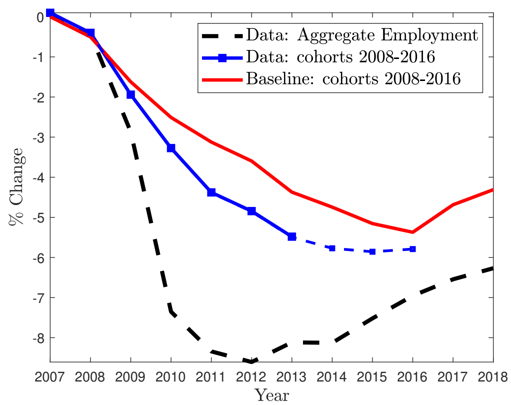
Figure 10: The Great Recession Exercise



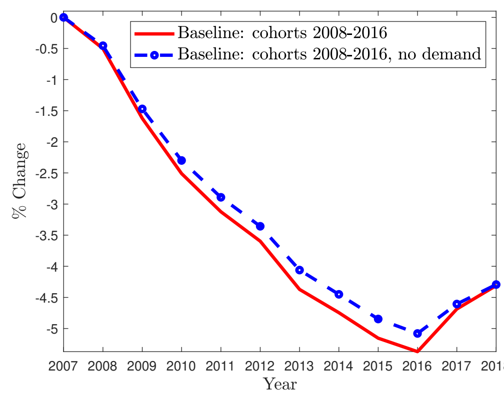
(a) Change in no. of entrants



(b) Aggregate demand process



(c) Cohorts 2008-2016



(d) Cohorts 2008-2016, no demand

changes in aggregate employment accounted by the cohorts born over $2008-2016$ in the model and data. The exercise shows that the combination of the aggregate demand shocks and the variation in the entry margin accounts for the major share of the documented contribution of 2008-2016 cohorts.[59] Next, to isolate the contribution of the changes in the number and composition of entrants at the entry margin, I consider a counterfactual scenario in which the aggregate demand shocks only affect the selection and not the post-entry dynamics of firms. Figure 40(d) shows that post-entry demand shocks play a minor role and most of the observed contribution comes from the variation at the entry margin.

[59] Other economic forces, not considered in the paper, could explain the drop in 2008-2016 cohrots' employment. For example, the credit crunch that occurred during the Great Recession, significantly increased the cost of financing. The existing literature also points out that a potential structural change in the entrants during the Great Recession might have played an important role in the protracted recovery in aggregate variables. Figure 33 shows that all sectors experienced a significant and persistent drop in the number of entrants compared to the pre-crisis level (Gourio, Messer, and Siemer(2016)).

6 Other Applications

In this section, I show that existing business cycle firm dynamics models that employ a traditional neoclassical entry decision rule cannot account for the observed dynamics of entrants without generating excessive variation in the aggregate variables. The latter leads to counterfactual predictions about the role of entry. Firm dynamics models use various approaches to overcome the puzzle. For example, Lee and Mukoyama (2018) introduce entry cost that varies over the cycles in a particular way. Sedlaćek and Sterk (2019) introduce entry function, which allows choosing the elasticity of the number of entrants with respect to aggregate shocks. Others rely on exogenous entry specific shock processes (e.g., Clementi and Palazzo (2016), Sedlaćek and Sterk (2017)). In the second part of the section, I show that not accounting for the option to delay entry may lead to imprecise predictions about the response of potential entrants to different shocks.

6.1 The Standard Model

I study a model without the option to delay entry (I refer to it as the *Standard model*) that produces the same set of facts as the baseline model described in Section 4.2. Because firms' values are relatively insensitive to the aggregate state, the Standard model requires a variance of the aggregate demand shock σ_z, almost seven times higher than a model with the option to delay entry. Appendix E.3 provides a detailed description of the Standard model's calibration procedure.[60]

First, I show that the Standard model that accounts for the observed business cycle dynamics of entrants lead to excessive variation in aggregate variables and counterfactual predictions about the role of entry. Column (c) of Table 10 summarizes the business cycle properties of the economy. One can see that the model generates a variance of the aggregate employment that is *1.7* times higher than the data counterpart. Column (d) of Table 10 shows that the post-entry shock process explains a major share of the cohort performance, and hence the dynamics of the aggregate variables. This result is also at odds with the recent empirical findings that emphasize the role of the pre-entry selection of firms in explaining cohorts' post-entry differences. Additionally, I use the Standard model to quantify the role of the

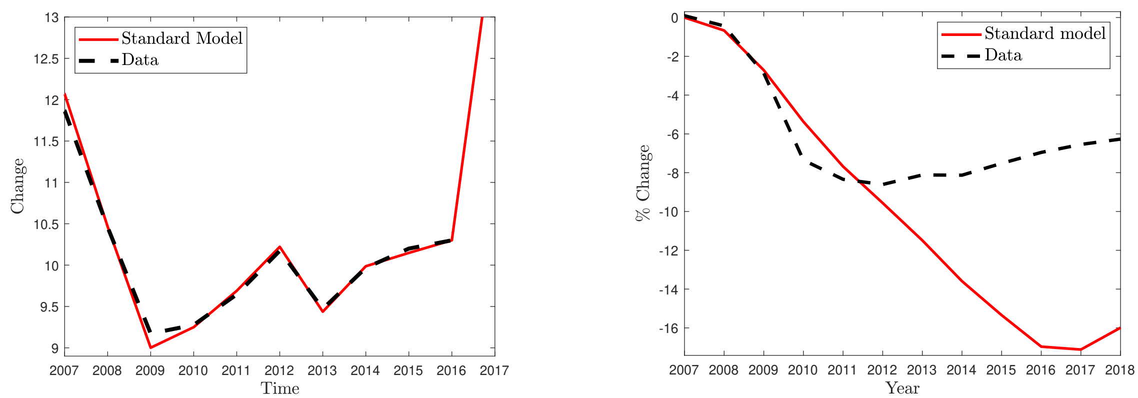
[60] In Appendix E.3, Table 17 summarizes the parameter values, and tables 18, and 19 summarize how the moments targeted in the Standard model compare with the data counterpart and the baseline model.

Table 10: Business Cycle Moments: Data and Model

		Data	Baseline	The Standard Model	
					only selection
		(a)	(b)	(c)	(d)
No. of firms	ρ	0.640	0.619	0.684	0.605
	σ	0.012	0.010	0.011	0.010
Employment	ρ	0.610	0.574	0.439	0.620
	σ	0.015	0.012	0.025	0.011
Entry Rate	ρ	0.250	**0.253**	**0.272**	0.265
	σ	0.062	**0.065**	**0.064**	0.063

Notes. The numbers that are in bold refer to the targeted model statistics. All other values indicate untargeted model statistics and their empirical counterparts.

Figure 11: The Great Recession and the Standard Model



(a) Entry rate (b) Total employment

entry margin in the anemic recovery observed after the Great Recession. Figure 11 shows that an aggregate demand shock series that generates the dynamics in the number of entrants observed over the period *2008 − 2016* leads to the drop in the aggregate employment that is twice as large as that observed during the Great Recession.

Next, I show that overlooking the observed variation in the entry margin undermines the role entry plays in propagating aggregate shocks. Following the existing literature, in the Standard model, I calibrate the aggregate demand shock process to match the business cycle fluctuations in aggregate employment, rather than the entry rate.[61] I find that in the

[61]For example, see Clementi and Palazzo (2016).

Standard model, matching the observed persistence and variance of aggregate employment requires the auto correlation and the variance of the aggregate demand shock process to be, respectively, 1.40 and 25 times higher than a model that accounts for the documented variation in the entry margin.[62]

To sum up, the option to delay entry is an important mechanism that enables standard firm dynamics models to reconcile the observed business cycle demographics of entrants, and quantify the role the variation in the entry margin plays in aggregate fluctuations.[63]

6.2 Policy Implications

Potential entrants' ability to postpone entry not only quantitatively but also qualitatively alters existing firm dynamics models, predictions about the response of potential entrants to different shocks. The reason is the following. With the option to delay entry, the dynamics of entrants depends on how the changes in the aggregate environment affect 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. In this section, I illustrate the point by analyzing potential entrants' reactions to the permanent, temporary, and future reduction in the entry cost with and without the option to postpone entry.

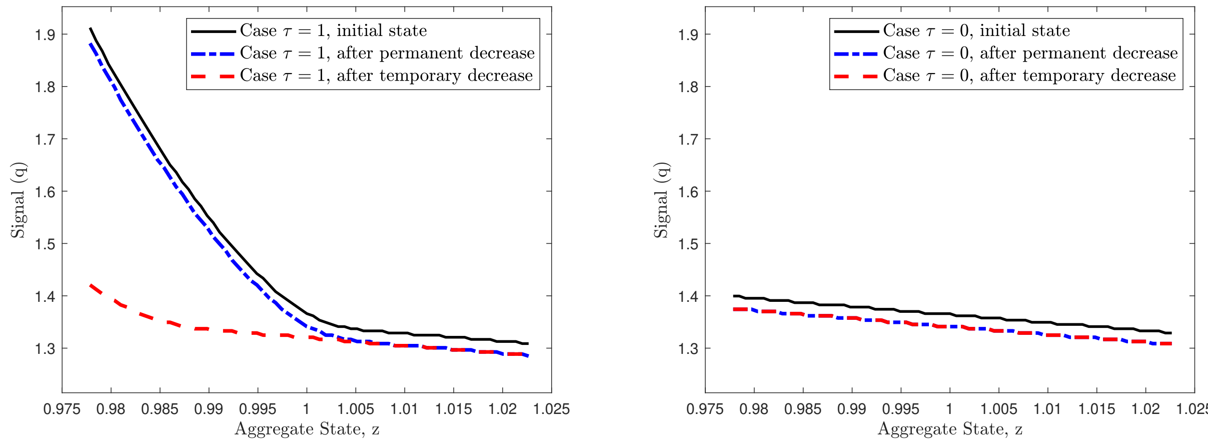
Permanent versus temporary policy Figures 12(a) and 12(b) contrast the changes in the threshold signal level as a response to a permanent and a temporary decrease in the fixed entry cost with and without the option to delay entry.[64] First, consider a model with the option to delay entry. If the goal 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

[62] Specifically, in the Standard model, the auto-correlation and the variance of the aggregate demand shock equal 0.80 and 0.05, respectively. In the baseline model, these values equal to 0.56 and 0.002, respectively.

[63] Even in general equilibrium settings, the model with persistent signal performs at least as good as standard firm dynamics models. The reason is as follows. The option value of delay is always non-negative, due to entrants' ability to obtain 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 a persistent signal than in the models without persistent signals. Appendix A.3 describes a general equilibrium version of the model.

[64] In Appendix G.3, Figures 42(c) and 42(d) translates the threshold signal into the number of entrants, using the assumed distribution $W(q)$ of potential entrants.

Figure 12: Permanent/Temporary Decline in the Fixed Entry Cost.



(a) Threshold signal, $\tau = 1$ (b) Threshold signal, $\tau = 0$

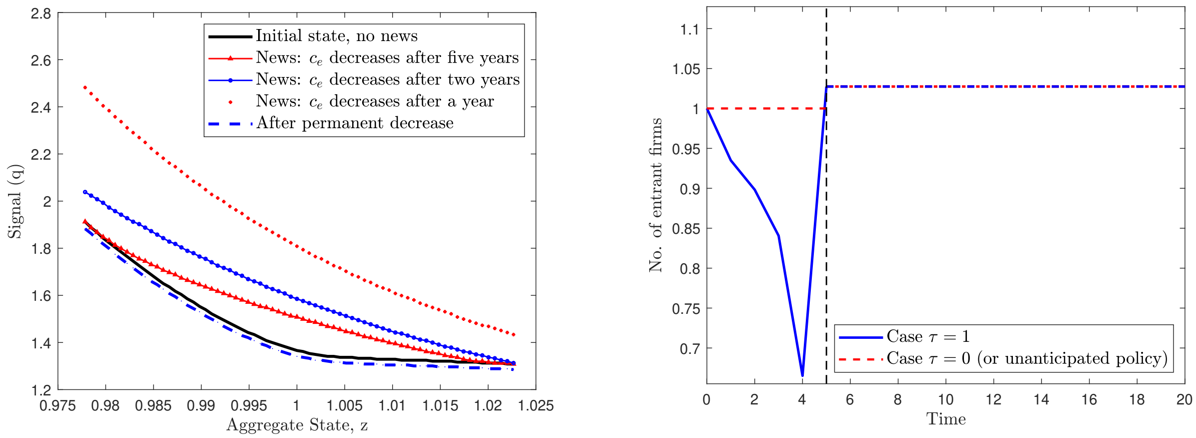
entrants who respond to the reduction of the fixed entry cost are mostly high-productivity firms during recessions and low-productivity firms during expansions. Without the option to delay entry, the response of entrants does not vary with the duration of the policy, neither quantitatively nor qualitatively.

The news shock Now, consider he response of potential entrants to an anticipated decline in the fixed entry cost after T periods from today. Figure 13(a) shows that the threshold signal in the news scenario is weakly higher than in the baseline (no-news) scenario in all aggregate states and for all T. The magnitude of the change depends on the distance between today and the policy's actual time. Interestingly, 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.[65] 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; see Figure 13(b) that compares the dynamics of entrants in the steady state as a response of news about the decline in the fixed entry cost with and without the option.[66]

[65] Constantini and Melitz (2007) also show that potential entrants respond differently to the news about trade liberalization depending on the timing and the implementation of the policy.

[66] In Appendix G.3.2, I describe and illustrates the dynamics of the economy as a response to the announcement; see 43. Figure 44 illustrates the dynamics of the economy as a response to the announcement,

Figure 13: News about the Anticipated Decline in the Fixed Entry Cost



(a) Threshold signal for different T and z

(b) Entrants' dynamics when $z = 1$ and $T = 5$

To conclude, after accounting for the ability to delay entry, the response of entrants to the changes in the aggregate environment depends on the relative variation in the benefits today versus tomorrow and any policy designed to affect entrants' behavior should take these channel into account.

7 Conclusions

In the paper, I show that potential entrants' ability to delay entry leads to the countercyclical opportunity cost of entry and significantly amplifies the role initial aggregate conditions play in the selection of entrants. The feature allows existing firm dynamics models to reconcile the observed variation in the number and composition of entrants without generating the counterfactual variance of the aggregate variables. I propose a model that is able to reconcile the documented life-cycle dynamics of US establishments, on average, and over the business cycles. I find that the observed variation in the number and composition of firms at entry is responsible for around three-fourths of the business cycle fluctuations in aggregate employment. To validate these findings, I show the model accounts closely for the recent cohorts' contribution to the persistent drop in aggregate employment observed after the Great Recession. Finally, I show that not accounting for the option to delay entry may result in misleading predictions about the response of potential entrants to different shocks or policies.

in which I allow accumulation of potential entrants.

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; How the heterogeneity in the ability to delay entry could explain the business cycle variation in the entry margins 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. In the paper, I study how allowing potential entrants to delay entry modifies their 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 Model Appendix

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

A.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 $q \sim W(q)$.[67]

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 which decomposes entrants between aspiring start ups, those that want to start a business and potential entrants that actual 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. If a potential entrant with a signal q postpones entry to the next period, the potential entrant gets the

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

same signal tomorrow with a probability $\tau \in [0,1]$. With a probability $(1-\tau)$, the potential entrant loses the signal and drops out from the pool of potential entrants.

