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Limited Re-Entry and Business Cycles

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Abstract This paper builds a model of firm dynamics to study the consequences of "limited re-entry" for macroeconomic dynamics. Matched individual-level data from the Current Population Survey indicate that only 8% of unemployed chief executives, on average, find employment again as a chief executive after 12 months. Given the close link between entrepreneurs and chief executives, this suggests that it is very difficult for exiting entrepreneurs to "re-enter" in the future. The model, calibrated to match this observation, indicates that "limited re-entry" has made business cycles more volatile and persistent.

Keywords: entry, exit, entrepreneurship, firm dynamics

JEL Classification Numbers: E32, L11, L26

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1 Introduction

Given the well-documented heterogeneity among both plants and firms,[1] a number of recent papers have explicitly modeled the entry and exit of plants or firms for the purpose of studying macroeconomic dynamics.[2] In the literature, exit has typically been modeled as a permanent decision whereby it is not possible for the exiting plant or firm to "re-enter" in the future. However, evidence from the venture capital literature suggests that the managers or directors of these exiting plants and firms are not permanently excluded from the market. For example, Gompers et al. (2005) report that when a company's sales are declining, employees tend to leave at a higher rate to found their own venture-capital backed startups. This suggests that higher exit rates today may lead to higher entry in the future. Furthermore, serial entrepreneurs, or entrepreneurs who have founded other startups in the past, constitute a relatively large fraction of all entrepreneurs. In particular, Gompers et al. (2010) report that serial entrepreneurs made up about 10% of all entrepreneurs in venture-capital backed startups during the 1990s. They also report that serial entrepreneurs all have a similar probability of founding a company that eventually goes public, regardless of whether they have failed to do so in the past. This suggests that failure or exit is not necessarily permanent.

Consequently, if higher exit rates today lead to higher entry rates in the future, the increase in establishment exit rates during the 2007-09 recession[3] could actually have contributed to the recovery that followed. Therefore, this paper seeks to address two questions. First, how much "re-entry" is possible? In this paper, I will take a broad view of "re-entry," in that "re-entry" can be loosely interpreted to mean that the managers of an exiting establishment directly lead to the entry of a new establishment in the future. Utilizing matched individual-level data from the Consumer Population Survey (CPS), I find that re-entry is very difficult. Using unemployed chief executives as a proxy for the managers of exiting establishments, I find that about 8% of these individuals on average find employment again as a chief executive after 12 months. This is in contrast to an overall 12-month job finding rate of 56%. Second, what are the consequences of this for the aggregate economy? Using a model of firm dynamics calibrated to be consistent with observations from the CPS, I find that "limited re-entry" has made output both more volatile and persistent.

[1] For example, see Bartelsman and Doms (2000) and Henly and Sánchez (2009).

[2] For example, Foster et al. (2001) argue that entry and exit is an important source of aggregate productivity growth. While studying aggregate fluctuations, entry and exit have been modeled endogenously in Samaniego (2008), Gomes and Schmid (2010), Arellano et al. (2012), Lee and Mukoyama (2013), Clementi and Palazzo (2014), and Macnamara (2014).

[3] Macnamara (2014) documents the behavior of establishment entry and exit rates during the 2007-09 recession.

More specifically, I first study matched individual-level data from the CPS. Using this data set, it is possible to track individuals over time by occupation and labor market status. Of particular interest is the occupational code for "chief executives," which is included in the 2002 and 2010 Census occupational classifications. As this occupation is most closely associated with the role of an entrepreneur in the model, I focus on the rate at which unemployed chief executives return to employment as a chief executive. Specifically, an individual is identified as an unemployed chief executive if he was last employed as a chief executive. Next, I compute the rate at which these individuals transition back into chief executive occupations. Between January 2003 and December 2012, only 4% of unemployed chief executives returned to employment as a chief executive in 3 months. In contrast, after 3 months, 30% of these individuals found any type of job and 15% left the labor force. After 12 months, 8% found another job as a chief executive, while 56% found any type of job and 19% left the labor force. Therefore, unemployed chief executives are much more likely to switch occupations or even leave the labor force than they are to return to employment as a chief executive. This suggests that when a plant exits, it is very difficult for the associated managers (i.e., entrepreneurs) to cause the entry of new establishments in the near future.

To assess the economic significance of these numbers, I build a model of firm dynamics calibrated to match these transition rates. Building on Macnamara (2014), I assume that the economy is populated by a continuum of perfectly competitive producers, where labor is the only input in a decreasing returns-to-scale production function. Each producer can be interpreted as consisting of an "entrepreneur" and some amount of labor. The "entrepreneur" in this model is then analogous to the "chief executive" position in the data. Entrepreneurs are heterogeneous in terms of their idiosyncratic productivity, which is stochastic and represents the management skills of entrepreneurs. Because entrepreneurs must pay fixed costs in order to operate, only those entrepreneurs with a sufficiently high idiosyncratic productivity will operate and enter. However, in contrast to Macnamara (2014), I assume that exit is not necessarily *permanent* for entrepreneurs. Specifically, I assume that exiting entrepreneurs can become potential entrants, enabling them to possibly "re-enter" in the future.

Next, I calibrate the model so that exiting entrepreneurs re-enter at the same rate unemployed chief executives find jobs as chief executives. Then, using the procedure of Chari et al. (2007), I measure an aggregate technology shock by setting the sequence of shocks so that the model-predicted fluctuations in output match the those seen in the data. This requires that the equilibrium of the model be solved to back out the sequence of technology shocks. After feeding this sequence of shocks back into the model, it does well accounting for the dynamics of observed entry and exit rates. This is consistent with the results of Macnamara (2014). Specifically, it matches the empirical observation that entry rates are procyclical and exit rates are countercyclical. It does particularly well accounting for the fall in entry and the increase in exit during the 2007-09 recession.

In the benchmark economy, as suggested by the CPS data, re-entry is very limited. In the steady state of the model, only 8.3% of exiting entrepreneurs are eventually able to re-enter. To evaluate the economic impact of limited re-entry, I conduct a counterfactual experiment in which exiting entrepreneurs can re-enter more easily. Specifically, I re-calibrate the model so that exiting entrepreneurs re-enter at the same rate unemployed chief executives find *any* kind of job. In the steady state, this implies that exiting entrepreneurs will eventually re-enter with a probability of 60%. I then feed into the model the exact same technology shock measured using the benchmark economy. I find that "quick re-entry" would have significant implications for the dynamics of entry rates. In particular, after the 2007-09 recession, entry rates would have recovered much more quickly than was seen in the data. The entrepreneurs who exited during the crisis would immediately start re-entering, causing a quick recovery in entry rates. Moreover, I show that this would have significant implications for the economy as a whole. In the data (and the benchmark model), real GDP grew at an annual rate of 2.2% between 2009-II and 2014-I. In contrast, with quick re-entry, real GDP would have grown at an annual rate of 2.7% over the same time period. This suggests that the limited ability of exiting entrepreneurs to re-enter has contributed to the slow recovery in output following the 2007-09 recession.

Furthermore, the predictions of the benchmark model with limited re-entry turn out to be very similar to a model with no re-entry. This indicates that re-entry is so limited in the data that models can safely abstract from this feature. While it has been assumed in the literature[4] that exit is permanent, the model, calibrated to be consistent with the empirical evidence reported in this paper, confirms that this is a justifiable assumption. Nevertheless, this paper still highlights the economic consequences of limited re-entry (or permanent exit), which have not been explored in the literature. For example, while the selection introduced by entry and exit tends to raise aggregate productivity in models along the lines of Hopenhayn (1992), this paper shows that limited re-entry actually hampers this mechanism. While entry and exit still do work to increase aggregate productivity with limited re-entry, the effect on aggregate productivity would be even larger with quick re-entry. With limited re-entry, many low-productivity entrepreneurs choose to operate because they do not have the option to re-enter later.

Moreover, while it has been documented that entry rates are procyclical,[5] this paper

[4]For example, see Hopenhayn (1992), Hopenhayn and Rogerson (1993), Samaniego (2008), Lee and Mukoyama (2013), Clementi and Palazzo (2014) and Macnamara (2014).

[5]Devereux et al. (1996) report that the number of new business incorporations is procyclical. The procyclicality of the entry rate has also been documented for manufacturing plants by Lee and Mukoyama

shows that this result is a consequence of limited re-entry. These results also highlight the importance of limited re-entry for the amplification result in the literature. In particular, Clementi and Palazzo (2014) find that entry and exit further amplify and propagate the effects of aggregate shocks. Macnamara (2014) obtains a similar result with technology and financial shocks. Devereux et al. (1996), Bilbiie et al. (2012), Jaimovich and Floetotto (2008) and Chatterjee and Cooper (2014) have found similar results in models with monopolistic competition. However, the quick re-entry experiment demonstrates that the magnitude of this effect is dependent on limited re-entry. With quick re-entry, not only would aggregate output be less volatile, but it would be quicker to recover in response to aggregate shocks.

This paper is organized as follows. First, Section 2 presents an overview of the model. Next, Section 3 reports evidence on the ability of entrepreneurs to re-enter. Section 4 reviews the model's calibration. Section 5 examines the main results and Section 6 concludes.

2 Model

In this model, time is discrete and the unit of observation can be thought to be an entrepreneur. Nevertheless, the words "producer," "establishment" or "entrepreneur" may be used interchangeably when discussing the theory. While this model is closely related to Macnamara (2014), two important modifications are made. First, to keep the focus on the effects of re-entry, only aggregate technology shocks are included. Second, to evaluate how re-entry affects the dynamics of entry and exit, the exit decision is modified to allow for the possibility that exiting producers can re-enter at some point in the future. For the same reason, the entry decision is modified to allow potential entrants to wait until the next period to enter. Nevertheless, these last two modifications are done in a way that nests a standard model of entry and exit under certain parameters.

In the following subsections, the components of the model are described in detail.

2.1 Producers

The economy is populated by a continuum of producers who are perfectly competitive and produce a single homogeneous good. Labor is the only input in the producer's production function, $f(z, s, n) = zsn^{\gamma}$, where z is aggregate productivity, s is idiosyncratic productivity and n is the labor input. It is assumed that $\gamma \in (0, 1)$, implying that there are decreasing returns to scale at the producer level.

(2013).

One way to interpret diminishing returns to scale at the producer-level is to think of the "span of control" models of Lucas (1978) and Rosen (1982). Here a "producer" can be interpreted as consisting of an entrepreneur and n units of labor. The idiosyncratic productivity, s, can reflect heterogeneity in the skill of managers and diminishing returns to scale is a consequence of the diminishing returns of an entrepreneur in managing larger operations. However, management is not being modeled directly and entrepreneurs earn positive profits because of diminishing returns to scale. Although there are decreasing returns to scale at the producer level, there still are constant returns to scale in the aggregate because the producer can be replicated. With perfect competition, producer-level diminishing returns allow for heterogeneity to exist in equilibrium and prevents the most productive producers from taking over the market completely.

In addition to the standard idiosyncratic productivity shock, producers face an aggregate productivity shock. The processes for both shocks are assumed to be AR(1). Specifically, the productivity processes are given by

$$\ln z' = (1 - \rho_z)\, a_z + \rho_z \ln z + \sigma_{\varepsilon z} \varepsilon_z \tag{1}$$

$$\ln s' = \rho_s \ln s + \sigma_{\varepsilon s} \varepsilon_s \tag{2}$$

where (z', s') are the next-period productivity shocks and $(\varepsilon_z, \varepsilon_s)$ are independent innovations drawn from a standard normal distribution.

2.1.1 Entry Decision and the Role of Delayed Entry

As in Clementi and Palazzo (2014) and Macnamara (2014), I assume that a finite mass $\bar{M}_e$ of prospective entrants are born every period. Each potential entrant receives a signal s_e at birth about its productivity. If a potential entrant with signal s_e chooses to operate today, it would immediately begin operation and its idiosyncratic productivity would be s_e. A new potential entrant's initial s_e is drawn from a distribution with the probability density function, $g_n(\cdot)$. Throughout this paper, I will assume that $g_n(\cdot)$ is the probability density function for a log normal variable with mean a_{se} (defined below) and the standard deviation $\sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$. After a potential entrant makes the decision to enter, it pays a fixed entry cost, $c_e \geq 0$. However, in contrast to Clementi and Palazzo (2014) and Macnamara (2014), I assume that a potential entrant can survive to the next period if it chooses *not* to enter. In particular, a potential entrant who does not enter dies with probability $\theta \in (0, 1]$.

Furthermore, if the potential entrant does survive to the next period, its signal tomorrow is given by

$$\ln s_e' = (1 - \rho_{se}) a_{se} + \rho_{se} \ln s_e + \sigma_{\varepsilon se} \varepsilon_{se} \tag{3}$$

where ε_{se} is an i.i.d. innovation drawn from a standard normal distribution. In the benchmark calibration, I set $\rho_{se} = 0$ and $\sigma_{\varepsilon se} = \sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$. This assumption makes the numerical calculations simpler. Nevertheless, in Section 5.4.1, I consider the case in which $\rho_{se} = \rho_s$ and $\sigma_{\varepsilon se} = \sigma_{\varepsilon s}$. The results in this case turn out to be qualitatively the same. Essentially, given the assumption about $g_n(\cdot)$ stated earlier, assuming $\rho_{se} = 0$ means that all potential entrants (new and old) draw a new s_e each period from a log normal distribution with mean a_{se} and standard deviation $\sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$. In other words, potential entrants draw a new signal from a distribution with the same variance as the invariant distribution for idiosyncratic productivity, but a different mean. In fact, in the benchmark calibration, it will be the case that $a_{se} < 0$.

Denote by $V(\mathbf{x}, s)$ a entrepreneur's value of operating in the current period, where $\mathbf{x}$ is the aggregate state today and s is the producer's idiosyncratic productivity. The aggregate state $\mathbf{x}$ is a vector of state variables which includes z and the distribution of potential entrants and incumbent entrepreneurs. Similarly, denote by $V^w(\mathbf{x}, s_e)$ a potential entrant's value of "waiting," where s_e is the potential entrant's signal. In other words, this is the value for a potential entrant if it chooses not to enter in the current period, and "wait" until the next period. These value functions are defined later in Equations 9 and 10, respectively. In making its entry decision, a potential entrant compares the value of operating it would receive if it enters against the fixed entry cost and the value of waiting. Thus, the potential entrant with signal s_e will enter if and only if $V(\mathbf{x}, s_e) - c_e \geq V^w(\mathbf{x}, s_e)$. This implies that there is an entry cutoff productivity for potential entrants, $\bar{s}_e(\mathbf{x})$, where $\bar{s}_e$ is defined as the value of s_e such that

$$V(\mathbf{x}, \bar{s}_e) - c_e = V^w(\mathbf{x}, \bar{s}_e). \tag{4}$$

A potential entrant will enter if and only if $s_e \geq \bar{s}_e(\mathbf{x})$. As will be seen in Section 2.1.4, $V^w(\mathbf{x}, s) = 0$ when $\theta = 1$. Therefore, the case of $\theta = 1$ corresponds to what has been commonly assumed in the literature.[6] In this case, an entrepreneur who chooses *not* to enter (1) permanently loses all information contained in its current-period signal, and (2) cannot enter in the future. In contrast, I refer to the case when $\theta < 1$ as a situation in which "delayed entry" is possible. In other words, if a potential entrant chooses not to enter today because of poor aggregate conditions, it can "delay" or "postpone" entry until aggregate conditions improve. Furthermore, if $\rho_{se} > 0$, it retains some information about its potential productivity.

