The Cyclicality of Entry and Exit: A General Equilibrium Analysis with Imperfect Information

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Abstract

Once household side is governed by standard preference elasticity, canonical models of industry equilibrium cannot explain volatility of establishment entry rate that is observed from the data. To reconcile this gap between theory and data, imperfect information is introduced. Potential entrants cannot disentangle aggregate productivity from their own one, leading to a signal extraction problem. When the volatility of idiosyncratic productivity dominates that of aggregate, potential entrants underestimate variations in equilibrium factor prices, and overestimates variations in the value of entering. This amplified entry margin combined with forward-looking factor demand behavior of incumbent works as internal propagation mechanism.

Keywords: Entry and exit, Plant Dynamics, Business Cycles, Imperfect Information

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1. Introduction

It is well known that entry and exit play important roles in the medium to long-run aggregate job flows and productivity growth.[1] But when it comes to the business cycle fluctuation, there is no consensus regarding the contribution of net entry margin in shaping the aggregate dynamics. Recently, industry equilibrium model a la Hopenhayn (1992) has been extended to account for the dynamics of entry and exit over the business cycle.[2] According to the papers in this literature, quantitative contribution of the net entry margin in shaping the aggregate fluctuation is critically hinges on the specification of the household or more generally factor supply side. For example, in the environment where there is no goods market clearing condition (Clementi and Palazzo (2016)) or equivalently representative household has a linear utility with respect to the consumption (Lee and Mukoyama (2016)), entry rate become as volatile as observed in the data and net entry margin plays an important propagation role. On the other hand, if one discipline household with standard value of risk aversion (Samaniego (2008) and Clementi et al. (2015) specified log utility with respect to the consumption) then model implied entry rate become much less volatile than the magnitude observed in the data and naturally net entry margin only have a negligible role regarding the aggregate fluctuations. This is because income effect and variations in interest rate–associated with introducing concave utility function with respect to the consumption–dampens variations in value of the entry along the business cycle fluctuations. Based upon these results in the related literature, this paper asks following questions. At first, how can we explain the observed cyclical behavior of plant entry within full-blown general equilibrium environment. And then, we want to investigate whether net entry margin matter for aggregate fluctuations over the business cycles or not.

To reconcile this gap between the general equilibrium model and data, imperfect information is introduced. Specifically, we construct a general equilibrium heterogeneous plant model where potential entrants cannot separately observe aggregate and idiosyncratic productivity. Beyond this informational friction, our model economy is distinguished from previous models in the heterogeneous firm literature by *jointly* incorporating: (i) endogenous entry and exit decision; (ii) non-convex adjustment costs in capital, which account for the plant level investment dynamics; (iii) non-convex adjustment costs in labor, which

[1] For example, Davis et al. (1996) and Foster et al. (2001).

[2] Notably including Lee and Mukoyama (2016), Clementi and Palazzo (2016), Clementi et al. (2015) and Samaniego (2008).

account for the job reallocation rate observed in the data; (iv) interaction between incumbent plants that exactly forecast future equilibrium price and potential entrants that cannot exactly forecast future equilibrium price; (v) a realistic degree of risk aversion; and (vi) a realistic elasticity of labor supply.[3]

Imagine a competitive market composed of incumbent plants which operate a decreasing returns to scale technology and face persistent aggregate and idiosyncratic productivity shocks. In this world, potential entrants must know both current aggregate productivity and their own idiosyncratic productivity upon entry in order to precisely form expected profit from entry. However, potential entrants can observe only the sum of aggregate productivity and their potential idiosyncratic productivity. One consequence of this information structure is that as long as the idiosyncratic shock is more volatile than the aggregate shock and potential entrants know this, potential entrants will underestimate variations in aggregate productivity.[4]

Potential entrants can also observe the current period equilibrium wage and the aggregate capital stock. Using these observables, potential entrants solve a signal extraction problem to estimate aggregate productivity and potential idiosyncratic productivity separately. But, potential entrants cannot perfectly learn about the aggregate state, despite the fact that they are allowed to observe the equilibrium wage accurately. To explain this, first recall that incumbent plants face a dynamic labor demand problem due to the labor adjustment cost. Following an aggregate productivity shock, the spot labor market clearing wage responds in a hump shaped manner, as incumbent plants slowly adjust their labor usage. As a result, in the early stages of the aggregate productivity shock potential entrants underestimate the shock to aggregate productivity, even after observing the current period market clearing wage.

This distorts the accurate formation of expected value from entry in two ways. One, potential entrants underestimate variations in future labor costs. Two, in equilibrium, the state contingent discount factor is determined by the representative household's marginal rate of substitution across states. In other words, plants' operating profit across different aggregate states is a function of the representative household's marginal utility of consumption in each state. When potential entrants calculate the present value of operating in the future, they will more aggressively discount profit from future states where the

[3] For example, Clementi et al. (2015) does not have a labor adjustment cost and uses an infinite Frisch elasticity. Bloom et al. (2014) does not have an entry and exit margin and also uses an infinite Frisch elasticity.

[4] According to Castro et al. (2015) and Cooper and Haltiwanger (2006), in the U.S. manufacturing sector, idiosyncratic shock (to the profitability of plants) is around 5$\sim$6 times more volatile than aggregate shock.

marginal utility of consumption is low. When profits from different aggregate states are discounted by different rates, the inability to form accurate expectations about future aggregate productivity distorts expected value from entry.

For example, when the economy booms, potential entrants do not immediately realize that aggregate productivity has improved very much. Instead, they largely believe that their potential idiosyncratic productivity has improved. Given the persistence of aggregate productivity shocks, potential entrants also underestimate next period's aggregate productivity. Consequently, they also underestimate next period's equilibrium wage and assign too high a probability to states where the marginal utility of consumption will be high. As a result they overestimate expected value from entry when the positive shock hits. The converse logic applies for negative shocks and therefore the response along the entry margin to aggregate productivity shocks is amplified.

During a boom, cohorts who entered the market based on their overestimation of the expected profit can realize their true productivity upon being an incumbent. But most of them still stay in the market because entry costs are sunk, are higher than the fixed costs of operating, and investment in physical capital is partially irreversible. The additional output–produced by young cohorts along their growing profile– during a boom keeps equilibrium aggregate output high even after the aggregate productivity shock starts dissipating. In this way, potential entrants' information friction in conjunction with hysteresis property of the entry and exit decision can works as internal propagation mechanism of business cycle fluctuation.

This overshooting along the entry margin caused by information friction mutes the exit margin response to aggregate shocks. Incumbent plants that observe aggregate productivity directly can accurately forecast the persistent equilibrium factor price dynamics. So, for marginal incumbent plants, the positive effect of the aggregate productivity shock on their expected profit from operating is canceled out by the amplified response of equilibrium factor prices. As a result our model economy with information friction implies acyclical exit rate as documented by Lee and Mukoyama (2015a).[5]

The key parameters of the model are tightly disciplined by (i) the characteristics (e.g., relative productivity and employment size) of entering and exiting plants, (ii) cross-sectional distribution of plant-level investment rates, and (iii) job flows rates in the manufacturing sector. The corresponding key parameters of the model economy are the relative size of entry and continuation costs, the degree of partial investment irreversibility, and the labor adjustment cost.

[5] We will reassure acyclical exit behavior using Business Dynamics Statistics (BDS).

The model economy driven by aggregate TFP shocks generates a realistic cyclical behavior of entry and exit even when household side is disciplined by intertemporal rate of substitution of 1 and Frisch elasticity of labor supply of 1.5. The average entry rate during booms is 7.7% (8.1% in the Annual Survey of Manufacturers). The average entry rate during recessions is 4.4% (3.4% in the data). The exit rate from the model is acyclical: the correlation coefficient with cyclical output is -0.06 (-0.02 in the data). To isolate the role of information frictions, we also simulate the model under full information, wherein potential entrants can separately observe aggregate and their potential idiosyncratic productivity. As the information friction is turned off, the entry rate become much less volatile and exit rate become counter-cyclical. The average entry rate during booms is 6.2% (considerably lower than the 8.1% in the data), whereas during recessions it is 5.9% (higher than 3.4% in the data). The correlation between the exit rate and output under full information is -0.49. That is, once general equilibrium forces are disciplined by standard values for risk aversion and the Frisch elasticity of labor supply, then the standard industrial equilibrium model cannot explain neither the magnitude of fluctuations in the entry margin nor acyclical exit. Consequently, the informational friction proposed is crucial.

In the model economy with information friction, the realistic entry margin combined with the growing profile of young plants works as an internal propagation mechanism. For example, the information friction model generated time series of aggregate output is 13% more persistent and 5% more volatile that those from full information model economy wherein entry rate is much less volatile than the magnitude observed from data.

This internal propagation role of net entry margin in the full-blown general equilibrium environment is not the outcome of efficient allocation but the result of potential entrants' information friction. According to the welfare analysis, it turned out that representative household in the model economy with information friction go through 0.6% of consumption equivalent welfare losses compared to the model economy without information friction. Naturally, welfare cost observed in the model economy with information friction justifies policy intervention that stabilize business cycle fluctuations in entry margin.

Although it is difficult to directly observe the information frictions that plants face, the mechanism proposed in this paper provides at least four testable implications.

If, at the enterprise level, information about economic conditions is shared, then plant entry from existing firms might be less procyclical than plant entry from new firms.

Another prediction following from an imperfect information friction is that potential entrants might overestimate their expected profit from entry during booms and underestimate profit from entry during recessions. This implies that the cohort of plants that entered during booms are more likely to exit the market relatively quickly compared to plants that entered the market during recessions.

In the baseline model economy, exit rate become acyclical because of the additional general equilibrium forces generated by young plants. Actually, partial equilibrium simulation of baseline model economy implies countercyclical exit rate. Given that pure sectoral shock might be immune to general equilibrium forces, if we measure cyclicality of plant exit rate in 2-digit manufacturing sector with controlling for industry and time fixed effect, it might be countercyclical differently from aggregate manufacturing level cyclical behavior of exit.

According to Castro et al. (2015), within the manufacturing sector there is huge variation in the volatility of idiosyncratic shocks[6] across sectors. Then the information friction implies that the establishment entry rate should be more procyclical in sectors with more volatile idiosyncratic shocks along the aggregate manufacturing sector's business cycle (not the disaggregated sector-specific business cycle).

We demonstrate that each of these predictions, respectively, is consistent with the data. (i) According to the Business Dynamics Statistics, the cyclical variation of establishment entry by new firms is 50% more volatile than entry by existing firms. (ii) According to the Business Dynamics Statistics, the one-year exit rate of plants established by new firms during booms is 7% higher than that during recessions. (iii) According to 2-digit manufacturing industry level panel regression with industry and time dummy, response of job destruction rate of exiting plants to the fluctuations in sector specific variations in cyclical indicator is significantly negative. (iv) According to the Annual Survey of Manufacturers, across 2-digit manufacturing industries, the cross-sectional correlation coefficient between the cyclicality of entry and the volatility of idiosyncratic component of sales growth is 0.38.

This paper is closely related to various recent literature that extends the Hopenhayn (1992) industrial equilibrium model by adding business cycle fluctuations in competitive equilibrium. Clementi and Palazzo (2016), Clementi et al. (2015), Lee and Mukoyama (2016), and Samaniego (2008) develop variants of this model to investigate the business cycle behavior of entry, exit, and plant dynamics.

Clementi and Palazzo (2016) clearly show that how firm entry and exit combined with growing profile of young firm can works as business cycle propagation mechanism and

[6] As measured by variations in sales growth or revenue factor productivity (TFPR) which is not explained by establishment characteristics, economy-wide, or industry-wide factors.

conclude that the net entry margin contributed to the slow recovery following the Great Recession. Clementi et al. (2015) extended Clementi and Palazzo (2016) into general equilibrium environment. Their stochastic simulation with productivity shock driven business cycle shows that introducing concave utility with respect to the consumption dampens propagation mechanism of net entry margin.[7] Using identical specification of household side with Clementi et al. (2015), Samaniego (2008) showed that propagation role of net entry margin is negligible with deterministic transition exercise. Our paper, by introducing the information friction of the potential entrants, tries to reconcile the gap between partial equilibrium and general equilibrium environment.

Lee and Mukoyama (2016) try to jointly explain procyclical entry, acyclical exit, and selection through entry margin across boom and recession.[8]. Their main mechanism is an exogenous cyclical entry cost. Our paper is complimentary to Lee and Mukoyama (2016) by showing that information friction of potential entrants can be one of the possible source of cyclical entry cost.

There are also papers using a similar information friction as a propagation mechanism with respect to an aggregate productivity shock. Venkateswaran (2014) used a firm's inability to distinguish between aggregate and idiosyncratic productivity as one way to resolve the Shimer (2005) puzzle in the context of a search and matching model. Li and Weinberg (2003) also use a similar information friction to explain the different cyclical sensitivities of investment across small and large firms. Our paper differs from these papers in two respects. First, in our paper potential entrants can learn about aggregate status by observing current equilibrium wages and the aggregate capital stock; in the other papers firms cannot observe any current period aggregate equilibrium variables. Second, in our paper, there is interaction between incumbents who have full information and potential entrants with imperfect information through the goods and labor market clearing conditions.

The paper is organized as follows. In Section 2, we recap the cyclical properties of plant entry and exit in the manufacturing sector using data from the BDS. In Section 3, the model economy is described formally. Section 4 discusses the calibration and various resulting life cycle profiles of plants. Section 5 discusses quantitative results, and through impulse response exercises it provides insight into the model mechanism. It also examines the model's implications for the cyclical behavior of entry and exit. In Section 6, we

[7]For example, aggregate output from their model with entry and exit is slightly *less* persistent than that from the model without entry and exit. For details, I refer to the table 3 of Clementi et al. (2015).

[8]That is plants that entering during booms are smaller and less productive than those that entering during recessions

investigate the role of the net entry margin as an internal propagation mechanism and welfare implications of potential entrants' information frictions. In Section 7, we look at plant entry and exit depending on firm age and the corresponding 2-digit manufacturing sectors entry rate in order to check some of the testable implications of our informational story. Section 8 concludes.