In what follows, I describe each phase in detail.

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.[68] The total mass of available business opportunities equal to the total number of business opportunities within each signal category $W(q)$ minus the mass of business opportunities that is held by the group of potential entrants that delayed entry in the previous periods. $n_t(q)$ refers to a number of aspiring startups competing for the business opportunities with signal q. The ratio in the equation represents a probability by which an individual receives a signal q and becomes a potential entrant.[69] $V^e(q,z_t)$ 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 $\dfrac{B_t(q)}{n_t(q)} V^o(q,z_t) = c_q$.

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 to

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

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 variation of $N_{t,\text{aspiring startups}}$ over the cycles depends available business opportunities at time t that is determined by the states in the

[68] $0 < B_t(q) < W(q)$

[69] $0 \leq \dfrac{B_t(q)}{n_t(q)} \leq 1.$

past period.

Stage 2. Stage 2, in which potential entrants make entry decisions, follows the same process as described in the 2.3.

Parametrization of the entry phase To parametrize the entry phase I use information from the newly developed Business Formation Statistics dataset that collects information about business applications and formation. Business application data is based on applications for Employer Identification Number (EINs) filed in the United States. From the business applications only around 12% transitions into employer businesses within the first year, and 14% in the second year from the date of the application.

In the entry phase described above the number of applications can be considered 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 indicates that only additional 2% of the applications transitions into employer businesses in the following year. In terms of the model setup the fact implies that $B(q)$ is close to $W(q)$; only few potential entrants that decide to delay entry enters 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 the future research.

Note that the entry phase also can 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 wants to start business and actually applies for the EIN, from the potential entrants, those that actually hold business ideas and make entry decisions. According to the model the restricted number of actual business ideas does not allow most of the aspiring start-ups to enter the market.

Interestingly, the simple modification of entry phase developed in Lee and Mukoyama (2008) could also address an additional challenge faced by the firm dynamics models developed in general equilibrium: the pro-cyclical variation in the wages and the free entry condition mitigate the effect of the aggregate conditions on the selection of entrants. However, in the set up above, allowing aspiring start ups to compete in a specific signal categories endogenously restricts entry margin to have an effect on aggregate prices. The business cycle variation in the willingness to start a business is absorbed at the free entry stage due to changes in the probability of becoming a potential entrant.

To conclude, the restriction on the number of available business opportunities implies that the aggregate distribution of potential entrants are constant over time, and accumulation of the entrants happens at aspiring start up level.

A.2 Accumulation of Potential Entrants

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 entrants, that decide to delay entry, modifies entrants' characteristics over the cycles and affects the dynamics of aggregate variables. I find that cohorts that enter during different aggregate economic conditions have significantly and persistently different characteristics, even after allowing the accumulation of potential entrants over time.

Figure 14: New potential entrants, $W(q)$

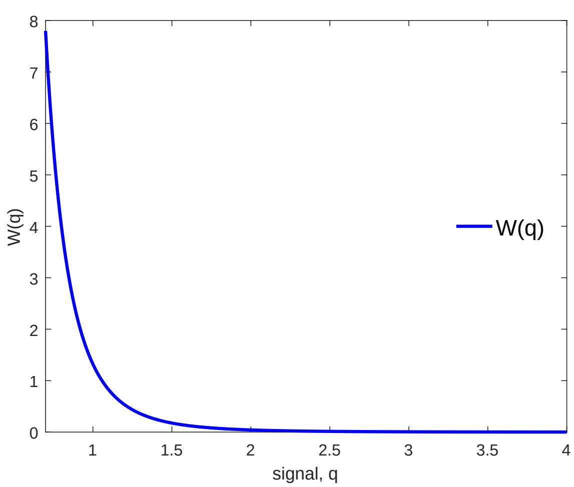
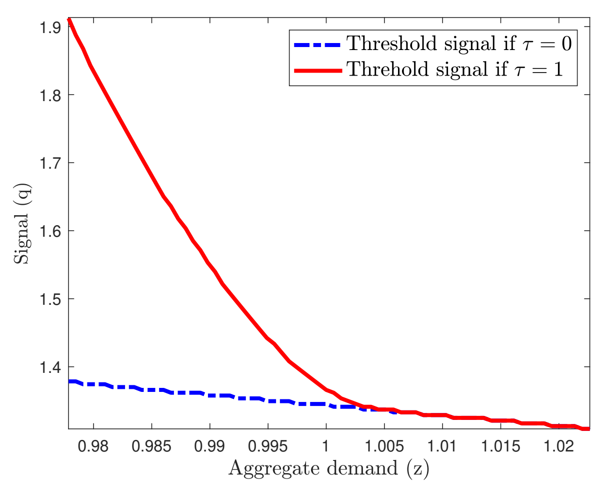


Figure 15: Threshold signal



In the baseline model, in every period, the distribution of new potential entrants, which make entry decisions for the first time, is equal to the distribution of potential entrants entering the market in the previous period. The assumption ensures that the number of potential entrants is constant over time. 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 14. In addition to the new potential entrants, the aggregate distribution of potential entrants consists of old potential entrants. Old potential entrants who chose to delay entry in the previous periods, while their expected value of being an incumbent was more than zero.[70] Figure 15 displays the threshold signal, $q^*_\tau(z)$ for each aggregate state when $\tau = 0$ (blue-dashed line) and $\tau = 1$ (solid red line). For given z, potential entrants that decide to delay entry hold signals in between $[q^*_{\tau=0}(z) \quad q^*_{\tau=1}(z)]$.

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 $\Lambda_t^{\text{old entrants}}(q)$.

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

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

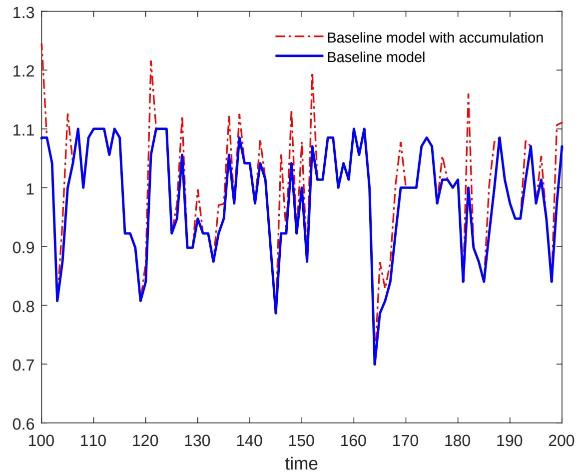
Then, the total mass of potential entrants with signal q at the beginning of period t, $\Psi_t(q)$ is given by

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

Figure 16 compares the dynamics of the entrants in the baseline model to a model that allows the accumulation of potential entrants. Note that when the aggregate demand decreases from z_{t-1} to z_t Then, the distribution/number of entrants in the baseline model and the model with signal accumulation coincide. If potential entrants delayed entry when the aggregate state was z_{t-1}, nobody from these old potential entrants is going to enter in an aggregate state z'_t ($< z_{t-1}$). As a result, selecting potential entrants at entry happens only from the distribution of new potential entrants, like in the baseline model. 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

[70] Consistent to the baseline model I keep $\tau = 1$, which means that potential entrants that delay entry can keep the signal forever.

Figure 16: Entrant firms



number of entrants to the model with signal accumulation compared to the baseline model.

It turns out that the increase in the number of entrants during expansions outweighs the increase in the number of entrants during recessions, and extending the baseline model to account for the accumulation of potential entrants increase procyclical variation in the entry rate. Moreover, the differences in cohorts' characteristics that start operating during different aggregate economic conditions increase after allowing potential entrants to accumulate. The latter feature modifies the distribution of the entrants over the cycles in the following way. During recessions, defined as periods when $log(z) < 0$, potential entrants that decide to start a business hold lower signals on average compared to the baseline scenario. Consequently, as shown in Figure 17 and Figure 18 the average productivity and the average survival rates of the cohorts that enter the market during recessions decrease compared to the baseline scenario. The accumulated groups of old potential entrants, on average, hold less productive signals, and most of them end up low-productivity firms after entering the market.

Consequently, average productivity and survival rate decreases significantly during expansionary periods compared to the baseline scenario. Altogether, the extension produces countercyclical average productivity and survival rates. Moreover, compared to the baseline model, the differences between the cohorts' post-entry characteristics that start operating at different aggregate conditions increases.

Allowing accumulation of potential entrants over time increases recessionary as well as expansionary cohorts employment compared to the baseline model. However, since the number

Figure 17: Average productivity

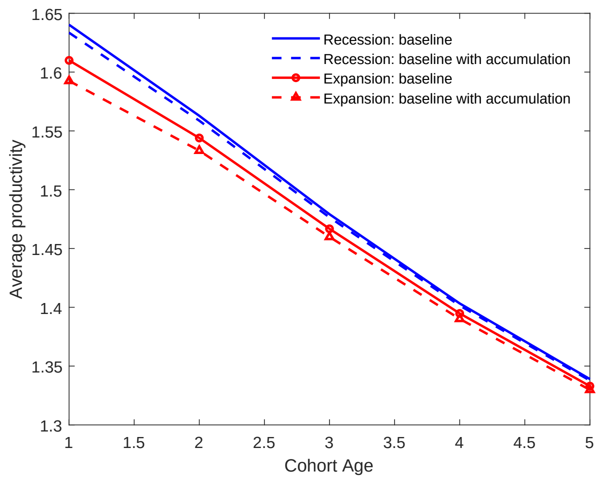


Figure 18: Average survival rate

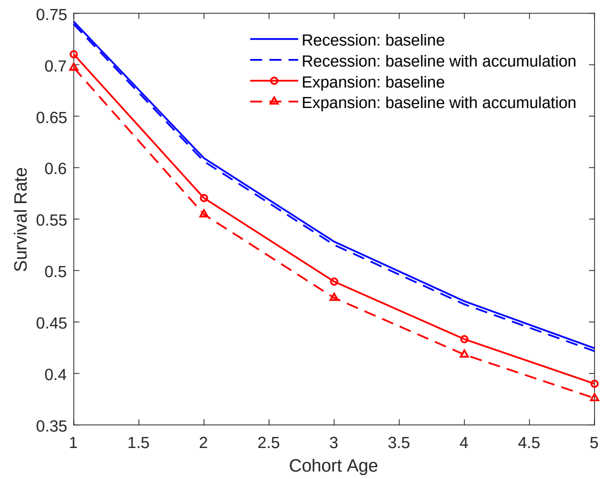
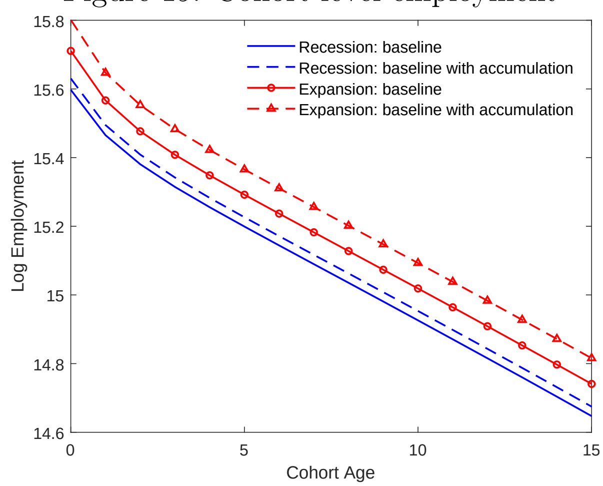


Figure 19: Cohort-level employment



of entrants significantly increases during expansionary periods the difference between recessionary and expansionary cohorts employment increases compared to the baseline scenario.

A.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 $P_t = C_t^{\rho}$.

A.3.1 Set up

A.3.2 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

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

A.3.3 The Mutual Fund

The household owns shares in the mutual fund. The mutual fund consists of the heterogeneous of 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 factor. 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.

$$y^s_t = s_t n_t;$$

$$y^d_t = \alpha z_t b^\eta_t \left(\frac{p_t}{P_t}\right)^{-\rho} Y_t;$$

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

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

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

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

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:

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

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

$$\Lambda_t = \int\limits_s \int\limits_b V(s,b,z)\Omega(b,s,z)dsdb + \int\limits_{q_*}^{\infty} \int\limits_s V(b_o, s, z)H(s|q)W(q)dq.$$

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

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

A.3.4 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 Mathematical Appendix

Proposition B.1. *(The properties of the gross value of entry)*

(a) For given aggregate demand level z, $V^{gross}(z,q)$ strictly increases with the signal q.

(b) For given signal q, $V^{gross}(z,q)$ strictly increases with the aggregate demand level z.

Proof. $V^{gross}(z,q)$ equals to expected value of being an incumbent $\int_{s'} V^I(b_0, s', z) dH_e(s'|q)$.

(a) Potential entrants first period distribution of the idiosyncratic productivity conditional on signal $H(s'|q)$ is a decreasing function of the signal q: the higher the signal, the higher the expected first period productivity s. An incumbent's value function $V^I(b,s,z)$ is an increasing function of the idiosyncratic productivity shock s. Therefore, the expected value of being an incumbent is a strictly increasing function of the signal q.

(b) $V^I(b,s,z)$ is an increasing function of the idiosyncratic productivity shock z. Therefore, for given signal q, expected value of being an incumbent increases with the aggregate demand level z. □

Proposition B.2. *(The properties of the entry value function)*

(a) For any given aggregate demand level z and $\tau \in [0,1]$, $V^e(z,q)$ weakly increases with the signal q.

(b) For any given signal q and $\tau \in [0,1]$, $V^e(z,q)$, $V^e(z,q)$ weakly increases with the aggregate demand level z.

Proof. Sketch of the proof. Show that $V^e(q,z)$ is increasing in both of the arguments, we need show that T satisfies contraction mapping theorem. And then using the Corollary 1 of the contraction mapping theorem we can show that $V^e(q,z)$ is increasing in both of the arguments. □

Proposition B.3. *(The properties of the option value of delay)*

(a) $V^w(q,z)$ is non-negative for all q and z.

(b) For a given aggregate demand level z, $V^w(q,z)$ is a weakly increasing function of the signal q.

(c) For a given signal q, $V^w(q,z)$ weakly increases with the aggregate demand level z.

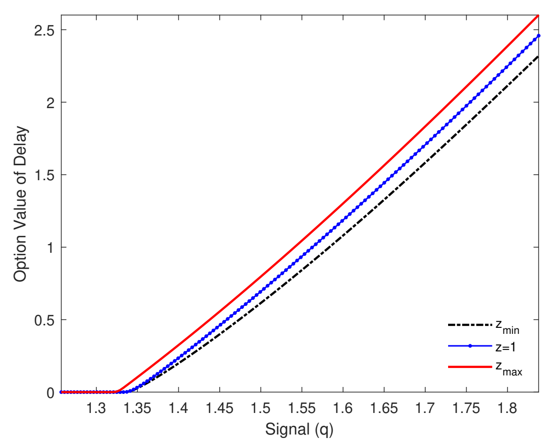
Proof. (a) $V^e(q,z)$ is non-negative, hence $V^w(q,z)$ is non-negative.

