Start-ups, House Prices, and the US Recovery

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Low job creation rates by start-ups and young firms were a main reason for the poor labor market performance during and after the 2007-09 U.S. recession. This paper quantitatively assesses the importance of the decline in house prices for the low number of new firms and the persistently high unemployment rate during and after the recession. I construct a heterogeneous firm model where start-ups require initial financing, for which real estate is used as collateral. As the value of this collateral falls, start-up costs increase and the number of new firms declines, creating a jobless recovery. I calibrate the model to the US labor market and compute that the decline in housing wealth can explain 80 % of the increase in unemployment since the recession. I then revisit the micro data: MSA-level measures of house prices and start-up activity strongly support the model's predictions.

JEL: *E24; E32; E44; G21; J2; L25; L26*

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1 Introduction

The 2007 to 2009 recession led to the largest decline in employment in the United States since the Great Depression, a total of over 8 million jobs were lost. Despite a recovery in aggregate output the labor market has been slow to rebound. This phenomenon has been termed a 'jobless recovery'. In this paper I show that a key reason for the observed labor market outcomes was that fewer new firms started operating since the sharp fall of house prices beginning in 2006.

Three facts are important in this context. First, the decrease in aggregate employment was mainly due to low job *creation*. This is shown in Figure 1. While *fewer* jobs as a fraction of total employment were destroyed in 2008 than in 1991 and 2001 the years since 2008 mark the lowest levels of gross job creation on record. The rebound in gross job creation since 2010 has been mainly driven by older firms.[1]

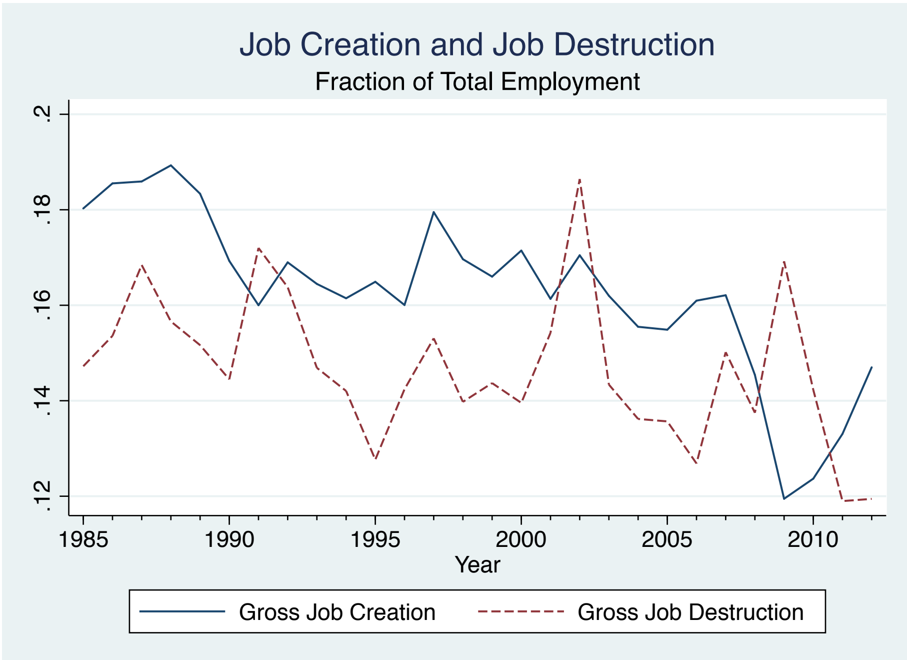


Figure 1: U.S. Gross Job Creation (solid) and Gross Job Destruction (dashed) divided by total employment. Source: Business Dynamics Statistics (BDS)

Second, the lion's share of the decline in job creation was due to start-ups and young firms.[2] Figure 2 shows changes in gross job creation with respect to the last year prior to the recession. The fall in job creation by start-ups and young firms stands out as a

[1]There has been no significant change in the respective fraction of job destruction coming from firm death and downsizing.