[6] For example, see Clementi and Palazzo (2014) and Lee and Mukoyama (2013). This paper is also consistent with a modified version of Hopenhayn (1992), in which the entry cost c_e varies with $\bar{M}_e$. For example, suppose c_e depends positively on $\bar{M}_e$ as follows: $c_e = \bar{c}_e \bar{M}_e^{\phi}$. Recall that $\bar{M}_e$ is endogenous in Hopenhayn (1992). However, if $\phi \to \infty$, the equilibrium value of $\bar{M}_e$ is fixed at 1. Therefore, that model of entry is the same as assuming $\theta = \theta_x = 1$ and $c_e = 0$ in this paper.

2.1.2 Exit Decision and the Role of Re-Entry

Each period the entrepreneur must pay a fixed operating cost, $c_f > 0$, denominated in terms of the output good. If the entrepreneur chooses to operate today, it pays the fixed cost and gets the present discounted value of profits. However, in contrast to the existing literature, I do not assume that exit is necessarily permanent for the entrepreneur. In particular, I assume that it is possible for exiting entrepreneurs to "re-enter" in the future. More specifically, with probability $\theta_x \in \{0, 1\}$, the exiting entrepreneur dies and is never able to re-enter. Otherwise, the entrepreneur immediately becomes a potential entrant. In practice, θ_x is just used to parameterize two scenarios. When $\theta_x = 1$, re-entry is not possible at all. However, when $\theta_x = 0$, all exiting entrepreneurs immediately become potential entrants. I will refer to the potential entrants who have previously operated as "potential re-entrants." Meanwhile, the term "potential entrants" will be used to refer to both potential re-entrants and potential entrants who have never entered.

When $\theta_x = 0$, an exiting entrepreneur needs a signal for its productivity when it joins the pool of potential entrants. This signal is assumed to be $s_e = s$, where s is the entrepreneur's idiosyncratic productivity when it exits. However, when $\rho_{se} = 0$, this signal will be irrelevant for the entrepreneur's signal tomorrow, s'_e, which will determine whether the entrepreneur re-enters next period. This is the case that will be considered in the benchmark calibration. However, for robustness purposes, I consider the case when $\rho_{se} > 0$ in Section 5.4.1 and find that the results are unaffected.

When making the exit decision, an entrepreneur compares the value of operating with its outside option. The value of operating is $V(\mathbf{x}, s)$ and the outside option is $(1 - \theta_x)V^w(\mathbf{x}, s)$. This outside option reflects two assumptions stated earlier. First, if $\theta_x = 1$, the exiting producer is destroyed and the entrepreneur receives nothing. Second, if $\theta_x = 0$, the exiting entrepreneur becomes a potential entrant with signal $s_e = s$ and receives the potential entrant's value of waiting. Therefore, the entrepreneur will exit today if and only if $V(\mathbf{x}, s) < (1 - \theta_x)V^w(\mathbf{x}, s)$. Then, there exists an exit cutoff productivity, $\underline{s}(\mathbf{x})$, such that the entrepreneur will exit if and only if $s < \underline{s}(\mathbf{x})$. This cutoff is defined as the value of s such that

$$V(\mathbf{x}, \underline{s}) = (1 - \theta_x)V^w(\mathbf{x}, \underline{s}). \tag{5}$$

If $\theta_x = 1$ or $\theta = 1$, the entrepreneur's outside option is zero. This corresponds to what has been commonly assumed in the literature. In that case, the decision to exit is a highly destructive one. As with entry, (1) all information contained in the entrepreneur's idiosyncratic productivity is permanently lost, and (2) exiting entrepreneurs cannot re-enter in the future. However, when $\theta_x = 0$ and $\theta < 1$, the entrepreneur's outside option is greater than zero. In other words, the decision to exit is no longer completely destructive, and it is possible for the entrepreneur to re-enter in the future. Furthermore, when $\rho_{se} > 0$, an exiting entrepreneur retains some information about its potential for future productivity.

In addition, since $c_e \geq 0$ and $\theta_x \in \{0, 1\}$, it follows that $\underline{s}(\mathbf{x}) \leq \bar{s}_e(\mathbf{x})$. In other words, all entrants will choose to operate. This also guarantees that exiting entrepreneurs will not have the incentive to re-enter in the same period they exit. In fact, when $c_e = 0$ and re-entry is allowed ($\theta_x = 0$), it follows from Equations 4 and 5 that $\underline{s}(\mathbf{x}) = \bar{s}_e(\mathbf{x})$. However, when $c_e = 0$ and re-entry is not allowed ($\theta_x = 1$), $\underline{s}(\mathbf{x}) = \bar{s}_e(\mathbf{x})$ only when $\theta = 1$. In this case, delayed entry is not allowed either.

2.1.3 Transition Rules for Entrepreneur Distributions

Given the description of the entry and exit conditions, it is now possible to define the law of motion for the distribution of entrepreneurs. Define $\mu(\cdot)$ to be a function over the current period's idiosyncratic shock, s. This function represents the distribution of incumbent entrepreneurs over idiosyncratic productivity at the beginning of the period before the entry and exit decisions are made. $M = \int_0^\infty \mu(s)ds$ is then the total mass of incumbent entrepreneurs. Similarly, let $g(\cdot)$ be a function over the current signal s_e. This function represents the distribution of all potential entrants, at the beginning of the period. This distribution includes new potential entrants, and if $\theta_x = 0$, potential re-entrants as well. $G = \int_0^\infty g(s_e)ds_e$ is then the total mass of potential entrants.

Let $\mathbf{x} \equiv (z, \mu, g)$ be the vector of aggregate state variables. Given today's aggregate state $\mathbf{x}$, tomorrow's distribution of incumbent entrepreneurs μ' is given by

$$\mu'(s') = \int_{\underline{s}(\mathbf{x})}^{\infty} h(s'|s)\mu(s)ds + \int_{\bar{s}_e(\mathbf{x})}^{\infty} h(s'|s_e)g(s_e)ds_e. \tag{6}$$

The function $h(s'|s)$ is the conditional probability density function for s', as determined by the process assumed in Equation 2. The first term represents the mass of incumbents who do not exit today and transition to s' tomorrow. Similarly, the second term represents the mass of potential entrants (including potential re-entrants) who enter today and transition to s' tomorrow.

Analogously, given today's aggregate state $\mathbf{x}$, tomorrow's distribution of potential entrants g' is given by

$$g'(s'_e) = \bar{M}_e g_n(s'_e) + (1-\theta)\int_0^{\bar{s}_e(\mathbf{x})} h_e(s'_e|s_e)g(s_e)ds_e +$$
$$(1-\theta_x)(1-\theta)\int_0^{\underline{s}(\mathbf{x})} h_e(s'_e|s)\mu(s)ds. \quad (7)$$

The function $h_e(s'_e|s_e)$ is the conditional probability distribution for s'_e, as determined by the process assumed in Equation 3. The first term represents the mass of potential entrants that will be born tomorrow with signal s'_e. Recall that $\bar{M}_e$ is the mass of potential entrants born each period, and $g_n(\cdot)$ is the probability density function from which new potential entrants tomorrow will draw their initial signal. The second term represents the mass of potential entrants who do not enter today, survive to tomorrow and transition to s'_e. And finally, the third term represents the mass of incumbents who exit today, survive to tomorrow and transition to s'_e. When $\rho_{se} = 0$ in the benchmark calibration, $g(s_e)/G$ will be equal to $g_n(s_e)$.

2.1.4 Entrepreneur's Problem

The entrepreneur's problem can now be formulated recursively. Given the wage w, the entrepreneur's labor demand is the solution to the following static problem:

$$\pi(z, s; w) = \max_n \{f(z, s, n) - wn\}. \quad (8)$$

Now, let r be the risk-free rate and recall that $\mathbf{x} \equiv (z, \mu, g)$ is the vector of aggregate state variables. Let $V(\mathbf{x}, s)$ be the value of continuing for an entrepreneur with aggregate state $\mathbf{x}$ and idiosyncratic productivity s in the current period, after any dividends from the operations of the current period have been issued. Then, $V(\mathbf{x}, s)$ is given by

$$V(\mathbf{x}, s) = \pi(z, s; w(\mathbf{x})) - c_f + \frac{1}{1+r}E\left[\max\left\{V(\mathbf{x}', s'), (1-\theta_x)V^w(\mathbf{x}', s')\right\}|z, s\right] \quad (9)$$

subject to

$$\mu' = T_\mu(\mathbf{x})$$
$$g' = T_g(\mathbf{x}).$$

$T_\mu(\mathbf{x})$ and $T_g(\mathbf{x})$ are the transition rules defined in Equations 6 and 7, respectively. If the entrepreneur operates today, it receives profits $\pi(\mathbf{x}, s; w(\mathbf{x}))$ minus the fixed operating cost. As discussed in Section 2.1.2, tomorrow an incumbent entrepreneur trades off the value of operating, $V(\mathbf{x}', s')$, with its outside option, $(1-\theta_x)V^w(\mathbf{x}', s')$.

Analogously, let $V^w(\mathbf{x}, s_e)$ be the value of waiting for an entrepreneur with aggregate state $\mathbf{x}$ and signal s_e. $V^w(\mathbf{x}, s_e)$ is then given by

$$V^w(\mathbf{x}, s_e) = \frac{1-\theta}{1+r} E\left[\max\left\{V(\mathbf{x}', s_e') - c_e, V^w(\mathbf{x}', s_e')\right\} | z, s_e\right] \tag{10}$$

subject to $\mu' = T_\mu(\mathbf{x})$ and $g' = T_g(\mathbf{x})$. If a potential entrant chooses to wait, it receives nothing today. Nevertheless, with probability $(1-\theta)$ it is able to survive to the next period. As discussed in Section 2.1.1, tomorrow the potential entrant trades off the value of entering with the value of waiting another period. $V(\mathbf{x}, s)$ and $V^w(\mathbf{x}, s_e)$ are then defined to be the value functions which jointly solve Equations 9 and 10. However, if $\theta = 1$, it trivially follows that $V^w(\mathbf{x}, s_e) = 0$.

2.1.5 Definition of Entry and Exit Rates

It is now possible to define entry and exit rates in the model. Let $m_e(\mathbf{x})$ be the equilibrium entry rate and $m_x(\mathbf{x})$ be the equilibrium exit rate. The entry rate is defined to be

$$m_e(\mathbf{x}) \equiv \frac{M_e(\mathbf{x})}{M(\mathbf{x})} \tag{11}$$

where $M_e(\mathbf{x}) \equiv \int_{\bar{s}_e(\mathbf{x})}^{\infty} g(s_e)ds_e$ is the mass of entrants and $M(\mathbf{x}) = \int_0^\infty \mu(s)ds$ is the mass of incumbent entrepreneurs. Note that the denominator is $M(\mathbf{x})$, not $G(\mathbf{x}) \equiv \int_0^\infty g(s_e)ds_e$, the mass of potential entrants. In contrast, the fraction of potential entrants who enter is defined to be the entry probability:

$$\bar{m}_e(\mathbf{x}) \equiv \frac{M_e(\mathbf{x})}{G(\mathbf{x})}. \tag{12}$$

Similarly, the exit rate is defined to be

$$m_x(\mathbf{x}) \equiv \frac{M_x(\mathbf{x})}{M(\mathbf{x})} \tag{13}$$

where $M_x(\mathbf{x}) = \int_0^{\underline{s}(\mathbf{x})} \mu(s)ds$ is the mass of exiting entrepreneurs. In contrast, Davis et al. (1994) divide both the mass of entrants and exiting producers by the average of producers who operated today and operated yesterday. However, since entry and exit rates are small, these two measures will be approximately equal.

2.2 Labor Supply

The supply of labor is assumed to be given by the function

$$N^s(w) = \left(\frac{w}{\psi}\right)^{\nu} \tag{14}$$

where w is the real wage, ν is the Frisch elasticity of labor supply.[7] The parameter ψ will just be used to normalize the wage to 1 in the steady state.

2.3 Recursive Competitive Equilibrium

A recursive competitive equilibrium can then be defined as follows. A recursive competitive equilibrium consists of (i) the value functions $V(\mathbf{x}, s)$, $V^w(\mathbf{x}, s_e)$ (ii) policy function $n(\mathbf{x}, s)$ (iii) cutoff rules $\underline{s}(\mathbf{x})$, $\bar{s}_e(\mathbf{x})$ (iv) wage function $w(\mathbf{x})$ and (v) law of motions $T_\mu(\mathbf{x})$ and $T_g(\mathbf{x})$ such that

1. $V(\mathbf{x}, s)$ and $V^w(\mathbf{x}, s)$ jointly solve the Bellman equations given by Equations 9 and 10.

2. The policy rule $n(\mathbf{x}, s) \equiv n(z, s; w(\mathbf{x}))$, where $n(z, s; w)$ is the solution to Equation 8 and $w(\mathbf{x})$ is the equilibrium wage as a function of $\mathbf{x}$.

3. The cutoff rules $\underline{s}(\mathbf{x})$, $\bar{s}_e(\mathbf{x})$ are given by 5 and 4, respectively.

4. The wage $w(\mathbf{x})$ specifies the market clearing wage given aggregate state $\mathbf{x}$. First, define aggregate labor demand, given $\mathbf{x}$ and w, as follows:

$$N^d(\mathbf{x}; w) = \int_{\underline{s}(\mathbf{x})}^{\infty} n(z, s; w)\mu(s)ds + \int_{\bar{s}_e(\mathbf{x})}^{\infty} n(z, s_e; w)g(s_e)ds_e.$$

   The function $n(z, s; w)$ is the solution to Equation 8. Therefore, the wage w clears the labor market when $N^d(\mathbf{x}; w) = N^s(w)$, where $N^s(\cdot)$ is the labor supply defined in Equation 14.

5. The actual transition rules, $T_\mu(\mathbf{x})$ and $T_g(\mathbf{x})$, are given by Equations 6 and 7, implying that they are consistent with the transition rules assumed by producers.

[7]This setup is observationally equivalent to a general equilibrium model in which labor is supplied by households with preferences linear in consumption and separable in consumption and leisure.

3 Empirical Evidence on Re-Entry

To ascertain how difficult it is for entrepreneurs to re-enter, I utilize matched monthly data from the Current Population Survey (CPS). The CPS uses a 4-8-4 rotating sample design. In other words, households are in the sample for four consecutive months, out of the sample for the next 8 months, and then back in the sample for the final four months.[8] The advantage of the CPS is that it not only categorizes individuals according to their labor market status, but also their occupation. Of particular interest is the occupational code for "chief executives," which is included in the 2002 and 2010 Census occupational classifications. This occupation is most closely associated with the role of an "entrepreneur" in the model. Namely, chief executives (like entrepreneurs in the model) influence the productivity of their businesses and are also responsible for decisions on entry and exit. Therefore, an empirical counterpart to "re-entry" is the rate at which unemployed chief executives transition back into employment as a chief executive. The resulting numbers will be used to discipline the model.