(b) For any given aggregate demand level z and $\tau \in [0,1]$, $V^e(z,q)$ weakly increases with the signal q. Hence,

(c) Expected value of aggregate demand level tomorrow $E(z'|z)$ increases with the aggregate demand level z today. Thus, the higher the z today the higher the expected aggregate demand level z' tomorrow. Besides, entry value function increases with the aggregate demand level. As a result, $V^w(q,z)$ weakly increases with the aggregate demand level.

Figure 20 displays option value of delay across the signal q and for different aggregate state z. The figure illustrates above described features of the option value of delay. □

Figure 20: Option value of delay



Proposition B.4. *Suppose for an aggregate demand level z there exist a signal $q^*_{\tau=0}(z)$ such that $V^{gross}\left(z,\ q^*_{\tau=0}(z)\right) = c_e$, then all potential entrants with $q \geq q^*_{\tau=0}(z)$ decide to enter the market, while the rest decide to stay outside.*

Proof. The gross value of entry and hence the net benefits of entry $V^{gross}(z,q)-c_e$ is a strictly increasing function of a signal q. For any $q \geq q^*_{\tau=0}(z)$, $V^{gross}(z,q)-c_e > V^{gross}\left(z,\ q^*_{\tau=0}(z)\right) - c_e = 0$, implying potential entrants who hold signals from the range $q \geq q^*_{\tau=0}(z)$ decide to enter the market. Similarly, for any $q < q^*_{\tau=0}(z)$, $V^{gross}(z,q)-c_e < V^{gross}\left(z,\ q^*_{\tau=0}(z)\right)-c_e = 0$, implying potential entrants that hold signals from the range $q < q^*_{\tau=0}(z)$ do not enter the market. □

Proposition B.5. *The threshold signal $q^*_{\tau=0}(z)$ is countercyclical.*

Proof. Define the net benefits of entry as $NPV(z,q) = V^{gross}(z,q) - c_e$. According to Proposition B.2(a) $V^{gross}(z,q)$ and hence the net benefits of entry strictly increases with the aggregate demand level. The higher the aggregate demand level z, the lower the required signal level that ensures nonnegative net benefits from entry. As a result, the minimum signal $q^*_{\tau=0}(z)$ required for a potential entrant to enter the the market decreases with the aggregate demand level. Blue dashed line on Figure 4(a) displays the threshold signal $q^*_{\tau=0}(z)$ for each aggregate demand level. The figure illustrates that the threshold signal is countercyclical. $\square$

C Appendix for Empirical Findings

C.1 Cyclicality of Business Formation

C.1.1 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.[71] 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. The business applications are matched to the set of firms in Business Dynamics Statistics Dataset (BDS) identified as new employer businesses based on payroll information.[72] Match process is straightforward since both of the 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 (BF4Q)* - the number of employer businesses that originate from the business applications within four quarters from the quarter of application. Time period: 2004Q3-2015Q4. In the analysis, I refer to this time series as First 4Q.

2. *Business formations within 8 quarters (BF8Q)* - the number of employer businesses that originate from the business applications (BA) within eight quarters from the quarter of application. Time period: 2004Q3-2014Q4.

3. *Average duration (in quarters) from business application to formation within 4 Quarters (DUR4Q)* - a measure of delay between business application and formation, conditional on business formation within four quarters. Time period: 2004Q3-2015Q4. I

[71] EIN is a unique number assigned to most of the business entities. 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 new EIN.

[72] The BDS dataset covers the universe of employer businesses in the U.S. and provides annual measures of business dynamics for the economy aggregated by the establishment and firm characteristics. Employer businesses are identified as start-ups based on their first payroll information by Longitudinal Business Database.The

refer to this time series as Av. duration, first 4Q.

4. *Average duration (in quarters) from business application for formation within eight quarters (DUR8Q* - a measure of delay between business application and formation, conditional on business formation within eight quarters. Time period: 2004Q3-2014Q4.

   Additionally, I construct the following two-time series:

5. *Business formations within the second half of eight quarters (Second 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:

$$\textit{Share of late start-ups} = \frac{BF8Q - BF4Q}{BF8Q}$$

7. *Average Duration (in Quarters) from Business Application to Formation from 5 to 8 Quarters:* average duration it takes for the group of applications that need to form business for more than 4 quarters. To re-construct this information using the following formula:

$$DUR(second4Q) = \frac{DUR8Q\ BF8Q - DUR4Q\ BF4Q_t}{BF8Q - BF4Q}$$

Summary Statistics The summary statistics of the considered time series are given in Table 11 and Table 12. Several facts stand out. (1) The average share of the applications that start business in the second four quarters equals 13.68%. The time series varies from 10.96% to 17.73%; see Table 13. (2) The business applications that form businesses within the first four quarters do so in the first two quarters. Specifically, it takes, on average, from five to six months to form an employer business from the date of the application. (3) The group of the business applications that form employer business with four quarter delay, do so, on average, in sixth quarters.

Table 11: Summary Statistics for Quarterly Business Formation (Thousands)

	Mean	St. Deviation	Min	Max
BF8Q	97.5208	18.1831	80.3434	134.1869
First 4Q	83.4509	17.0360	68.3442	119.4842
Second 4Q	13.0668	1.1480	11.3703	15.2153
Share	0.1368	0.0191	0.1096	0.1773

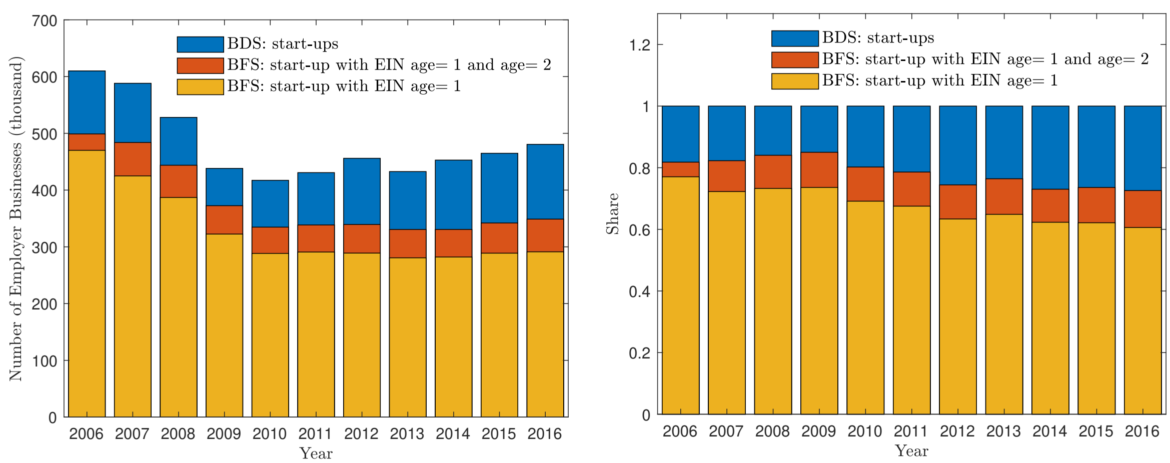
Table 12: Summary Statistics for Average Delays (in Quarters)

	Mean	St. Deviation	Min	Max
DUR8Q	1.66	0.16	1.39	1.93
DUR4Q	1.66	0.16	1.39	1.93
DUR(second 4Q)	5.46	0.11	5.22	5.78

C.1.2 Comparability of the Publicly Available BFS dataset with the BDS

All firms that show up in the BDS have EINs. Thus, they show up in the BFS dataset before entry.[73] 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.

Figure 21: BDS and BFS



(a) The number of business formation (b) The share of business formation

Notes. The figure shows the annual total number of employer business start-ups from 2005 to 2016 from the BDS and from the BFS. The number of employer birth from the BDS is constructed from the number of employer birth within eight-quarters window.

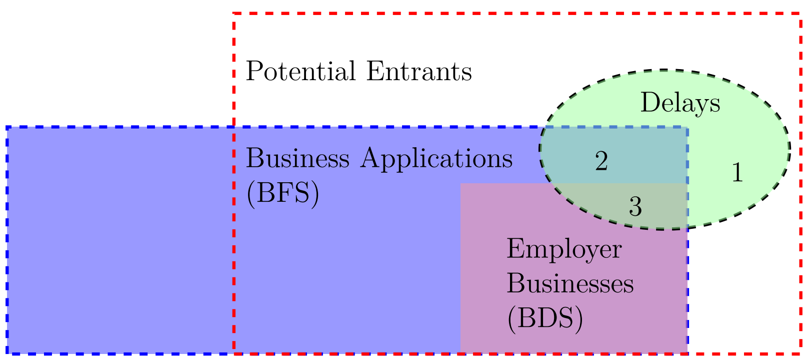
[73]There is a small group of employer businesses that get EINs after submitting the first payroll information.

I compare the information in the BFS dataset to the one provided by the BDS dataset. Toward that end, I convert the quarterly data from the BFS into yearly time series. I defined business formation for a year t as the total number of businesses generated from the cohort of applications applied within the first quarter of year t to the fourth quarter of year t. The average duration of the business formation within four quarters happen within 1.5 quarters. In that case, the applications from the fourth quarter of year t are going to become employer business before March 12 and show up in the BDS dataset. Figure 21 shows that these employer businesses comprise more than 80% of the total start-ups in the BDS.

C.1.3 Discussion

The goal of the empirical section is to identify how the aggregate conditions at entry affect business formation through the "wait-and-see" channel of the entry decision. To explain the identification strategy, Figure 22 illustrates the potential links between the Business Formation Statistics Dataset (BFS), the Business Dynamics Statistics Dataset (BDS), and potential entrants in the model. I use the diagram to discuss also the relevance of different parts of the BFS dataset in answering the question.

Figure 22: The potential links between the Business Formation Statistics Dataset (BFS), the Business Dynamics Statistics Dataset (BDS), and potential entrants in the model.



Notes. The figure illustrates potential links between the BDS, the BFS datasets, and the potential entrants that could potentially choose to delay entry. Segment 1: Potential entrants who decide to delay entry and do not apply for the EIN. Segment 2: Potential entrants who apply for the EIN, decide to delay entry, and never start a business. Segment 3: The potential entrants that applied for the EIN, decide to delay entry and come back in the market after a year.

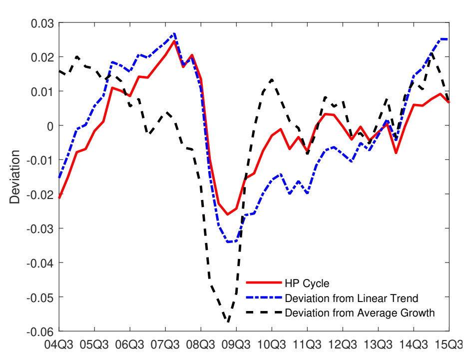
The potential entrants that delay entry could belong to the following three groups. First, the group of potential entrants that delay entry and also delay applying for the EIN; Second, the group of potential entrants that apply for the EIN, delay starting a business at least first eight quarters from 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.

Initially, I argue that the first and the second group of entrants can not be identified 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 part 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. 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), the transition rate does not exceed 36%. Bayard et al. (2018) claim that the lower transition rates is due to the fact that a major share of the business applications ends up becoming 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 time it takes for the third group of entrants to become employer businesses to identify delays in potential entrants entry decisions.

C.1.4 Time Series for the Business Cycle Conditions

Figure 23: The time series of the business cycle indicators



C.1.5 Robustness: annual data

In this section, I repeat the analyses for the annualized business formation time series. I construct the following time series: 1. The annual number of applications that form a business in a year ($BF1Y$); The annual number of applications that form businesses within two years ($BF2Y$); The annual number of applications that form businesses after a year from the date of the applications ($BF2Y$); The share of the business applications that form business after a year in the total number of business applications that form business within two years ($Share$);

To be consistent with the BDS dataset, I construct annual data by summing up to $BF4Q$ and $BF8Q$ 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 $2006-2015$.[74]

Summary statistics for the annual time series is given in Table 13. For comparison, the table also reports summary statistics for the employer business start-ups from the BDS dataset.

Table 13: Summary statistics for yearly business formation (thousands)

	Mean	St. Deviation	Min	Max
Firms (BDS)	491.4534	70.8420	417.2020	610.006
BF in 2 years	376.0336	62.5343	330.7949	505.902
First year	326.2789	59.6975	281.5538	462.239
Second year	51.2315	4.8027	43.6623	59.377

Table 14: Correlations between the cyclical variation in the business application time series with the business cycle indicators

	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 in 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)

Cyclicality of the business formation at annual frequency In this section I study the cycle properties of the annual business formation data. Table 14 reports the results. The

[74] $BF4Q$ and $BF8Q$ data starts from the year $2004Q4$ which means that for the year 2005 only three-quarters of application data is available ($2004Q3 + 2004Q4 + 2005Q1$). Since I do not have the complete number of applications for the year 2005 I had to drop from the analyzes

results implies that during the recessionary periods the number of applications that form business within a year decreases. The subset of the applications that take more than a year to form a business also decreases if the initial state in the year of entry is recession. On the other hand, the share of the applications that from business in one year delay increases in the total number of applications that form businesses in two years. Since we saw that the variation in the average duration of delays does not exceeds to two month, at least the part of the countercyclical variation in share supports to the “wait and see” channel of business formation.

C.2 Cyclicality of Average Survival Rates

C.2.1 Firm level Analyses

In this section, I show results how the average survival rates calculated using firm-level data vary with the business cycles conditions.

Table 15: Correlations between the Average Survival Rates with the Business Cycle Conditions. Firm-level Data

	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t	NBER$(0,1)$
$corr(S_{1,t+1}, Y_t)$	-0.21 (0.22)	-0.23 (0.18)	-0.10 (0.56)	0.16 (0.33)	0.04 (0.82)
$corr(S_{2,t+2}, Y_t)$	-0.35 (0.04)	-0.39 (0.02)	-0.32 (0.06)	0.33 (0.05)	0.07 (0.70)
$corr(S_{3,t+3}, Y_t)$	-0.41 (0.02)	-0.47 (0.01)	-0.46 (0.01)	0.43 (0.01)	0.11 (0.52)
$corr(S_{4,t+4}, Y_t)$	-0.35 (0.05)	-0.43 (0.01)	-0.42 (0.01)	0.43 (0.01)	0.14 (0.42)
$corr(S_{5,t+5}, Y_t)$	-0.22 (0.23)	-0.29 (0.11)	-0.31 (0.08)	0.34 (0.05)	0.15 (0.39)

Notes. Unit of analyzes is cohort of firms. The table reports correlations (p-values) of the cohorts' survival rates at age g with the business cycle indicator at the time of entry. $Y_{hp,t}$ refers to the cycle of log real GDP. $I_{hp,t}$ refers to an indicator that defines an aggregate state as a recession (expansion) if the cycle component of log real GDP is more than 1% below (above) the trend. $Y_{linear,t}$ describes cycle component of log real GDP after applying the linear trend. Δu_t refers to the deviations of annual unemployment rates from the average unemployment rate. NBER$(0,1)$ describes the NBER-based recession indicators for the US from the period following the peak through the trough.

C.2.2 Sector Level Analyzes

In this section, I show results how the average survival rates at sector level vary with the business cycles. Sector level data by age is available from the year 1979 to the year 2014.