[2]Throughout this paper I define start-ups as firms of age zero, while firms aged one to five years will be referred to as young firms. A start-up is defined as a new *firm*, not as a new establishment. Unless otherwise noted the data comes from the US Census' Business Dynamics Statistics (BDS) database. Details regarding all the data used in this paper can be found in the Data Appendix.

main factor for low job creation since the beginning of the last recession: In each of the years 2009-2012 start-ups created over 1 million *fewer* new jobs than in 2006. It is worth noting that the average size of a start-up has remained virtually unchanged, suggesting an important extensive margin effect: fewer entrepreneurs are starting a business.[3]

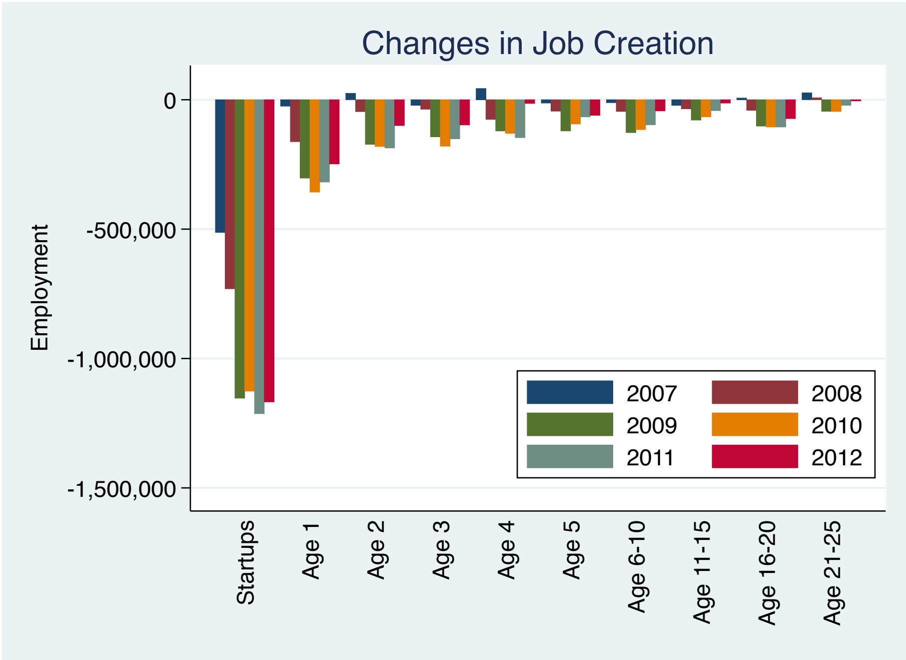


Figure 2: Changes in gross job creation by age with respect to the year 2006. Source: Business Dynamics Statistics (BDS)

The third observation regards the link between house prices and start-up activity. As Figure 2 shows, low start-up job creation persisted even *after* the end of the recession. As a driving force behind this pattern I propose a link between entrepreneurship and the value of home equity. The main idea is that the fall in the value of real estate (and thus household net worth) provoked a decline in the amount of equity available for the creation of new businesses. To test this idea and to quantitatively assess the importance of the decline in house prices for the low number of new firms and the persistently high unemployment rate during and after the recession, I both use a theoretical model and the micro data.

In recent years, firm age has emerged as a key statistic in explaining employment growth (Haltiwanger *et al.* (2012)). The fact that firm characteristics such as size or age matter for outcomes is in itself indicative of frictions in the assignment of workers

[3] Gali *et al.* (2012) argue that the 2008/09 downturn only produced a *quantitative* change in the relation between GDP and employment. However, the composition of net job creation by firm age and the unprecedented decline in house prices differs substantially from previous recessions. In Figure 13 in the Appendix I replicate Figure 2 for the 2001 recession. The picture looks strikingly different because there has been no long-lasting decline in job creation by start-ups.

to firms. Financial frictions are among the most cited explanations for such limits to reallocation (Kiyotaki and Moore (1997), Bernanke *et al.* (1999), Gilchrist and Zakrajsek (2012), Jermann and Quadrini (2012), Khan and Thomas (2013), and Midrigan and Xu (2014)). However, these papers either do not feature entry and exit or do not attempt to match their relative contributions for labor market dynamics over the business cycle. In many existing models, firm default and exit are key drivers of firm dynamics, whereas the data shows that this margin is quantitatively much less important than firm entry (Lee and Mukoyama (2015)). Following the recent recession, a number of papers have looked specifically at new firms. While some papers are concerned with the general downwards trend in entrepreneurial activity since the 1970s (Decker *et al.* (2014), Pugsley and Sahin (2014), Sedlacek and Sterk (2014)), others focus on the cyclical properties of business formation in the light of financial shocks (Clementi and Palazzo (2015), Moscarini and Postel-Vinay (2012), Drautzburg (2013), and Siemer (2013)).