Since the chief executive occupational code is only available in the 2002 and 2010 Census occupational classifications, I restrict attention to observations between January 2003 and December 2012. I define an "unemployed chief executive" as an unemployed individual whose last reported job was as a chief executive. Over this time period, there were 90,638 raw observations of chief executives and 1,745 observations for unemployed chief executives. Since this time period covers 120 months, this is a relatively small sample size, with observations on about 15 unemployed chief executives each month. For this reason, I pool all the observations together to compute average transition rates. The numbers are very similar if I calculate transition rates by month, and then average the resulting rates.

To calculate the transition rates, I compute the fraction of unemployed chief executives who are employed as a chief executive after 1 month, 3 months and 12 months. For comparison purposes, I also calculate the rate at which these workers transition into four broad occupational categories. For these four categories, I adapt the occupational classifications used in the occupational mobility literature. In particular, using the occupational classifications of Acemoglu and Autor (2011), jobs can be classified along two dimensions: (1) routine versus non-routine, and (2) manual versus cognitive. Since non-routine cognitive (NRC) jobs include chief executives, the first category I use is all NRC jobs except chief executives (NR-CxE). The final three categories are then routine cognitive (RC), routine manual (RM) and non-routine manual (NRM). The total job finding rate is then the sum of the transition rates into these five occupational groups. I also report the fraction who exit the labor force.

[8] For details on the construction of this data set, see Nekarda (2009).

The top panel of Table 1 reports the resulting transition rates for chief executives. This shows that it is very difficult for unemployed chief executives to find another job as a chief executive. After 1 month, 3.60% of unemployed chief executives find another job as a chief executive. However, 8.30% take a NRCxE job and 15.67% find a job of any kind. Moreover, 13.77% exit the labor force after 1 month. Therefore, after 1 month, few unemployed chief executives find chief executive jobs.

[Table 1 about here.]

At longer horizons, a similar story holds. After 3 months, only 3.92% of unemployed chief executives return to employment as a chief executive. However, after 3 months, the job finding rate rises to 30.49%. After 12 months, these numbers increase to 7.64% and 56.46%, respectively. Moreover, almost a quarter of these workers transition into the lowest ranked occupations (RC, RM and NRM) after 12 months, and 18.98% leave the labor force. Therefore, unemployed chief executives are more likely to switch occupations (or even leave the labor force) than they are to find another job as a chief executive. While this exercise is not perfect, it does nevertheless indicate that it is relatively difficult for entrepreneurs to re-enter.

One concern, however, might be that the chief executive position is too narrowly defined. Nevertheless, after expanding the analysis to all managers,[9] not just chief executives, a similar story holds. To see this, consider the bottom panel of Table 1, which repeats the analysis for unemployed managers over the same time period. Between January 2003 and December 2012, there were 887,332 raw observations of managers, and 25,640 observations of unemployed managers. The management occupations are much more broadly defined, and may include many occupations that are not entrepreneurial in nature. Nevertheless, the results are qualitatively similar to those reported for chief executives. After 3 months, only about 8% of unemployed managers obtain another management job. After 12 months, this increases to 14%. In fact, as was the case with chief executives, unemployed managers are more likely to switch occupations or even leave the labor force than find another management job.

In the calibration, I will use the transition rates for chief executives to discipline the rate at which exiting entrepreneurs re-enter. Given the low rates at which unemployed chief executives find chief executive jobs, I will refer to this calibration as one in which re-entry is "limited." This is an interpretation that is guided by the model. In fact, as will be seen in the results, the model's predictions for entry and exit rates with "limited re-entry" turn out to be very similar to one in which there is no re-entry at all.

[9] In the 2002 and 2010 Census occupational classifications, the management occupations have codes between 10 and 430. The chief executive occupation has code 10.

4 Calibration

The model can now be calibrated. The model period is a quarter. Table 2 lists the calibrated parameters. First, in Section 4.1, I discuss how I calibrate the key parameters which govern the ability of entrepreneurs to re-enter. Second, in Section 4.2, I explain how the historical technology shock is measured from the data. And finally, in Section 4.3, I cover the calibration of the remaining parameters.

[Table 2 about here.]

4.1 Backing Out the Key Entry Parameters from the Data

I calibrate the model to be consistent with the unemployment-to-employment transition rates for chief executives, which were reported in Section 3. Specifically, I allow re-entry by assuming $\theta_x = 0$ and I calibrate the model so that potential re-entrants re-enter at the same rate unemployed chief executives find jobs as a chief executive. Very similar results are obtained when the model is calibrated to be consistent with the transition rates of managers. Consider the pool of surviving potential re-entrants in the steady state of the model at date 0. Let $p_{re,t}$ be the fraction of these potential entrants who re-enter in period $t \geq 1$. Since the model period is quarterly, in the benchmark calibration, I calibrate the model so that $p_{re,1}$ and $\sum_{t=1}^{4} p_{re,t}$ equal the 3-month and 12-month transition rates, respectively. Using the numbers reported in Table 1 for chief executives, this implies that $p_{re,1} = 3.92\%$ and $\sum_{t=1}^{4} p_{re,t} = 7.64\%$.

In the benchmark calibration, I assume that $\rho_{se} = 0$ (see Section 4.1.1 for a further discussion of this choice). Under this scenario, $p_{re,t}$ can be expressed analytically as follows:

$$p_{re,t} = \frac{\bar{m}_e}{1 - \bar{m}_e} \left[(1-\theta)(1-\bar{m}_e)\right]^t . \tag{15}$$

Here, $\bar{m}_e$ is the steady state fraction of potential entrants who enter (i.e. the entry probability). The entry probability was defined in Equation 12. Given the targets in the benchmark calibration for $p_{re,1}$ and $\sum_{t=1}^{4} p_{re,t}$, this requires that $\theta = 43.5\%$ and $\bar{m}_e = 6.9\%$. Now let $p_{re} \equiv \sum_{t=1}^{\infty} p_{re,t}$ be the fraction of surviving potential re-entrants at date 0 who *eventually* re-enter in the steady state. Using Equation 15, it can easily be shown that:

$$p_{re} = \frac{(1-\theta)\bar{m}_e}{\theta + (1-\theta)\bar{m}_e}. \tag{16}$$

Therefore, the calibrated values of $\theta = 43.5\%$ and $\bar{m}_e = 6.9\%$ imply that $p_{re} = 8.3\%$. Furthermore, let m_{re} be the steady-state fraction of all potential entrants who are potential re-entrants. It turns out that $m_{re} = p_{re}$. Therefore, to be consistent with unemployment-to-employment transition rates for chief executives, it needs to be the case that (1) exiting entrepreneurs have a low probability of re-entry, and (2) the number of potential re-entrants (or "serial entrepreneurs") should be small relative to all potential entrants.

Furthermore, this calibration approach implies that $\bar{m}_e$ should be a low number. This is consistent with the calibrated value for $\bar{m}_e$ in Macnamara (2014). It is perhaps also consistent with evidence from the venture capital literature. For example, Sahlman (1990) notes that typical large venture capital firms only invest in about 1% of the proposals it receives each year. However, venture capital plays a small role in the entry decisions. In particular, Robb et al. (2010) reports that in the Kauffman firm survey, less than 1% of startups receive any funding from venture capitalists. Nevertheless, this does potentially illustrate the difficulty in turning an idea into a new business.

4.1.1 Remaining Entry Parameters

As noted earlier, I set $\rho_{se} = 0$ in the benchmark calibration. Essentially, the entry signal is assumed to be independent across periods. In this sense, the decision not to enter is a destructive one, as the potential entrant does not retain its signal for productivity. Nevertheless, in Section 5.4.1, I compare the benchmark calibration to one in which $\rho_{se} = \rho_s$ and the results are unaffected. Given that $\rho_{se} = 0$, I set $\sigma_{\varepsilon se} = \sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$. The distribution, $g_n(\cdot)$, from which new potential entrants draw their signal is assumed to be log normal with mean a_{se} and standard deviation $\sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$. These assumptions will then imply that $V^w(\mathbf{x}, s_e)$ does not depend on s_e. Furthermore, the probability distribution of all potential entrants (over signal s_e) will be log normal with mean a_{se} and standard deviation $\sigma_{\varepsilon se}$. However, the total mass of potential entrants, $G = \int_0^\infty g(s_e)ds_e$, will vary with the aggregate state.

Furthermore, the target for $\bar{m}_e$ in the benchmark calibration is 6.9%. However, either c_e or a_{se} could be used to target the entry probability $\bar{m}_e$. Increasing c_e would tend to increase the entry threshold $\bar{s}_e(\mathbf{x})$. Given the distribution of potential entrants, $g(s_e)$, a higher entry threshold would tend to reduce $\bar{m}_e$. The alternative to this is to reduce a_{se} below zero. This would shift the potential entrant distribution $g(s_e)$ to the left. Holding the entry threshold constant, this would tend to cause $\bar{m}_e$ to fall. The latter approach does not require $\bar{s}_e$ to be above $\underline{s}$ to calibrate to a low $\bar{m}_e$. In contrast, calibrating c_e, by pushing $\bar{s}_e$ above $\underline{s}$, would tend to push up the relative size of entrants. For low $\bar{m}_e$, entrants would need to be larger than incumbent producers, which is not true in the data. Therefore, in the benchmark calibration, I set $c_e = 0$, and calibrate a_{se} to target $\bar{m}_e$. Nevertheless, in Section 5.4.3, I consider an alternative calibration in which $c_e > 0$ and find that the results are unaffected.

The remaining parameters related to entry and exit are $\bar{M}_e$ and c_f. First, consider the mass of potential entrants born each period, $\bar{M}_e$, which influences the number of entrepreneurs who operate in the steady state. If $\bar{M}_e$ is doubled, the equilibrium number of entrepreneurs who operate in the steady state is doubled as well. Given that $\bar{M}_e$ merely changes the scale of the economy, $\bar{M}_e$ is normalized to 1. Second, consider the fixed operating cost, c_f. This is set to target an average entry or exit rate of 3.2%. This is the average quarterly establishment entry rate between 1993:II and 2007-III from the BLS's Business Employment Dynamics (BED) survey.

4.2 Construction of the Technology Shock

Later in Section 5, I will feed into the model a sequence of technology shocks. Following Chari et al. (2007), I measure this shock by setting the sequence of $\{z_t\}$ so that the model-predicted fluctuations in output match those seen in the data. To be more precise, let $Y^m(\mathbf{x}_t)$ denote the model-predicted aggregate output, given the aggregate state $\mathbf{x}_t$ at date t. Now let $\hat{Y}^m(\mathbf{x}_t)$ denote the cyclical component of $Y^m(\mathbf{x}_t)$, which is constructed using a log-linear trend. Similarly, let $\hat{Y}_t^d$ be the corresponding series from the data. Then, I construct a sequence of shocks, $\{z_t\}$, to ensure that $\hat{Y}^m(\mathbf{x}_t) = \hat{Y}_t^d$ for each t. This procedure is not trivial, as the equilibrium of the model needs to be solved repeatedly to back out z_t.

Using quarterly seasonally adjusted real GDP from the BEA's National Income and Product Accounts (NIPA), I measure the technology shock between 1964-I and 2014-I. Figure 1 plots the resulting technology shock calculated using this procedure. Also plotted is the cyclical component of real GDP, which is constructed using the log-linear trend. The correlation of the technology shock with real GDP is very high (0.96).

[Figure 1 about here.]

Fitting this technology shock to the AR(1) process in Equation 1 yields estimates $\rho_z = 0.947$ and $\sigma_{\varepsilon z} = 0.0045$. The mean a_z is normalized to zero. While ρ_z is similar to the typical value used in the literature, this shock is less volatile than technology shocks constructed using the Solow residual. In particular, the standard calibration follows Cooley and Prescott (1995) who choose $\rho_z = 0.95$ and $\sigma_{\varepsilon z} = 0.007$. However, because of the assumption of decreasing returns to scale, the Solow residual[10] is not equivalent to the technology shock in this model. In fact, the model-predicted Solow residual has a higher volatility than the input technology shock. Moreover, it is highly correlated with the residual from the data, and exhibits similar volatility.

[10] Since there is no capital in the model, the Solow residual can be calculated assuming that the quarterly change in capital is zero.

4.3 Calibration of Remaining Parameters

This still leaves a the process for idiosyncratic productivity. The persistence of the idiosyncratic productivity shock was set to $\rho_s = 0.850$ and the standard deviation of the innovation was set to $\sigma_{\varepsilon s} = 0.103$. As in Macnamara (2014), these parameters were chosen to be consistent with values assumed in the literature. At an annual frequency, Khan and Thomas (2013) assume a persistence of 0.659 and an innovation standard deviation of 0.118. Meanwhile, Clementi and Palazzo (2014) assume a persistence of 0.55 and an innovation standard deviation of 0.22, at an annual frequency. In contrast, at an annual frequency, the values used in this paper are consistent with $\rho_s = 0.653$ and $\sigma_{\varepsilon s} = 0.135$.[11] Therefore, the persistence assumed in this paper is close to the value assumed by Khan and Thomas (2013) and more persistent than in Clementi and Palazzo (2014). Furthermore, the assumed value of $\sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$ in this paper falls in between the values assumed by Khan and Thomas (2013) and Clementi and Palazzo (2014). Nevertheless, in Section 5.4.2, I consider some alternative calibrations in which I let the persistence of idiosyncratic productivity be even higher. The results are unaffected.

The Frisch elasticity of labor supply, ν, was set to 1.5. According to Keane and Rogerson (2012), values commonly assumed in the literature range between 1 and 2. As for returns to scale in the model, I assumed that $\gamma = 0.6$. This implies that the labor share will be 60%. Given the estimation procedure for the technology shock, these parameters are not particularly important. A higher labor supply elasticity or higher returns to scale will tend to make aggregate labor demand more elastic as well as making entry and exit rates more sensitive to aggregate shocks. However, in such a case, the estimated technology shock would be less volatile. And finally, since the model period is assumed to be a quarter, the risk-free rate r was chosen to be 1%. The labor disutility parameter, ψ, was set to normalize the equilibrium wage to 1 in the steady state.

5 Results

The model is solved using dynamic programming techniques. Because the distribution of incumbents and entrants in the aggregate state $\mathbf{x}$ is a high-dimensional object, I apply the algorithm of Krusell and Smith (1998). When applying this algorithm, one potential problem is that forecast errors may accumulate over time. Applying the suggested accuracy

[11] Some caution is required when converting between annual and quarterly frequencies. Given the parameters for a productivity process at a quarterly frequency, (ρ_q, σ_q), the corresponding annual parameters (ρ_a, σ_a) were set so that one would obtain (ρ_a, σ_a) if the quarterly AR(1) process were estimated at an annual frequency.

check in Den Haan (2010), I find that this does not occur. Appendix A goes into more specific detail on the numerical methods used and reports the results of several accuracy tests.

First, in Section 5.1, I report the results of the benchmark calibration. Second, in Section 5.2, I conduct an experiment in which exiting entrepreneurs can re-enter at a higher rate than is observed in the data. I will label this the "Quick Re-Entry" experiment. In Section 5.3, I examine the mechanism behind these results by considering further alternative calibrations. I will label these the "Slow Re-Entry" and "No Re-Entry" calibrations, respectively, and they will differ in the ability of entrepreneurs to re-enter. And finally, in Section 5.4, I perform some robustness checks.