Table 16: Correlations between the Average Survival Rates with the Business Cycle Conditions. Sector-level Data

	Agricultural, Forestry, and Fishing			
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
$corr(S_{1,t+1}, Y_t)$	-0.10 (0.58)	-0.10 (0.56)	0.01 (0.97)	-0.08 (0.65)
$corr(S_{2,t+2}, Y_t)$	-0.28 (0.11)	-0.32 (0.07)	-0.16 (0.37)	0.11 (0.52)
$corr(S_{3,t+3}, Y_t)$	-0.28 (0.12)	-0.36 (0.04)	-0.18 (0.33)	0.14 (0.45)
$corr(S_{4,t+4}, Y_t)$	-0.19 (0.29)	-0.27 (0.13)	-0.05 (0.78)	0.00 (0.97)
$corr(S_{5,t+5}, Y_t)$	0.02 (0.93)	-0.07 (0.72)	0.10 (0.58)	-0.16 (0.40)
	Mining			
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
$corr(S_{1,t+1}, Y_t)$	0.10 (0.53)	0.08 (0.64)	0.28 (0.10)	-0.20 (0.23)
$corr(S_{2,t+2}, Y_t)$	0.16 (0.33)	0.14 (0.42)	0.42 (0.01)	-0.30 (0.07)
$corr(S_{3,t+3}, Y_t)$	0.19 (0.26)	0.16 (0.36)	0.54 (0.00)	-0.40 (0.01)
$corr(S_{4,t+4}, Y_t)$	0.29 (0.10)	0.26 (0.15)	0.71 (0.00)	-0.59 (0.00)
$corr(S_{5,t+5}, Y_t)$	0.36 (0.04)	0.32 (0.08)	0.84 (0.00)	-0.76 (0.00)

	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
	Construction			
$corr(S_{1,t+1}, Y_t)$	-0.21 (0.22)	-0.16 (0.36)	-0.14 (0.43)	0.59 (0.59)
$corr(S_{2,t+2}, Y_t)$	-0.43 (0.01)	-0.40 (0.02)	-0.29 (0.09)	0.10 (0.10)
$corr(S_{3,t+3}, Y_t)$	-0.53 (0.00)	-0.52 (0.00)	-0.38 (0.03)	0.04 (0.04)
$corr(S_{4,t+4}, Y_t)$	-0.50 (0.00)	-0.53 (0.00)	-0.39 (0.03)	0.09 (0.09)
$corr(S_{5,t+5}, Y_t)$	-0.37 (0.04)	-0.46 (0.00)	-0.34 (0.06)	0.32 (0.33)
	Manufacturing			
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
$corr(S_{1,t+1}, Y_t)$	-0.19 (0.29)	-0.15 (0.44)	-0.24 (0.16)	0.28 (0.10)
$corr(S_{2,t+2}, Y_t)$	-0.29 (0.09)	-0.23 (0.22)	-0.42 (0.01)	0.52 (0.00)
$corr(S_{3,t+3}, Y_t)$	-0.31 (0.08)	-0.25 (0.18)	-0.48 (0.01)	0.59 (0.00)
$corr(S_{4,t+4}, Y_t)$	-0.22 (0.22)	-0.13 (0.47)	-0.41 (0.02)	0.51 (0.00)
$corr(S_{5,t+5}, Y_t)$	0.07 (0.70)	0.17 (0.39)	-0.23 (0.21)	0.32 (0.08)
	Transportation, Communication, and Public Utilities			
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
$corr(S_{1,t+1}, Y_t)$	-0.37 (0.03)	-0.30 (0.08)	-0.44 (0.01)	0.47 (0.00)
$corr(S_{2,t+2}, Y_t)$	-0.44 (0.01)	-0.34 (0.05)	-0.55 (0.00)	0.60 (0.00)
$corr(S_{3,t+3}, Y_t)$	-0.46 (0.01)	-0.36 (0.04)	-0.67 (0.00)	0.69 (0.00)
$corr(S_{4,t+4}, Y_t)$	-0.34 (0.06)	-0.24 (0.19)	-0.59 (0.00)	0.59 (0.00)
$corr(S_{5,t+5}, Y_t)$	-0.07 (0.72)	-0.01 (0.97)	-0.42 (0.02)	0.40 (0.03)
	Wholesale Trade			
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
$corr(S_{1,t+1}, Y_t)$	0.09 (0.62)	0.11 (0.53)	-0.03 (0.88)	0.22 (0.59)
$corr(S_{2,t+2}, Y_t)$	0.12 (0.51)	0.19 (0.28)	-0.15 (0.40)	0.13 (0.15)
$corr(S_{3,t+3}, Y_t)$	0.13 (0.46)	0.21 (0.25)	-0.15 (0.44)	0.06 (0.30)
$corr(S_{4,t+4}, Y_t)$	0.20 (0.28)	0.26 (0.14)	-0.07 (0.69)	0.02 (0.41)
$corr(S_{5,t+5}, Y_t)$	0.37 (0.04)	0.39 (0.03)	0.06 (0.77)	0.05 (0.76)
	Retail Trade			
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
$corr(S_{1,t+1}, Y_t)$	0.00 (0.97)	-0.13 (0.44)	0.07 (0.68)	-0.12 (0.48)
$corr(S_{2,t+2}, Y_t)$	0.03 (0.85)	-0.11 (0.54)	0.13 (0.48)	-0.15 (0.40)
$corr(S_{3,t+3}, Y_t)$	0.21 (0.25)	0.10 (0.60)	0.43 (0.01)	-0.38 (0.03)
$corr(S_{4,t+4}, Y_t)$	0.25 (0.17)	0.14 (0.44)	0.56 (0.00)	-0.55 (0.00)
$corr(S_{5,t+5}, Y_t)$	0.34 (0.06)	0.21 (0.25)	0.69 (0.00)	-0.75 (0.00)
	Finance, Insurance, and Real Estate			
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
$corr(S_{1,t+1}, Y_t)$	-0.11 (0.55)	-0.12 (0.50)	-0.03 (0.87)	-0.01 (0.93)
$corr(S_{2,t+2}, Y_t)$	-0.27 (0.12)	-0.29 (0.10)	-0.15 (0.40)	0.07 (0.45)
$corr(S_{3,t+3}, Y_t)$	-0.32 (0.07)	-0.35 (0.05)	-0.22 (0.22)	0.12 (0.30)
$corr(S_{4,t+4}, Y_t)$	-0.21 (0.26)	-0.30 (0.10)	-0.15 (0.42)	0.06 (0.70)
$corr(S_{5,t+5}, Y_t)$	-0.19 (0.31)	-0.24 (0.19)	-0.21 (0.26)	0.07 (0.68)
	Services			
	$Y_{hp,t}$	$I_{hp,t}$	$Y_{linear,t}$	Δu_t
$corr(S_{1,t+1}, Y_t)$	-0.11 (0.55)	-0.13 (0.45)	-0.02 (0.93)	0.81 (0.93)
$corr(S_{2,t+2}, Y_t)$	-0.13 (0.47)	-0.13 (0.47)	-0.11 (0.55)	0.40 (0.45)
$corr(S_{3,t+3}, Y_t)$	-0.10 (0.58)	-0.13 (0.48)	-0.15 (0.40)	0.28 (0.30)
$corr(S_{4,t+4}, Y_t)$	-0.06 (0.77)	-0.07 (0.72)	-0.14 (0.44)	0.35 (0.70)
$corr(S_{5,t+5}, Y_t)$	0.10 (0.61)	0.08 (0.67)	-0.07 (0.72)	0.65 (0.68)

Notes. The table reports correlations (p-values) of the cohorts' survival rates at age g with the business cycle indicator at the time of entry. $Y_{hp,t}$ refers to the cycle of log real GDP after applying the HP filter with a smoothing parameter of 100. $I_{hp,t}$ refers to an indicator that defines an aggregate state as a recession (expansion) if the cycle component of log real GDP is more than 1% below(above) the trend. $Y_{linear,t}$ describes the aggregate state at entry using the cycle component of log real GDP after applying the linear trend. Δu_t refers to the deviations of annual unemployment rates from the average unemployment rate.

D Numerical Solution

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

D.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: $|\dfrac{V^I_{n+1}(b,s,z) - V^I_n(b,s,z)}{V^I_n(b,s,z)}| \leq 10.0^{-8}$.

D.2 Potential Entrants' Distribution

Figure 24: $W(q)$

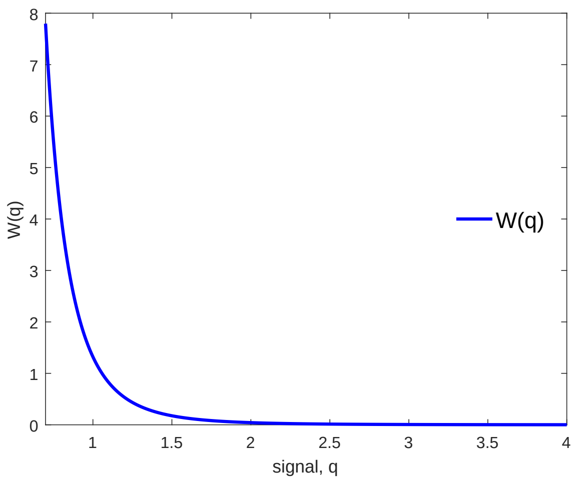
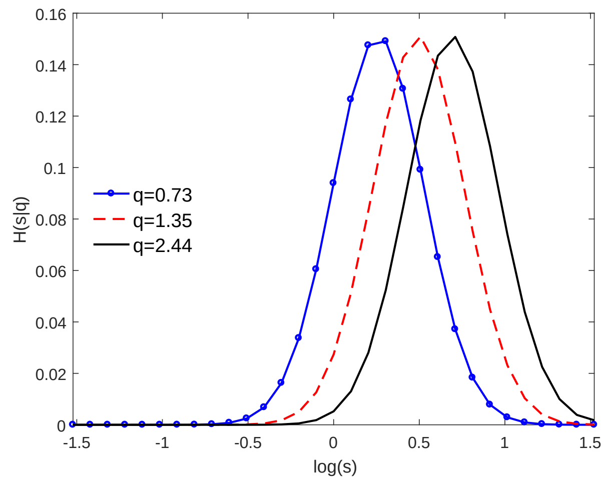


Figure 25: $H(s|q)$



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 $V^I(b, s, z)$.

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

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

E Calibration Appendix

E.1 Micro-level Data

Establishment-level/firm-level data comes from the publicly available Business Dynamic Statistics (BDS) dataset. The dataset covers U.S. economy-wide active establishments/firms over the period 1977-2015.[75] The establishment is defined as a single physical location, whereas as the firm is defined at an enterprise level. The data report establishment/firm-level activity (entry, exit, job-creation, employment) based on the employment status on March 12. Specifically, at year t, establishment/firm-level activity describes the period from the second quarter of year $t-1$ through the first quarter of year t. In the project I use the following time series:

1. *Economy Wide Establishment Data* - information about the annual number of establishments, the entry rate, and the total non-farm employment over the period 1977-2015.

2. *Establishment by Age* - information about the annual number of establishment by age, and the annual number of employment by establishment age. The establishment age is calculated by taking the difference between the current year of operation and the birth year. The establishment birth (age 0) is defined as the year when the establishment first reports positive employment in the Longitudinal Business Database (LBD).

Define a cohort at year t as the group of establishments that entered the market in year t. The data follow 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+].

Corrections: BDS database is assembled using various datasets. In every five years (on years ending 2 and 7), BDS is updated using the information from the Economic Census, which gives much more detailed information about the universe of employer establishments in the U.S. According to Jarmin and Miranda (2002) the update produces a 5-year cycle in the BDS data. I create a dummy variable for the years ending with 2 and 7 to check the 5-year cycle trend for each establishment-level data series to address the issue. The trend was significant only for the number of entrant establishments (establishments at age 0) with

[75] $https://www.census.gov/ces/dataproducts/bds/data\_estab.html$

p-value respectively 0.028. The trend coefficient for all other series was insignificant. As a result, I take out the 5-year cycle trend only from the number of the entrant establishments.[76]

E.2 Aggregate-level Data

To measure aggregate activity I use time series for real GDP, and aggregate employment. The quarterly real GDP data comes from the Federal Reserve Economic Data (FRED) and covers the period 1976Q1-2019Q1.[77] The monthly time series of aggregate employment comes from the FRED and covers the period from March of 1976 to February of 2019.[78]

I construct annual aggregate data so that they match the contemporaneous level of establishment activity. Establishment-level activity at year t describe business activity from March $t-1$ to March t. Thus, I construct the annual real GDP data for year t by averaging the time series of quarterly real GDP from second quarter of year $t-1$ to the first quarter of year t. For example, since establishment-level data on year 1977 gives establishment-level activity from March 1976 to March 1977, the annual contemporaneous level Real GDP will be average real GDP from the second quarter of 1976 to the first quarter of 1977. The annual contemporaneous level of employment will be average employment from March 1976 to March 1977.

[76] The other problems connected to the BDS dataset such as inaction periods (which might overestimate birth and death rates) is addressed during the construction of the Database. For more information see Jarmin and Miranda (2002).

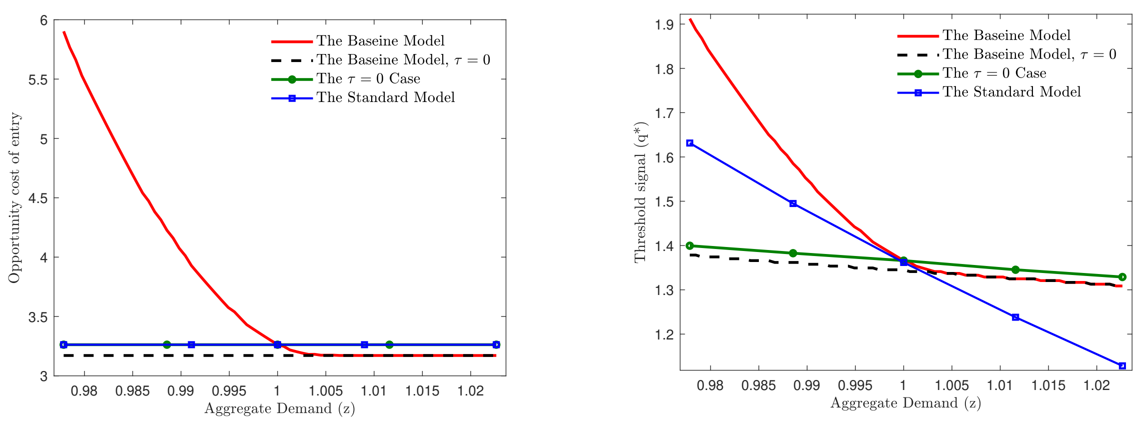
[77] Formal name of the time series: Real Gross Domestic Product, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate.

[78] The formal name of the time series: Civilian non institutional employment 16 over, yearly monthly, seasonally adjusted.