2. The Cyclical Behavior of Establishment Entry and Exit in the Manufacturing Sector

Lee and Mukoyama (2015a) have documented that in the U.S. manufacturing sector the establishment entry rate is procyclical and the exit rate is acyclical. Their findings rely on the Annual Survey of Manufacturers over the sample period 1972 to 1997.

Table 1: Manufacturing firm entry and exit rates

	Boom	Recession	Total avg.	p-value
Entry(birth)	8.1%	3.4%	6.2%	0.023
Exit(death)	5.8%	5.1%	5.5%	0.371

Note: This table is from Table 2 of Lee and Mukoyama (2015a). Entry (exit) rate is defined as the number of entering (exiting) plants as percentage of the total number of plants each period. p-values are from the t-test of the mean difference in entry and exit rate between boom and recession years.

Table 1 is taken from Lee and Mukoyama (2015a), which breaks down establishment entry and exit rates over different parts of the business cycle. Here, 'boom' years are those when the manufacturing sector's output growth rate is higher than the sample average manufacturing output growth rate, while 'recession' years are those where manufacturing output growth is below the sample average. From Table 1 it is clear that the entry rate varies considerably through the business cycle but there is no significant variation in the exit rate between boom and recession years.

We checked the robustness of their findings using the establishment entry and exit rate derived from the BDS (Business Dynamics Statistics) data set. Compared to the ASM, which is biased towards large employment plants, the BDS includes all plants with a positive payroll. The BDS is also available for a longer sample period, 1977 to 2012. As entry and exit rates in a given year of the BDS measure what has occurred from the previous year's March to the current year's March, we need to construct a properly re-timed annual business cycle indicator for the manufacturing sector from high frequency data. This can be accomplished by using monthly industrial production of the manufacturing sector and quarterly aggregate employment in the manufacturing sector.[9] [10]

Table 2: The cyclical behavior of manufacturing entry and exit rates

	Industrial Production	Employment
corr(entry$_t$,indicator$_t$)	0.35(0.05)	0.49(0.02)
corr(exit$_t$,indicator$_t$)	-0.02(0.90)	0.01(0.95)
corr(exit$_t$,indicator$_{t-1}$)	0.5(0.00)	0.16(0.47)
corr(exit$_t$,indicator$_{t-2}$)	0.46(0.01)	0.25(0.27)

Note: *Indicator* represents either industrial production or employment. Numbers in the parenthesis are p-value associated with the correlation coefficient.

From Table 2 the resulting establishment entry rate is procyclical and the exit rate is acyclical. If we look at the correlation of the exit rate with the generated lagged cyclical indicator, there is still no evidence of countercyclical exit. Rather, in the case of industrial production, the establishment exit rate is significantly procyclical with respect to the lagged indicator.

3. Model

The model economy is composed of incumbent plants, a fixed measure of potential entrants and a representative household. Incumbent plants produce output using capital and labor in the presence of both capital and labor adjustment costs. Potential entrants observe wages and aggregate capital, plus an exogenous signal which contains information about both aggregate economic conditions and their idiosyncratic status, and then solve a Kalman filter problem to attempt to disentangle aggregate and idiosyncratic productivity. Based on their resulting estimates, they make an optimal entry decision. The representative household owns all the plants in the economy and makes consumption and labor

[9]For the output measure, we used the industrial production index for the manufacturing sector. From this monthly industrial production series, we constructed a re-timed annual measure that is consistent with March to March timing in the BDS. In case of the employment measure, we used BLS's manufacturing sector employment index based on SIC classification. From the quarterly index, we again constructed a re-timed annual measure.

[10]When we use output as the cyclical indicator, the sample period is 1980 to 2012 and we excluded 2002 observations. That is because the BDS is mainly constructed based on the Census Bureau's Business Register and starting from 2002 new identification numbers, especially for multi-unit plants, were implemented. This raises concerns about the possibility of spurious entry or exit in 2002 in the BDS. When we use employment as the cyclical indicator, the sample period is 1980 to 2001. This is because the BDS is based on the SIC classification system, and the BLS stopped providing SIC-based quarterly manufacturing sector employment after 2002.

supply decisions.

3.1. Incumbents

Time is discrete. At time t, any price-taking incumbent plant i produces a homogeneous good using a decreasing returns to scale production function $y_{t,i} = \exp(z_t + x_{t,i})(k_{t,i}^{\alpha} n_{t,i}^{1-\alpha})^{\theta}$. z_t and $x_{t,i}$ are aggregate and idiosyncratic productivity, respectively. The stochastic processes for these two shocks are given as follows.

$$z_{t+1} = \rho_z z_t + \epsilon_{z,t+1} \tag{1}$$

$$x_{t+1} = \rho_x x_t + \epsilon_{x,t+1} \tag{2}$$

Here, $\epsilon_{z,t+1} \sim N(0, \sigma_z^2)$ and $\epsilon_{x,t+1} \sim N(0, \sigma_x^2)$. Denote the conditional distribution of x_{t+1} given x_t as $H(x_{t+1}|x_t)$. In contrast to potential entrants, incumbent plants can observe each of the z_t and $x_{t,i}$ separately. This means that incumbent plants can accurately form expectations with respect to future equilibrium prices, the evolution of the distribution of plants, and therefore their own expected profit from continuing operation.

At the beginning of the each period, an individual incumbent plant is characterized by its predetermined level of capital(k), labor(n_{-1}), and its current idiosyncratic productivity level(x). At the beginning of the period, the distribution of incumbent plants over (n_{-1}, k, x) constitutes one aggregate state variable along with the aggregate productivity level z and the distribution of potential entrants over their prior beliefs.

Given these state variables, incumbent plants also observe their stochastic fixed operating cost, ξ, which is drawn from a time-invariant distribution and is i.i.d. across both time and plants. If the expected profit from continuing to operate is large enough to justify paying this output-denominated fixed operating cost then plants will do so and remain as incumbents at the beginning of the next period. Otherwise, they will not pay the fixed operating cost and permanently shut down from next period on. Note that shut down occurs at the end of the period, so current incumbents produce this period regardless, but due to the labor adjustment costs their employment decisions depend on whether they intend to shut down or not.

When the incumbent chooses to continue to operate, it has to choose this period's labor and investment. In order to discipline plants' investment and labor adjustment decisions to be consistent with micro level factor adjustment behavior, we will introduce partial irreversibility in capital adjustment and linear costs in labor adjustment.

$$k' = k(1-\delta) + i \tag{3}$$

$$AC^k = (1-p_s)|i|\mathbb{1}_{(i<0)} \tag{4}$$

$$AC^n = (n - n_{-1})c_p\mathbb{1}_{(n\geq n_{-1})} + (n_{-1} - n)c_n\mathbb{1}_{(n<n_{-1})} \tag{5}$$

Specifically, capital depreciates at rate δ, the resale price of installed capital is discounted by fraction $1-p_s$, and whenever plants adjust labor they pay c_n per unit of adjustment. Unlike the capital adjustment, labor adjustment is immediately reflected in current period production. The sluggish and forward-looking factor adjustment behavior introduced by these adjustment costs will detach equilibrium wage dynamics from the dynamics of aggregate productivity. Consequently potential entrants, even after observing the equilibrium wage, cannot fully infer the current aggregate status, a point which we will return to.

If a plant decides to not pay the fixed operating cost, it first determines current period labor demand taking into account that after the current period's production the plant will fire all the labor hired and pay the associated labor adjustment cost. After production, these plants that do not pay their operating cost exit the market with the resale value of the remaining capital stock after depreciation.

Denote the incumbent distribution over (n_{-1}, k, x) as Γ, the distribution of potential entrants over $(a, \mu^z_{t|t-1}, \mu^q_{t|t-1})$[11] as Ω and define $\Lambda = (\Gamma,\ \Omega)$. Now we can summarize the incumbent's optimization problem using the following value functions.

$$V(n_{-1}, k, x; z, \Lambda) = \int \max\{V_c(n_{-1}, k, x; z, \Lambda) - \xi, V_x(n_{-1}, k, x; z, \Lambda)\}dG(\xi) \tag{6}$$

$$\begin{aligned} V_c(n_{-1}, k, x; z, \Lambda) = \max_{\{i,n\}} & \ y - w(z,\Lambda)n - i - AC^k(k,i) - AC^n(n_{-1}, n) \\ & + \mathbb{E}[d(z',\Lambda')V(n, k', x'; z', \Lambda')] \end{aligned} \tag{7}$$

$$V_x(n_{-1}, k, x; z, \Lambda) = \max_{\{n\}} y - w(z,\Lambda)n - AC^n(n_{-1}, n) - AC^n(n, 0) + p_s(1-\delta)k \tag{8}$$

$$\chi(n_{-1}, k, x; z, \Lambda) = G(\xi \leq \max\{V_c - V_x, 0\}) \tag{9}$$

$d(z', \Lambda')$ represents the state contingent discount factor. Both the spot labor market equilibrium wage and the state contingent discount factor are determined jointly with

[11] Where a is sum of the their potential idiosyncratic productivity and current period aggregate productivity. $\mu^z_{t|t-1}$, $\mu^q_{t|t-1}$ are prior beliefs about aggregate productivity and potential idiosyncratic productivity respectively. Details will be provided in section 3.2.

the representative household's optimization problem and the market clearing conditions. $\chi(n_{-1}, k, x; z, \Lambda)$ represents the probability that plants whose beginning of period state variables are (n_{-1}, k, x) continue operating. Because the operating cost is given stochastically, the optimal exit decision is represented in terms of probability.

3.2. Potential Entrants

There exists a fixed measure M of potential entrants in every period. Each period, based on their current information set, potential entrants form expectations about profits from operating next period onwards. For a potential entrant to accurately evaluate their expected profit from entry they need to know about both their idiosyncratic productivity $(x_{t+1,i})$ and aggregate productivity (z_{t+1}) next period, the first period they would be able to produce. One critical question is whether potential entrants have the same amount of information as incumbent plants. The standard approach taken so far in this literature[12] is that potential entrants get a signal about their own idiosyncratic productivity and they can observe current aggregate productivity, just as incumbent plants do. That is, a potential entrant is modeled as having the same information set as incumbent plants. This paper departs from this symmetric information structure between potential entrants and incumbents. Specifically, potential entrants here only receive a signal on the sum of their own potential idiosyncratic productivity and current aggregate productivity.

The stochastic processes for a potential entrants' potential idiosyncratic productivity (q_t), and how it evolves into an actual idiosyncratic productivity next period in the case of entry, are given by the following AR(1) specifications.

$$q_{t+1} = (1-\rho_q)\bar{q} + \rho_q q_t + \epsilon_{q,t+1} \tag{10}$$

$$x_{t+1} = \rho_x q_t + \epsilon_{x,t+1} \tag{11}$$

Here, $\bar{q} < 0$ is the long-run mean of the process and $\epsilon_{q,t+1} \sim N(0, \sigma_q^2)$, $\epsilon_{x,t+1} \sim N(0, \sigma_x^2)$ are the realized innovations.

Denote the conditional distribution of x_{t+1} given q_t as $H(x_{t+1}|q_t)$ and the conditional distribution of q_{t+1} given q_t as $J(q_{t+1}|q_t)$. The stationary distribution of the potential entrants in terms of their would-be productivity is stochastically dominated by the stationary distribution of the incumbent's idiosyncratic productivity process. Combined with the mean-reverting property of x - incumbent idiosyncratic productivity - this generates

[12] Mostly extensions of Hopenhayn (1992) with business cycle fluctuations, including Lee and Mukoyama (2015a), Clementi and Palazzo (2016), and Clementi et al. (2015).

an increasing age profile in terms of plant productivity. To keep the distribution of potential entrants stationary, if one decides to enter it is replaced by a new potential entrant who inherits the same potential productivity q. In terms of the distribution of q this is identical to an economy where a fixed measure of potential entrants draw their idiosyncratic productivity from the long-run stationary distribution implied by (10). Note that a potential entrant i cannot observe their current period $q_{t,i}$ but they can only observe the sum of aggregate productivity and $q_{t,i}$. We denote that combined signal as $a_{t,i}$.

$$a_{t,i} = q_{t,i} + z_t \tag{12}$$

While potential entrants cannot observe the components directly, they are aware of the structure (long-run mean, persistence, and variance) of each of the component processes.

For example, in a given period if there is positive shock to aggregate productivity then every potential entrant will receive a more positive signal but they cannot distinguish whether it resulted from aggregate productivity or potential idiosyncratic productivity. If they could observe the aggregate shock directly, they could account for its effect on future wages and consumption[13] when they calculate expected profit from entry. But given that a potential entrant cannot observe aggregate productivity separately from their signal, they attribute some portion of the positive movement in the signal to the idiosyncratic shock and underestimate the movements in future equilibrium wages and consumption. This leads potential entrants to overestimate their expected profit from entry when the economy booms. Conversely, potential entrants underestimate their expected profit from entry when the economy slumps.

Fluctuations in aggregate productivity generate fluctuations in the equilibrium wage but changes in an individual potential entrant's potential productivity would not have any effect on aggregate variables. Therefore potential entrants can get some information about aggregate economic conditions by observing the current period wage. Compared to previous papers that used similar information frictions, this paper differs in that even after observing current period spot labor market equilibrium wage, there still remains a problem of imperfect information.