I develop a model of heterogeneous firms which operate in a frictional labor market. The starting point is the competitive industry model in Hopenhayn (1992) to which I add several components. First, I add two aggregate shocks, a standard profitability shock to generate business cycles and a shock to the value of real estate. Second, I add a search-and-matching framework where firms fill vacancies with endogenous probability (as in Cooper *et al.* (2007)).[4] This allows me to study the implications of the model for unemployment and creates an important link between entering firms and incumbent firms through the labor market tightness. Third, I introduce a friction in the start-up process: In order to pay the costs of entry, new entrepreneurs must take a one-period loan from a bank. They use their real estate holdings to partially collateralize this loan (Liu *et al.* (2013), Chaney *et al.* (2012)). Since firms may exit/default, the bank efficiently prices interest rates by charging a default premium. As the value of real estate falls, the costs of entry increase since a lower fraction of the loan can be collateralized. This reduces the number of new entrants (Schmalz *et al.* (2013)). Because young firms' job creation rates are over-proportional to their share of output, this decline in the share of young firms can lead to a jobless recovery. In Clementi and Palazzo (2015) entry and exit also propagate the effects of aggregate shocks. A negative shock to aggregate productivity has long-lasting effects on output through a "missing generation" of entrants. Similarly, Siemer (2013) generates this effect through a financial shock which over-proportionally increases borrowing costs for small and young firms. In Siemer's model, entry levels jump back to their unconditional mean once the financial shock has passed. Empirically we observe that the number of new firms continues to be at historically low levels even *after* financial conditions had returned to pre-crisis levels. The housing collateral channel I propose has the potential to explain this fact because house prices remained depressed in the years following the end of the recession.[5] Furthermore, linking the hiring conditions

[4]For bargaining problems of multi-worker firms see also Kaas and Kircher (forthcoming), Elsby and Michaels (2013), and Acemoglu and Hawkins (2013). Bachmann (2012) explains the jobless recovery through factor adjustment costs which generate a jobless recovery after a short and shallow recession.

[5]Drautzburg (2013) estimates that approximately one third of the change in start-up job creation following the recent recession can be attributed to higher risk. I do not model risk-aspects in my

of incumbents and entrants through the endogenous labor market tightness implies that during a recovery job creation by incumbent firms recoveries *before* job creation by start-ups, exactly as we see in the data.

I calibrate the model to match certain cross-sectional data moments, such as the vacancy-filling probability and the distributions of firm size and and employment change. I estimate firm-level labor adjustment costs via a simulated method of moments (SMM) approach. The calibrated model can replicate the average life cycle of firms and the negative correlation between employment growth and size observed in the data. The model with aggregate fluctuations significantly outperforms alternative specifications because it can produce sluggish recoveries of the labor market after a decline in GDP. I carry out policy experiments showing that around 80% of the increase and persistence in unemployment since the end of 2006 can be explained by the model with variations in house prices. In Section 4 I go back to the micro data to test the model's predictions. I show that in Metropolitan Statistical Areas (MSAs) with larger decreases in house prices employment in young firms fell significantly more and the recovery was slower than in MSAs with small price declines. These differences cannot be explained by the changes in GDP.

The paper is structured as follows. The next section develops the model and explains the computational strategy to solve it. Results are presented in Section 3. In Section 4 I test the model's predictions using MSA level data. Section 5 concludes.

2 The Model

Time in the model is discrete and indexed by $t = 0, 1, 2, \ldots$. The economy consists of a fixed mass of workers and a mass of entrepreneurs who operate a decreasing-returns-to-scale production function. Agents derive utility from consumption and housing. Workers and entrepreneurs interact on a frictional labor market. Real estate serves as collateral when new entrepreneurs start operating. Firms face time-varying shocks to idiosyncratic productivity. The economy is subject to exogenous shocks to aggregate productivity and the value of real estate.[6]

2.1 The Labor Market

The market for (perfectly divisible) labor is frictional. To hire unemployed workers, firms must post vacancies v which are filled with endogenous probability. Following the search and matching literature a matching function captures those frictions. It is denoted as $m(U, V) = \mu U^{\gamma} V^{1-\gamma}$. Its inputs are the unemployment rate U and the vacancy rate V. Vacancies posted by firms are filled with probability $H(\theta) = m/V$ and have to be re-posted each period. An unemployed worker finds a job with probability $\phi(U, V) = m/U$. The ratio $\theta \equiv V/U$, labor market tightness, is a sufficient statistic

model. In Berger (2012) the focus is on the *intensive* margin of job *destruction*: firms lay off unproductive workers during recessions, while my paper is about the *extensive* margin of job *creation*.