5.1 Fit of Benchmark Calibration

As discussed in Section 4.2, I used the benchmark model to back out an historical sequence of technology shocks. Then, starting with the steady state distributions of entrepreneurs and potential entrants, I fed these shocks back into the model. This procedure generates predictions for entry and exit rates, which can be compared to the data. As for data on entry and exit, I utilize establishment birth and death rates from the BLS's Business Employment Dynamics (BED) survey. In the BED survey, an establishment death is defined to occur when an establishment reports zero employment in the third month of a quarter and does not report positive employment in the third month of the next four quarters. The establishment birth rate is defined analogously. This strict definition of entry and exit eliminates most temporary or seasonal entry and exit. The data for entry begins in 1993-II, while the data for exit begins in 1992-III. This time period covers two recessions: the 2001 recession and the 2007-09 recession. Because the technology shock begins in 1964-I and the entry/exit data do not begin until 1992-III, this means that the model was simulated for 114 quarters (or 28.5 years) until it could generate results on entry and exit that could be compared to the data.

The left two panels of Figure 2 plot the benchmark calibration's predictions for entry and exit rates against the data. Entry and exit rates, in the model and in the data, are both de-trended with a linear trend. As in the data, entry rates are predicted to be procyclical and exit rates are predicted to be countercyclical. Table 3 reports the raw correlations and standard deviations. The model does well accounting for the decrease in entry rates and the increase in exit rates which occurred during the 2007-09 recession. It also does well accounting for the increase in exit rates which occurred during the 2001 recession. However, the model does predict a decrease in exit rates during the 2001 recession, which did not occur. Nevertheless, under the benchmark calibration in which few exiting entrepreneurs are able to re-enter, the model does very well overall explaining both entry and exit rates.

[Figure 2 about here.]

Meanwhile, the right panels of Figure 2 plot the benchmark calibration's predictions for output and hours against the data. The data for output is quarterly seasonally adjusted real GDP from the BEA's National Income and Product Accounts. Hours is obtained as the quarterly average of aggregate weekly hours of production and non-supervisory employees from the BLS's Current Employment Statistics survey. A log-linear trend is used to de-trend both output and hours, in the model and the data. In Figure 2, it can be seen that the model's predictions for output coincides with the data (by construction). The model's prediction for hours is highly correlated with the data, but less volatile. With only a technology shock in this paper, the model is better suited to explain fluctuations in output.

Moreover, the benchmark economy does well accounting for stylized facts that have not been targeted. Table 3 also reports the model's predictions for several of these statistics. In particular, in the steady state of the model, 66.6% of entrants survive after one year. According to the BLS's BED survey, 78.9% of private sector establishments survive after one year. In fact, for establishments born between 1994 and 2012, this survival rate has been stable around 79%. Furthermore, the benchmark calibration predicts that entrants will be smaller (in terms of employment) than incumbents, with entering producers on average 51.7% of the size of incumbents. According to the BED survey, the average relative size of entering establishments between 1994 and 2013 was 37.3%. However, since 1999, the relative size of entrants has been declining. In 1999, the relative size of entrants was about 45%, while by 2013 it had declined to 29%. Furthermore, in the steady state of the benchmark calibration, the productivity of entrants (relative to incumbents who operate) is 78.2%. Similarly, the productivity of exiting entrepreneurs (relative to incumbents who operate) is 67.8%. For manufacturing plants, Lee and Mukoyama (2013) report that entrants are 75% as productive as incumbent plants, while exiting plants are 65% as productive as incumbents.[12]

[Table 3 about here.]

5.2 Quick Re-Entry Experiment

At this stage, it is hopefully apparent that the benchmark calibration produces a reasonable description of the economy, since it does well accounting for the dynamics of entry

[12]Lee and Mukoyama (2013) report the relative productivity of entering and exiting plants to be 75% and 65%, respectively, when productivity is measured without capital.

and exit. Moreover, the results of the benchmark model are similar to Macnamara (2014), where it was assumed that exit is permanent. In contrast, exit is not permanent in this model, but it is still difficult for exiting entrepreneurs to re-enter in the future. This was motivated by the observation in Section 3 that very few unemployed chief executives (a proxy for entrepreneurs) return to employment as a chief executive after 12 months. Specifically, in Table 1, it was reported that only 7.64% of unemployed chief executives return to employment as chief executives after 12 months. This stands in contrast to a 56.46% job finding rate after 12 months. Therefore, to evaluate the economic significance of these transition rates, I now perform an experiment in which exiting entrepreneurs can re-enter more quickly than is suggested by the data. I label this calibration the "Quick Re-Entry" calibration.

To be more precise, I first feed into the model the *same* technology shock constructed with the benchmark economy, using the method described in Section 4.2. Second, I now calibrate the re-entry process so that exiting entrepreneurs re-enter at the same rate unemployed chief executives find *any* kind of job. Specifically, I calibrate the model to match the 3-month and 12-month job finding rates in Table 1. In other words, I calibrate the model so that $p_{re,1} = 30.49\%$ and $\sum_{t=1}^{4} p_{re,t} = 56.46\%$. Here, $p_{re,t}$ is the fraction of potential re-entrants who re-enter in period $t \geq 1$, conditional on surviving to period 0. Using Equation 15, this now requires that $\theta = 20.4\%$ and $\bar{m}_e = 38.3\%$. Following the same strategy as in the benchmark calibration, I set a_{se} to meet the new target for $\bar{m}_e$. Table 4 reports the new parameter values. Whereas in the benchmark calibration exiting entrepreneurs would eventually re-enter with a probability of 8.3%, these new calibration targets imply that 60.0% of exiting entrepreneurs will eventually re-enter (in the steady state). All other calibration targets are the same as in the benchmark calibration.

[Table 4 about here.]

The left two panels of Figure 3 plot the results of this experiment for entry and exit rates. It is apparent that quick re-entry would have a significant effect on the dynamics of entry rates, but less of an effect on the dynamics of exit rates. First, as confirmed in Table 3, entry rates would be significantly less volatile with quick re-entry. Second, after the 2007-09 recession, entry rates would have recovered much more quickly than was seen in the data. In fact, as seen in Table 3, the quick re-entry model produces the counterfactual implication that entry rates would be countercyclical. This is because many of the entrepreneurs that exit during the crisis would immediately start re-entering, causing an increase in entry rates. This suggests that the procyclicality of entry rates is a consequence of limited re-entry.

[Figure 3 about here.]

While quick re-entry certainly has large effects on the dynamics of entry, the important question is whether this has broader effects on the economy as a whole. For this purpose, consider the right two panels of Figure 3, which plots the Quick Re-Entry model's predictions for output and hours against the data. This shows that quick re-entry makes both output and hours less volatile, predictions which are confirmed in Table 3. Furthermore, quick re-entry has significant implications for the recovery of output after the 2007-09 recession. Whereas in the data (and the benchmark calibration), output is about 9.5% below trend in 2014-I, it would have only been 7% below trend in 2014-I with quick re-entry.

To see this result in another way, consider Figure 4, which plots the predicted recovery in output after the 2007-09 recession with quick re-entry. First, it restricts attention to the time period after 2007-IV, which is identified by NBER as the peak of the 2007-09 recession. Second, the model's prediction for output is shown with the data's log-linear trend. Therefore, while it does ignore any level effects on output, it nevertheless illustrates more clearly the effect quick re-entry has on the recovery of output after the 2007-09 recession. In the data, real GDP grew at an annual rate of 2.2% between 2009-II and 2014-I. In contrast, the model predicts that real GDP would have grown at an annual rate of 2.7% over the same time period with quick re-entry. This difference of 0.5% in growth is significant. This suggests that the inability of exiting entrepreneurs to re-enter, as suggested by the CPS data, has been a contributing factor to the slow recovery in output that followed the 2007-09 recession.

[Figure 4 about here.]

5.2.1 Impulse Responses

To gain more intuition about these results, consider Figure 5, which compares the impulse responses generated by the Quick Re-Entry experiment to those generated under the benchmark economy. Each impulse response is generated by a one standard deviation *decrease* in the innovation to aggregate productivity at date 0. First, consider the left two panels of Figure 5, which plot the impulse responses for entry and exit rates. As seen before, quick re-entry has a large effect on the response of entry rates. While entry rates fall on impact, they increase above the steady state level only one quarter after the shock. In contrast, the dynamics of exit rates are similar under the two calibrations. However, with quick re-entry, exit rates take longer to return to normal.

[Figure 5 about here.]

Moreover, with quick re-entry, both entry and exit rates are less sensitive to technology shocks. Using the results of Macnamara (2014), elasticities for entry and exit rates can be derived for entry and exit rates as follows:

$$\frac{d\ln m_e}{d\ln z} = -h_e(\bar{s}_e)\frac{d\ln \bar{s}_e}{d\ln z}$$
$$\frac{d\ln m_x}{d\ln z} = h_x(\underline{s})\frac{d\ln \underline{s}}{d\ln z}.$$

Note that $h_e(\bar{s}_e) = [g(\bar{s}_e)\bar{s}_e/G]/\bar{m}_e$ is the hazard rate for entry and $h_x(\underline{s}) = [\mu(\underline{s})\underline{s}/M]/m_x$ is the hazard rate for exit. Therefore, for both entry and exit rates, there are two components which determine the quantitative impact of a technology shock. The first is the hazard rate, which reflects how many entrepreneurs are near the productivity cutoff relative to all entrepreneurs who enter or exit, respectively. The second component is the slope of the corresponding productivity cutoff, which reflects how much the cutoff responds to the aggregate shock.

Table 5 reports the steady state hazard rates for entry and exit under each calibration. With quick re-entry, it turns out that the hazard rate for entry is smaller in the steady state. Nevertheless, the hazard rate for exit is very similar in the two calibrations. The reason for this is that $\bar{m}_e$ is higher under Quick Re-Entry, but m_x is still calibrated to the same value. With a higher entry probability, a change in the entry threshold has a smaller effect on the total number of entrants. Nevertheless, it turns out that both the entry and exit productivity cutoffs are less sensitive to technology shocks with quick re-entry. This can be seen in the middle panels of Figure 5, which show the impulse responses for the entry and exit thresholds. The intuition behind this result can be seen from the entry and exit cutoff rules defined in Equations 4 and 5. A decrease in technology tends to reduce the value of operating. Everything else being equal, this tends to increase the cutoff productivity for both entry and exit. However, a decrease in technology also lowers the value of waiting. Since the value of waiting is affected more with quick re-entry, this implies that the entry and exit cutoffs are less affected by the same technology shock in the Quick Re-Entry calibration.

Moreover, the different response of entry and exit rates has implications for the behavior of output and hours. The right two panels of Figure 5 plot the impulse responses for output and hours. It can be seen that both output and hours are less affected on impact under the Quick Re-Entry experiment. Moreover, because entry and exit are less affected by the technology shock, the number of entrepreneurs who operate is also less affected. As a consequence, both output and hours recover more quickly. This suggests that output would be less persistent with quick re-entry.

Furthermore, these results highlight the importance of limited re-entry for the amplification result in the literature. In particular, Clementi and Palazzo (2014) find that entry and exit further amplify and propagate the effects of aggregate shocks. Macnamara (2014) obtained a similar result in a model with both financial and technology shocks. Devereux et al. (1996), Bilbiie et al. (2012), Jaimovich and Floetotto (2008) and Chatterjee and Cooper (2014) have found similar results in models with monopolistic competition. However, the quick re-entry experiment demonstrates that the magnitude of this effect is dependent on limited re-entry. With quick re-entry, not only would aggregate output be less volatile, but it would be quicker to recover in response to aggregate shocks. Therefore, when exit is more permanent, entry and exit tend to make aggregate output more volatile and more persistent.

5.2.2 Contribution of Re-Entry to the Total Entry Rate

Given the quick recovery in entry rates in the Quick Re-Entry experiment, one question is how much of this prediction is driven by the re-entry of old entrepreneurs and how much is driven by the entry of new entrants. It turns out that most of the recovery in entry rates after 2007-09 is driven mostly by re-entry. To see this, it is useful to decompose the entry rate as follows: $m_e = m_{ne} + m_{xe}$. Let m_{ne} denote the "new entry rate." In other words, this is the part of the entry rate arising only from entrants who have never previously operated. Analogously, let m_{xe} denote the "re-entry rate." This is the portion of the entry rate arising from re-entrants. In the steady state of the benchmark model, it was the case that $m_{ne} = 3\%$ and $m_{xe} = 0.3\%$. Consequently, re-entry made up a very small portion of the total entry rate. In contrast, in the quick re-entry model, $m_{ne} = 1.3\%$ and $m_{xe} = 2\%$. Not surprisingly, with quick re-entry, potential re-entrants made up a larger portion of all potential entrants. Therefore, re-entry made up a larger portion of the total entry rate.

Furthermore, it can be seen from Figure 6 that changes in re-entry drive changes in entry rates in the Quick Re-Entry experiment. For the benchmark economy, the top panel of Figure 6 plots m_{ne}, m_{xe} and m_e against the entry rate in the data. The bottom panel of Figure 6 does the same for the Quick Re-Entry experiment. In the benchmark economy, m_{xe} is so small that changes in m_{ne} drive changes in m_e. However, in the Quick Re-Entry economy, m_{xe} is relative large. Consequently changes in re-entry appear to drive most of the changes in the overall entry rate, m_e.

[Figure 6 about here.]

5.2.3 Effect of Quick Re-Entry on Aggregate Productivity

Furthermore, quick re-entry has consequences for aggregate productivity. For example, Foster et al. (2001) find that entry and exit contribute to long-run productivity growth, as entrants tend to be more productive than the exiting plants they replace. While the long-run growth rate is zero in this model, this is the mechanism by which entry and exit will increase the level of aggregate productivity. To see this, consider Table 5, which reports the average log productivity of entrants and exiting producers under the benchmark calibration and the Quick Re-Entry experiment. In both economies, entering producers are more productive than the exiting producers they replace. As a consequence, the average productivity of *all* producers (who operate) is above zero. Without entry and exit, the average productivity would have been zero, which is the mean of the invariant distribution for idiosyncratic productivity.

[Table 5 about here.]

In fact, the productivity advantage of entrants over exiting producers is larger under the Quick Re-Entry experiment. As a consequence, the average productivity of all producers (who operate) is higher under the Quick Re-Entry experiment. This is because the cutoff productivity for entry and exit is higher with quick re-entry. The intuition behind this result can be seen from the entry and exit cutoff rules defined in Equations 4 and 5. The ability to re-enter quickly under the Quick Re-Entry experiment tends to increase the value of waiting. As a consequence, marginal entrepreneurs, who would have operated in the benchmark calibration, will choose to exit and wait under the Quick Re-Entry calibration. The same is true for potential entrants. This tends to raise the productivity of all entrepreneurs who operate. Therefore, while models along the lines of Hopenhayn (1992) predict that the selection introduced by entry and exit will raise aggregate productivity, these results indicate that this selection effect is hampered by limited re-entry.

5.3 Further Alternative Calibrations

To further clarify the mechanism behind these results, I compare the benchmark calibration to an additional two calibrations. In the first alternative calibration, I assume $\theta = \theta_x = 1$, implying that exiting entrepreneurs cannot re-enter and potential entrants cannot delay entry. I label this the "No Re-Entry" calibration. To be consistent with the benchmark calibration, I maintain the original target for $\bar{m}_e$, which was 6.9%. In the second calibration, I allow re-entry, but assume that it takes much longer for exiting entrepreneurs to re-enter. Consequently, I label this the "Slow Re-Entry" calibration. All other calibration targets remain the same. Table 4 reports the parameter values assumed in these calibrations.