Potential entrants can also learn about the aggregate state by observing the beginning of period aggregate capital stock. This economy is characterized by a non-degenerate distribution of plants and the aggregate fluctuation. To forecast equilibrium price dynamics consistently, agents in this economy rely on the law of motion for the distribution

[13]Given that the representative household is risk averse, the value of the final good across different aggregate states is determined by the goods market clearing consumption level in each aggregate state.

of plants. Under a bounded rationality assumption agents approximate the distribution with a bounded set of its moments. In this economy, agents use the mean of the capital distribution - they are always aware of the current period aggregate capital stock. Given that yesterday's capital choice was a function of yesterday's aggregate productivity and productivity is persistent, capital today gives some information about economic conditions. So it is natural that potential entrants use current period capital stock in price forecasting but also in estimating the current period's aggregate productivity. Potential entrants learn about aggregate productivity by using the observed wage and aggregate capital stock to follow these projection equations.[14]

$$\log w = \beta_{w,c} + \beta_{w,z} z + \epsilon_w, \; Var(\epsilon_w) = \sigma_w^2 \tag{13}$$

$$\log K = \beta_{K,c} + \beta_{K,z} z + \epsilon_K, \; Var(\epsilon_K) = \sigma_K^2 \tag{14}$$

After some potential entrant i observes $(a_{t,i}, w_t, K_t)$, they try to estimate $(z_t, q_{t,i})$ which are necessary to precisely estimate the expected profit from entering the market. Potential entrants solve a Kalman filter problem comprised of the following measurement and transition equation.

$$\underbrace{\begin{bmatrix} a_t \\ \log w_t \\ \log K_t \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} 1 & 1 \\ \beta_{w,z} & 0 \\ \beta_{K,z} & 0 \end{bmatrix}}_{\beta} \begin{bmatrix} z_t \\ q_t \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ \beta_{w,c} \\ \beta_{K,c} \end{bmatrix}}_{\beta_c} + \begin{bmatrix} 0 \\ \epsilon_w \\ \epsilon_K \end{bmatrix} \quad \text{Measurement Equation} \tag{15}$$

$$\begin{bmatrix} z_t \\ q_t \end{bmatrix} = \underbrace{\begin{bmatrix} \rho_z & 0 \\ 0 & \rho_q \end{bmatrix}}_{T} \begin{bmatrix} z_{t-1} \\ q_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ (1-\rho_q)\overline{q} \end{bmatrix}}_{T_c} + \begin{bmatrix} \epsilon_z \\ \epsilon_q \end{bmatrix} \quad \text{Transition Equation} \tag{16}$$

$$\text{where} \begin{pmatrix} \epsilon_z \\ \epsilon_q \end{pmatrix} \sim i.i.d.\ \mathrm{N}\left[0, \underbrace{\begin{pmatrix} \sigma_z^2 & 0 \\ 0 & \sigma_q^2 \end{pmatrix}}_{Q_t}\right]$$

One issue is whether the residuals in (13) and (14) follow a normal distribution or not.[15] According to the Jarque-Bera test with a null hypothesis that residuals from (13)

[14]Coefficients and the variance of residuals in these projection equations are determined as per a typical Krusell and Smith (1998) algorithm for price forecasting. Details are in the appendix.

[15]If either of the residuals does not follow a normal distribution then a Kalman filter is not the best filter but the best linear filter. In that case, if a potential entrant used a non-linear filter, for example a

or (14) follow a normal distribution using model generated time series, the null *cannot* be rejected at a 10% significance level for both (13) and (14).

Denote the time t information set *after* observing time t variables (a_t, w_t, K_t) using subscript $t|t$. Similarly the subscript $t|t-1$ indicates the time t information set *before* observing time t variables (a_t, w_t, K_t). $\mu = [\mu^z \mu^q]'$ denotes a potential entrant's estimates for aggregate and idiosyncratic productivity given their information set. Then for each period these estimates and the potential entrant's perceived conditional distribution over next period's aggregate and idiosyncratic productivity are updated as follows.

$$\mu^z_{t|t-1} = \rho_z \mu^z_{t-1|t-1} \tag{17}$$

$$\mu^q_{t|t-1} = \rho_q \mu^q_{t-1|t-1} + (1-\rho_q)\overline{q} \tag{18}$$

$$\mu^z_{t|t} = \mu^z_{t|t-1} + G_z(Y_t - \beta\mu_{t|t-1} - \beta_c) \tag{19}$$

$$\mu^q_{t|t} = \mu^q_{t|t-1} + G_q(Y_t - \beta\mu_{t|t-1} - \beta_c) \tag{20}$$

$$F(z'|a, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w, K) = \mathbf{N}(\rho_z \mu^z_{t|t}, V^z_{t+1|t}) \tag{21}$$

$$F(x'|a, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w, K) = \mathbf{N}(\rho_x \mu^q_{t|t}, V^x_{t+1|t}) \tag{22}$$

Here, G is the stationary Kalman gain and $V_{t+1|t}$ is the stationary prediction variance. Derivations of G and $V_{t+1|t}$ are provided in the appendix. Then, a potential entrant's expected value from entry and optimal entry decision are:[16]

$$V_{en}(a, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w, K) = -k'_{en} + \int_{z'}\int_{x'} [d(z', \Lambda')V(0, k'_{en}, x'; z', \Lambda')]dF(x')dF(z') \tag{23}$$

$$\varepsilon(a, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w, K) = \mathbb{1}_{\{V_{en}(a, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w, K) \geq c_e\}} \tag{24}$$

where k_{en} is the fixed amount of capital that potential entrants must install if they decide to enter the market. If the expected value from entry $V_{en}(a, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w, K)$ is larger than the fixed entry cost c_e, then the potential entrant chooses to enter. If so they pay c_e, invest k_{en}, and next period become an age-0 incumbent plant with beginning of period labor and capital of 0 and k_{en} respectively. As each individual potential entrant has a different history for the composite signal $\{a_{t,i}\}_{t=0}^{\infty}$ there is non-degenerate distribution of potential entrants over $(a, \mu^z_{t|t-1}, \mu^q_{t|t-1})$. Denote it as Ω.

The current period posteriors $(\mu^z_{t|t},\ \mu^q_{t|t})$ of entrants are inherited as the priors of new potential entrants next period. Note that if the priors of new potential entrants were

particle filter, they would get more efficient estimates.

[16] $F(x')$ and $F(z')$ are abbreviations of $F(x'|Y_t, \mu^z_{t|t-1}, \mu^q_{t|t-1})$ and $F(z'|Y_t, \mu^z_{t|t-1}, \mu^q_{t|t-1})$ respectively.

given by the unconditional mean of z and q then potential entrants' learning about the aggregate status would be further dampened and the quantitative effect of learning would be amplified. In that sense our current choice on the information set of new potential entrants is a conservative one.

Figure 1: Timeline of the model economy

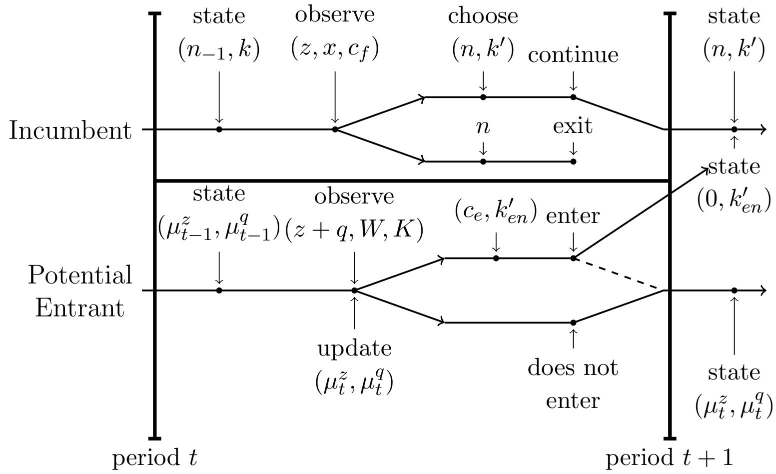


Figure 1 summarizes decision problems of incumbents and potential entrants. Potential entrants start the period with prior beliefs over aggregate productivity, μ^z_{t-1}, and their own idiosyncratic productivity, μ^q_{t-1}. With current period observables, potential entrants update their beliefs and decide whether or not to enter. If they do enter, they pay the output denominated entry cost c_e and buy the fixed amount of capital required to enter, k'_{en}. Incumbents adjust their employment and capital stock and decide whether to shut down or not, after observing current period aggregate and idiosyncratic productivity separately.

3.3. Household

The representative household consumes the final good, makes a labor supply decision and owns all plants, including potential entrants.

$$\max_{\{c_t, n_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{c_t^{1-\sigma_c} - 1}{1-\sigma_c} - \gamma \frac{n_t^{1+1/\sigma_n}}{1+1/\sigma_n} \right] \tag{25}$$

$$\text{s.t. } c_t = w_t n_t + \Pi_t \tag{26}$$

Π_t in (25) represents aggregated profits including entry costs paid by entrants. Compared to previous general equilibrium models with explicit heterogeneous production units, one critical distinction in this paper is that the Frisch elasticity of labor supply is finite. [17] Previous models in the literature have specified an infinite Frisch elasticity with resorting to Hansen (1985) and Rogerson (1988)'s indivisible labor argument. But Chang and Kim (2006) showed that with empirically plausible wealth distribution of household, Frisch elasticity of labor supply implied from heterogenous-household model with extensive margin labor supply decision is between 1 and 2. Based on their results, our baseline model uses a Frisch elasticity of 1.5. Formal definition of recursive competitive equilibrium of the model economy and numerical algorithm based on Krusell and Smith (1998) for calculating approximate dynamics of the model economy are presented in the appendix.

4. Calibration

The model period is annual. We used a time discount rate (β) of 0.9615 so that the average annual implied interest rate is approximately 4%. The depreciation rate of capital (δ) is set at 6.5%, in the middle of the range that has been used in the prior literature discussing micro level plant behavior in the manufacturing sector.[18] We set the returns to scale parameter (θ) as 0.805 - close to the lower end of the estimates of the manufacturing sector's returns to scale from Lee (2005). According to Atkeson and Kehoe (2005), the physical capital share in manufacturing is 19.9% and the intangible capital income share is 8%. Given that we do not explicitly modeled the intangible capital, we attribute half of the intangible capital share to the physical capital share and then targeted capital share of 24%. Risk aversion and the Frisch elasticity of labor supply of the representative household are set as 1 and 1.5 respectively.

In the model economy, the only aggregate shock is the aggregate productivity shock. So we try to match the cyclical behavior of the *model economy's aggregate output* with the cyclical behavior of the *manufacturing sector's real output that is explained by productivity shocks*. To construct this in the data, we projected HP filtered real manufacturing output (BLS annual data) on three lags of HP filtered manufacturing sector TFP in levels (constructed from NBER CES data), plus quadratic and cubic terms. We then calibrated the persistence and volatility of the aggregate shock process by targeting the standard deviation and AR(1) coefficient of the fitted output series. Currently model generated

[17] For example, Khan and Thomas (2008) and Clementi et al. (2015) used an infinite Frisch elasticity.

[18] For example, Atkeson and Kehoe (2005) used 5.5% and Cooper and Haltiwanger (2006) used a depreciation rate of 6.9%.

Table 3: Parameter values

Description	Symbol	Value
Time Discount	β	0.9615
Capital Share	α	0.3
Return to Scale	θ	0.805
Depreciation Rate	δ	6.5%
Risk Aversion	σ_c	1
Frisch Elasticity	σ_n	1.5
S.D. of innovation to aggregate productivity	σ_z	0.025
Persistence of aggregate productivity	ρ_z	0.68
S.D. of innovation to idiosyncratic productivity	σ_x	0.15
Persistence of idiosyncratic productivity	$\rho_x(=\rho_q)$	0.68

cyclical output is slightly more persistent than the data counterpart. But as we have explained in the previous section, in the model economy with information friction, as aggregate productivity shock become more persistent amplification role of the information friction become weaker. In that sense, our choice of the persistency of the aggregate shock process is conservative one.

Table 4: Cyclical properties of output

	S.D. (%)	ρ
Data(fitted y)	3.7	0.45
Baseline Model	3.6	0.53

To prevent the information friction from mechanically amplifying entry, we choose the persistence of incumbents' idiosyncratic shock process and potential entrants' potential idiosyncratic shock process to be identical with the persistence of the aggregate shock process. Our choice for the persistence of the idiosyncratic shock process falls into the middle of the range of estimates in the related literature.[19] Regarding the volatility of the idiosyncratic shock process, what matters for potential entrants' learning problem is the relative variance between innovations to aggregate productivity and *potential idiosyncratic productivity*. But, estimates of the volatility of the idiosyncratic shock process in the literature are for incumbent plants. Therefore, we only choose the volatility of the

[19] Cooper and Haltiwanger (2006) reported 0.92 using structural estimation. Foster et al. (2008), Castro et al. (2015), and Lee and Mukoyama (2015b) reported $0.757 \sim 0.814$, 0.439, and 0.969 respectively.

idiosyncratic shock process of incumbent plants from estimates in the literature. We pin down the volatility of the potential entrants' potential idiosyncratic shock process through an endogenous calibration procedure.

We match moments generated from the steady state version of the model economy where there is no aggregate shock with empirical moments reported in the literature[20] based on the LRD (Longitudinal Research Database). One critical advantage of relying on LRD data instead of BDS data (Business Dynamics Statistics) is that the LRD provides information on both the relative employment size and productivity (which is not available in the BDS) of entering and exiting plants. Also, moments associated with plant level investment rates documented by Cooper and Haltiwanger (2006) are constructed from LRD.

The first set of moments to be calibrated are the entry rate, exit rate, relative (to continuing plants) employment size and productivity of entering plants and relative (to continuing plants) employment size and productivity of exiting plants. Between two successive periods $t-1$ and t, exiting plants are defined as those who operated at time $t-1$ but do not operate at t, while continuing plants are those who operate during both $t-1$ and t. Entering plants are those who start operating at t. Relative characteristics are constructed in a consistent way as empirical counterpart in Lee and Mukoyama (2015a). That is, we used time t characteristics of entering and continuing plants and time $t-1$ characteristics of exiting plants when we calculate relative employment size or productivity. Entry and exit rates are calculated as a measure of entering or exiting plants compared to the average total measure of plants between period $t-1$ and t. Because the entry rate and exit rate are identical in the steady state of the model economy, we target the midpoint of the entry and exit rates from the data.

The second set of moments are the fraction of plants whose investment rate is higher than 20%, and the fraction of plants whose investment rate is less than -20%. These moments are mainly related to the adjustment cost of capital. Cooper and Haltiwanger (2006) constructed these statistics from a balanced panel without entry and exit margins. To be consistent with the data, we calculated these moments in the model economy using only continuing plants.