[6] In the Appendix I lay out an alternative model in which shocks do not affect house prices directly but indirectly through agents' preferences for housing.

to compute the vacancy-filling and job-finding rates in this economy. It is taken as given by workers and firms and evolves endogenously. Employed workers may lose their job if the entrepreneur they are matched with reduces employment. Furthermore, a fraction χ of workers exogenously quits each period. There is no on-the-job search. The workers' compensation for their labor input is specified through a simple bargaining process between the entrepreneur and the worker. This is described after the agents' maximization problems. The size of the labor force is normalized to one.

2.2 Entrepreneurs

Entrepreneurs maximize their lifetime discounted utility stream over housing h and consumption c given log-linear preferences

$$U_E(c_E, h_E) = c_E + \varphi_E \log(h_E). \tag{1}$$

The parameter φ_E is a preference weight for housing. Entrepreneurs own the production technology which generates the homogenous consumption good (the numeraire). The proceeds constitute the entrepreneurs' only source of income.[7] The entrepreneurs' budget constraint is given by

$$c_E + p^h(h_E - h_{E,-1}) \leq \pi. \tag{2}$$

The entrepreneur's wealth consists of firm profits π and the value of the stock of housing carried over from last period. The house price is p^h. This formulation implies that wealth can be frictionlessly assigned between c_E and h_E within the period. Note that in what follows I let $\varphi_E \to 0$ and write the entrepreneur's problem net of housing. The problem can then be written as a standard profit-maximization problem.[8] Entrepreneurs dynamically adjust their labor input subject to search frictions and adjustment costs. A fraction δ_x of firms exogenously exits at the end of the period.[9] New firms can enter at the start of each period. Next, I describe the maximization problem of an incumbent firm, followed by the decision of a potential entrant.

2.2.1 Incumbent Firms

An incumbent firm is a firm that did not exit at the end of the last period. Its timing is summarized in Figure 3. Each incumbent firm starts the period with an inherited stock of workers e_{-1}. The exogenous states realize next. They consist of an aggregate and idiosyncratic profitability shock (a and ε) as well as the vacancy-filling rate $H(\theta)$. This is summarized in the state vector $s = (e_{-1}, \varepsilon; a, H)$ or simply $s = (e_{-1}.\zeta)$.[10] Firms then

[7] Moskowitz and Vissing-Jorgensen (2002) show that entrepreneurial risk is not diversified and that dividends from the firm are often the only source of income for owners.

[8] See Appendix for details.

[9] With endogenous exit it is difficult to generate exit of older firms, since they are typically large and profitable. Furthermore, endogenous exit makes it difficult to match the distribution of entrants while keeping the labor adjustment costs at reasonable levels. The reason is that very small entrants exit after the first period, which skews the distribution of surviving entrants towards very large firms, which is at odds with the data.

[10] For notational convenience H stands for $H(\theta)$, the vacancy filling rate as a function of labor market tightness.

make a (potentially costly) labor adjustment decision e and production takes place given the new level of employment. Denote the state at the end of the period as $S = (e, e_{-1}, \zeta)$. The profit function is given by

$$\pi(S) = a\varepsilon F(e) - e\omega(a, \varepsilon, e) - \mathbb{C}(S)\mathbb{1}_{e \neq e_{-1}(1-\chi)}. \tag{3}$$

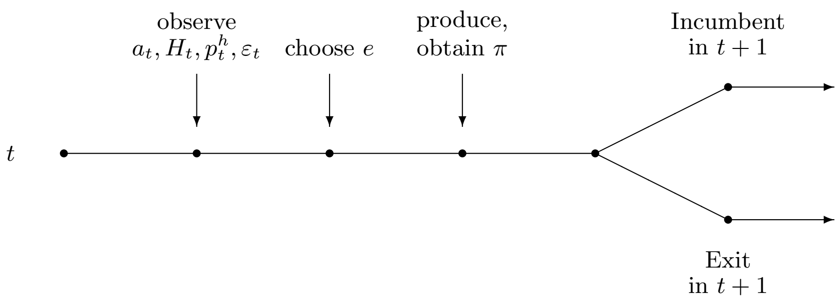


Figure 3: Timing for an Incumbent Firm.