E.3 Alternative Models and Counterfactual Scenarios

In this section, I describe in detail the construction of the alternative scenarios that I use to understand how the option to delay entry affects the dynamics of the model. First, in Section E.3.1, I describe the $\tau = 0$ *case*, that is a baseline model after shutting down the option to delay channel. I use the scenario to study how much the option to delay entry amplifies and propagates aggregate shocks over the business cycles. Second, in Section E.3.2, I describe the *Standard model*, which is a model without the option value of delay re-calibrated to match the same set of facts as the baseline model. I use the Standard model to understand what drives the business cycles in the model without the option value of delay. Section E.3.3 describes the construction of the counterfactual scenarios that help me to disentangle the role of the variation in the number and the composition of entrants.

Figure 26: Calibration of the alternative scenarios



(a) The opportunity cost of entry

(b) The threshold signal

E.3.1 The $\tau = 0$ case

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 where potential entrants keep the signal with $\tau = 0$ probability ($\tau = 0$ *case*).

Setting $\tau = 0$ in the baseline model decreases the opportunity cost of entry by the amount of the option value of delay, see equation (6). As a result, compared to the baseline model, the threshold quality signal is lower in the baseline model with $\tau = 0$. The latter means that these two scenarios exhibit different dynamics in the steady state. The reason is as follows. 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.[79] 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 $\tau = 0$ to match the same set of facts in the steady state, as the baseline model.

$$V^{gross}\left(z_{ss}, q^*_\tau(z_{ss})\right) = c_e + \tau V^w(z_{ss}, q^*_\tau(z_{ss})) \tag{6}$$

The gross value of entry does not vary with τ. The threshold signal depends on the total opportunity cost of entry $c_{e,\tau} + \tau V^w(z_{ss}, q^*_\tau(z_{ss}))$. For any τ and τ', equating the threshold signals in the stochastic steady state $q^*_\tau(z_{ss}) = q^*_{\tau'}(z_{ss})$ requires the opportunity cost of entry (the right hand side of the equation (6)) to equal each other across these scenarios. The value of the option is endogenously determined within the model, while the fixed cost of entry $c_{e,\tau}$ 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 $c_{e,\tau=0} = c_e + V^w(z_{ss}, q^*_{\tau=1}(z_{ss}))$ in the baseline model with $\tau = 0$. Figure 26(a) summarizes the difference in the fixed entry cost. The Column (b) of Table 17 summarizes the parameter values used in the $\tau = 0$ case and shows that the $\tau = 0$ case is identically parameterized except the fixed entry cost. Table 18 reports the steady state moments for the $\tau = 0$ case. By comparing the business cycle dynamics in the baseline model against the $\tau = 0$ case allows me to quantify the role of the option to delay entry in accounting for the observed dynamics of the cohorts over the business cycles. To see the difference refer to Figure 26(b).

E.3.2 The Standard Model

Here, I describe the *Standard model*, a model without the option value of delay that matches the same set of facts as the baseline model. Below, I describe the construction of this scenario.

Following the previous section's argument, as a baseline scenario for a model without the option value, I choose the $\tau = 0$ case. Again, the latter ensures that the average character-

[79] The distribution of firms in the stochastic steady state is just many generations of same entrant firms at different ages.

Table 17: Calibration of alternative scenarios

Description	**Symbol**	**Baseline** (a)	$\tau = 0$ (b)	**Standard** (c)
Prob. of keeping signal	τ	1.0	0.0*	0.0*
Discount factor	β	0.96	0.96	0.96
Persistence of agg. shock	ρ_z	0.57	0.57	0.57
St.Dev. agg. shock	σ_z	0.0022	0.0022	0.016*
Persistence of product.	ρ_s	0.814	0.814	0.814
Price elasticity	ρ	1.622	1.622	1.622
Capital elasticity	η	0.919	0.919	0.919
Capital Depreciation	δ	0.188	0.188	0.188
Initial customer capital	b_o	12.0	12.0	12.0
Std. dev. prod.	σ_s	0.16	0.16	0.16
Std. dev. initial prod.	σ_s^e	0.26	0.26	0.26
Demand shift.	α	0.26	0.26	0.26
Pareto Location	$\underline{q}$	0.70	0.70	0.70
Pareto Exponent	ξ	3.98	4.41	4.41
Mean c_f	μ_f	0.62	0.62	0.62
Std. Dev. c_f	σ_f	0.41	0.41	0.41
Exit shock	γ	0.07	0.07	0.07
Entry cost	c_e	3.17	3.26*	3.26*

Note. 'Baseline' refers to the baseline scenario. '$\tau = 0$' refers to a case which sets $\tau = 0$ in the baseline scenario. 'Without' refers to a model with $\tau = 0$ and everything is re-calibrated to match the same set of moments as in the baseline scenario. The value indicated with (*) highlights the parameters used as free parameters in contrast to the baseline scenario. Fixed entry cost in the case with $\tau = 0$: $3.26 = 3.17(c_e) + 0.9$ (the value of waiting in the stochastic steady state)

istics of entrants matches to the data counterpart. Table 19 compares the dynamics of the entry rate in the $\tau = 0$ case and the model. Without the option to delay entry, the elasticity of the threshold signal with respect to aggregate demand is significantly lower, producing entry rate that is 7-times less volatile than the data counterpart.

To match the dynamics of entrants, one needs to increase the business cycle variation in the expected lifetime profits, which can be achieved by using parameters that govern aggregate demand shock process ρ_z, and σ_z.[80] The autocorrelation of the aggregate demand shock process determines the persistence of the entry rate and can not be altered freely. Leaving the variance of the exogenous shock to match the cyclical variation in the entry rate to the

[80]For more details, see Section 3.

Table 18: Calibration targets for establishment level charachteristics

Statistics	**Data**	**Baseline Model**	$\tau = 0$ **Case**	**Standard Model**
Average entry rate (1991-2006) (%)	12.1	12.1	12.1	12.1
Average size of all establishments	17.0	16.3	16.3	16.3
Entrant employment share in total employment (%)	5.9	6.4	6.4	6.4
Age 5 cohort share in agg. employment (%)	4.2	4.2	4.2	4.2
Average size of entrants (age 0)	8.7	8.5	8.5	8.5
Average size of cohort at age 5	13.9	14.1	14.1	14.1
Average size of cohort between 21 and 25 years	21.4	22.4	22.4	22.4
Survival until 5 years old	0.48	0.41	0.41	0.41
Survival between 21 and 25 years	0.15	0.10	0.10	0.10
Establishments exit rate at age 5	0.12	0.09	0.09	0.09

Notes. The moments are calculated from the BDS dataset covering the economy-wide establishment level data over the period 1977-2015.

Table 19: Calibration targets for aggregate demand shock process

Statistics	**Data**	**Baseline Model**	$\tau = 0$ **Case**	**Standard Model**
Autocorrelation of the cycle component of entry rate	0.25	0.25	0.22	0.27
Standard Deviation of the cycle component of entry rate	0.06	0.06	0.01	0.06

Notes. Entry Rate comes from the BDS and covers period from 1977 to 2015. The cyclical component of the log entry rate is calculated using the HP filter with smoothing parameter 100.

data counterpart.[81]

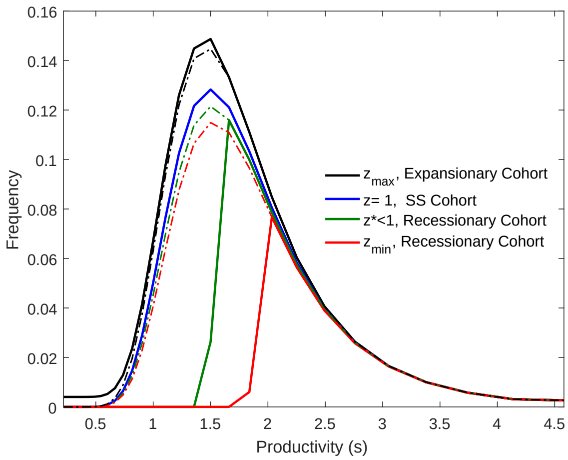
The final values for the aggregate process are $\rho_{z,\tau=0} = 0.57$ and $\sigma_{z,\tau=0} = 0.015$.[82] Implying that the Standard model requires σ_z that is almost 7-times higher compared to the baseline model. Table 17 summarizes parameter values, Table 18, and Table 19 summarizes how the moments targeted in the Standard model compares to the data counterpart and other scenarios.

Finally, Figure 26 summarizes the difference in equilibrium opportunity cost of entry across

[81] One can also increase the variation in the number of entrants for the lower aggregate demand shock variance by altering the slope of the distribution of entrants ($W(q)$) around the steady state threshold signal. However, this way does not lead to variation in the threshold signal, which means that the model can not generate the variation in the composition of entrants.

[82] Changing the process for the aggregate demand shock, specifically changing ρ_z and σ_z, has no effect on the statistics in the stochastic steady state. Since as discussed above, the statistics are uniquely determined by choice of the threshold signal, which in the Model Without Option Value of delay does not change unless the fixed entry cost changes. The latter argument means that I can choose the process for the aggregate demand shock without altering the good match of the model to average cohorts' dynamics.

Figure 27: Selection of entrants across the baseline and the counterfactual scenarios



(a) The case with $\tau = 0$, lowest

(b) The case with $\tau = 0$, highest

different aggregate states for these two cases. Note that with $\tau = 0$ opportunity cost of entry is constant over the cycles and equals the fixed entry cost. Selection mechanism when $\tau = 0$ is similar to the standard-firm dynamics model with fixed entry cost. The difference between the benchmark model and the case explains the amplification of the aggregate shocks through option value of delay.

E.3.3 Counterfactual: the number versus composition of entrants

The increased elasticity of the threshold signal with respect to aggregate demand level through the option value of delay has two effects on the distribution of entrants. First, it increases the variation in the number of entrants. Second, it increases variation in the composition of entrants. Below I describe counterfactual scenarios that help me to disentangle these two affects.

I consider the following two alternative scenarios that generate the same observed variation in the number of entrants, while I systematically vary the entrants' productivity composition. Specifically, I compare the dynamics of the baseline scenario to the dynamics of the economies where the selection at entry comes from the highest productivity or the lowest productivity entrants.

Figure 28: The variation in the number of entrants across the baseline and the counterfactual scenarios

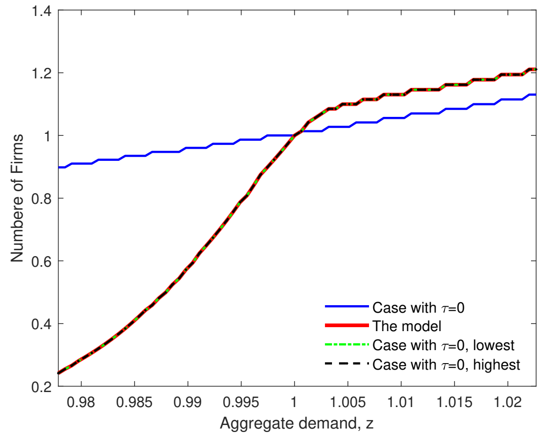


Table 20: Business Cycle Moments: Data, the baseline model, and the counterfactual scenarios.

		Data	Baseline	Case $\tau = 0$	Counterfactual, adjust lowest s	Counterfactual, adjust highest s
		(a)	(b)	(c)	(d)	(e)
No. of firms	ρ	0.640	0.619	0.607	0.481	0.680
	σ	0.012	0.010	0.010	0.009	0.076
Employment	ρ	0.610	0.574	0.622	0.457	0.657
	σ	0.015	0.012	0.010	0.009	0.126
No. of Entrants	ρ	0.311	0.278	0.278	**0.278**	**0.278**
	σ	0.066	0.073	0.073	**0.073**	**0.073**

Notes. The numbers that are in bold refer to the targeted model statistics. All other values indicate untargeted model statistics and their empirical counterparts. 'Baseline' refers to the economy with the baseline specification. '$\tau = 0$, adjust lowest s ' ('$\tau = 0$, adjust highest s') refers to the scenario where the distribution of entrants in the case with $\tau = 0$ is adjusted using lowest (highest) productive entrants to generate data-conforming variation in the entry rate.

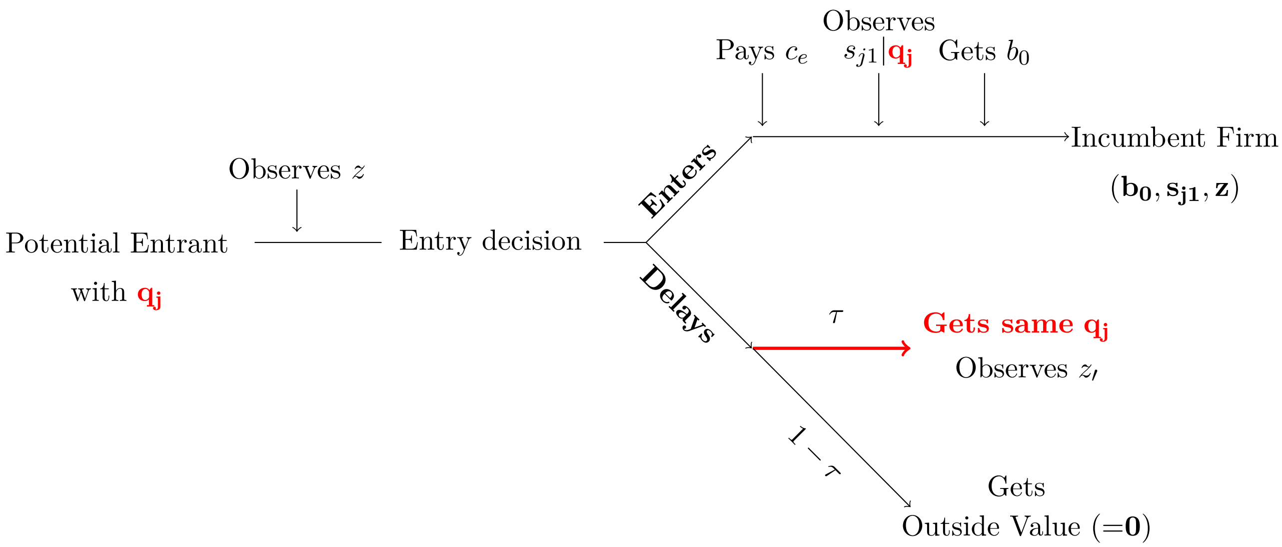
That said, I produce the variation in the number of entrants from the steady state distribution by adjusting the lowest productivity entrants. For example, to generate a drop in the number of entrants during the recessions, I cut the highest productivity entrants from the distribution. During the expansion, I generate an increase in the number of entrants by adding the steady state distribution of entrants into the lowest productivity entrants. figure 28(a)(b) and figure 28(a)(c) illustrates these adjustment process. figure 28 shows that the number of entrants at all aggregate states equal to each other across these scenarios.

Table 20 summarizes the business cycle dynamics of these economies. These results emphasize the role of the variation in the high productivity entrants in propagation of the aggregate shocks.