We disciplined the magnitude of the linear adjustment cost of labor by matching gross job flows in the manufacturing sector. Specifically, we matched the sum of the job creation rate from entering and continuing plants and the job destruction rate from exiting and

[20] Moments related to entry and exit behavior are reported in Lee and Mukoyama (2014). Plant level investment rate related statistics are available from Cooper and Haltiwanger (2006) and job flow data are available at the webpage of John Haltiwanger.

continuing plants. There is one issue in matching total flow rates. We already targeted the entry rate and the relative average employment size of entering plants. Targeting these two moments pins down the job creation rate from entering plants which is higher than the corresponding statistics from job flows data. To prevent our model economy from consistently overestimating general equilibrium pressure generated from entering plants, we also magnify job flows from continuing plants. So rather than matching a total job flow rate of around 19% in the job flows data from the webpage of John Haltiwanger, we target a somewhat magnified 23% total job flow rate.

We calibrate scale of disutility from work so that one third of the available time of the representative household is spent on market work.

The complete set of model parameters we used to jointly match all the just mentioned target moments are as follows: The entry cost, fixed operating cost, stochastic process for the potential idiosyncratic process (long-run mean and volatility of the process), capital stock for entering plants, capital adjustment cost, labor adjustment cost, fixed measure of potential entrants, and scale of disutility from work. We specified the stochastic process for the fixed operating cost as a log-normal distribution.[21]

Table 5: Parameter values associated with matching moments

Description	Symbol	Value
Entry Cost	c_e	0.02
Operating Cost(Mean)	μ_{c_f}	-4.68
Operating Cost(S.D.)	σ_{c_f}	1.38
Mean of Potential Idio.	$\overline{q}$	-0.41
S.D. of Potential Idio.	σ_q	0.11
Entrant's Capital	k_{en}	0.15
Resale Value of Capital	p_s	0.91
Labor Adj. Cost-Hiring	c_p	0.23
Labor Adj. Cost-Firing	c_n	0.20
Measure of Entrants	M	27.52
Disutility from work	γ	5.08

The model economy has strong implications for the life cycles of plants. From the BDS, (Business Dynamics Statistics)[22] we can construct age dependent average employment

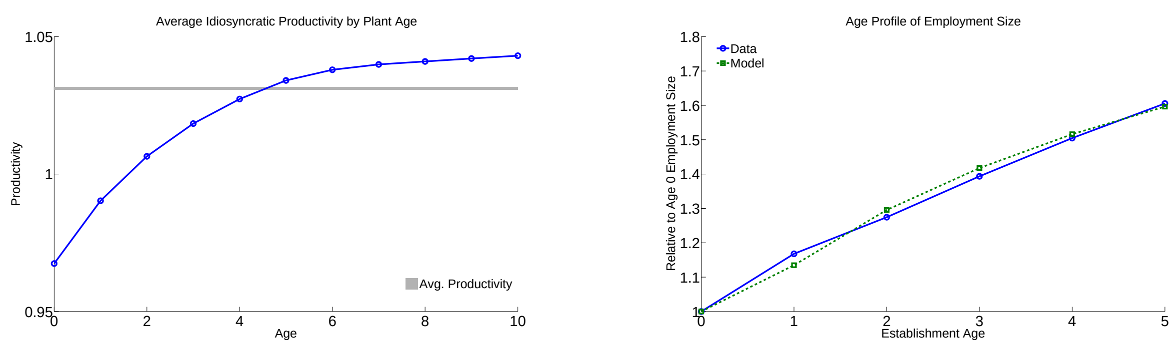
[21]Given that our choice of the log-normal distribution is somewhat arbitrary we will provide robustness checks using the Pareto distribution in the accompanying online-appendix. Results from the model economy following Pareto innovations are almost identical to those from the model economy using a log-normal distribution.

[22]We have not found detailed age dependent average employment size statistics constructed using the

Table 6: Target moments

Moment	Target	Model
Entry Rate	6.0%	6.0%
Exit Rate	6.0%	6.0%
Relative Size of Entering Plants	56%	56%
Relative Size of Exiting Plants	46%	47%
Relative Prod. of Entering Plants	94%	94%
Relative Prod. of Exiting Plants	85%	85%
Positive Spike($\frac{i}{k} > 0.2$)	18.6%	19.1%
Negative Spike($\frac{i}{k} < -0.2$)	1.8%	2.9%
Hours	33%	33%
Job Reallocation Rate	23%	23%

Figure 2: Model Implied Average Idiosyncratic Productivity by Plant Age



(a) (b)

sizes. We then compare the steady state of the model economy's (which is used for the calibration) implied life cycle pattern and those constructed from the BDS. Recall that not the whole age profile is the calibration target. We only targeted the relative employment size and productivity of entering and exiting plants. The gap in productivity between entering plants and continuing plants together with the mean reverting property of the incumbent's idiosyncratic shock process generates an increasing age profile in idiosyncratic productivity. The age profiles of average employment size in the model economy is mainly driven by interaction between the age profile of idiosyncratic productivity and the presence of factor adjustment costs.

Figure 2 shows the age profiles for average idiosyncratic productivity and average employment size respectively. Average idiosyncratic productivity grows as a concave

LRD.

function of age. But in the average employment size profile, the concave pattern is not as transparent as it was for the productivity profile. This is because the presence of both capital and labor adjustment costs defers plants from growing enough to catch up to the steep productivity profile during infancy. The relatively smooth growing pattern of average employment size at ages between $0 \sim 5$ is quite consistent with what is observed from the BDS.[23]

5. Quantitative Results

5.1. Impulse Response Exercise

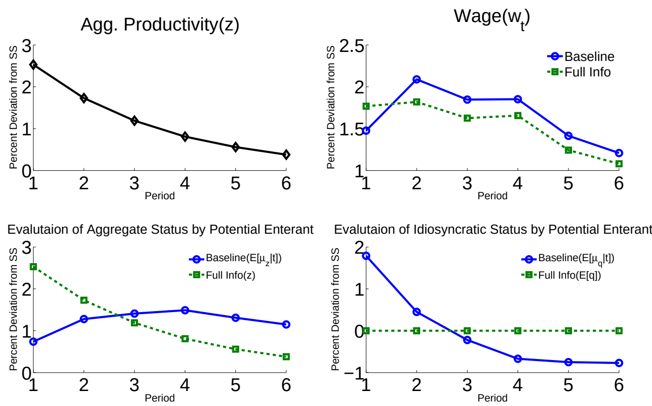
To understand the model economy's dynamics and especially the role of the information friction faced by potential entrants, we provide impulse response functions from both the 'baseline model' and the 'full information model'. In the baseline economy, potential entrants cannot separately observe the aggregate and potential idiosyncratic productivity shocks, while in the full information model potential entrants can observe aggregate productivity directly. The only difference across the two economies is this difference in the information set of potential entrants. Therefore, any different dynamic responses generated via a positive aggregate productivity shock will be solely attributable to the different information structure of potential entrants.

In Figure 3, we plot the dynamics of aggregate productivity, equilibrium wages, and the average of potential entrants' estimates about both aggregate and idiosyncratic productivity. At time 0 the economy is at its steady state.[24] At period 1, the economy is hit by a one unit positive impulse in aggregate productivity. Recall that in the baseline model, potential entrants learn about the aggregate state from some exogenous signal $(z_t + q_t)$, current period equilibrium wages (w_t), and the aggregate capital stock (K_t). On impact of the aggregate productivity shock, given that potential entrants aware that idiosyncratic component of exogenous signal is much more volatile than aggregate one, and aggregate capital stock can response with one period lag, variation in the current

[23]Because the publicly available portion of the BDS only provides pooled data between age $6 \sim 10$, we only compared employment size profiles at ages between $0 \sim 5$.

[24]One caution is that the concept of the steady state used in the impulse response exercise is different from that used in the calibration. The steady state used in the calibration is the version of the economy where there is no aggregate shock. But the steady state used as an initial period in the impulse response exercise is where there is an aggregate shock and all agents account for equilibrium price dynamics when they form expectation with respect to the aggregate state. But, the actual realization of the aggregate shock is fixed at its median level for 100 years.

Figure 3: Impulse response of wages and beliefs



period equilibrium wage is the most important source of learning regarding the status of aggregate productivity for potential entrants.

But on impact of the shock, because of incumbent plants' forward-looking labor demand decision, the response of the equilibrium wage is somewhat dampened. As a result potential entrants underestimate the fluctuations in z_t. In the third and fourth panel of the Figure 3, we plot dynamics of $\int \mu^z_{t|t}(z_t+q_t, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w_t, K_t)d\Omega(z+q, \mu^z, \mu^q)$ and $\int \mu^q_{t|t}(z_t+q_t, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w_t, K_t)d\Omega(z+q, \mu^z, \mu^q)$ respectively. In words, the average estimates of aggregate productivity and potential idiosyncratic productivity across potential entrants at the point in period t when they have to make their entry decision. Until period 2, potential entrants underestimate fluctuations in z_t. But because equilibrium wage stay higher level compared to aggregate productivity, and because the aggregate capital stock increases in a sluggish manner, from period 3 on potential entrants overestimate z_t. Given that potential entrants can observe $z_t + q_t$, estimates of q_t move inversely with estimates of z_t.

In the first panel of Figure 4, we plot the average one period ahead wage forecast across potential entrants.[25] As potential entrants underestimate z_t until period 2, they also underestimate $E_{en}[w_{t+1}|t]$ until period 2 and consequently overestimate expected profit from entry until period 2. Since at period 1, $E_{en}[z_2 + x_2|t]$ is much higher than $E_{en}[w_2|t]$, the number of potential entrants who decide to enter increases much more in the baseline model compared to the full information model. As a result, a large number of new plants start operating in period 2 and the entry rate in period 2 responds by more

[25] In the baseline economy, potential entrants are aware of the equilibrium price forecasting rule and the law of motion of the aggregate capital stock, as are incumbent plants, but they cannot observe z_t. Rather they use posterior estimates of z_t when forming expectations for tomorrow's wage. Given that each potential entrant has a different posterior estimate for z_t, each also has a different wage forecast.

Figure 4: Impulse responses of wage forecasts and the entry rate

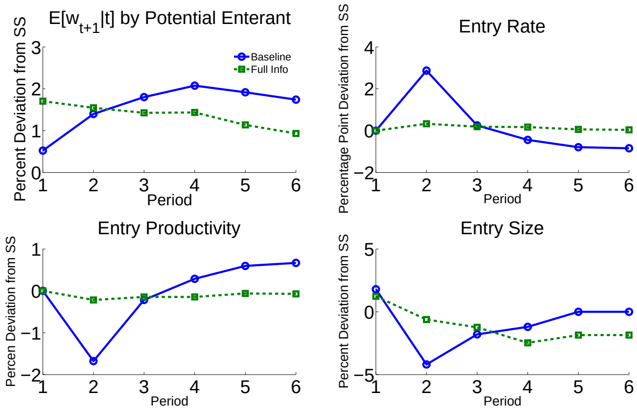
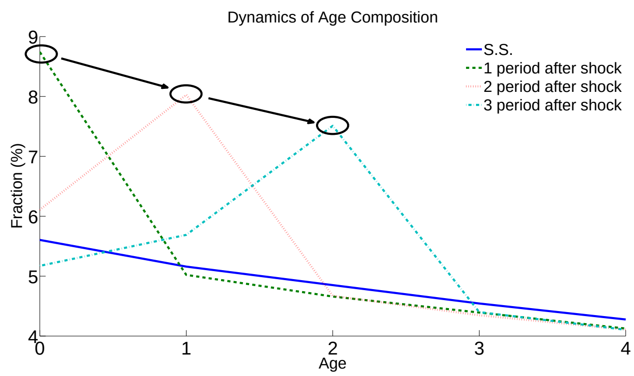


Figure 5: Dynamics of Age Composition



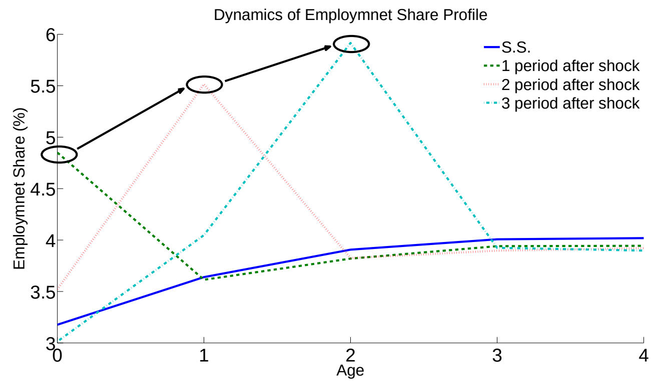
in the baseline economy.[26] Whereas, in the full information model, because potential entrants can accurately form expectations over the equilibrium wage dynamics associated with the positive aggregate productivity shock, the response in the entry rate is quite dampened.

The dynamics of the characteristics of entering plants mirror the dynamics of the entry rate. In period 1 of the baseline model, as more of the potential entrants decide to enter based on their overestimation of the expected profit from the entry, average productivity and the average employment size of the entering plants deteriorates. This pattern is also consistent with the data. According to Lee and Mukoyama (2015a), plants that enter during recessions have significantly better TFPR and larger employment size than plants that enter during booms.

Regarding the issue of whether potential entrants' information friction has an effect

[26] We defined the entry rate at period t as $\frac{\text{measure of plants that start operating at period } t}{\text{average total number of plants between period } t-1 \text{ and } t}$ which is consistent with how BDS measures the entry rate.

Figure 6: Dynamics of Employment Share Profile

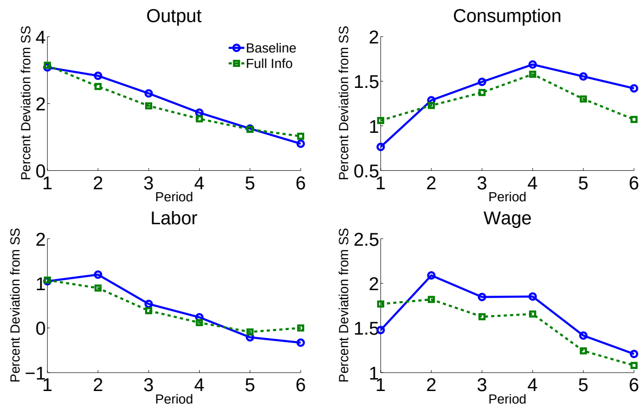


on the aggregate dynamics, the important question is what will happen to those plants who entered the market based on an incorrect estimation of the aggregate state. To see what happens to the cohort who entered the market at period 2, in Figure 5 and Figure 6 we plot how the age composition and employment share profiles change after the positive aggregate productivity shock in the baseline model. In both figures, "1 period after the shock" indicates period 2 in the impulse response exercise. To track the cohort who entered the market in period 2 we track the measure of age 0 plants "1 period after the shock", the measure of age 1 plants "2 period after the shock" and the measure of age 2 plants "3 period after the shock".