To be more specific, recall that in the Quick Re-Entry calibration, $p_{re} = 60\%$. In other words, 60% of exiting entrepreneurs eventually re-enter in the steady state. Moreover, let $t_{re} = \frac{1}{p_{re}} \sum_{t=1}^{\infty} t p_{re,t}$ denote the average number of quarters it takes for an exiting entrepreneur to re-enter in the steady state, conditional on re-entry. Using Equations 15 and 16, this can be shown to be

$$t_{re} = \frac{1}{\theta + (1-\theta)\bar{m}_e} \tag{17}$$

when $\rho_{se} = 0$. In the Quick Re-Entry calibration, t_{re} was equal to 2 quarters. Therefore, in the Slow Re-Entry calibration, I assume that $p_{re} = 60\%$, but now assume that $t_{re} = 12$ quarters (or three years). In other words, exiting entrepreneurs are just as likely to re-enter as in the Quick Re-Entry experiment, but it will take six times as long. Using Equations 16 and 17, this requires that $\theta = (1 - p_{re})/t_{re} \approx 3.33\%$ and $\bar{m}_e = p_{re}/(p_{re} + t_{re} - 1) \approx 5.17\%$ in the Slow Re-Entry calibration.

Next, for each of the two alternative calibrations, I feed into the model the technology shock measured using the benchmark economy. It turns out that the dynamics of both entry and exit are very similar to the benchmark calibration under both the No Re-Entry and Slow Re-Entry calibrations. The same is true for output and hours. Although 60% of exiting entrepreneurs are eventually able to re-enter in the steady state of the Slow Re-Entry calibration, only 5% re-enter in the first quarter after exit. In the benchmark calibration, the corresponding number was 3.9%. In contrast, 30% of exiting entrepreneurs re-enter in the first quarter after exit under the Quick Re-Entry calibration. Therefore, in the benchmark calibration and the Slow Re-Entry calibration, few entrepreneurs actually re-enter shortly after exit, which means that re-entry has a small effect on the dynamics of entry.

To understand this further, it is useful to decompose fluctuations in entry rates as follows:

$$\hat{m}_e = \hat{M}_e - \hat{M} = \left[\hat{G} + \hat{\bar{m}}_e\right] - \hat{M}. \tag{18}$$

This uses the definition of the entry rate in Equation 11. To express each variable in terms of the percentage deviation from its steady state value, I indicate this using a circumflex (e.g., $\hat{m}_e$ is the percent deviation of m_e from its steady state value). Therefore, fluctuations in the entry rate can be decomposed into fluctuations in the mass of entrants ($\hat{M}_e$) minus fluctuations in the mass of incumbent entrepreneurs ($\hat{M}$). Using Equation 12, $\hat{M}_e$ can be decomposed further into fluctuations in the mass of potential entrants ($\hat{G}$) plus fluctuations in the entry probability ($\hat{\bar{m}}_e$).

For each calibration, Figure 7 plots the impulse responses for the individual components of $\hat{m}_e$ in Equation 18. Each impulse response is generated by a unit standard deviation decrease in technology at date 0. The top-left panel of Figure 7 plots the impulse response for the mass of potential entrants and the bottom-left panel shows the entry probability. The top-right panel shows the mass of entrants, which is just the sum of the left two panels. The bottom-right panel shows fluctuations in the mass of incumbents. Consequently, the percentage change in the entry rate is just the top-right panel minus the bottom-right panel.

[Figure 7 about here.]

First, consider the benchmark, Slow Re-Entry and No Re-Entry calibrations. From Figure 7 it can be seen that the model's predictions are very similar for these economies. The only exception to this is the model's predictions for fluctuations in the mass of potential entrants. In the No Re-Entry calibration, the mass of potential entrants is constant by assumption. In the benchmark calibration, the mass of potential entrants is still quite stable, but does tend to rise during periods of low aggregate productivity. However, in the Slow Re-Entry calibration, the mass of potential entrants is much more volatile. However, despite the fact that $\hat{M}_e = \hat{G} + \hat{\bar{m}}_e$, the mass of entrants still behaves quite similarly for these three economies. Even though $\hat{G}$ is more volatile in the Slow Re-Entry calibration, it is not enough to have a large effect on $\hat{M}_e$. In fact, in the Slow Re-Entry calibration, the mass of potential entrants ($\hat{G}$) rises too slowly to have a large effect on the dynamics of $\hat{M}_e$.

Not surprisingly, the starkest differences can be seen in the predictions of the Quick Re-Entry calibration. The mass of potential entrants is most volatile in this calibration. A decrease in technology leads to an increase in exit rates, which causes a large increase in the mass of potential entrants with quick re-entry. However, since the entry threshold is less sensitive to technology shocks, the entry probability is less affected by the negative technology shock. As a consequence, the mass of entrants is much less affected, which dampens the effect of the technology shock on the mass of incumbent producers.

The similarity of the benchmark and No Re-Entry calibrations suggests that models can safely abstract from re-entry. While not shown, the benchmark and No Re-Entry calibrations are also very similar to one in which re-entry is disabled, but not delayed entry. Re-entry is so limited in the data that a model with (limited) re-entry performs just as well as a model without this feature. While it has been assumed in the literature that exit is permanent, the benchmark model, calibrated to be consistent with the empirical evidence reported in Section 3, confirms that this is a justifiable assumption. Nevertheless, the quick re-entry experiment highlights the economic consequences of limited re-entry (or permanent exit), which have not been explored in the literature.

5.4 Robustness Checks

I now evaluate whether these results are robust to some of the key modeling assumptions. First, in Section 5.4.1, I consider how the results change if $\rho_{se} > 0$. Second, in Section 5.4.2, I consider different assumptions for the idiosyncratic productivity process. And finally, in Section 5.4.3, I examine alternative assumptions on the entry cost.

5.4.1 Persistence of Signal Process

One key assumption of the benchmark calibration was that $\rho_{se} = 0$. This meant that an exiting entrepreneur's idiosyncratic productivity had no relevance for its entry signal. The skills or intellectual capital encompassed by the producer are essentially lost by the decision to exit. Similarly, a potential entrant's signal today had no relevance for its signal tomorrow. The skills of a potential entrant are assumed to be lost by the decision not to enter. However, one advantage of this assumption was that it made it possible to derive closed form expressions for p_{re} and t_{re}. To evaluate whether this has affected the results, I now relax this assumption.

Specifically, I assume that $\rho_{se} = \rho_s$ and $\sigma_{\varepsilon se} = \sigma_{\varepsilon s}$. In other words, the persistence of the signal is the same as the persistence of idiosyncratic productivity. Assuming $\sigma_{\varepsilon se} = \sigma_{\varepsilon s}$ implies that the invariant distribution of $\ln s_e$ will still have the same variance as the invariant distribution of $\ln s$. Furthermore, I still assume that $g_n(\cdot)$, the distribution from which new potential entrants draw their initial signal, is log normal with mean a_{se} and standard deviation $\sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$. All other parameters are re-calibrated to maintain the original targets of the benchmark model. However, now θ and $\bar{m}_e$ cannot be determined directly as Equation 15 no longer holds. Therefore, I directly calibrate θ and a_{se} to meet the benchmark calibration's targets for $p_{re,1}$ and $\sum_{t=1}^{4} p_{re,t}$.

I then repeat the same exercise as in Sections 5.1 and 5.2. Specifically, I used the model with persistent signals to back out a historical sequence of technology shocks. It turns out that the sequence of technology shocks calculated using the calibration with persistent signals is very similar to those obtained under the benchmark calibration. Specifically, the maximum percentage difference (in absolute value) between the two shock sequences was 0.27%. Then, as before, I feed in this sequence of technology shocks back into the model with persistent signals. It turns out that the model's predictions for entry, exit rates, output and hours are unchanged. In fact, the differences are negligible.

[Figure 8 about here.]

Next, I repeat the Quick Re-Entry experiment with persistent signals. Figure 8 plots the resulting dynamics of entry and exit rates against the data. Also plotted are the dynamics of entry and exit rates under the original Quick Re-Entry experiment. With persistent signals, entry and exit are more volatile. Focusing in particular on 2007-09 recession, entry rates recover even faster with persistent signals. Exit rates increase even more with persistent signals, as now exit is less destructive to the entrepreneur. The effect on the dynamics of output and hours (not shown) are similar as before. However, with persistent signals, model predicts that the average growth rate of real GDP between 2009-II and 2014-I would have been 2.8%, instead of 2.7%. Therefore, the assumption of $\rho_{se} = 0$ in the benchmark calibration has no effect on the core results.

5.4.2 Process for Idiosyncratic Productivity

Up to this point, it has been assumed that $\rho_s = 0.850$ and $\sigma_{\varepsilon s} = 0.103$. To evaluate whether this has affected the results, I consider two alternative calibrations in which the process for idiosyncratic productivity differs. First, I suppose $\rho_s = 0.90$, but $\sigma_{\varepsilon s} = 0.085$. In this case, the persistence is higher, but $\sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$ is still equal to 19.6%. Second, I suppose $\rho_s = 0.90$, but $\sigma_{\varepsilon s} = 0.103$. This will now imply that $\sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$ is higher. I then repeat same exercises as in Sections 5.1 and 5.2. Specifically, I first use the model to back out a sequence of technology shocks, and then feed these shocks back into the model. Second, I repeat the Quick Re-Entry experiment.

Under both calibrations, the results turn out to be very similar. In particular, the alternative assumptions on $(\rho_s, \sigma_{\varepsilon s})$ do reduce the sensitivity of entry and exit rates to aggregate shocks. Nevertheless, the estimated technology shock tends to be more volatile for $(\rho_s, \sigma_{\varepsilon s}) = (0.90, 0.085)$, and even more volatile for $(\rho_s, \sigma_{\varepsilon s}) = (0.90, 0.103)$. Whereas $(\rho_z, \sigma_{\varepsilon z}) = (0.947, 0.0045)$ in the benchmark economy, $(\rho_z, \sigma_{\varepsilon z}) = (0.952, 0.0046)$ when $(\rho_s, \sigma_{\varepsilon s}) = (0.90, 0.085)$. In other words, the technology shock becomes more persistent, and $\sigma_{\varepsilon z}/\sqrt{1-\rho_z^2}$ rises from 1.41% to 1.50%. When $(\rho_s, \sigma_{\varepsilon s}) = (0.90, 0.103)$, it turns out that $(\rho_z, \sigma_{\varepsilon z}) = (0.954, 0.0047)$. The technology shock, therefore, becomes even more persistent and $\sigma_{\varepsilon z}/\sqrt{1-\rho_z^2}$ increases to 1.58%. Therefore, changes in the aggregate productivity process offset the impact of changes in the idiosyncratic productivity process.

5.4.3 Entry Cost

And finally, up until this point, it has been assumed that $c_e = 0$. In contrast, I now consider two alternative calibrations where $c_e > 0$. Because $c_e > 0$, it will now be the case that $\underline{s}(\mathbf{x}) < \bar{s}_e(\mathbf{x})$, and this will tend to push up the relative size of entrants. In Clementi and Palazzo (2014), the ratio between c_e and the expected value of c_f (which was stochastic) was 0.96. Therefore, in one scenario, I assume c_e is constant and $c_e = 0.96c_f$. In another scenario, I allow c_e to vary countercyclically. In particular, I assume $c_e = \bar{c}_e \exp\left[-\beta_z \left(\ln z - a_z\right)\right]$, where $\beta_z > 0$. This will imply that the entry cost will rise during recessions, making entry more difficult. For this calibration, I assume $\beta_z = 3$ and $\bar{c}_e = 0.96c_f$. Therefore, when $\ln z = a_z$, the entry cost will be the same as in the case when c_e is constant. Moreover, because $\beta_z = 3$, a 1% decrease in technology will lead to a 3% increase in the entry cost. While they had a two-stage entry condition, this is roughly consistent with the cyclical entry costs assumed by Lee and Mukoyama (2013). All other calibration targets are the same.

As before, I repeat the same exercises as in Section 5.1 and 5.2. The results turn out to be very similar. On the one hand, the estimated technology shocks turn out be less volatile when the entry costs are positive. Whereas $(\rho_z, \sigma_{\varepsilon z}) = (0.947, 0.0045)$ in the benchmark economy, $(\rho_z, \sigma_{\varepsilon z}) = (0.944, 0.0044)$ in the case of a constant entry cost. In other words, $\sigma_{\varepsilon z}/\sqrt{1-\rho_z^2}$ falls from 1.41% to 1.34%. When the entry cost is countercyclical, $(\rho_z, \sigma_{\varepsilon z}) = (0.940, 0.0044)$ and $\sigma_{\varepsilon z}/\sqrt{1-\rho_z^2}$ falls to 1.29%. Despite a technology shock that is less volatile, entry rates in the (re-calibrated) benchmark economy turn out to be more volatile when the entry cost is countercyclical. For example, in the original benchmark calibration, the standard deviation of HP-filtered entry rates was 3.8%. In the cast of a constant entry cost, this falls to 3.4%, but rises to 4.3% in the case of a countercyclical entry cost. Despite the small differences, the results of the benchmark and quick re-entry economies are qualitatively the same.

6 Conclusion

This paper studies the consequences of "limited re-entry" for macroeconomic dynamics. First, matched individual-level data from the CPS indicate that it is very difficult for exiting entrepreneurs to re-enter in the future. Using unemployed chief executives as a proxy for exiting entrepreneurs, it is observed that only about 4% of these individuals find employment again as a chief executive after 3 months. After 12 months, this number increases to only 8%. Given the close relationship between chief executives and the role of entrepreneurs in the model, I take this as evidence that re-entry is "limited." Second, this paper builds a model of firm dynamics to study the consequences of limited re-entry for the aggregate economy. Calibrating the model to be consistent with the observed unemployment-to-employment transition rates for chief executives, the model indicates that limited re-entry has increased the volatility of output and slowed the recovery in output following the 2007-09 recession.

While it has been assumed in the literature that exit is permanent, the empirical evidence reported in this paper confirms that this is a justifiable assumption. Nevertheless, this paper still highlights the economic consequences of limited re-entry or permanent exit, which has not been explored in the literature. For example, these results demonstrate that aggregate output is more volatile and more persistent because of permanent exit. Moreover, while entry and exit tend to raise aggregate productivity in models derived from Hopenhayn (1992), these results demonstrate that aggregate productivity would be even higher if quick re-entry was possible. With permanent exit, many low-productivity entrepreneurs choose to operate because they do not have the option to re-enter later.

While the data in this paper refers to the entry and exit of establishments, the analysis can be extended to the entry and exit of firms, the creation or discontinuation of product lines, or a company's entry into or exit from markets. Nevertheless, this paper suggests that limited re-entry of any form has significant effects on the aggregate economy. The model, however, does not take a stand as to why re-entry is difficult. This is a question for future research. However, it does suggest that policies which make re-entry easier could raise aggregate productivity and reduce the volatility of output.