F The Probability of Keeping Signal τ

F.1 Aggregate Selection of Entrants for Different τ

Figure 29: **Potential Entrants' Timing**



To compare the selection of entrants with and without the option to delay entry, I rewrite equation (1) as follows

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

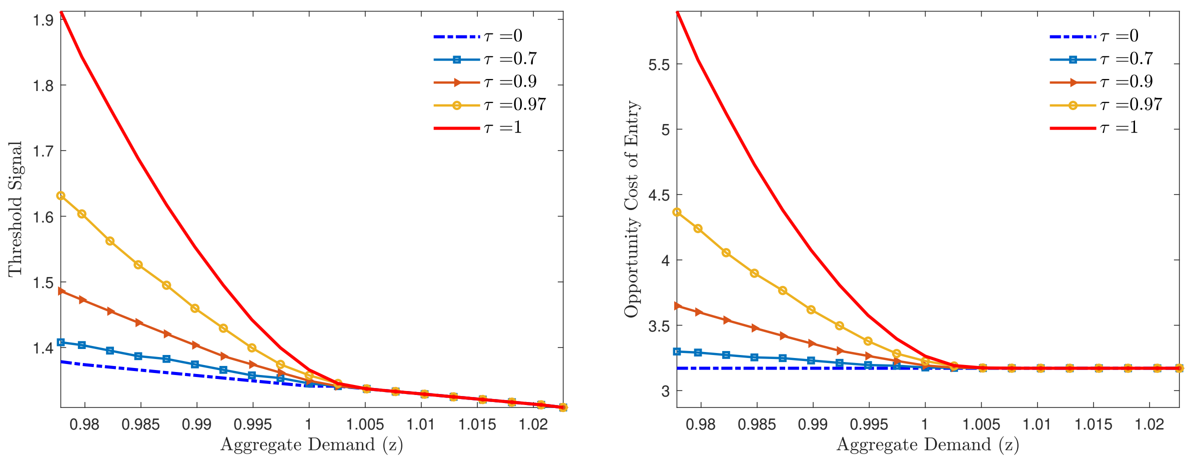
where τ describes the probability that a potential entrant with a signal q receives the same signal tomorrow if it decides to wait. With probability $1-\tau$, the potential entrant loses the signal tomorrow and obtains the outside option value. If $\tau = 0$, firm cannot keep the signal over time, and the value of the option to wait equals 0. In this case, the baseline model reduces to a standard framework where potential entrants enter the market if the net lifetime benefits of entry are non-negative.[83] If $\tau = 1$, the entry decision coincides with the baseline model. Comparing the case $\tau = 1$ with the case $\tau = 0$ allows me to isolate the selection of firms at entry through the option-to-wait channel.

In the main part of the paper, I consider only two cases $\tau = 0$ and $\tau = 1$. In this section, I

[83] For example, see Moreira (2015), and Clementi and Palazzo (2016).

study the dynamics of the model for different values of τ. I find that the results 3.1 and 3.2 hold for all $\tau \in [0, 1]$. The probability of keeping signal τ affects the option value of delay, hence the potential entrants entry decisions. Figure 30 illustrates the equilibrium threshold signal and the equilibrium opportunity cost of entry for different values of τ. As one can see, for the given aggregate demand shock process, the elasticity of the threshold signal with respect to the aggregate demand level decreases with τ. Hence, the higher τ, the higher the variation in the number and composition of entrants over the business cycles.

Figure 30: Aggregate Selection of Entrants for Different τ.



(a) Equilibrium threshold signal

(b) Equilibrium opportunity cost of entry

F.2 Estimation Strategy for τ

In this section, I propose a potential estimation strategy for the probability of keeping signal τ. The aggregate demand shock process affects incumbent firms' production and continuation decisions, as well as, potential entrants' entry decisions. The level of τ affects only potential entrants entry decisions. Utilizing the differential effect, one can use the aggregate demand shock process and the probability of keeping signal to match jointly the process of aggregate employment and the entry rate. As a reminder, in the baseline model, I am able to use the aggregate demand shock process to estimate only the business cycle dynamics of the entry rate.

Toward the end, I use τ, ρ_z, σ_z and re-calibrate the model to generate match to the persistence and the standard deviation of the entry rate and the standard deviation of aggregate employment. Column (e) of table 17 summarizes parameter values that accomplish the goal.

I find that the probability of keeping signal that accomplishes the goal is $\tau = 0.965$, close to the $\tau = 1$ that was considered throughout the paper and the variance of the aggregate demand shock process increased by only 1.7 times; see Talbe 22 for a full description of parameters.

Table 21: Calibration Targets for Aggregate Demand Shock Process

Statistics	**Data**	**Baseline Model**	**Calib τ**
Autocorrelation of the cycle component of entry rate	0.25	0.25	0.27
St. deviation of the cycle component of entry rate	0.06	0.06	0.065
St. deviation of the cycle component of employment	0.015		0.016

Table 22: Calibration

Description	**Symbol**	**Baseline** (a)	**Calib τ** (b)
Prob. of keeping signal	τ	1.0	0.965*
Discount factor	β	0.96	0.96
Persistence of agg. shock	ρ_z	0.57	0.57
St. dev. agg. shock	σ_z	0.0022	0.0038*
Persistence of product.	ρ_s	0.814	0.814
Price elasticity	ρ	1.622	1.622
Capital elasticity	η	0.919	0.919
Capital Depreciation	δ	0.188	0.188
Initial customer capital	b_o	12.0	12.0
Std. dev. prod.	σ_s	0.16	0.16
Std. dev. initial prod.	σ_s^e	0.26	0.26
Demand shift.	α	0.26	0.26
Pareto Location	$\underline{q}$	0.70	0.70
Pareto Exponent	ξ	3.98	4.41
Mean c_f	μ_f	0.62	0.62
Std. Dev. c_f	σ_f	0.41	0.41
Exit shock	γ	0.07	0.07
Entry cost	c_e	3.17	3.17*

F.3 Aggregate Dynamics

Table 23 compares the aggregate dynamics in the economy with $\tau = 0.965$ to the baseline model.

Table 23: Business Cycle Moments: Data, the baseline model, and the counterfactual scenarios.

		Data (a)	Baseline (b)	Calib τ (c)	Case $\tau = 0$ (d)
No. of firms	ρ	0.640	0.619	0.608	0.603
	σ	0.012	0.010	0.010	0.003
Employment	ρ	0.610	0.574	0.531	0.41
	σ	0.015	0.012	**0.014**	0.006
No. of Entrants	ρ	0.250	**0.253**	**0.254**	0.255
	σ	0.062	**0.065**	**0.065**	0.017

Notes. The numbers that are in bold refer to the targeted model statistics. All other values indicate untargeted model statistics and their empirical counterparts. "Baseline" refers to the economy with the baseline specification. "Calib τ" refers to economy, in which τ is calibrated to match the dynamics of the entry rate and the variance of the aggregate employment. "$\tau = 0$" refers to a case where in the case "Calib τ" I set $\tau = 0$

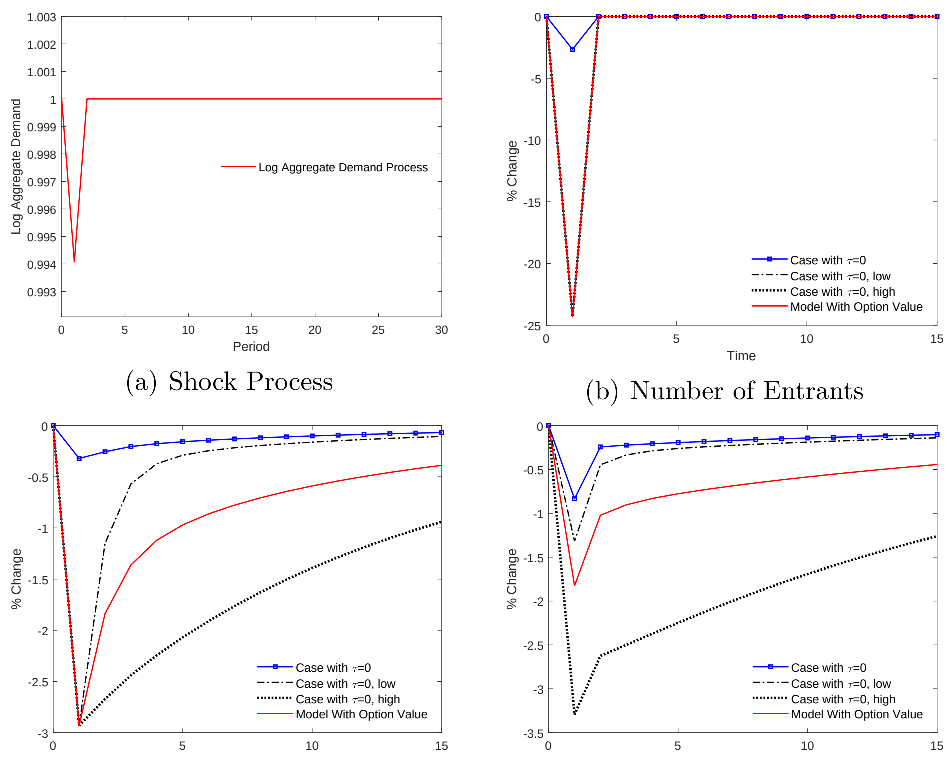
G Quantitative Evaluation Appendix

G.1 Impulse Response Analysis

G.1.1 Composition versus Number of Entrants

Here, I illustrate the importance of the change in the composition of entrants in the propagation of the aggregate shocks, I consider the responses of the two counterfactual scenarios to the same aggregate demand shock process considered before. I keep the drop in the number of entrants at 25%, while varying the composition of entrants systematically across these scenarios. In particular, I generate the decline in the number of entrants from the steady state entry distribution by cutting the lowest (*Baseline, low s*) and the highest(*Baseline, high s*) productivity entrants.[84]

Figure 31: Impulse response to 1-time aggregate demand shock



(a) Shock Process

(b) Number of Entrants

(c) Number of Firms

(d) Employment

Notes: The figure shows the response of the baseline economy to a one-time negative aggregate demand shock.

Comparing the dynamics of these economies on Figure 31 highlights the importance of the

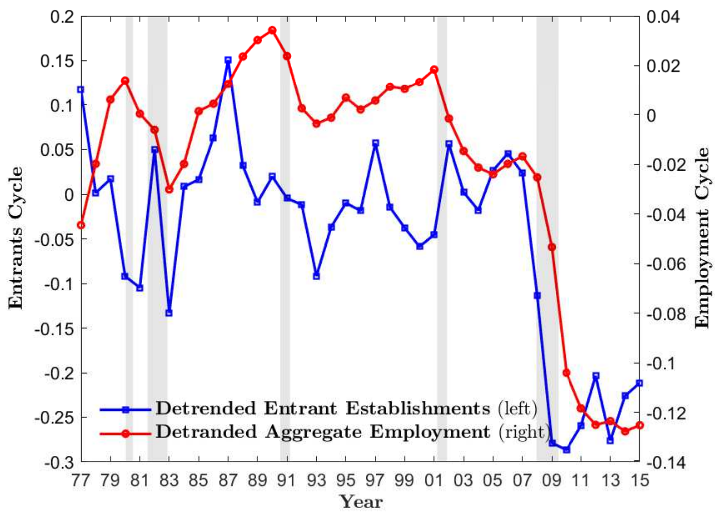
[84] For more details refer to the appendix E.3.3.

variation in the composition of entrants. In particular, if aggregate conditions at entry only affect and reduces low-productive firms then the counterfactual evolution of the aggregate employment mimics the dynamics of the $\tau = 0$ case, where the shock only decreases the number of entrants by 2.5% (*10*-times less than the decline in other scenarios). On the other hand, if the shock affects only high productivity entrants, then the recovery becomes significantly protracted. The baseline model is in between these two scenarios. Meaning that the disproportionate effect of the aggregate shock on the high and low productivity entrant accounts for the propagation of the shocks.

G.2 The Great Recession

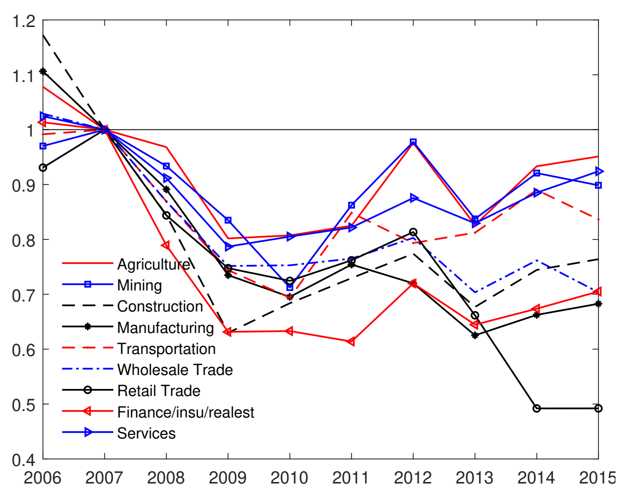
G.2.1 Some Facts

Figure 32: The dynamics of the detrended number of establishments and aggregate employment



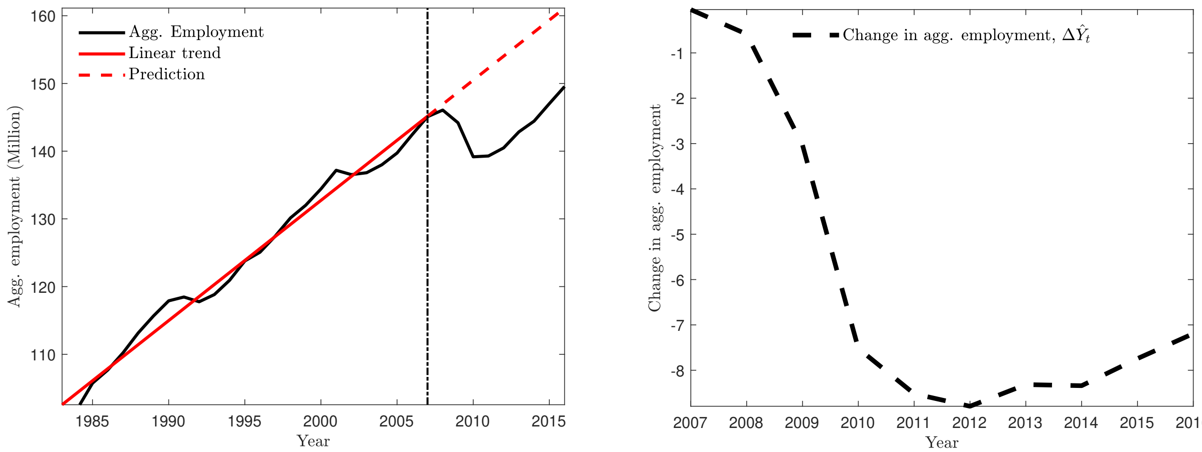
Notes. The figure plots the cyclical variation in the number of entrant establishments and the aggregate employment in the U.S. over the period 1977 − 2016. I calculate the cycle component of these variables after applying linear trend over the period 1979 − 2016.

Figure 33: The number of entrant establishments across sectors and over time relative to the number of entrant establishments in respective sector in year 2007.