What we can see is that most of the plants who entered the market in period 2 do not exit the market immediately. Although many of them entered due to a overestimation of the expected profit from entry, not all immediately exit the market after they realize the true aggregate state. The reasons for their continuing operation are that the entry cost is relatively larger than the fixed operating cost and there is partial irreversibility regarding the investment in physical capital. Given that the entry cost is sunk, once potential entrants become incumbent plants, what matters for their exit decision is whether the expected profit from operating is larger than the stochastic operating fixed cost or not. As the cost of keep operating is relatively low, even after boom induced cohorts realized their true productivity, they rationally choose to keep operating. Exit value of the plants are mainly determined by the resale value of the installed physical capital. But because of the presence of the partial irreversibility, plants cannot fully recover their investment in physical capital when they exit the market. Instead given that idiosyncratic productivity shock is volatile, there is option value of keep staying in the market. That is another critical factor that makes boom induced cohorts postpone their exit.

To see the effect of this period 2 entering cohort on labor market equilibrium, in Figure

Figure 7: Impulse Response of Aggregate Variables

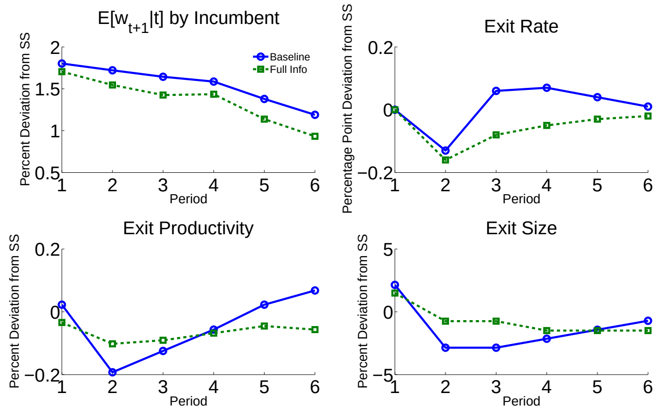


6 we plotted how the age profile of the employment share changes after the aggregate productivity shock. From Figure 6 we can see that as the period 2 entrants grow in their employment size as they age, they account for a larger share of total employment and generate additional wage pressure. This additional labor demand associated with the growth of boom induced cohort keeps the equilibrium wage from declining as aggregate productivity reverts to its steady state level.

The dynamics of the age and employment shares composition affects dynamics of aggregate variables. In Figure 7, we plot dynamics for aggregate output, consumption, labor, and wages. In the baseline economy, all aggregate variables slowly return to their stationary level compared to in the full information economy. The information friction faced by potential entrants amplifies fluctuations in the entry margin, which acts as an effective internal propagation mechanism.

Particularly, aggregate labor and wages show a clear hump shaped response in the baseline model. This is mainly caused by the incumbent plants' forward-looking labor demand behavior. When $E[w_2|1]$ is relatively higher than $E[z_2|1]$, period 2's static optimal labor demand is on average lower than period 1's static optimal labor demand. So if incumbents in period 1 choose to employ period 1's static optimal labor demand then they must pay adjustment costs to reduce their labor in period 2. By accounting for their future labor decisions, the period 1 response of incumbent plants' labor demand to the increase in aggregate productivity is lessened. With less aggregate labor demand in period 1, the equilibrium wage in period 1 is also lower and potential entrants, by observing the slight increase in w_1 relative to w_0, underestimate z_1. Then entry in period 2 responds strongly and as the entry cohort grows, aggregate economic activity slowly return to stationary level relative to the decay of aggregate productivity. Recall Figure 3,

Figure 8: Impulse response of the exit rate



where we generated an impulse response from how potential entrants evaluate aggregate productivity by observing the dynamics of the equilibrium wage. Eventually, potential entrants' belief that aggregate component of the shock is not that large combined with dynamic labor decision of incumbent plant actually dampens on impact response of the equilibrium wage.

Table 7: Cross correlation between employment and output (y_t)

	n_t	n_{t+1}	n_{t+2}
Data	0.89	0.69	0.13
Baseline	0.92	0.51	0.0
Full Info	0.96	0.33	−0.17

Note: In the data, output and employment are BLS manufacturing sector annual real output and employment series. All correlations are calculated using HP filtered series.

Table 7 provides cross-correlations between manufacturing sector aggregate output and employment. In the data, the contemporaneous correlation between output and employment is much less than 1 but the correlation of employment with lagged output declines slowly. The corresponding statistics from the baseline economy are more consistent with the data than those from the full information model economy. This shows that hump shaped aggregate labor dynamics implied from baseline model economy is consistent with the data.

Now we turn to the impulse response of the plant exit rate.[27] The period t exit rate is mainly determined by the exit decisions of period $t-1$ incumbent plants. Then, the

[27]We defined the exit rate at period t as $\frac{\text{measure of plants who exit between period } t-1 \text{ and } t}{\text{average total measure of plants between period } t-1 \text{ and } t}$ which is consistent with how BDS measures the exit rate.

period t exit rate critically hinges on the wage forecasts of period $t-1$ incumbents, $E[w_t|t-1]$. In the first panel of Figure 8, we plot the dynamics of incumbent plants' one period ahead wage forecast. In period 2, the additional labor demand generated by the cohort who entered in response to the shock[28] is not large enough compared to the level of the aggregate productivity (z_2) to significantly affect exit. In other words, from the perspective of the period 1 incumbents, $E[w_2|1]$ is not particularly large compared to $E[z_2|1]$. As a result, the number of plants who decide to exit the market decreases and the period 2 exit rate falls below the steady state exit rate. But as time goes by, the additional labor demand generated by the growing boom cohort outgrows aggregate productivity, pushing the exit rate from period 3 on above the steady state level. This oscillation in the exit rate implies that the absolute value of correlation between exit and aggregate output will be very low. As a result, in the baseline model, plant exit rate become acyclical. Conversely, in the full information economy, the exit rate decreases significantly in period 2 and then as aggregate productivity declines it returns to its steady state level smoothly. Naturally, in the full information model, plant exit rate become countercyclical.

5.2. The Business Cycle Behavior of Entry and Exit

Using the time series generated from stochastic simulation of the model economy, we can test which model economy generates cyclical behavior in entry and exit that is more consistent with the data. For the stochastic simulation, we used the same randomly generated sequence for aggregate productivity ($\{z_t\}$) in both the baseline and full information economy. Table 8 presents the contemporaneous correlation of HP filtered output with either the HP filtered entry rate or the HP filtered exit rate. Both of the model economies imply that the entry rate comoves positively with output, which is consistent with the data. But the full information model implies a countercylical exit rate that is at odds with the data. As we have seen from Figure 8, the baseline model generates an oscillating exit rate, which gives a realistic correlation between output and the exit rate that is close to 0.

Another important aspect of the cyclical behavior of entry and exit is the magnitude of the fluctuations. To see this dimension of the cyclicality, following Lee and Mukoyama (2015a), we categorize each period in the model economy: as a boom if output growth rate is higher than time series average of output growth rate and as a recession if output growth rate is lower than the average. Table 9 provides the average entry and exit rates

[28] See age 0 plants' employment share in the "1 period after the shock" profile of Figure 6.

Table 8: Correlation with output

	Entry Rate	Exit Rate
Data	0.35	−0.02
Baseline	0.49	−0.06
Full Info	0.48	−0.49

Note: In the data, the reported correlations are between the entry (exit) rate from BDS and industrial production in the manufacturing sector. In the model economy, correlations are between the entry (exit) rate and aggregate output. All correlations are calculated using HP filtered series.

across all boom and recession periods. The baseline model generates more volatile entry margin than full information model, which is closer to the magnitude of volatility observed in the data.

Table 9: Magnitude of Fluctuations

	Entry Rate(%)		Exit Rate(%)	
	Boom	Rec.	Boom	Rec.
Data	8.1	3.4	5.8	5.1
Baseline	7.7	4.4	5.8	5.8
Full Info	6.2	5.9	6.0	6.1

Note: The data column is taken from Lee and Mukoyama (2015a). In the model economy, booms and recessions are categorized depending on whether output growth rate is above or below the average output growth rate as in Lee and Mukoyama (2015a).

The cyclical behavior from the full information model clearly shows that once we impose market clearing conditions with proper general equilibrium forces (realistic risk aversion and Frisch elasticity), and adjustment frictions both for capital and labor, then it is hard to match the fluctuations in entry margin as observed in the data.

Then what can explain the observed fluctuations in the entry margin? To be consistent with the data, a potential mechanism should be able to amplify the fluctuations along the entry margin and the generated exit should be simultaneously acyclic. But under a full information structure, as shown, this is far from trivial. Because both the potential entrant's incentive to enter the market and the incumbent's incentive to keep operating depend on the incumbent's expected value, under the symmetric information structure, exit is just as countercyclical as the entry rate is procyclical. However, the baseline model with potential entrants' imperfect information can generate both a volatile entry rate and an acyclical exit rate at the same time, by cutting this tight linkage between perceived expected profit for the potential entrant and incumbent. In the baseline economy, the exit rate is acyclical because entry is too strongly procylical.[29]

6. Aggregate Implications

6.1. Internal Propagation Mechanism

In the previous section, we have shown that the baseline model can generate cyclical behavior in entry and exit that is consistent with the data. A natural question is then what is the effect of the cyclical behavior of the net entry margin on the cyclical behavior of aggregate variables.

Table 10: Cyclical properties of aggregate output

	S.D.(%)	AR(1) of Output	AR(1) of Solow Residual
Baseline	3.6	0.51	0.73
Full Info	3.3	0.4	0.65

Table 10 provides the cyclical properties of aggregate output from stochastic simulation. By comparing the cyclical behaviors of aggregate output across two economies, we can see that the baseline model economy has both amplification and internal propagation effects. Especially, internal propagation effect is more transparent. This result shows that even in the full-blown general equilibrium environment, once net entry margin become volatile enough as observed in the data, then it can work as quantitatively meaningful internal propagation mechanism. Two key elements for this internal propagation mechanism are potential entrants' inability to forecast equilibrium factor prices and incumbent plants' forward looking factor demand behavior.

Another way to see the internal propagation effect of baseline model economy is to compare persistency of model generated Solow residuals. Using model economy generated time series of aggregate output, labor, and physical capital, we calculated Solow residual with assuming aggregate cobb-douglas production function. From the last column of the Table 10, we can see that the AR(1) coefficient of the Solow residual from baseline model economy is more persistent than that from the full information model economy

[29] This implication of the baseline model economy is reminiscent of the result from Caballero and Hammour (1994). Inside a model of creative destruction, they showed that in response to the aggregate demand fluctuation there is a trade-off between the cyclicality of the creation and destruction margins.

even though both model economy is simulated with exactly identical exogenously given aggregate productivity shock process.

6.2. Welfare Cost of Imperfect Information

As we have seen, with exactly identical aggregate productivity shock sequence, representative household in the baseline model economy go through more volatile and persistent business cycle fluctuation. This result implies that welfare cost of business cycle might be also amplified in the baseline model economy because of potential entrants' information friction.

To formally test this hypothesis, we calculate magnitude of consumption equivalence welfare change across baseline model economy and full information model economy. That is how much of per period additional consumption should be provided to compensate for the additional fluctuations in equilibrium path of consumption and labor. Using the model economy generated time series of aggregate consumption and labor, we can calculate the consumption equivalence welfare change as in (27).

$$\begin{aligned}&\sum_{t=1}^{T}\beta^{t}\left[\frac{(1+\omega)c_{t,\text{base}}^{1-\sigma_c}-1}{1-\sigma_c}-\gamma\frac{n_{t,\text{base}}^{1+1/\sigma_n}}{1+1/\sigma_n}\right]\\ &=\sum_{t=1}^{T}\beta^{t}\left[\frac{c_{t,\text{full info}}^{1-\sigma_c}-1}{1-\sigma_c}-\gamma\frac{n_{t,\text{full info}}^{1+1/\sigma_n}}{1+1/\sigma_n}\right]\end{aligned}\tag{27}$$

We get 0.6% of consumption equivalence (ω). This positive amount of consumption equivalence means that amplified business fluctuations in the baseline model economy actually deteriorate the welfare of representative household. Given that amplified volatility of aggregate consumption and labor is driven by potential entrants' information friction, we can interpret 0.6% of consumption equivalence welfare change as cost of imperfect information.

Observed volatility in the plant entry margin in the data that could be properly explained only in the baseline model economy might cause considerable amount of welfare loss. Naturally, welfare cost observed in the baseline model economy justifies policy intervention that stabilize business cycle fluctuations in entry margin. According to the policy exercise presented in the appendix, when government subsidize 20% of entry cost when realized aggregate productivity is below its median level (that is $z_t < 0$), welfare of the representative household is improved as much as 0.13% of consumption equivalence.

7. Testable Implications

7.1. The Cyclicality of the Establishment Entry Rate By Firm Age

According to the BDS, among the entries that have occurred during 1977 to 2012, around 76% of entering establishments come from new firms.[30] The remaining 24% come from existing firms[31] opening new establishments, such as GM opening a new plant. If information about aggregate economic conditions or firm level productivity is shared at the enterprise level, then existing firms' decisions about establishment entry might be immune to the informational friction. But if inexperienced new firms are actually facing an information friction that makes it difficult to disentangle aggregate and idiosyncratic productivity, then establishment entry from new firms should be more procylical than entry from existing firms.

Table 11 gives the contemporaneous correlation between the HP filtered establishment entry rate for new and preexisting firms and the constructed business cycle indicator for the manufacturing sector, using either aggregate manufacturing industrial production or employment.[32] Entry from new firms is more procyclical than from existing firms. Table 12 provides the magnitudes of the cyclical fluctuations in entry by firm age. The boom period is again defined as when the HP filtered cyclical component of the cyclical indicator (either industrial production or employment) is above its trend, and vice versa for the recession period. Then we can calculate the average value of the cyclical component of the entry rate during booms and recessions. Consistent with the correlation pattern from Table 11, establishment entry from new firms shows larger fluctuations across booms and recessions.