The production technology $F(\cdot)$ exhibits decreasing returns, which I interpret as stemming from managerial span-of-control as in Lucas (1978). The two profitability shocks enter multiplicatively. The term $e\omega(\cdot)$ is the wage bill. The term $\mathbb{C}(\cdot)$ defines labor adjustment costs. The adjustment costs include a fixed and a variable term, and will be parameterized below. $\mathbb{C}$ is equal to zero if labor is not adjusted.

The value function for an incumbent firm is denoted $V^i(s)$. The firm's program can be written as a discrete choice between posting vacancies, firing workers, and remaining inactive.

$$V^i(s) = \max\{V^v(s), V^f(s), V^n(s)\} \tag{4}$$

When the firm hires new workers

$$e = e_{-1}(1-\chi) + Hv \qquad \text{with } h > 0$$

and the value is given by

$$V^v(s) = \max_v \ \pi(S) + \beta\left((1-\delta_x)E_{\zeta'|\zeta}V^i(s') + \delta_x V^x(s')\right). \tag{5}$$

If the firm fires workers

$$e = e_{-1}(1-\chi) - f \qquad \text{with } f > 0$$

$$V^f(s) = \max_f \, \pi(S) + \beta \left((1-\delta_x)E_{\zeta'|\zeta}V^i(s') + \delta_x V^x(s')\right). \tag{6}$$

Finally, if the firm remains inactive

$$e = e_{-1}(1-\chi)$$

$$V^n(s) = \pi(S) + \beta \left((1-\delta_x)E_{\zeta'|\zeta}V^i(s') + \delta_x V^x(s')\right) \tag{7}$$

In (5)-(7) the expectation operator $E_{\zeta'|\zeta}$ denotes the conditional expectation over next period's exogenous states ε, a, and H. Equation (4) says that the value $V^i(s)$ is given by the maximum of the values of posting vacancies, firing, and inaction. The values of posting vacancies, firing, and remaining inactive differ in the evolution of employment e and the labor adjustment costs. When hiring additional workers, the firm chooses the number of vacancies v that maximizes (5). Employment next period is then given by past employment (net of quits) plus the fraction of filled vacancies. When firing the evolution of employment is simply given by past employment (net of quits) minus fires. The firm chooses f to maximize (6). Finally, if the firm remains inactive employment evolves only due to quits. The policy function for employment will be denoted as $\phi_e(s)$. Because the entrepreneur may exit at the beginning of the next period, in (5), (6), and (7) the continuation value is a weighted sum. The survival probability is $1-\delta_x$. In the case of exit the firm reduces employment to zero and pays the adjustment costs of firing its remaining workers. Exit is permanent and irrevocable.

$$V^x(s) = 0 - \mathbb{C} \tag{8}$$

2.2.2 New Entrants

At the beginning of each period there is a continuum of ex-ante identical potential entrepreneurs, drawn from the stock of workers. A potential entrepreneur has to decide whether to begin operating a firm. The entry decision is made in expectation of the firm's initial idiosyncratic profitability draw ε_0, which is taken from a distribution ν and is allowed to differ from the distribution of incumbents productivity shocks. After the initial period, profitability evolves identically to that of all other incumbent firms. The timing of potential entrants is summarized in Figure 4. If the value function $V^i(\cdot)$ is known, the value of entry gross of entry costs is given by the value of an incumbent firm evaluated at zero employment and the expected initial productivity draw

$$V^e(a,H) \equiv \int_{-\infty}^{\infty} V^i(0,\varepsilon_0;a,H)\nu(\varepsilon_0)d\varepsilon_0. \tag{9}$$

The value of entry is increasing in a and H. To enter, a new firm must pay a start-up cost F_e, which has to be borrowed from a bank. The randomness in the production process as well as the possibility of exit make this loan inherently risky for the bank, which charges a risk-premium. Because new entrepreneurs are drawn from the stock of workers, their beginning-of-period assets consist of a worker's stock of housing carried over from last period, $h_{W,-1}$, evaluated at the current price p^h. New entrants can use