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A Computational Method

The entrepreneur's value functions are approximated by value function iteration. The aggregate state $\mathbf{x}$ includes μ and g, both of which are high-dimensional objects. Therefore, I applied the algorithm of Krusell and Smith (1998) by assuming that agents are boundedly rational in their perceptions of μ and g. In particular, I assumed that agents only perceived the aggregate state as $(z, \bar{\Gamma})$, where $\bar{\Gamma}$ is the productivity-weighted mass of incumbents and potential entrants:

$$\bar{\Gamma} \equiv \int_0^\infty s^{1/(1-\gamma)} \mu(s) ds + \int_0^\infty s_e^{1/(1-\gamma)} g(s_e) ds_e.$$

Moreover, define a_Γ to be the mean of $\ln \bar{\Gamma}$ in the steady state. Similarly, Γ is defined as the productivity-weighted mass of incumbents and potential entrants who actually operate:

$$\Gamma \equiv \int_{\underline{s}}^\infty s^{1/(1-\gamma)} \mu(s) ds + \int_{\bar{s}_e}^\infty s_e^{1/(1-\gamma)} g(s_e) ds_e.$$

When $f(z,s,n) = zsn^\gamma$, the optimal labor demand is $n(z,s;w) = [\gamma zs/w]^{1/(1-\gamma)}$. The policy rule $n(z,s;w)$ is the function which solves the static maximization problem in Equation 8. Then, the equilibrium wage should satisfy

$$\ln w = c + \frac{1}{1+\nu(1-\gamma)} \ln z + \frac{1-\gamma}{1+\nu(1-\gamma)} \ln \Gamma \tag{A.1}$$

where the parameter c is a constant which depends only on parameters. Since Γ depends on the entry and exit thresholds, I use $\bar{\Gamma}$ instead of Γ in the numerical calculations to approximate Equation A.1 with

$$\ln w \approx \frac{1}{1+\nu(1-\gamma)} \left(\ln z - a_z\right) + \frac{1-\gamma}{1+\nu(1-\gamma)} \left(\ln \Gamma - a_\Gamma\right). \tag{A.2}$$

The parameter c depends on ψ, which determines the household's disutility from working. Therefore, I set ψ to guarantee that the wage is 1 in the steady state. Using $\bar{\Gamma}$ instead of Γ turns out to be a reasonable approximation. After simulating the benchmark model for 10,500 periods and dropping the first 500 observations, the maximum wage error (in absolute value) from this approximation was 0.21%. In the Quick Re-Entry model, the maximum wage error was even lower (0.06%). Furthermore, since agents need to know tomorrow's $\bar{\Gamma}$ to determine wages in the future, I suppose that $\bar{\Gamma}$ obeys the following law of motion:

$$\ln \bar{\Gamma} = \beta_0 + \beta_1 \ln \bar{\Gamma} + \beta_2 \ln z. \tag{A.3}$$

In Appendix A.4 , I discuss the accuracy of this forecasting rule.

Then, to solve the model, the following algorithm is used.

1. Construct an artificial sequence of technology shocks, $\{z_t\} = (z_1, z_2, \ldots, z_T)$, for $T = 10,500$.
2. Start with an initial guess for $(\beta_0, \beta_1, \beta_2)$.
3. Approximate the value functions $V(\ln z, \ln \bar{\Gamma}, \ln s)$ and $V^w(\ln z, \ln \bar{\Gamma}, \ln s_e)$ using the algorithm from Appendix A.1.
4. Approximate the steady state distributions, $\mu(\ln s)$ and $g(\ln s_e)$, using the algorithm in Appendix A.2.
5. Simulate the economy under $\{z_t\}$, using the algorithm in Appendix A.3.

6. Using the simulation results, estimate $(\beta_0', \beta_1', \beta_2')$ via the following OLS regression:

$$\ln \bar{\Gamma}_{t+1} = \beta_0' + \beta_1' \ln \bar{\Gamma}_t + \beta_2' \ln z_t + u_t.$$

   Drop the all observations for $t = 1, \ldots, t_0$, where $t_0 = 500$. If $(\beta_0', \beta_1', \beta_2')$ is sufficiently close to the initial guess, $(\beta_0, \beta_1, \beta_2)$, stop. Otherwise, return to step 2. To ensure convergence, return to step 2 with a convex combination of $(\beta_0, \beta_1, \beta_2)$ and $(\beta_0', \beta_1', \beta_2')$.

A.1 Approximation of Value Functions

In this case, the entrepreneur's value function has three state variables, current-period productivity $\ln s$ and the aggregate state $(\ln z, \ln \bar{\Gamma})$. The value of operating and the value of waiting are then jointly solved by iterating on the Bellman equations defined in Equations 9 and 10. The details of the algorithm can then be described as follows.

1. Define the grid points for the state variables $(\ln z, \ln \bar{\Gamma}, \ln s)$.
2. Start with an initial guess for $(\beta_0, \beta_1, \beta_2)$.
3. Start with some initial guess for the value functions $V_0(\ln z, \ln \bar{\Gamma}, \ln s)$ and $V_0^w(\ln z, \ln \bar{\Gamma}, \ln s)$.
4. Given $V_n(\ln z, \ln \bar{\Gamma}, \ln s)$ and $V_n^w(\ln z, \ln \bar{\Gamma}, \ln s)$, do the following for each $(\ln z, \ln \bar{\Gamma}, \ln s)$ on the grid:
   (a) Calculate the optimal labor demand, $n(z, s; w) = [\gamma z s / w]^{1/(1-\gamma)}$. Calculate the equilibrium wage using Equation A.2.
   (b) Using the law of motion for $\ln \bar{\Gamma}$ in Equation A.3, calculate the tomorrow's set of liquidation cutoffs, $\underline{s}(\ln z', \ln \bar{\Gamma}')$, and entry cutoffs, $\bar{s}_e(\ln z', \ln \bar{\Gamma}')$. To interpolate the value functions between grid points, the log of V_n and V_n^w are interpolated with trilinear interpolation.
   (c) Given the optimal choice of labor, approximate the entrepreneur's value, $V_{n+1}(\ln z, \ln \bar{\Gamma}, \ln s)$ and the value of waiting $V_{n+1}^w(\ln z, \ln \bar{\Gamma}, \ln s)$. The key difficulty is the need to calculate the continuation values in the value of operating and the value of waiting. For accuracy reasons, the processes for z and s are *not* approximated with a discrete Markov process as in Tauchen (1986). Thus, this integral is numerically approximated using an adaptive integration routine from the GNU Scientific Library.
5. Keep iterating until $V_n(\ln z, \ln \bar{\Gamma}, \ln s)$ and $V_n^w(\ln z, \ln \bar{\Gamma}, \ln s)$ converge.

A.2 Approximation of Steady State Distributions

Let $\mu(\ln s)$ be a function representing the distribution of incumbent entrepreneurs over productivity at the beginning of the period. Similarly, let $g(\ln s_e)$ be a function representing the distribution of potential entrants over the entry signal. The steady state μ and g are calculated by jointly iterating on the transition rules in Equations 6 and 7. The details of the algorithm can then be described as follows.

1. Define a grid for the idiosyncratic productivity $\ln s$ and the signal $\ln s_e$.

2. Given the value functions $V(\ln z, \ln \bar{\Gamma}, \ln s)$ and $V^w(\ln s, \ln \bar{\Gamma}, \ln s_e)$, calculate the entry cutoff $\bar{s}_e$ and exit cutoff $\underline{s}$ for $\ln z = a_z$ and $\ln \bar{\Gamma} = a_\Gamma$. Given $(\beta_0, \beta_1, \beta_2)$, a_Γ is computed as $a_\Gamma = (\beta_0 + \beta_2 a_z)/(1 - \beta_1)$. This procedure yields the steady state entry and exit cutoffs.

3. Start with some initial guess for the distributions, $\mu_0(\ln s)$ and $g_0(\ln s_e)$.

4. Given $\mu_n(\ln s)$ and $g_n(\ln s_e)$, compute $\mu_{n+1}(\ln s')$ and $g_{n+1}(\ln s'_e)$ using Equations 6 and 7. These integrals are numerically approximated using an adaptive quadrature routine from the GSL Scientific Library. When calculating this integral, the prior distributions, $\mu_n(\ln s)$ and $g_n(\ln s_e)$, are interpolated using linear interpolation.

5. Keep iterating until $\mu_n(\ln s)$ and $g_n(\ln s_e)$ converge.

A.3 Simulation

To simulate the model by feeding in a history of aggregate shocks, $\{z_t\} = (z_1, z_2, \ldots, z_T)$, the following approach was used.

1. Take as a given the entrepreneur's value functions $V(\ln z, \ln \bar{\Gamma}, \ln s)$ and $V^w(\ln z, \ln \bar{\Gamma}, \ln s_e)$, which implicitly depend on $(\beta_0, \beta_1, \beta_2)$.

2. Initialize the distributions, $\mu_0(\ln s)$ and $g_0(\ln s_e)$, to their steady state values.

3. For each t, given distributions $\mu_t(\ln s)$ and $g_t(\ln s_e)$ at the beginning of the period, do the following:

   (a) Calculate the current period productivity-weighted mass of incumbents and entrants, $\bar{\Gamma}_t$.

   (b) Solve for $\underline{s}(\ln z_t, \ln \bar{\Gamma}_t)$ and $\bar{s}_e(\ln z_t, \ln \bar{\Gamma}_t)$. To interpolate the value functions between the grid points, the log of V and V^w are interpolated with trilinear interpolation.

(c) Calculate the mass of entrants ($M_{e,t}$), mass of exiting entrepreneurs ($M_{x,t}$) and the mass of incumbent entrepreneurs (M_t) in period t. These statistics are calculated by approximating the following integrals:

$$\begin{aligned} M_{e,t} &= \int_{\ln \bar{s}_e(\ln z_t, \ln \bar{\Gamma}_t)}^{\infty} g_t(\ln s_e) d \ln s_e \\ M_{x,t} &= \int_{-\infty}^{\ln \underline{s}(\ln z_t, \ln \bar{\Gamma}_t)} \mu_t(\ln s) d \ln s \\ M_t &= \int_{-\infty}^{\infty} \mu_t(\ln s) d \ln s. \end{aligned}$$

These integrals are numerically approximated using an adaptive quadrature routine from the GSL Scientific Library. The distributions $g_t(\cdot)$ and $\mu_t(\cdot)$ are interpolated using linear interpolation.

(d) Calculate the period-t entry and exit rates:

$$\begin{aligned} m_{e,t} &= M_{e,t}/M_t \\ m_{x,t} &= M_{x,t}/M_t. \end{aligned}$$

(e) Using Equations 6 and 7, update the distributions, $\mu_{t+1}(\ln s)$ and $g_{t+1}(\ln s_e)$, for next period.

A.4 Accuracy of Forecasting Rule

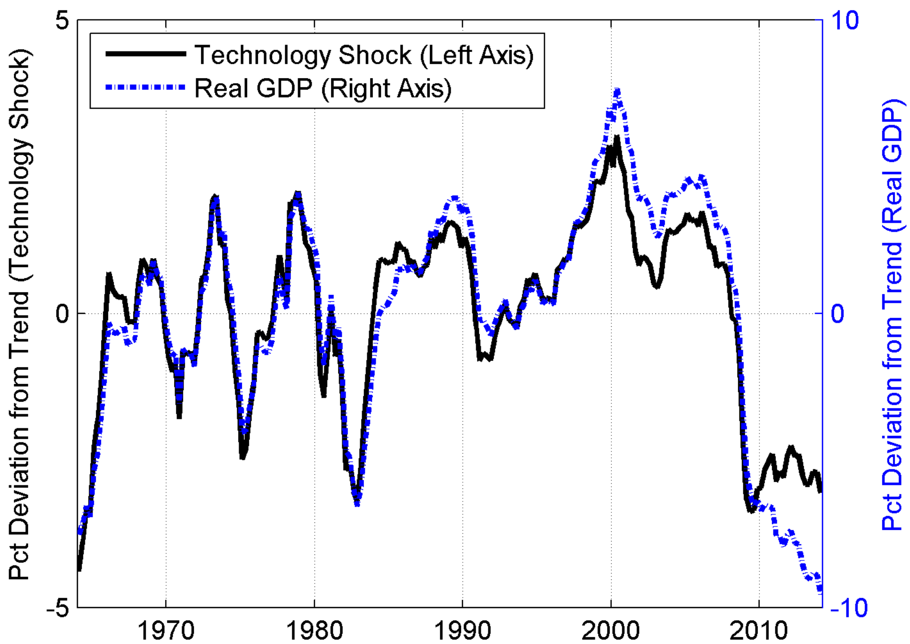
As noted before, I applied the algorithm of Krusell and Smith (1998) to solve the model. In the benchmark economy, the parameters of the forecasting rule in Equation A.3 were estimated to be $(\beta_0, \beta_1, \beta_2) = (0.15433, 0.91604, 0.21500)$. In the quick re-entry case, the forecasting rule was found to be $(\beta_0, \beta_1, \beta_2) = (0.15064, 0.96452, 0.06600)$. Two standard measures to assess the accuracy of the forecasting rule are the R^2 and root mean square error of the regression equation. In the benchmark economy, the R^2 turned out to be 0.99992 and the root mean square error was 2.7854×10^{-4}. In the quick re-entry economy, the R^2 was 0.99991 and the root mean square error was 1.5013×10^{-4}.

However, as demonstrated by Den Haan (2010), these tests are flawed. Therefore, following Den Haan (2010), I assess the accuracy of the forecasting rule by calculating the maximum error between the actual $\bar{\Gamma}$ and the forecasted $\bar{\Gamma}$ generated by the rule without updating. More specifically, I first construct an artificial sequence of technology shocks, $\{z_t\}_{t=1}^{T}$ for $T = 20,500$. Next, I simulate the model under $\{z_t\}_{t=1}^{T}$. After doing this, I obtain a sequence of realized moments $\{\bar{\Gamma}_t\}_{t=1}^{T}$. Next, I drop the first 500 observations. Using only the forecasting rule and the initial realized value, $\bar{\Gamma}_{501}$, I generate a forecast for $\bar{\Gamma}_t$ for all $t > 501$. I denote this forecast by $\hat{\bar{\Gamma}}_t$. I then compute the simulated percentage error as $\hat{e}_t = \ln \hat{\bar{\Gamma}}_t - \ln \bar{\Gamma}_t$ for all $t > 501$.

[Figure 9 about here.]