[30] According to BDS terminology, age 0 firms. More specifically, BDS defines age 0 firms in the following way. "Startups are firms with an age of 0. No previous activity is associated with these firms and all its establishments are de novo establishments."

[31] According to BDS terminology, age 1 firms and older.

[32] Refer back to section 2 for details on the construction of these series.

Table 11: Correlation of the entry rate and cyclical indicator by firm age

	IP		Employment	
Firm Age	Correlation	p-value	Correlation	p-value
New	0.4	0.01	0.44	0.04
Existing	0.2	0.39	0.27	0.23

Note: p-values correspond to whether the correlation is nonzero. "IP" abbreviates industrial production.

Table 12: Magnitudes of fluctuations in the entry rate by firm age (% deviation from trend)

Indicator: Output				Indicator: Employment			
Firm Age	Boom	Recession	p-value	Firm Age	Boom	Recession	p-value
New	1.3%	−1.7%	0.08	New	1.4%	−3.4%	0.01
Existing	0.6%	−1.2%	0.31	Existing	0.0%	−1.8%	0.34

Note: p-values are from the t-test of the mean difference in deviations of the entry rate from trend between plant entry from new firms and existing firms.

7.2. Are plants that entered the market during booms more likely to fail?

The existence of an imperfect information friction also implies that potential entrants systematically overestimate their expected profit from entry during booms and underestimate their expected profit during recessions. Unfortunately, we are not able to directly observe how potential entrants form these expectations over the business cycle. But, given high entry costs, we can think of exits by one year or two year old establishments as a result of their incorrect estimation of expected profit before entry. If three years of profits cannot cover the cost of entry, then such exits must be a consequence of an incorrect judgment of profits ex ante. Therefore, we check if plants that entered the market during a boom period are more likely to exit the market quickly compared to plants that entered the market during recessions.

From the BDS, we categorized establishments that entered between 1980 and 2005[33] into two groups: plants that entered during boom periods[34] are categorized as the 'boom

[33]For this exercise we exclude cohorts who were affected by the Great Recession. That is we exclude sample periods after 2006. During the Great Recession, the exit rate for young plants rose. This increased exit rate of young plants during the Great Recession is more likely related to their weak financial structures and economy-wide deteriorations in credit availability than an informational friction.

[34]As before, defined as when HP filtered re-timed annual industrial production of the aggregate manufacturing sector is above trend.

cohort' and other plants are categorized as the 'recession cohort'. For each cohort, the survival rate $1 \sim 3$ years after entry is then calculated. Table 13 provides these calculated survival rates. The table illustrates that plants who entered the market during boom periods are more likely to exit the market within three years after entry than cohorts who entered the market during recessions. If early exit actually reflects poor estimation of the expected profit from entry, then these statistically significant differences across boom and recession cohorts indicate that during boom periods potential entrants overestimate expected profit from entry.

To make clear that above-mentioned state-dependent early fail of young plants can be explained only by baseline model economy, we run the impulse response exercise (as presented in Section 5.1 both with positive (boom) and negative (recession) aggregate productivity shock. And then compare up to three year survival rate of the cohort of plants who entered the market one year after the aggregate shock. Figure 9 shows difference between survival rate of recession entered cohort and boom entered cohort up to 3 years after entry from the BDS (data), baseline model, and full information model economy. It clearly shows that in the baseline model economy boom entered cohort has lower survival rate up to three years after entry as some of them entered market based on the overestimation of expected profit from entry. Whereas in the full information model economy, early fail rate of the plants does not systematically differ depending on whether they enter the market during boom or recession.

Table 13: Establishment survival rate by cohort

Year After Entry	Boom Cohort	Rec. Cohort	p-value
1	80.8%	81.7%	0.09
2	67.6%	69.0%	0.02
3	57.9%	59.8%	0.00

Note: p-values are from the t-test of the mean difference in survival rate between boom and recession cohorts.

If existing firms are actually not subject to the proposed information friction, then for new establishments from existing firms, early exits would not depend on whether the new plant was built during a boom or recession. In general, BDS does not provide statistics based on both firm and establishment age. But in case of the one year old establishments, we can identify how many of them came from new firms or existing firms. We can thus calculate the one year after entry survival rate of the boom and recession cohorts separately for establishments from new firms and from existing firms. Table 14 shows that in case of entry from new firms, cohorts who entered the market during booms

Figure 9: Survival rate by cohort across model economies

Note: Each bar represent difference between survival rate of recession entered cohort and boom entered cohort up to 3 years after entry.

are more likely to exit the market within one year. In contrast, for establishments from existing firms, there is no significant difference in their one year survival rate across boom and recession cohorts. This observation indicates that having market experience is critical in making good entry decisions over the business cycle.

Table 14: One year survival rates by cohort and firm age

Firm Age	Boom Cohort	Rec. Cohort	p-value
New Firm	79.6%	80.9%	0.04
Existing Firm	88.0%	87.5%	0.62

Note: p-values are from the t-test of the mean difference in survival rate between boom and recession cohorts.

7.3. Cyclicality of exit rate in 2-digit level

In the baseline model economy, exit rate become acyclical because of additional factor price variations generated by amplified volatilities in the entry margin. If we simulated baseline model economy with spot market clearing equilibrium wage and stochastic discount factor fixed at their steady state value, then amplified response of entry margin does not affect cyclical behavior of exit. Naturally, in this partial equilibrium version of baseline model economy, exit rate become countercyclical. Different cyclicality of exit rate across general equilibrium and partial equilibrium observed in the baseline model economy can be used as another testable implication.

We would interpret cyclical behavior of plant exit rate observed in the non-farm pri-

Table 15: Correlation between output and exit rate in the baseline model

	Correlation
General Equilibrium	-0.06
Partial Equilibrium	-0.64

vate sector or aggregate manufacturing sector as general equilibrium counterpart of real world data. And we might think of cyclicality of 2-digit level exit rate associated with corresponding sector specific variations as partial equilibrium counterpart of real world data. It would be ideal if we could use more dis-aggregated level (e.g. 3-digit or 4-digit) specific cyclical behavior of exit rate. But because of data availability, we focuses on 2-digit level cyclicality of exit rate. Specifically, we use "job destruction rate from exiting plants" in 2-digit manufacturing sector as measure of sectoral level employment size weighted exit rate.[35] This measure compromises cylicality of exit rate itself and average employment size of exiting plants, so we should keep this limitation of data in mind when interpreting result based on this data set.

In order to make comparison across cylicality in aggregate level and 2-digit level consistent, we also check cyclicality of "job destruction rate from exiting plants" in the non-farm private sector or aggregate manufacturing sector from Business Dynamics Statistics.

For the aggregate level cyclicality of (employment size weighted) exit rate, we measure correlation coefficient between HP filtered aggregate cyclical indicator and HP filtered job destruction rate from exiting plants. In case of non-farm private sector, we used re-timed quarterly aggregate real GDP and aggregate employment in the non-farm private sector as cyclical indicator. For aggregate manufacturing sector, we used re-timed monthly industry production and quarterly manufacturing sector employment as cyclical indicator.

For 2-digit level, it is critical to control for industry fixed effects and any economy-wide cyclical variations. So we use panel regression approach with including industry and year dummy to measure cyclicality of 2-digit specific (employment size weighted) exit rate. And for 2-digit level cyclical indicator, we used sector level total value of shipment and employment that is constructed from NBER-CES data as cyclical indicator.

$$\log(JDREX)_{i,t} = \beta \log(\text{Cyclical Indicator})_{i,t} + \text{Industry}_i + \text{Year}_t + \epsilon_{i,t} \tag{28}$$

(28) shows our specification of 2-digit level panel regression. For both job destruction rate from exiting plants ("JDREX") and cyclical indicators are entered as HP filtered.

[35] Available at the webpage of John Haltiwanger.

And β measures 2-digit specific cyclicality of employment size weighted exit rate.

Table 16: Cyclicality of employment size weighted exit rate

Sample Period	Whole Sample		1977 $\sim$ 1998	
Cyclical Indicator	Output	Employment	Output	Employment
Non Farm Private	0.16(0.39)	0.24(0.19)	0.00(0.99)	0.02(0.93)
Manufacturing-Aggregate	0.06(0.74)	0.04(0.87)	0.25(0.25)	0.09(0.69)
Manufacturing-2 digit level	−0.11(0.03)	−0.19(0.00)	−0.12(0.03)	−0.18(0.00)

Note: For "Non Farm Private" and "Manufacturing-Aggregate", each entities represent correlation coefficients. For "Manufacturing-2 digit level" each entities represent standardized regression coefficient of β in (28). Numbers in the parenthesis are p-values associated with coefficients.

Table 16 reports, resulting correlation coefficients for non-farm private sector and aggregate manufacturing sector and standardized regression coefficient of β for 2-digit manufacturing sector. "1977 $\sim$ 1998" panel shows result when using data only from overlapping sample period (that is 1977 $\sim$ 1998) for BDS and job flows data from John Haltiwanger.

At the non-farm private or aggregate manufacturing sector level (which is empirical counterpart of general equilibrium model), regardless of sample period and cyclical indicator, there is no significant correlation between job destruction rate from exiting plant and cyclical indicator. Whereas at the 2-digit manufacturing level (which is empirical counterpart of partial equilibrium), in all the cases we have considered, the standardized regression coefficient of β is significantly negative.

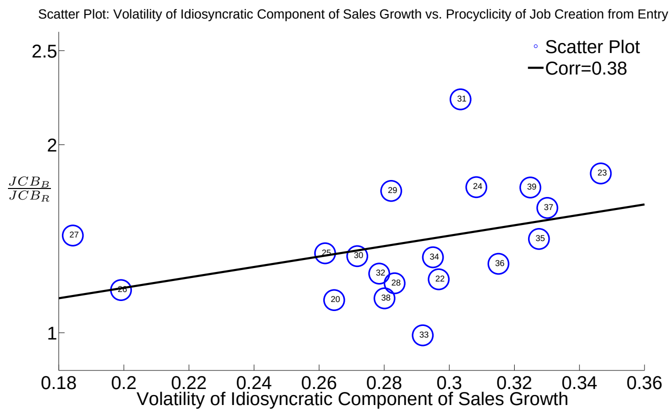
To make comparison between model economy and data more sharp, we calculate cyclicality of job destruction rate from exiting plants both from baseline model economy and full information model economy with general and partial equilibrium condition. Table 17 clearly shows that as baseline model economy predicts employment size weighted exit rate is acyclical only in the aggregate manufacturing level.

Table 17: Cyclicality of employment size weighted exit rate

	GE(Aggregate)	PE(2digit)
Baseline Model	0.18	−0.26
Full Info. Model	−0.64	−0.26
Manufacturing Data	0.25	−0.12

Note: For "Manufacturing Data", "GE(Aggregate)" represent correlation coefficients between output and job destruction rate from exiting plants at aggregate manufacturing sector and "PE(2digit)" represent standardized regression coefficient of β from 2-digit level regression.

Figure 10: Volatility of the idiosyncratic component of sales growth vs. procyclicality of job creation from entry



7.4. Is entry more procyclical in sectors where the idiosyncratic shock is more volatile?

Within the manufacturing sector, the volatility of the idiosyncratic component of uncertainty[36] individual plants face varies across disaggregated sectors. According to Castro et al. (2015), across 3-digit manufacturing industries, the size of the standard deviation of idiosyncratic shocks to Revenue Total Factor Productivity (TFPR) growth varies from 6.7% (producers of leather soles) to 35.2% (manufactures of non-ferrous metals). For the sectors which have a more volatile plant level idiosyncratic shock, the information friction in separating aggregate and idiosyncratic productivity will be more severe. As a result, sectors with more volatile plant level idiosyncratic shocks should have more procyclical entry.

To test this implication, we need disaggregated data on entry across manufacturing sectors and a measure of the volatility of the plant level idiosyncratic shock. Foster et al. (2006) provides job creation flows from entering plants up to 2-digit manufacturing sectors. Castro et al. (2015) provides the volatility of the idiosyncratic component of plant level sales growth up to 3-digit levels.[37] With the lower-level data on industry shares in Foster et al. (2006), we aggregate up the idiosyncratic volatility to the 2-digit industry code level.

[36]Uncertainty with respect to any element that might drive profit at the plant level and not the industry level.

[37]Both statistics are constructed from the LRD. The volatility calculations are made across a sample period of 1972 to 1997 and job flows through entering plants are available for 1973 to 1998. We therefore used job flow data only for 1973 to 1997.

Then, we can use the ratio between the job creation rate from entry during aggregate manufacturing sector boom periods to the creation rate in aggregate manufacturing sector recession periods as a measure of the cyclicality for each 2-digit sector in terms of entry. Figure 10 shows a scatter plot of the volatility of the idiosyncratic component of sales growth and the cyclicality of job creation from entry. The correlation between the two series is 0.38 and the corresponding p-value against a null of zero is 0.11. Given the small number of observations, the potential for a very significant correlation is quite limited, but there is still a noticeably positive relation.

8. Concluding Remarks

Using the general equilibrium heterogeneous plant model where the growth of plants is governed by non-convex capital and labor adjustment costs, we showed that once general equilibrium forces are disciplined by standard values for risk aversion and Frisch elasticity, a standard industry dynamics model cannot generate empirically realistic cyclical behavior in entry and exit. This paper provides a mechanism that can jointly match the observed cyclicality of entry and exit with full-blown general equilibrium environment: an information friction among potential entrants that are considering entry. Once the model economy generates the cyclical behavior of entry and exit consistent with observed in the data, then net entry margin combined with incumbent plants' forward-looking factor demand behavior works as quantitatively meaningful internal propagation mechanism. At the same time, another critical implication of the model economy with information friction is that volatile entry margin observed in the data might not be the efficient allocation. So the model economy with information friction justifies policy intervention that stabilizing entry margin along the business cycle.

Even though we cannot directly test for the presence of an information friction, several testable implications of the model economy are consistent with the data: plant entry from new firms is more procyclical than entry from existing firms; plants from new firms that entered the market during booms are more likely to exit the market rapidly compared to those that entered the market during recessions; employment size weighted exit rate is acyclical along the aggregate manufacturing sector's cyclical variations but it is counter-cyclical along the 2-digit level sector-specific cyclical variations; industries where the idiosyncratic component of productivity is more important exhibit more procyclical job creation from entry over the business cycle.