G.2.2 Accounting Exercise

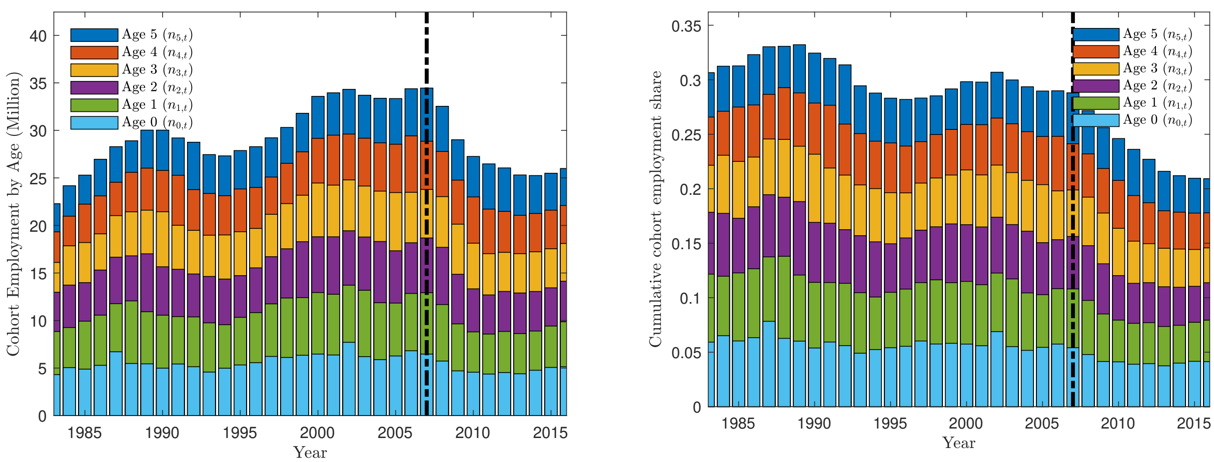
Figure 34: Dynamics of the aggregate employment



(a) Linear trend

(b) Change in agg. employment

Figure 35: Employment dynamics by cohort age



(a) Employment by cohort age

(b) Employment share by cohort age

In this section, I present how the results of the exercise change if I alter predictions for the dynamics of the aggregate employment and cohort-level employment had the Great Recession not happened.

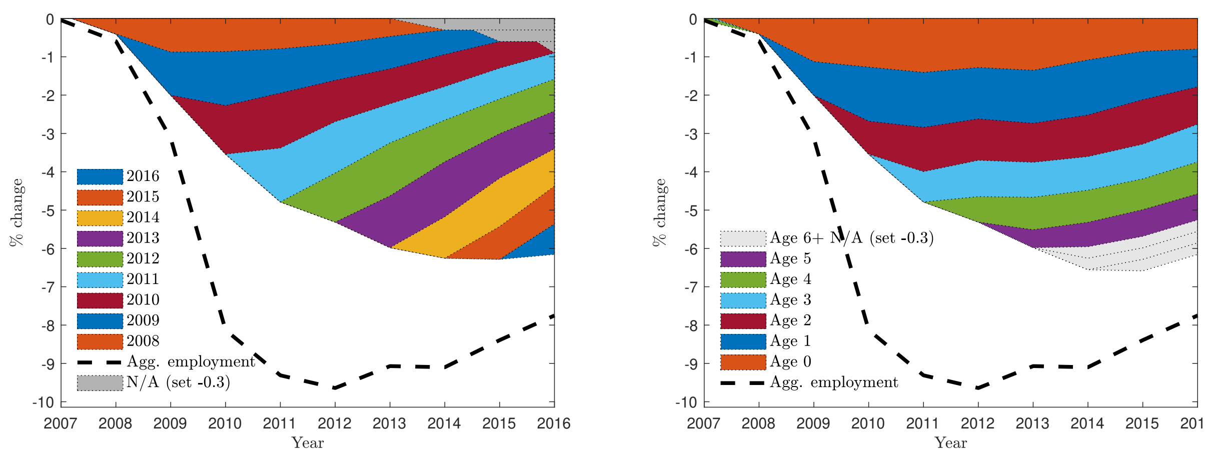
First, in the main text, I considered the share of the cohort level employment in the predicted aggregate employment. As robustness, I consider an exercise where I divide changes in the cohort level employment by actual aggregate employment level, rather than the trend. One can also think about it as a percentage deviation of the actual cohort level employment from the predicted cohort-level employment multiplied by the weight of the cohort employment in the actual aggregate employment:

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

Figure 36 illustrates that the results are robust to this modification.

Second, I consider different variations of the pre-crisis cohort-level employment by age. On Figure 37 I consider ten-year average (1997-2007) of cohort-level employment by age. The result is close to the one considered in the main text. On Figure 38 I consider twenty-year average (1987-2007) of cohort-level employment by age. Figure 35 shows that cohort-level employment by age had an increasing trend before crisis. Thus, while the twenty-year average produces a cohort with relatively smaller employment by age than a representative cohort, the following figure still emphasize on the importance of the persistent decrease in cohort-level employment in propagation of the aggregate shocks.

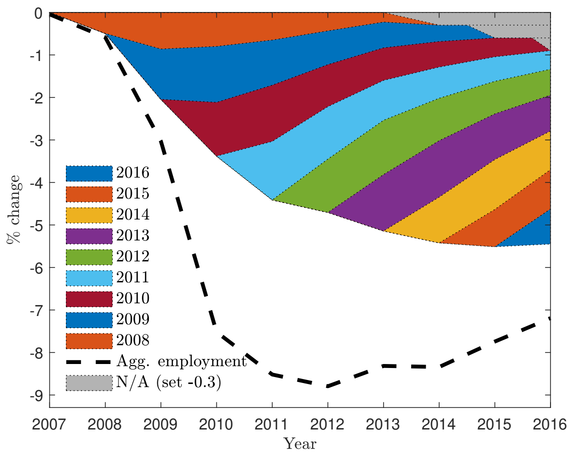
Figure 36: The contribution of the cohorts that entered the market over the period $2008-2016$ to the slow recovery of aggregate employment. In this exercise, I divide changes in the cohort level employment by actual aggregate employment level, rather than the trend



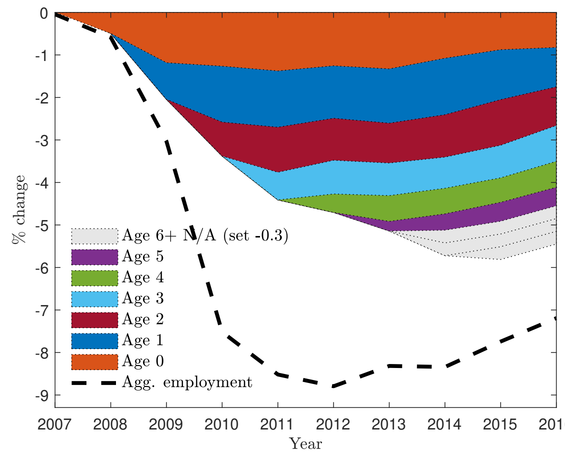
(a) By cohort

(b) By age

Figure 37: The contribution of the cohorts that entered the market over the period 2008 − 2016 to the slow recovery of aggregate employment. In this exercise, I consider ten-year average (1997-2007) of cohort-level employment by age.

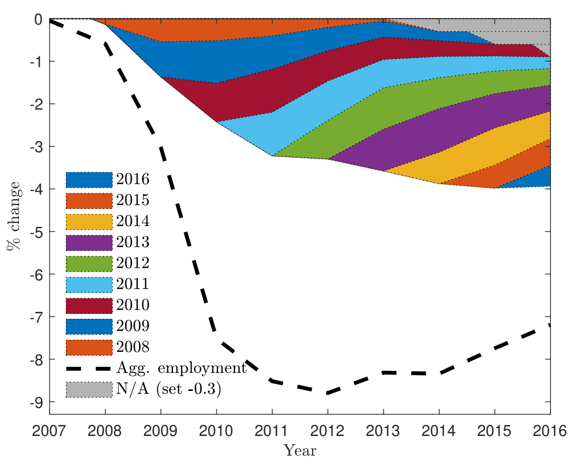


(a) By cohort

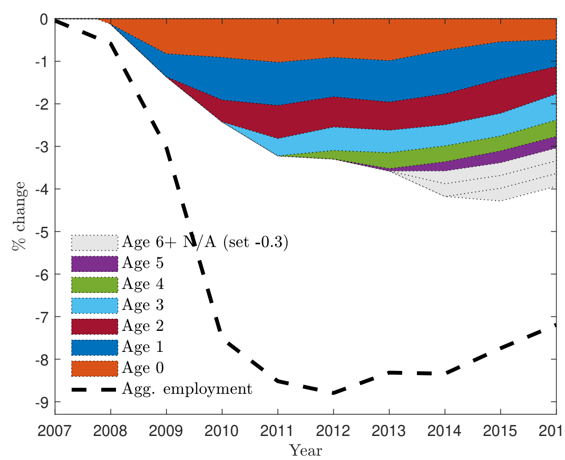


(b) By age

Figure 38: The contribution of the cohorts that entered the market over the period 2008 − 2016 to the slow recovery of aggregate employment. In this exercise, I consider twenty-year average (1987-2007) of cohort-level employment by age.



(a) By cohort

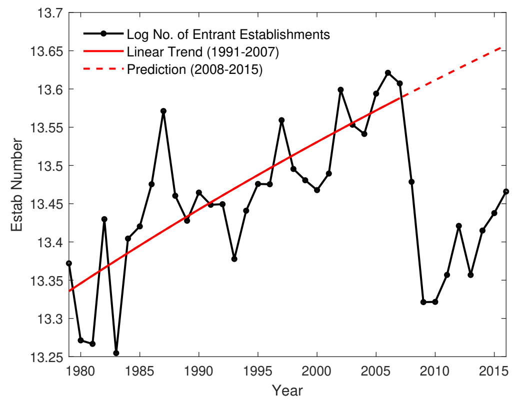


(b) By age

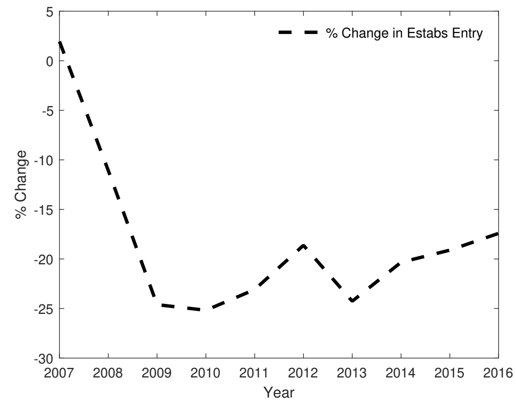
G.2.3 The Great Recession and the Model

In this section, I extend the analyses covered in Section 5.3. I construct an aggregate demand shock series that matches the changes in the simulated number of entrant establishments to the data counterpart over the period 2008-2016. Like the empirical part, I used a linear trend over the period $1979-2007$ to predict the evolution of the number of entrant establishments starting from the year 2008, as if the Great Recession not happened. Figure 39 displays the evolutions, pre-crisis trends and predictions for the entry rate and the number of entrant establishments. Figure 39(e)-(f) also displays the evolutions, pre-crisis trends and predictions for these time series.

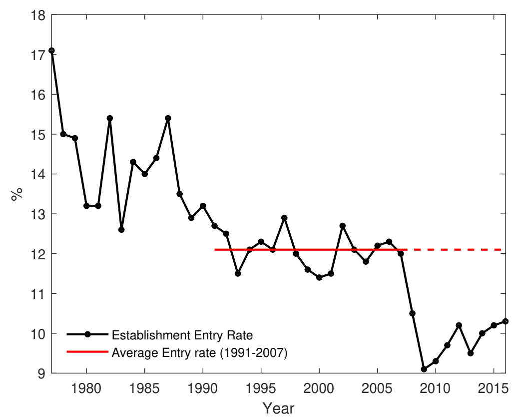
Figure 39: Dynamics of Entrant Establishments



(a) No. of entrant estabs.

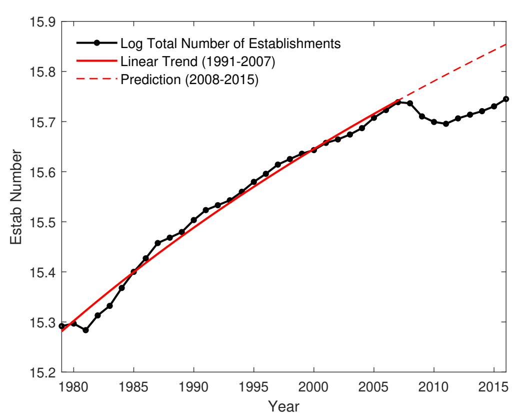


(b) Deviations from the trend

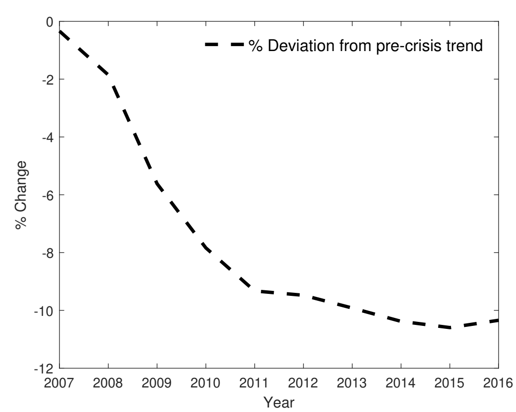


(c) Entry rate

(d) Deviations from the trend



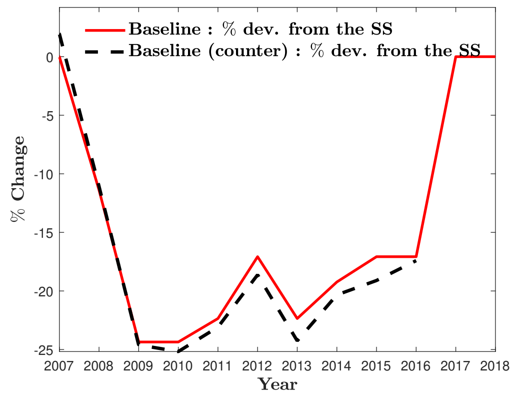
(e) Total Estabs.



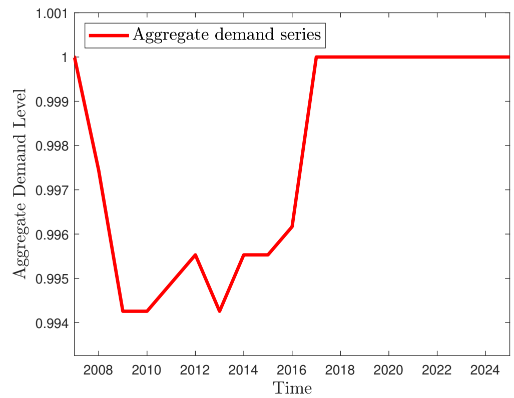
(f) Deviations from the trend

Figure 40(b) illustrates the evolution of the number of entrant establishments in the model and in the data and Figure 40(a) displays the series of the aggregate demand shocks that generate the match.