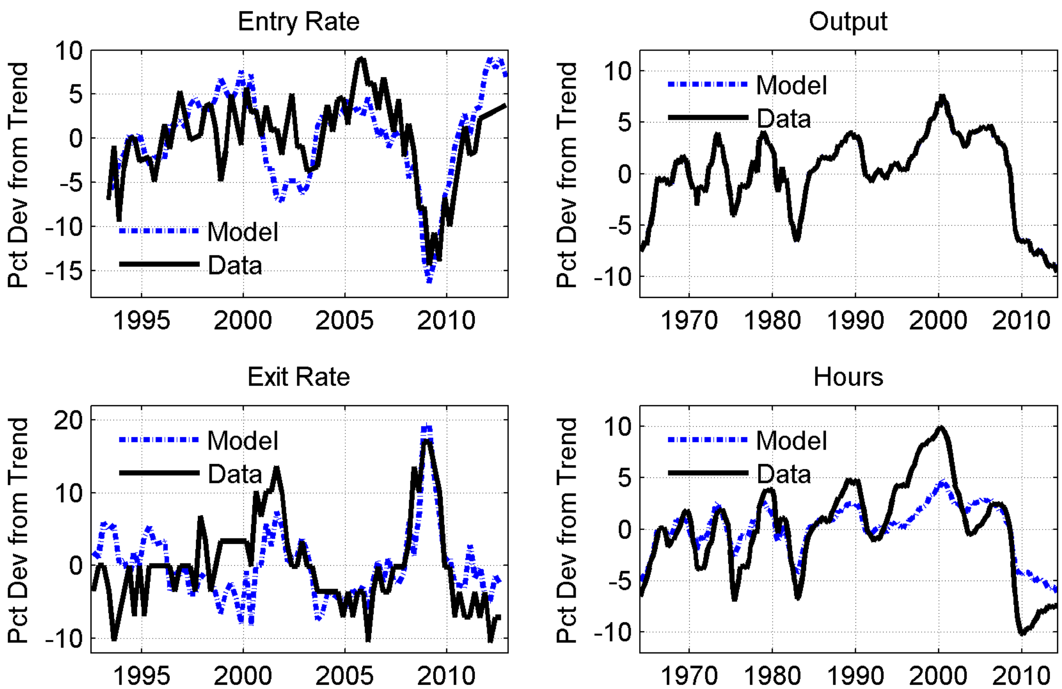
The left two panels of Figure 9 plot a histogram of the simulated forecast error, $\hat{e}_t$, for the benchmark and quick re-entry economies. The mean error was 0.0053% in the benchmark economy and 0.0020% in the quick re-entry model, indicating that the forecasting rules were essentially unbiased. In the benchmark model, the maximum error (in absolute value) was 0.66% and only 0.75% of observations had a forecast error above 0.5% in absolute value. In the quick re-entry model, the maximum error was 0.70% and 0.98% of observations had a forecast error above 0.5%. Moreover, the right two panels of Figure 9 plot $\hat{e}_t$ against t for the benchmark and quick re-entry models. This shows that the forecast errors do not accumulate in either model.

Figure 1: Constructed Technology Shock



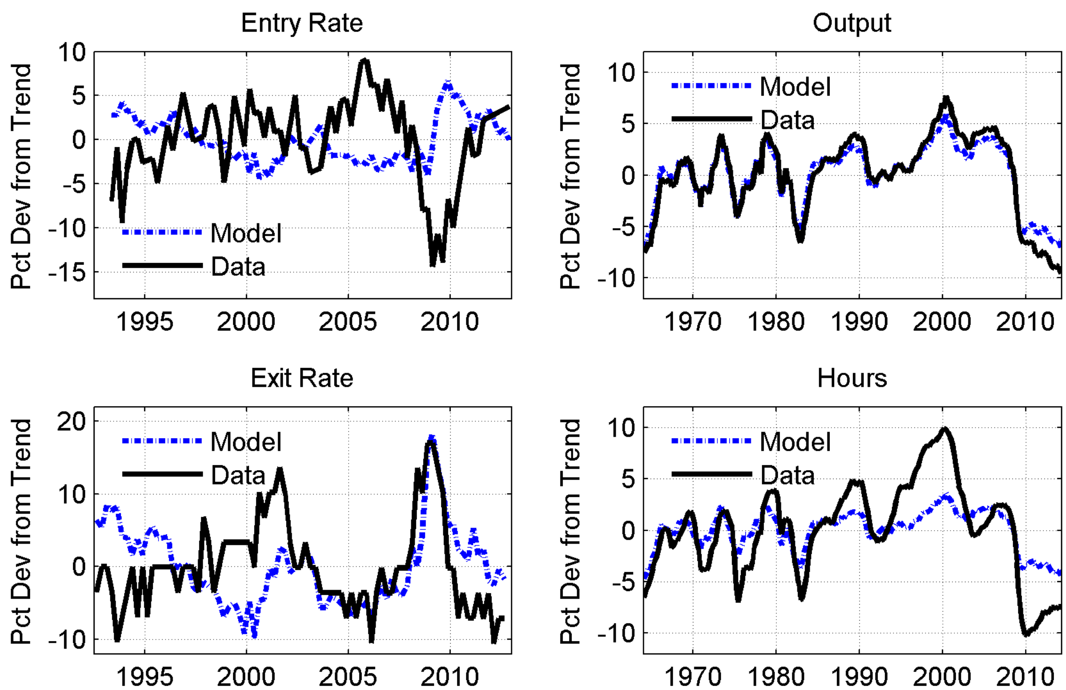
Note: The technology shock (plotted on the left axis) is measured by setting the sequence of each shock so that the model-predicted fluctuations in output match those seen in the data. Seasonally-adjusted Real GDP (plotted on the right axis) is obtained from the BEA's National Income and Product Accounts. Real GDP is de-trended using a log-linear trend.

Figure 2: Fit of Benchmark Calibration



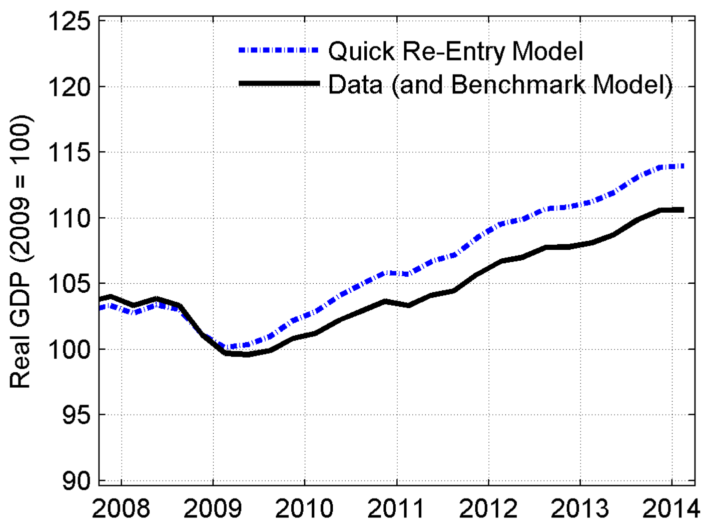
Note: The left panels plot the model-generated entry and exit rates against the data, under the benchmark calibration. The right panels plot the model-generated output and hours against the data. Entry and exit rates (model and data) are de-trended with a linear trend. Output and hours (model and data) are both de-trended with a log-linear trend. Note that the model-predicted output coincides with the data by construction. Data for entry and exit rates are obtained from the BLS's Business Employment Dynamics survey. Output is quarterly seasonally adjusted real GDP from the BEA's National Income and Product Accounts. Hours is obtained as the quarterly average of aggregate weekly hours of production and non-supervisory employees from the BLS's Current Employment Statistics Survey.

Figure 3: Results of Quick Re-Entry Experiment



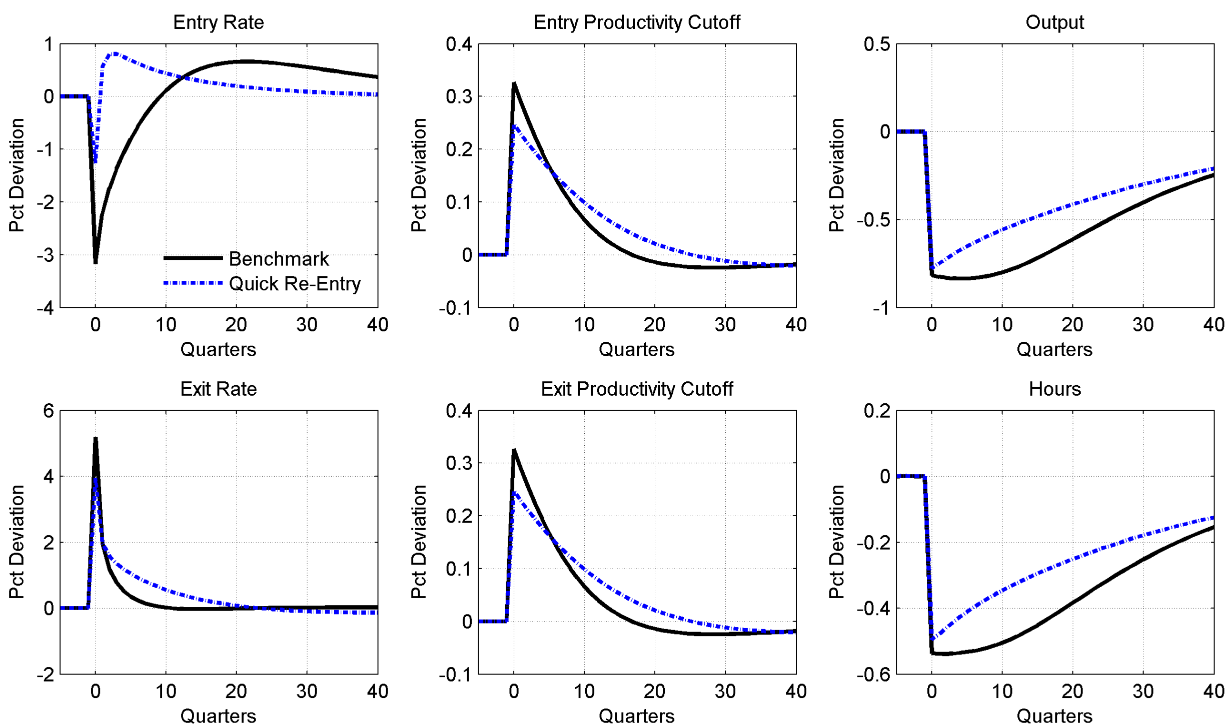
Note: The left panels plot the model-generated entry and exit rates against the data, under the Quick Re-Entry experiment. The right panels plot the model-generated output and hours against the data. Entry and exit rates (model and data) are de-trended with a linear trend. Output and hours (model and data) are both de-trended with a log-linear trend. Data Sources: BLS's Business Employment Dynamics survey, BEA's National Income and Product Accounts, BLS's Current Employment Statistics Survey.

Figure 4: Hypothetical Recovery in Output under Quick Re-Entry Experiment



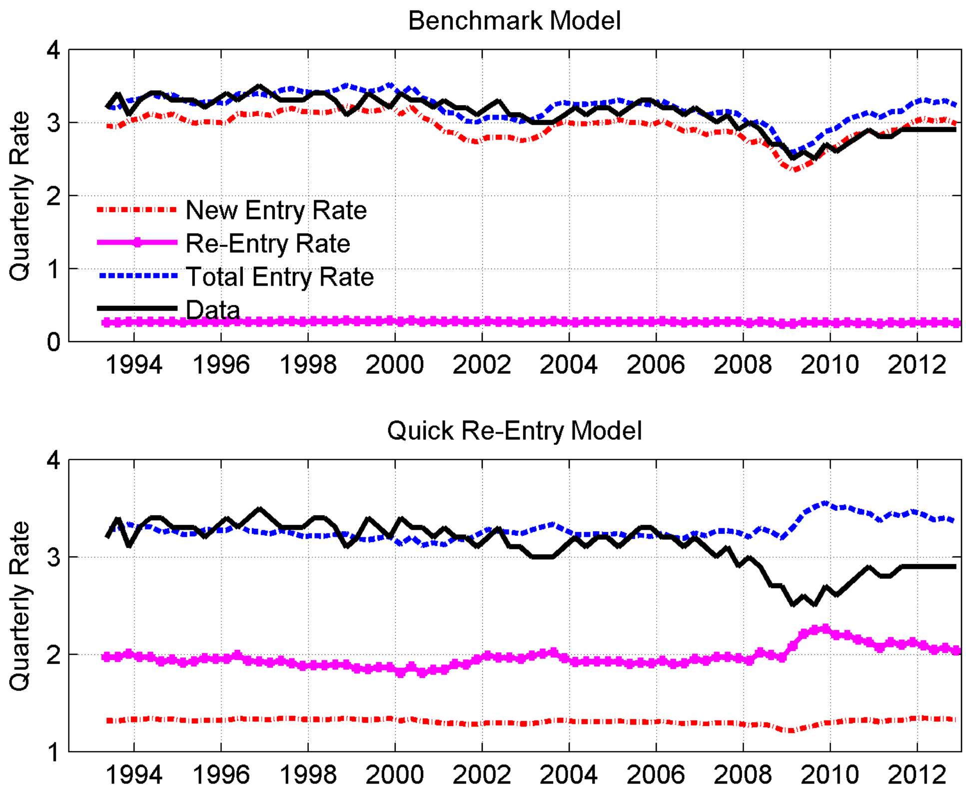
Note: Plotted is the hypothetical recovery in output after the 2007-09 recession, under the Quick Re-Entry experiment. The log-linear trend from the data is added to the model-predicted cyclical fluctuation in output. Data for real GDP is quarterly seasonally adjusted real GDP from the BEA's National Income and Product Accounts. Real GDP is reported as an index, with 100 referring to real GDP in 2009. The average annual growth rate of Real GDP between 2009-II and 2014-I was 2.2%. With quick re-entry, it would have been 2.7%.

Figure 5: Model Impulse Responses: Benchmark versus Quick Re-Entry



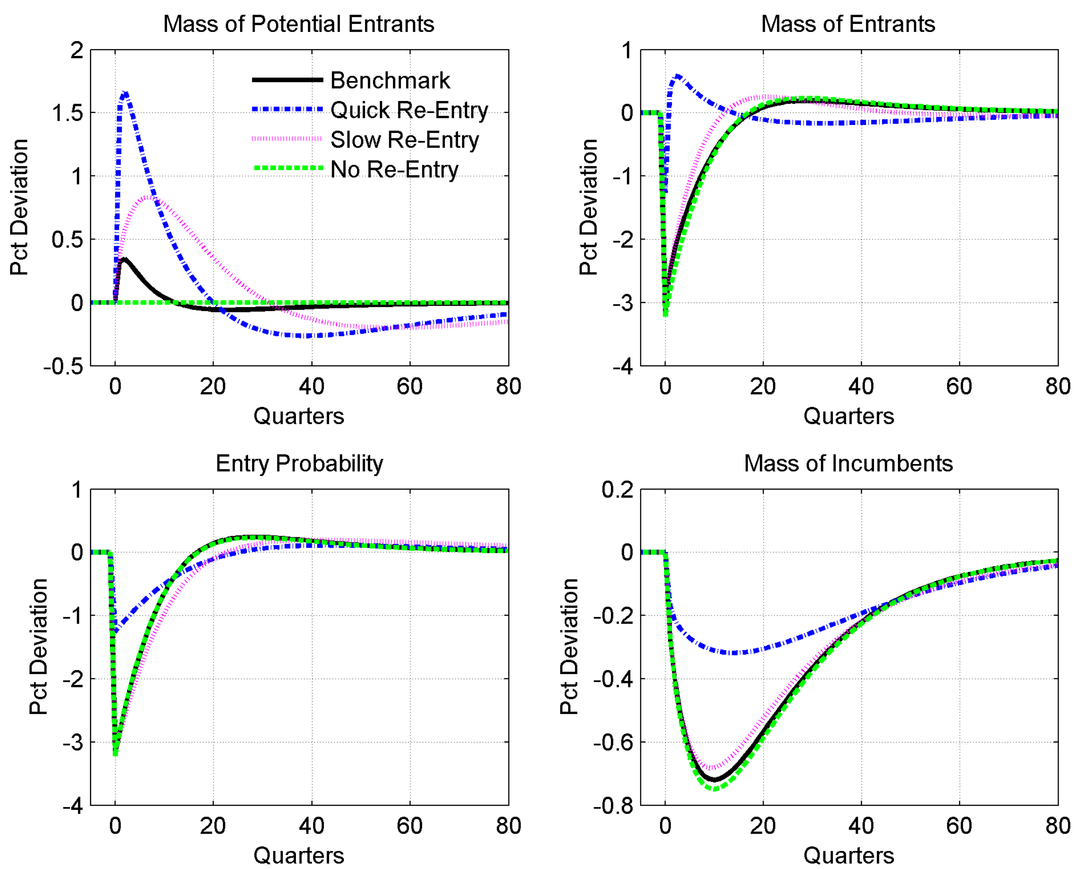
Note: These figures plot the evolution of several variables given a 1-standard deviation *decrease* in aggregate productivity at date 0. Impulse responses are generated for the benchmark calibration and Quick Re-Entry calibrations. Each variable is shown as the percentage deviation from its corresponding steady state value.