One limitation of our framework is that the endogenous variables that potential entrants can use as source of learning about the aggregate state are exogenously fixed. Introducing an endogenous choice of observable through a rational inattention style argument could be an interesting extension of the developed framework.

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Appendices

A. Derivation of Stationary Kalman Gain

Unobservable Stochastic Process

$$z_{t+1} = \rho_z z_t + \epsilon_{z,t+1} \tag{29}$$

$$q_{t+1} = (1-\rho_q)\bar{q} + \rho_q q_t + \epsilon_{q,t+1} \tag{30}$$

Observable Variables

$$a_t = z_t + q_t \tag{31}$$

$$\log w_t = \beta_{w,c} + \beta_w z_t + \epsilon_w \tag{32}$$

$$\log K_t = \beta_{K,c} + \beta_K z_t + \epsilon_K \tag{33}$$

Measurement Equation

$$\underbrace{\begin{bmatrix} a_t \\ \log w_t \\ \log K_t \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} 1 & 1 \\ \beta_w & 0 \\ \beta_K & 0 \end{bmatrix}}_{\beta} \begin{bmatrix} z_t \\ q_t \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ \beta_{w,c} \\ \beta_{K,c} \end{bmatrix}}_{\beta_c} + \begin{bmatrix} 0 \\ \epsilon_w \\ \epsilon_K \end{bmatrix} \tag{34}$$

$$\text{where } \begin{pmatrix} \epsilon_w \\ \epsilon_K \end{pmatrix} \sim i.i.d.\ \mathrm{N}\left[0, \underbrace{\begin{pmatrix} \sigma_w^2 & 0 \\ 0 & \sigma_K^2 \end{pmatrix}}_{R_t}\right]$$

Transition Equation

$$\begin{bmatrix} z_t \\ q_t \end{bmatrix} = \underbrace{\begin{bmatrix} \rho_z & 0 \\ 0 & \rho_q \end{bmatrix}}_{T} \begin{bmatrix} z_{t-1} \\ q_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ (1-\rho_q)\overline{q} \end{bmatrix}}_{T_c} + \begin{bmatrix} \epsilon_z \\ \epsilon_q \end{bmatrix} \tag{35}$$

$$\text{where } \begin{pmatrix} \epsilon_z \\ \epsilon_q \end{pmatrix} \sim i.i.d.\ \mathrm{N}\left[0, \underbrace{\begin{pmatrix} \sigma_z^2 & 0 \\ 0 & \sigma_q^2 \end{pmatrix}}_{Q_t}\right]$$

Notation

Denote the prior mean and variance of state variables before realization of time t observations as $\mu_{t|t-1}$ and $V_{t|t-1}$ respectively.

$$\mu_{t|t-1} = \begin{bmatrix} \mu_z \\ \mu_q \end{bmatrix}, \quad V_{t|t-1} = \begin{bmatrix} \sigma_z^2 & \sigma_{zq} \\ \sigma_{qz} & \sigma_q^2 \end{bmatrix}$$

Updating Equation

$$\mu_{t|t} = \mu_{t|t-1} + \underbrace{V_{t|t-1}\beta_t' H_t^{-1}}_{\text{Kalamn Gain} \equiv G_t} (Y_t - \beta_t \mu_{t|t-1} - \beta_c) \tag{36}$$

$$V_{t|t} = V_{t|t-1} - V_{t|t-1}\beta_t' H_t^{-1} \beta_t V_{t|t-1} \tag{37}$$

$$\text{where } H_t \equiv \beta_t V_{t|t-1} \beta_t' + R_t$$

We can then do some rewriting:

$$\begin{aligned} H_t &= \begin{bmatrix} 1 & 1 \\ \beta_w & 0 \\ \beta_K & 0 \end{bmatrix} \begin{bmatrix} \sigma_z^2 & \sigma_{zq} \\ \sigma_{qz} & \sigma_q^2 \end{bmatrix} \begin{bmatrix} 1 & \beta_w & \beta_K \\ 1 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & \sigma_w^2 & 0 \\ 0 & 0 & \sigma_K^2 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_z^2 + 2\sigma_{zq} + \sigma_q^2 & \beta_w(\sigma_z^2 + \sigma_{zq}) & \beta_K(\sigma_z^2 + \sigma_{zq}) \\ \beta_w(\sigma_z^2 + \sigma_{zq}) & \beta_w^2 \sigma_z^2 + \sigma_w^2 & \beta_w \beta_K \sigma_z^2 \\ \beta_K(\sigma_z^2 + \sigma_{zq}) & \beta_w \beta_K \sigma_z^2 & \beta_K^2 \sigma_z^2 + \sigma_K^2 \end{bmatrix} \end{aligned}$$

$$\begin{bmatrix} \mu_z \\ \mu_q \end{bmatrix}_{t|t} = \begin{bmatrix} \mu_z \\ \mu_q \end{bmatrix}_{t|t-1} + \begin{bmatrix} \sigma_z^2 + \sigma_{zq} & \beta_w \sigma_z^2 & \beta_K \sigma_z^2 \\ \sigma_{qz} + \sigma_q^2 & \beta_w \sigma_{qz} & \beta_K \sigma_{qz} \end{bmatrix} \times H_t^{-1} \times \begin{bmatrix} a_t - (\mu_z + \mu_x)_{t|t-1} \\ \log w_t - \beta_w \mu_z|_{t|t-1} - \beta_{w,c} \\ \log K_t - \beta_K \mu_z|_{t|t-1} - \beta_{K,c} \end{bmatrix}$$

$$\begin{bmatrix} \sigma_z^2 & \sigma_{zq} \\ \sigma_{qz} & \sigma_q^2 \end{bmatrix}_{t|t} = \begin{bmatrix} \sigma_z^2 & \sigma_{zq} \\ \sigma_{qz} & \sigma_q^2 \end{bmatrix}_{t|t-1} - \begin{bmatrix} \sigma_z^2 + \sigma_{zq} & \beta_p \sigma_z^2 & \beta_k \sigma_z^2 \\ \sigma_{qz} + \sigma_x^2 & \beta_p \sigma_{qz} & \beta_k \sigma_{qz} \end{bmatrix} \times H_t^{-1} \times \begin{bmatrix} \sigma_z^2 + \sigma_{zq} & \sigma_{qz} + \sigma_x^2 \\ \beta_p \sigma_z^2 & \beta_p \sigma_{qz} \\ \beta_k \sigma_z^2 & \beta_k \sigma_{qz} \end{bmatrix}$$

Prediction Equation

$$\begin{bmatrix} \mu_z \\ \mu_q \end{bmatrix}_{t+1|t} = \begin{bmatrix} \rho_z \mu_z \\ (1-\rho_q)\overline{q} + \rho_q \mu_q \end{bmatrix}_{t|t} \tag{38}$$

$$\begin{bmatrix} \sigma_z^2 & \sigma_{zq} \\ \sigma_{qz} & \sigma_q^2 \end{bmatrix}_{t+1|t} = \begin{bmatrix} \rho_z^2 \sigma_z^2 + \sigma_{\epsilon,z}^2 & \sigma_{zq} \\ \sigma_{qz} & \rho_x^2 \sigma_x^2 + \sigma_{\epsilon,q}^2 \end{bmatrix}_{t|t} \tag{39}$$

Iterations on (37) and (39) with a positive semi-definite $V_{0|0}$ converge to the stationary Kalman gain (G) and prediction covariance (V).[38] These converged stationary Kalman gain and prediction variance are used in the potential entrants' learning problem.

The measurement equations associated with wages (32) and the aggregate capital stock (33) are endogenously determined via stochastic simulation of the baseline model and are given as follows:

$$\ln w_t = 0.65 + 1.03 z_t, \quad \sigma_{\epsilon_w} = 0.028 \tag{40}$$

$$\ln K_t = 0.93 + 0.53 z_t, \quad \sigma_{\epsilon_K} = 0.042 \tag{41}$$

B. Recursive Competitive Equilibrium

A recursive competitive equilibrium consists of (i) value functions V, V_c, V_x and V_{en}, (ii) policy functions χ, n^{con}, n^{ex}, k', μ'^z, μ'^q, ε, C and N, (iii) a wage w and state contingent discount factors $d(z', \Lambda')$, $\forall$ (z', Λ') and (iv) measures for incumbents, Γ, and potential entrants, Ω, such that:

1. (V, V_c, V_x) solve (6)–(8), and $(\chi, n^{con}, k', n^{ex})$ are the resulting policy functions for incumbent plants.

2. V_{en} is given as (23), and ε is the policy function for the optimal entry decision. $(\mu'^z,\ \mu'^q)$ are given from (17)–(20).

3. (C, N) are the policy functions associated with the household optimization problem. (25)–(26).

4. Labor market clears:

$$\begin{aligned} N(z,\Lambda) = &\int n^{con}(n_{-1},k,x;z,\Lambda)\chi(n_{-1},k,x;z,\Lambda)d\Gamma(n_{-1},k,x) \\ &+ \int n^{ex}(n_{-1},k,x;z,\Lambda)(1-\chi(n_{-1},k,x;z,\Lambda))d\Gamma(n_{-1},k,x) \end{aligned} \tag{42}$$

5. Goods market clears:

$$\begin{aligned} C(z,\Lambda) = &\int f(z,x,k,n^{con}(n_{-1},k,x;z,\Lambda))\chi(n_{-1},k,x;z,\Lambda)d\Gamma(n_{-1},k,x) \\ &+ \int f(z,x,k,n^{ex}(n_{-1},k,x;z,\Lambda))(1-\chi(n_{-1},k,x;z,\Lambda))d\Gamma(n_{-1},k,x) \end{aligned} \tag{43}$$

[38] Detailed conditions that guarantee convergence are provided in Anderson et al. (1996).

$$
\begin{aligned}
&- \int (k'(n_{-1}, k, x; z, \Lambda) - k(1-\delta))\chi(n_{-1}, k, x; z, \Lambda) d\Gamma(n_{-1}, k, x) \\
&+ \int p_s k(1-\delta)(1 - \chi(n_{-1}, k, x; z, \Lambda)) d\Gamma(n_{-1}, k, x) \\
&- \int \xi \chi(n_{-1}, k, x; z, \Lambda) d\Gamma(n_{-1}, k, x) dG(\xi) \\
&- \int AC^n(n_{-1}, k, x; z, \Lambda) d\Gamma(n_{-1}, k, x) \\
&- \int AC^k(n_{-1}, k, x; z, \Lambda) d\Gamma(n_{-1}, k, x) \\
&- \mathbb{M}(\int (c_e + k_e)\varepsilon(a, \mu^z, \mu^x; z, \Lambda) d\Omega(a, \mu^z, \mu^x)))
\end{aligned}
$$

6. Intra-temporal Euler equation holds:

$$\gamma N(z, \Lambda)^{1/\sigma_n} = w(z, \Lambda) C(z, \Lambda)^{-\sigma_c} \tag{44}$$

7. State contingent discount factors coincide with the household's marginal rate of substitution across aggregate states:

$$d(z', \Lambda') = \beta \frac{C'(z', \Lambda')^{-\sigma_c}}{C(z, \Lambda)^{-\sigma_c}}, \ \forall \ (z', \Lambda') \tag{45}$$

8. The laws of motion for the distribution of incumbents and potential entrants are consistent:

   (a) If ($0 \notin \mathcal{N}$ or $k_{en} \notin \mathcal{K}$)

$$\Gamma'(\mathcal{N}, \mathcal{K}, x') = \int_{\mathcal{B}(\mathcal{N}, \mathcal{K}; z, \Lambda)} \chi(n_{-1}, k, x; z, \Lambda) H(x'|x) d\Gamma(n_{-1}, k, x) \tag{46}$$

   $\mathcal{B}(\mathcal{N}, \mathcal{K}; z, \Lambda) = \{(n_{-1}, k, x) | n^{con}(n_{-1}, k, x; z, \Lambda) \in \mathcal{N}$ and $k'(n_{-1}, k, x; z, \Lambda) \in \mathcal{K}\}$

   (b) If ($0 \in \mathcal{N}$ and $k_{en} \in \mathcal{K}$)

$$
\begin{aligned}
\Gamma'(\mathcal{N}, \mathcal{K}, x') = &\int_{\mathcal{B}(\mathcal{N}, \mathcal{K}; z, \Lambda)} \chi(n_{-1}, k, x; z, \Lambda) H(x'|x) d\Gamma(n_{-1}, k, x) \\
&+ \mathbb{M} \int \varepsilon(z + q, \mu^z, \mu^q; z, \Lambda) H(x'|q) d\Omega(z + q, \mu^z, \mu^q)
\end{aligned} \tag{47}
$$

(c)

$$\Omega'(z'+q',\mathcal{Z},\mathcal{Q}) = \int_{\mathcal{B}(\mathcal{Z},\mathcal{Q};z,\Lambda)} J(q'|q)d\Omega(z+q,\mu^z,\mu^q) \tag{48}$$

$$\mathcal{B}(\mathcal{Z},\mathcal{Q};z,\Lambda) = \{(a,\mu^z,\mu^q)|\mu'^z(a,\mu^z,\mu^x;z,\Lambda)\in\mathcal{Z} \text{ and } \mu'^q(a,\mu^z,\mu^x;z,\Lambda)\in\mathcal{Q}\}$$

C. Subsidy Policy

Compared to the full information model economy where business cycle fluctuations in entry margin is allocation from competitive equilibrium without other sources of inefficiencies, in the baseline model economy, entry rate is too high during booms and too low during recessions. As we have seen in the previous subsection, this amplified net entry margin causes considerable welfare loss. In this context, policy that stabilizing entry margin is recommended as long as business cycle is concerned.

Rather considering sort of policies that directly fixing information frictions, here we think of policy intervention that subsidizing entry cost during recessions. Although our model economy also justifies taxing entry during boom periods, if we consider growth enhancing roles of entry margin emphasized in the Schumpeterian growth theory, policy intervention that weakening entry during boom might cause harmful side effect that cannot be captured by our model economy that focusing on business cycle. Therefore, we only consider policy that subsidizing entry cost during recessions.