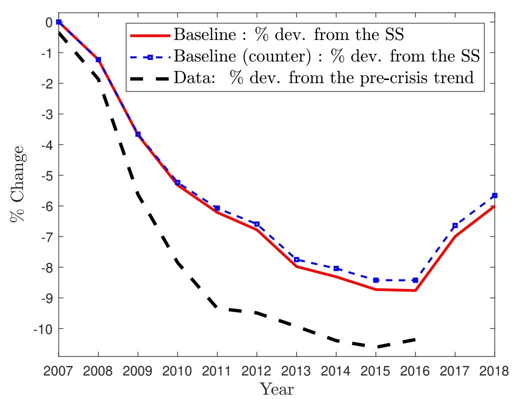
Figure 40: The Great Recession Exercise



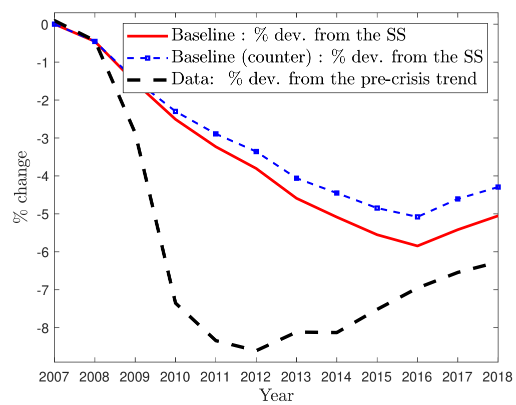
(a) Change in no. of entrants



(b) Aggregate demand process



(c) Change in total no. of firms

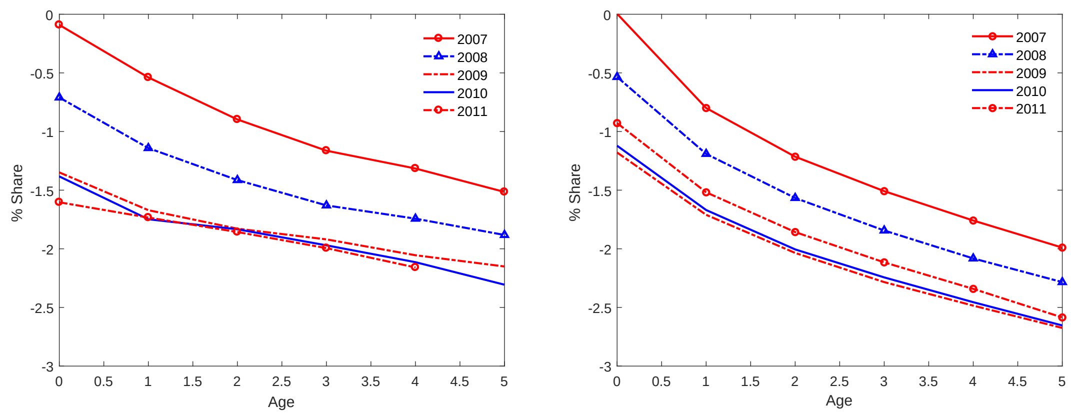


(d) Change in aggregate employment

I simulate the economy for the constructed aggregate demand shock series. Alongside, to evaluate the role of the post-entry aggregate demand shock process, I also consider a counterfactual scenario where aggregate demand shocks only effect selection but not post-entry dynamics of firms. Figure 40(c) and Figure 40(d) compares the dynamics of the total number of establishments and aggregate employment in the baseline economy, and in the counterfactual scenario to the data counterpart. The exercise shows that a model that accounts for the observed demographics of the U.S. establishments is capable of accounting for the slow recovery observed after the Great Recession. Specifically, by the year 2016, the model explains more than 85% of the deviation of the aggregate employment from the pre-crisis trend. Also, note that the post-entry aggregate demand shocks account for a minor role in the dynamics of the aggregate variables.

Figure 41 compare changes in the employment of cohorts that started operating over 2007-2011 in the model and the data.

Figure 41: Cohort-level employment over 2007-2011



(a) Data (b) Baseline model

The exercise illustrates that sources other than the low aggregate demand have played an important role in the historical drop in aggregate variables during the Great Recession. In particular, persistently low aggregate demand level seems insufficient to explain the significantly increased exit rates and a significant drop in incumbent firms' employment observed during the Great Recession.

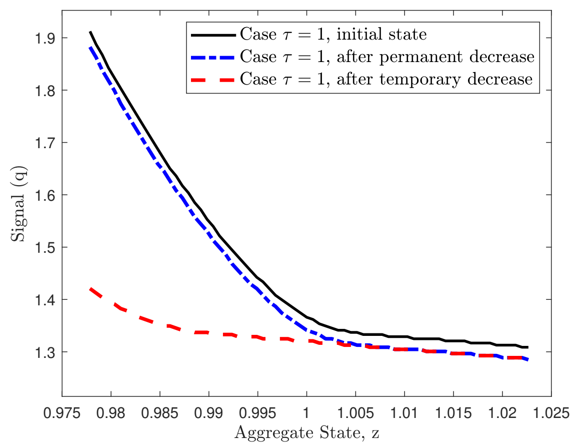
G.3 Other Applications

This appendix provides supplementary figures for Section 6.2.

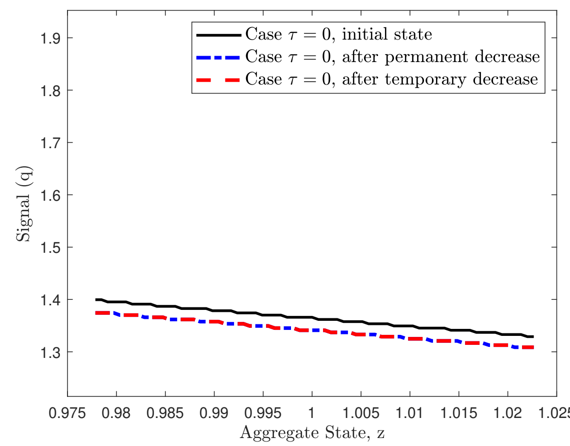
G.3.1 Temporary/Permanent Decrease in the Fixed Entry Cost

Figures 42(a) and 42(b) contrast the changes in the threshold signal level as a response to a permanent and a temporary decrease in the fixed entry cost with and without the option to delay entry. Figures 42(c) and 42(d) translates the threshold signal into the number of entrants, using the assumed distribution $W(q)$ of potential entrants.

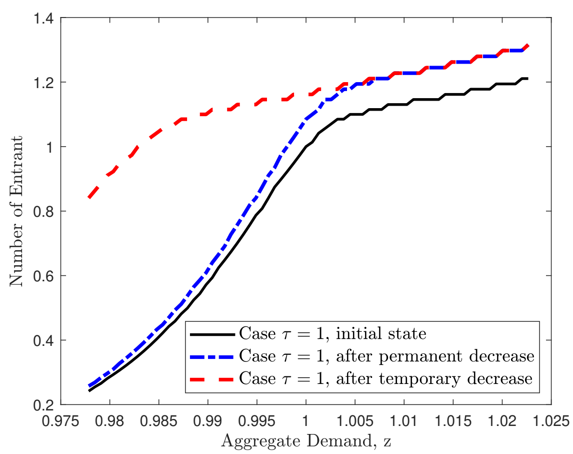
Figure 42: The response of entrants to the permanent/temporary decline in the fixed entry cost across aggregate states.



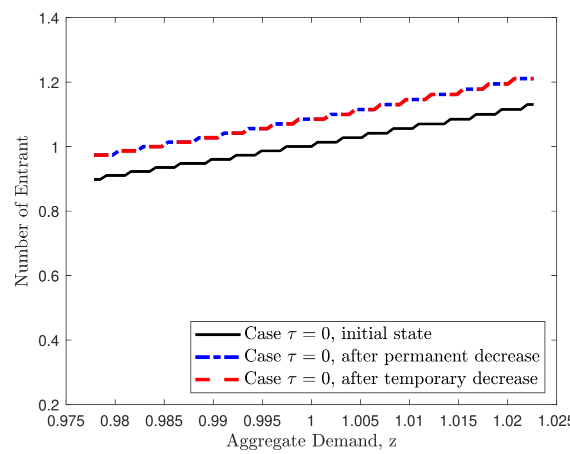
(a) Threshold signal, $\tau = 1$



(b) Threshold signal, $\tau = 0$



(c) Number of firms, $\tau = 1$

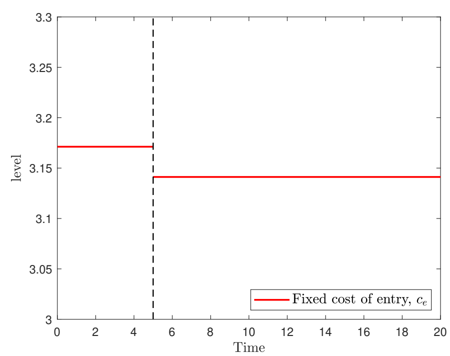


(d) Number of firms, $\tau = 0$

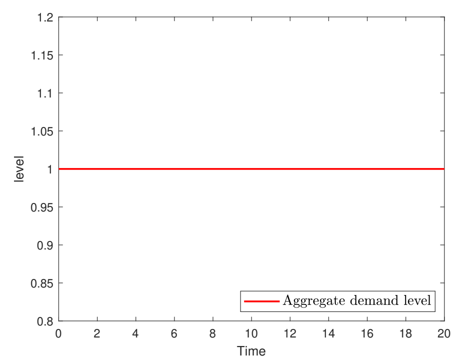
G.3.2 The News Shock and the Aggregate Dynamics

Figure 43 describes the response of the baseline economy to this announcement (news), the timing of which is as follows. The economy starts at the stochastic steady state at time zero. At time one, an unanticipated policy announcement happens. Potential entrants learn that there will be 0.05 unit decline in the fixed entry cost beginning five periods later.[85] As a response to the news, potential entrants start postponing entry to the market starting from period one. The evolution of the number of entrant firms with and without the option to delay entry is given in Figure 43(c). Figure 43(b) shows that the dynamics of the aggregate employment as a response of the news shock, driven by the changes in the number of entrants. Note that since the aggregate demand level is fixed at the steady state level all the dynamics are due to the news shock.

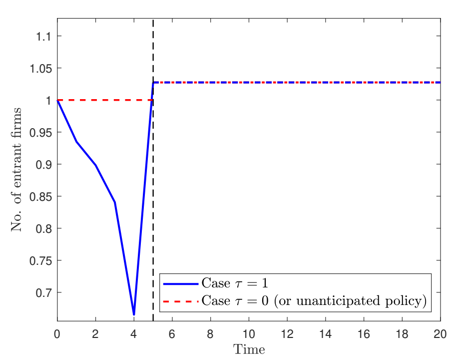
Figure 43: Response of the aggregate variables to an anticipated decline in entry barriers that is going to take place after five years from the announcement



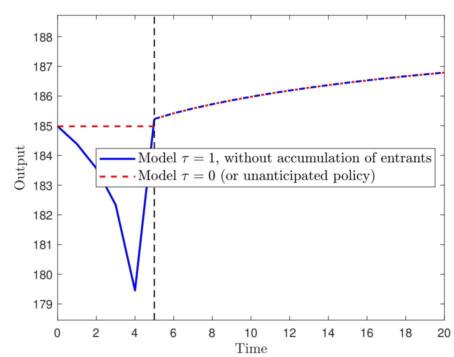
(a) Fixed entry cost



(b) Aggregate demand level



(c) No. of entrant firms

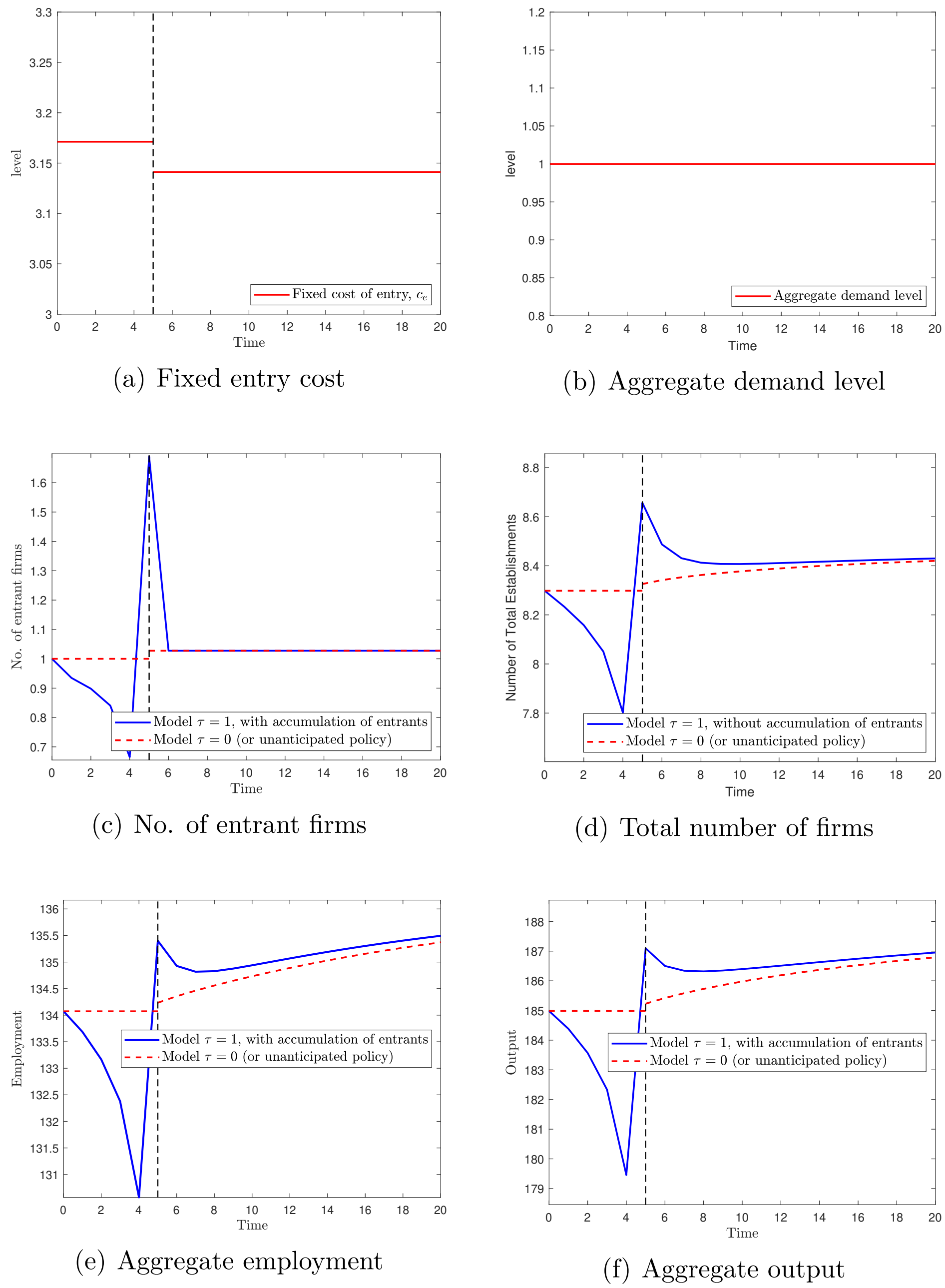


(d) Aggregate output

[85] The the magnitude of the decline is chosen to result in a 3.0 percent decline in entry rate, the decline observed during the Great Recession.

On Figure 44 I illustrate the dynamics of the economy as a response to the announcement when I allow the potential entrants. Again, note that the policy's direct effect on the number of entrants is much milder compared to indirect effect through the option to delay entry.

Figure 44: The dynamics of the economy as a response to the announcement



(a) Fixed entry cost

(b) Aggregate demand level

(c) No. of entrant firms

(d) Total number of firms

(e) Aggregate employment

(f) Aggregate output