Figure 6: Contribution of Re-Entry to Entry Rates



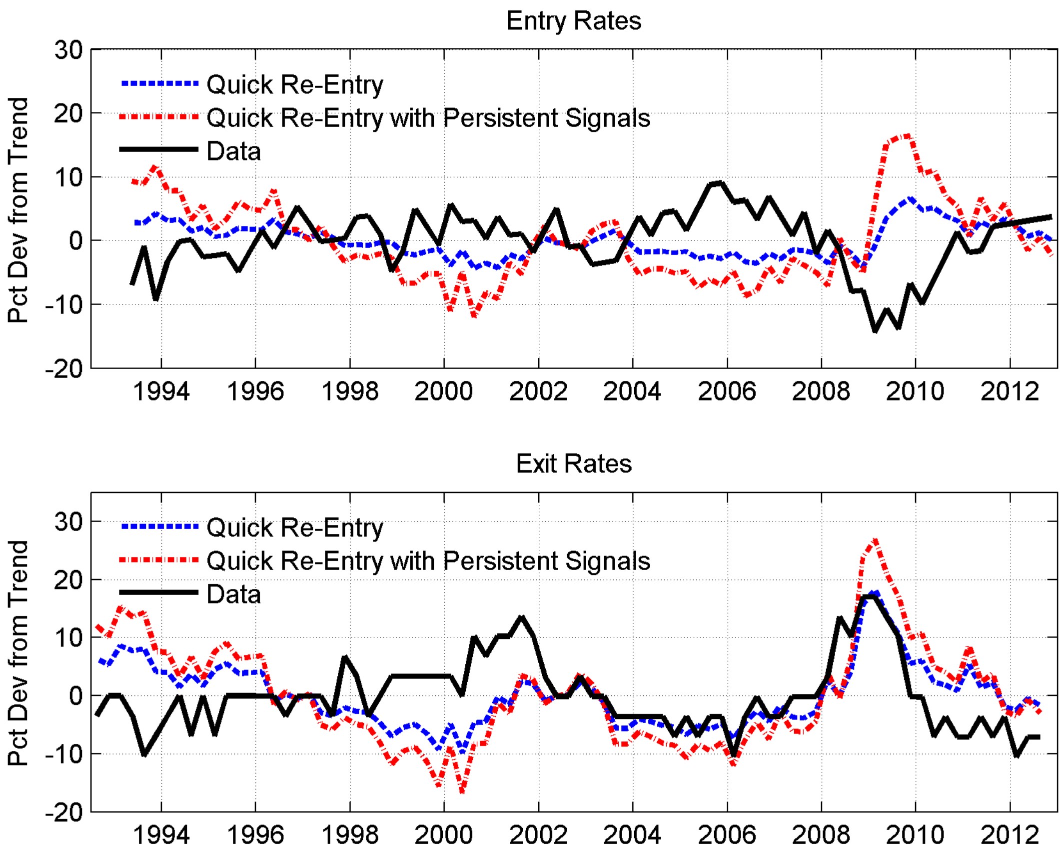
Note: Entry rates, m_e, can be decomposed into the sum of the "New Entry Rate" (m_{ne}) and the "Re-Entry Rate" (m_{xe}). The new entry rate is the part of the total entry rate arising from entrants who have never previously operated. The re-entry rate is the portion arising from re-entry. The top panel plots m_{ne}, m_{xe} and m_e against the data for m_e in the benchmark model. The bottom panel does the same for the Quick Re-Entry experiment.

Figure 7: Impulse Responses for Components of Entry Rates



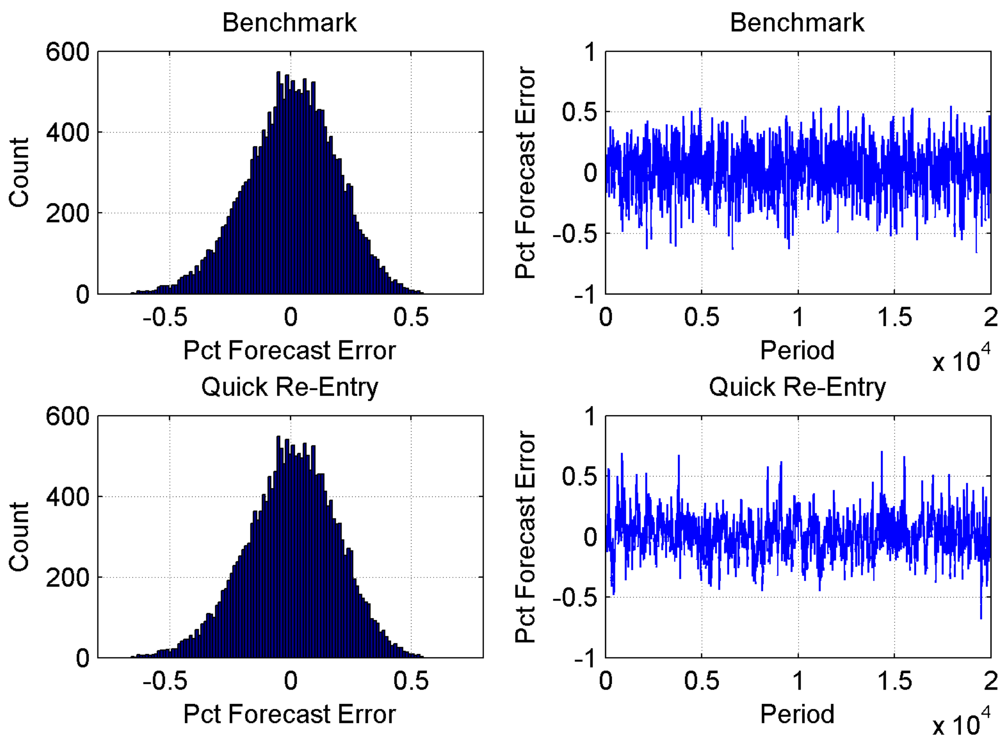
Note: Using Equation 18, the percentage change in entry rates ($\hat{m}_e$) can be decomposed into fluctuations in the mass of entrants ($\hat{M}_e$) minus fluctuations in the mass of incumbents ($\hat{M}$). $\hat{M}_e$ can be further decomposed into the fluctuations in the mass of potential entrants ($\hat{G}$) plus fluctuations in the entry probability ($\hat{\bar{m}}_e$). The top left panel plots $\hat{G}$ and the bottom left panel plots $\hat{\bar{m}}_e$. The top right panel plots $\hat{M}_e$ and the bottom right panel plots $\hat{M}$. Each of these components of $\hat{m}_e$ are shown for four different calibrations: (1) benchmark calibration, (2) the Quick Re-Entry calibration, (3) the Slow Re-Entry calibration and (4) the No Re-Entry calibration.

Figure 8: Effect of Persistent Signals on Quick Re-Entry Experiment



Note: This top panel plots the model's predictions for entry rates against the data. The bottom panel plots exit rates. Entry and exit rates are de-trended with a linear trend. The results for two models are shown here. The first is the "Quick Re-Entry" model, considered in Section 5.2. In this model, $\rho_{se} = 0$. The second is "Quick Re-Entry with Persistent Signals." In this model, $\rho_{se} > 0$. Data source: BLS's Business Employment Dynamics survey.

Figure 9: Accuracy of Forecasting Rule in Benchmark Model



Note: This figure plots the results of the accuracy check suggested by Den Haan (2010). Forecasts for the future aggregate state are generated by the rule without updating. The left panels plot the histogram of the resulting forecast errors, and the right panels plot these forecast errors over time. The top two panels show the results for the benchmark economy and the bottom two panels show the results for the quick re-entry model.

Table 1: Unemployment-to-Employment Transition Rates for CEOs and Managers

A. Chief Executives

	1 month	3 months	12 months
to CEO	3.60%	3.92%	7.64%
	(0.59%)	(1.10%)	(1.74%)
to NRC excluding CEOs	8.30%	18.72%	24.71%
	(0.90%)	(2.27%)	(2.83%)
to RC	2.35%	5.86%	15.50%
	(0.46%)	(1.33%)	(2.57%)
to RM	1.05%	1.38%	3.32%
	(0.31%)	(0.68%)	(1.34%)
to NRM	0.36%	0.61%	5.28%
	(0.18%)	(0.40%)	(1.80%)
Total Job Finding Rate	15.67%	30.49%	56.46%
	(1.19%)	(2.67%)	(3.42%)
to Not in the Labor Force	13.77%	15.07%	18.98%
	(1.20%)	(2.10%)	(2.49%)

B. Managers

	1 month	3 months	12 months
to Manager	5.34%	7.77%	14.35%
	(0.19%)	(0.40%)	(0.65%)
to NRC excluding Managers	3.96%	7.63%	11.71%
	(0.17%)	(0.40%)	(0.58%)
to RC	4.10%	8.46%	14.27%
	(0.17%)	(0.42%)	(0.64%)
to RM	3.10%	4.38%	6.80%
	(0.15%)	(0.31%)	(0.44%)
to NRM	2.08%	3.66%	5.21%
	(0.12%)	(0.28%)	(0.40%)
Total Job Finding Rate	18.59%	31.89%	52.33%
	(0.35%)	(0.72%)	(0.92%)
to Not in the Labor Force	14.50%	16.43%	20.08%
	(0.31%)	(0.56%)	(0.66%)

Note: The top panel reports unemployment-to-employment transition rates for chief executives (i.e., CEOs). The bottom panel does the same for all managers (which includes chief executives). The 1-month, 3-month and 12-month transition rates are reported. Standard errors are in parentheses. These numbers are calculated using matched individual-level data from the Current Population Survey. Given the occupational classifications of Acemoglu and Autor (2011), NRC denotes "Non-Routine Cognitive," RC denotes "Routine Cognitive," RM denotes "Routine Manual" and NRM denotes "Non-Routine Manual."

Table 2: Parameter Values (Benchmark Calibration)

Parameter	Value	Notes
		Process for Aggregate Productivity Shock
a_z	0.000	Normalized to zero
ρ_z	0.947	Match output
$\sigma_{\varepsilon z}$	0.0045	Match output
		Process for Idiosyncratic Productivity Shock
ρ_s	0.850	Consistent with literature
$\sigma_{\varepsilon s}$	0.103	Consistent with literature
		Process for Entry Signal
a_{se}	-0.574	Match transition rates for chief executives
ρ_{se}	0.000	Set to zero in benchmark calibration
$\sigma_{\varepsilon se}$	0.196	Set to $\sigma_{\varepsilon s}/\sqrt{1-\rho_s^2}$
		Production Function Parameters
γ	0.600	Set labor share to 60%
		Household Parameters
ψ	0.748	Normalize wage to 1 in steady state
ν	1.500	Consistent with literature
		Risk-Free Rate
r	0.010	Set risk-free rate to 4% annually
		Entry and Exit Parameters
$\bar{M}_e$	1.000	Normalize to 1
c_f	0.200	Target quarterly entry/exit rate = 3.2%
c_e	0.000	Set to zero in benchmark calibration
θ	0.435	Match transition rates for chief executives
θ_x	0.000	Set to zero in benchmark calibration

Table 3: Predictions of the Model versus the Data

Statistic	Benchmark	Quick Re-Entry	Data
$\rho(m_e, Y)$	0.730	-0.488	0.557
$\rho(m_x, Y)$	-0.491	-0.845	-0.218
$\sigma(m_e)$	3.8%	1.6%	3.7%
$\sigma(m_x)$	4.2%	3.6%	4.7%
$\sigma(Y)$	1.5%	1.4%	1.5%
$\sigma(N)$	1.0%	0.9%	2.0%
Yearly Survival Rate, Entrants	66.6%	72.6%	78.9%
Relative Size, Entrants	51.7%	60.9%	37.3%
Relative Productivity, Entrants	78.2%	83.0%	75.0%
Relative Productivity, Exits	67.8%	68.3%	65.0%

Note: This table reports additional model-generated statistics against the data. $\rho(m_e, Y)$ is the correlation of HP-filtered entry rates with HP-filtered output. $\rho(m_x, Y)$ is the correlation of HP-filtered exit rates with HP-filtered output. An HP filter is used here as it better captures the business cycle correlations. $\sigma(m_e)$, $\sigma(m_x)$, $\sigma(Y)$, $\sigma(N)$ is the standard deviation of (HP-filtered) entry rates, exit rates, output and hours. The data for the yearly survival rate of entrants and the relative size of entrants is obtained from the BLS's Business Employment Dynamics. The data for the relative productivity of entrants and exiting plants is obtained from Lee and Mukoyama (2013).

Table 4: Parameters for Alternative Calibrations

Calibration	θ	θ_x	a_{se}	c_f	$\bar{m}_e$
Benchmark	0.435	0.000	-0.574	0.200	0.069
Quick Re-Entry	0.204	0.000	-0.328	0.202	0.383
Slow Re-Entry	0.033	0.000	-0.605	0.201	0.052
No Re-Entry	1.000	1.000	-0.574	0.200	0.069

Note: This table reports the parameters for several alternative calibrations considered in the text. Since $\bar{m}_e$ (the entry probability) is not a parameter, a_{se} is calibrated to meet the specified target for $\bar{m}_e$. All parameters not reported here are the same as in the benchmark calibration.

Table 5: Comparison of Benchmark and Quick Re-Entry Calibrations

Statistic	Benchmark	Quick Re-Entry
Avg. Log Productivity, All Operators	0.031	0.042
Avg. Log Productivity, Entrants	-0.196	-0.131
Avg. Log Productivity, Exits	-0.337	-0.321
Entry/Exit Cutoff Productivity	-0.283	-0.268
Entry Hazard Rate	9.8	5.1
Exit Hazard Rate	15.6	15.7

Note: "Avg. Log Productivity, All Operators" is the average log idiosyncratic productivity (in the steady state) of all producers who choose to operate. Corresponding averages are also reported for entrants (who operate) and exiting entrepreneurs (who do not operate). "Entry/Exit Cutoff Productivity" is the log of the steady state cutoff productivities for entry and exit, defined in Equations 4 and 5. Since $c_e = 0$ and $\theta_x = 0$ in these calibrations, the exit cutoff productivity is equal to the entry cutoff productivity. The entry (exit) hazard rate is the steady state measure of entering (exiting) entrepreneurs at the entry (exit) cutoff productivity, divided by the mass of entrepreneurs who enter (exit).