Specifically, we implement policy that government subsidize 20% of entry cost when realized aggregate productivity is below its median level (that is $z_t < 0$). This subsidy is provided with period by period government budget balancing. Then representative household's budget constraint (26) and goods market clearing condition (43) should be properly adjusted. Regarding information structure of potential entrants, we assume that potential entrants do not aware of the fact that entry subsidy is provided only when $z_t < 0$. That is they cannot use information associated with timing of the entry subsidy.

Table 18 shows fluctuations in entry rate across baseline model economy, model economy with entry subsidy, and full information model economy. Left panel shows result when booms and recessions are categorized depending on whether output growth rate is above or below the average output growth rate. And the right panel shows result when booms and recessions are categorized depending on whether level of aggregate productivity is above or below the median level. Given that entry subsidy is provided based on level of aggregate productivity, the effect of subsidy is more transparent in the "Aggregate Productivity" panel. We can see that entry subsidy actually brings level of plant entry

Table 18: Magnitude of Fluctuations in Entry Rate

	Output Growth(%)		Aggregate Productivity(%)	
	Boom	Recession	Boom	Recession
Baseline	7.7	4.4	7.7	4.4
Subsidy	7.4	4.7	7.5	5.4
Full Info.	6.2	5.9	6.5	5.7

Note: The data column is taken from Lee and Mukoyama (2015a). In the "Output Growth" panel, booms and recessions are categorized depending on whether output growth rate is above or below the average output growth rate as in Lee and Mukoyama (2015a). In the "Aggregate Productivity" panel, booms and recessions are categorized depending on whether level of aggregate productivity is above or below the median level.

when $z < 0$ closer to the level observed in the full information model economy.

Table 19: AR(1) Coefficients of Aggregate Variables

	Output	Labor
Baseline	0.51	0.66
Subsidy	0.5	0.64
Full Info	0.4	0.46

Table 19 compares AR(1) coefficients of model generated aggregate output and labor. With entry subsidy, as entry become less volatile, internal propagation mechanism of net entry margin get weakened. But given that subsidy is imposed only in recessions, quantitative effect of subsidy on persistency of aggregate variables is somewhat limited.

Eventually, our most interested question is whether the policy that stabilizing entry margin can improve welfare of the representative household or not. In that regard, we calculate magnitude of consumption equivalence welfare change across baseline model economy with and without entry subsidy. And it turned out that policy that providing entry subsidy during recessions improve welfare as much as 0.13% of consumption equivalence.

This policy exercise shows that subsidy schemes that stabilizing entry margin can be used as relieving the inefficient resource allocation caused by potential entrants' inability to precisely form the expected profit from the entry.

D. Computation

D.1. Solution Algorithm

Our solution algorithm is based on Krusell and Smith (1998) and Khan and Thomas (2008). We need two main modifications compared to Khan and Thomas (2008). At first, because of the finite Frisch elasticity of labor supply, we need a forecasting rule for both the marginal utility of consumption and wages. Second, in addition to the forecasting rules for prices and aggregate capital stock, we need consistent projection equations (see, (13) and (14) in Section 3.2) for wages and aggregate capital stock onto aggregate productivity. This enables potential entrants to learn about aggregate productivity by observing current period equilibrium wages and the aggregate capital stock.

1. Approximate the distribution of plants by the aggregate capital stock. Make initial guesses for (i) the log-linear law of motion for the aggregate capital stock, (ii) the forecasting rule for wages, (iii) the forecasting rule for marginal utility of consumption, (iv) the log-linear projection equation of wages onto aggregate productivity, and (v) the log-linear projection equation of aggregate capital stock onto aggregate productivity.

$$(i)\ \ln K_{t+1} = \kappa_0^0 + \kappa_1^0 \ln K_t + \kappa_2^0 z_t \tag{49}$$

$$(ii)\ \ln w_t = a_0^0 + a_1^0 \ln K_t + a_2^0 z_t \tag{50}$$

$$(iii)\ \ln p_t = b_0^0 + b_1^0 \ln K_t + b_2^0 z_t \tag{51}$$

$$(iv)\ \log w_t = \beta_{w,c}^0 + \beta_{w,z}^0 z + \epsilon_w,\ \ S.D.(\epsilon_w) = \sigma_w^0 \tag{52}$$

$$(v)\ \log K_t = \beta_{K,c}^0 + \beta_{K,z}^0 z + \epsilon_K,\ \ S.D.(\epsilon_K) = \sigma_K^0 \tag{53}$$

p_t in (51) represents the marginal utility of consumption $C_t^{-\sigma_c}$. The superscript for each coefficient represents an index for the iteration. Note that (52) and (53) are used as the measurement equation in potential entrants' Kalman filter problem. Unlike the forecasting rules, potential entrants' perceived variance of the residual does matter. The goal of the whole algorithm is then to find a set of

$$\{(\kappa_0, \kappa_1, \kappa_2),\ (a_0, a_1, a_2),\ (b_0, b_1, b_2),\ (\beta_{w,c}, \beta_{w,z}, \sigma_w),\ (\beta_{K,c}, \beta_{K,z}, \sigma_K)\}$$

such that they are consistent with the actual aggregate dynamics of the model economy.

2. To make sure both the goods and labor market are actually cleared in each period we follow a two step procedure suggested by Krusell and Smith (1998). One, current period market clearing consumption and wages come from explicit market clearing conditions. Two, forecasting rules given by (49)∼(51) are only used when calculating incumbent and potential entrant perceptions of future prices. Following Khan and Thomas (2008), we will describe the optimization problems of incumbents and potential entrants in terms of the marginal-utility transformed Bellman equation. That is, we will denominate plants' profit and costs by the marginal utility of consumption. We will denote the actual market clearing wage and marginal utility of consumption as w and p, and the wage and marginal utility of consumption implied by the forecasting rules, (50) and (51), as $W(z, K)$ and $P(z, K)$.

   Step.1: Value function based on forecasted prices

   Incumbent plants' value functions are defined on 5 dimensions of state variables. 3 of them are individual state variables (last period's labor (n_{-1}), individual capital stock (k), idiosyncratic productivity (x)) and 2 of them are aggregate state variables (aggregate productivity (z), aggregate capital stock (K)). For state variables that take a continuous value ($n_{-1},\ k,\ K$), we used trilinear interpolation when we needed to evaluate off-grid-point values. The AR(1) processes specified for an incumbents' idiosyncratic shock and aggregate productivity are discretized using the Tauchen (1986) method.

   Denote this first stage value function as $\hat{V}$. For each of the aggregate state variables (z, K), we can calculate the wage and marginal utility of consumption implied by a combination of aggregate state variables using the price forecasting rules given by (50) and (51).

$$W(z, K) = a_0^0 + a_1^0 \ln K + a_2^0 z \tag{54}$$

$$P(z, K) = b_0^0 + b_1^0 \ln K_t + b_2^0 z \tag{55}$$

   For each point in the state space, $(n_{-1}, k, x; z, K)$, we can re-write incumbent plants' value function ((6)∼(8) given in Section 3.1) combined with (54) and (55).

$$\hat{V}(n_{-1}, k, x; z, K) = \int \max\{\hat{V}_c(n_{-1}, k, x; z, K) - \xi, \hat{V}_x(n_{-1}, k, x; z, K)\} dG(\xi) \tag{56}$$

$$\begin{aligned}\hat{V}_c(n_{-1}, k, x; z, K) = \max_{\{i,n\}} & P(z, K)(y - W(z, K)n - i - AC^k(k, i) - AC^n(n_{-1}, n)) \\ & + \beta \mathbb{E}[\hat{V}(n, k', x'; z', K')]\end{aligned} \tag{57}$$

$$\hat{V}_x(n_{-1}, k, x; z, K) = \max_{\{n\}} P(z, K)(y - W(z, K)n - AC^n(n_{-1}, n) - AC^n(n, 0) + p_s(1-\delta)k) \tag{58}$$

$$\ln K' = \kappa_0^0 + \kappa_1^0 \ln K + \kappa_2^0 z \tag{59}$$

<u>Step.2: Search for actual market clearing $(w,\ p)$</u>

The converged value function $(\hat{V}(n_{-1}, k, x; z, K))$ from step 1 will be used to evaluate forward values in the incumbent and potential entrant optimization problems inside the actual stochastic simulation. At each point in time, incumbents solve the following problem:

$$V(n_{-1}, k, x; z, K) = \int \max\{V_c(n_{-1}, k, x; z, K) - \xi, V_x(n_{-1}, k, x; z, K)\} dG(\xi) \tag{60}$$

$$\begin{aligned} V_c(n_{-1}, k, x; z, K) = \max_{\{i,n\}} & \, p(y - wn - i - AC^k(k, i) - AC^n(n_{-1}, n)) \\ & + \beta \mathbb{E}[\hat{V}(n, k', x'; z', K')] \end{aligned} \tag{61}$$

$$V_x(n_{-1}, k, x; z, K) = \max_{\{n\}} p(y - wn - AC^n(n_{-1}, n) - AC^n(n, 0) + p_s(1-\delta)k) \tag{62}$$

$$\ln K' = \kappa_0^0 + \kappa_1^0 \ln K + \kappa_2^0 z \tag{63}$$

The main difference compared to the step 1 optimization problem is here the optimization problem depends on actual prices (p, w) instead of forecasting rule implied prices $(P(z, K), W(z, K))$.

Now think about potential entrants' entry decision. Because potential entrants learn about the current aggregate productivity from the current actual market clearing wage, in the process of searching for the current period market clearing (p, w), whenever a different value of w is proposed, potential entrants' Kalman filter problem should be re-solved and the expected value from entry should be re-evaluated. In each period, for a given predetermined beginning of period aggregate capital stock and proposed wage, w, potential entrants solve their Kalman filter problem composed of (15)∼(22) in Section 3.2.

$$V_{en}(a, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w, K) = -pk'_{en} + \beta \mathbb{E}[\hat{V}(0, k'_{en}, x'; z', K') | \mu^z_{t|t}, \mu^q_{t|t}] \tag{64}$$

$$\text{Enter if } V_{en}(a, \mu^z_{t|t-1}, \mu^q_{t|t-1}; w, K) \geq pc_e \tag{65}$$

$$\ln K' = \kappa_0^0 + \kappa_1^0 \ln K + \kappa_2^0 \mu^z_{t|t} \tag{66}$$

$$\tag{67}$$

Given the beginning of period distributions of incumbents $\Gamma(n_{-1}, k, x)$ and potential entrants $\Omega(a, \mu^z_{t|t-1}, \mu^q_{t|t-1})$, for a proposed pair of (p, w), by aggregating the optimal decisions of incumbents and potential entrants, we can calculate the supply of consumption that is given by the right hand side of (43) and the demand for labor that is given by the right hand side of (42) in Section B. On the other hand, given that p is marginal utility of consumption ($p = C^{-\sigma_c}$), it implies consumption demand from the household. w together with p also, by the household intratemporal Euler equation ($\gamma N^{1/\sigma_n} = wC^{-\sigma_c}$), imply labor supply from the household. Then each period, we search pairs of (p, w) that clear both the goods and labor market. We find $(p.w)$ by nesting the Brent's method. Once market clearing (p, w) are found, we update the incumbent distribution over (n_{-1}, k, x) and the potential entrant distribution over $(a, \mu^z_{t|t-1}, \mu^q_{t|t-1})$ using optimal decision rules under market clearing (p, w).

3. Starting from the steady state distribution, we generate 500 periods of $\{K_t, p_t, w_t\}_{t=1}^{500}$. After discarding the first 100 observation, using OLS on the simulated data we can get new values of:

$$\{(\kappa_0, \kappa_1, \kappa_2),\ (a_0, a_1, a_2),\ (b_0, b_1, b_2),\ (\beta_{w,c}, \beta_{w,z}, \sigma_w),\ (\beta_{K,c}, \beta_{K,z}, \sigma_K)\}$$

If the new values are close enough to the previous values then we have a consistent law of motion for the aggregate capital stock, price forecasting rules, and projection equations used as the measurement equation in potential entrants' Kalman filter problem. Otherwise, update the set of coefficients and repeat the stochastic simulation.

D.2. Accuracy of Forecasting Rules

As we described in Section 5.1, because of the interaction between incumbent plants' forward-looking factor demand problem and potential entrants' learning from the market clearing wage, equilibrium dynamics become history dependent in the baseline model. It turned out that approximating the whole distribution by the aggregate capital stock alone cannot fully capture the equilibrium dynamics of the baseline model economy.

1. Forecasting rules from the baseline model economy:

$$\ln K_{t+1} = 0.16 + 0.83 \ln K_t + 0.36 z_t, \quad R^2 = 0.989 \tag{68}$$

$$\ln w_t = 0.06 + 0.63 \ln K_t + 0.69 z_t, \quad R^2 = 0.973 \tag{69}$$

$$\ln p_t = 0.99 - 0.81 \ln K_t - 0.34 z_t, \quad R^2 = 0.994 \tag{70}$$

2. Forecasting rules from the full information economy:

$$\ln K_{t+1} = 0.12 + 0.87 \ln K_t + 0.37 z_t, \quad R^2 = 0.999 \tag{71}$$

$$\ln w_t = 0.23 + 0.46 \ln K_t + 0.74 z_t, \quad R^2 = 0.998 \tag{72}$$

$$\ln p_t = 0.74 - 0.54 \ln K_t - 0.47 z_t, \quad R^2 = 0.999 \tag{73}$$

Comparing (69) and (72) makes it clear that in the baseline model, particularly the labor market equilibrium dynamics cannot be fully captured by tracking the aggregate capital stock alone. Instead of including higher order moments as an additional aggregate state variable to improve the precision of the price forecast, we keep the bounded rationality so that potential entrants' ability to learn about aggregate productivity from the equilibrium wage is limited.

Regarding how much potential entrants can learn about z_t using w_t and K_t, what matters is not the R^2 in (69) but the fraction of variation in z_t that can be explained by w_t and K_t. In that sense, the more informative statistic regarding how much potential entrants can learn is the R^2 from the projection of z_t onto a constant, $\ln w_t$, and $\ln K_t$. That value is 0.92.