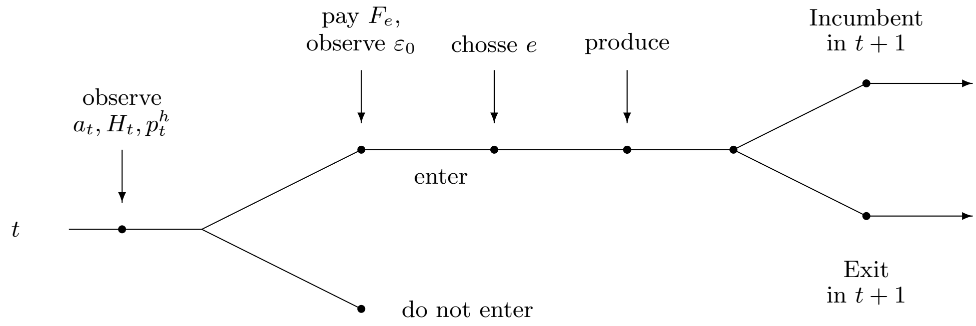


Figure 4: Timing for a Potential Entrepreneur.

their assets as collateral. This will be explained in the next subsection. I denote the start-up costs including the costs of raising funds as $\tilde{F}_e$. The free-entry condition states that entry occurs as long the cost of entry is below the value of entry V^e. Along the equilibrium path the condition holds with equality.

$$\tilde{F}_e = V^e(a, H) \tag{10}$$

The mass of firms entering in period t is denoted as M_t.

Proposition 1. *There is a unique M_t which solves (10).*

The intuition is that as M_t increases, more vacancies are created, the labor market tightness θ increases. The subsequent decline in H reduces V^e since a firm needs to post more (costly) vacancies to fill the same number of jobs. With V^e monotonically increasing in H and $\tilde{F}_e$ fixed, the point where (10) holds is unique.

2.3 The Bank

The bank is owned by all agents in the economy and behaves competitively, i.e. makes zero profits.[11] To pay the entry cost F_e new firms must obtain a loan from the bank. After the realization of ε_0 the firm may be unable to meet its debt obligations. This can be the case either because the firm exits, or the because the realization of ε_0 generates too little profits to pay back the loan. Given this default option the bank efficiently

[11] For this reason redistributed profits are omitted from entrepreneur's and worker's problem.

prices interest rates by charging a default premium on the loan.[12] In order to reduce the interest burden the firm can post its real-estate as collateral. In case of (partial) default, the collateral is claimed by the bank. At the end of the period a start-up that did not exit will be able to repay

$$q(S) = \min \left\{ RF_e \, , \, \pi(\varepsilon_0) + p^h h_{W,-1} \right\} . \tag{11}$$

The first term corresponds to a start-up drawing a high enough ε_0 to repay the loan plus any accrued interest payments. For a low realization of ε_0 the firm may be unable to meet its debt obligations. The firm's profits plus the collateral then go to the bank. If the new firm exits, it walks away from its obligations before the loan has been repaid. In that case the bank claims the collateral up to a maximum of the outstanding debt. The bank's break-even condition is given by

$$rF_e = (1 - \delta_x) \int_{-\infty}^{\infty} q(S)\nu(\varepsilon)d\varepsilon + \delta_x \min \left\{ RF_e, p^h h_{W,-1} \right\} . \tag{12}$$

Equation (12) determines the interest rate R. The left-hand side of (12) shows the bank's outside option of receiving the risk-free rate for the amount of the loan. The first term on the right-hand side is the expected repayment in case of no exit. The last term is the repayment in case of exit. The interest rate does not depend on idiosyncratic conditions because entrants are ex-ante identical.[13] The total costs of entry, which from (10) are relevant for a potential entrepreneur's entry decision are given by $\tilde{F}_e = RF_e$. Changes in $\tilde{F}_e$ are a key driver for the dynamics of the model because changes in the cost of entry have important effects on the number of entrants and hence on job creation and unemployment. This is the link between house prices and job creation by start-ups.

2.4 Workers

Workers can either be employed or unemployed, $i = \{e, u\}$. They maximize their lifetime discounted utility stream over consumption c and housing h given preferences

$$Z(c, h) = \log(c_W) + \varphi \cdot \log(h_W) \tag{13}$$

Their budget constraint is given by

$$c^i + p^h (h^i_W - h^i_{W,-1}) \leq y^i, \tag{14}$$

where y^i is income. Labor income is defined by a state-contingent contract, $y^e = \omega(S)$, while unemployed workers receive an outside option $y^u = b(a)$ which may vary with

[12] This is similar to Townsend (1979) and Bernanke *et al.* (1999) where the bank faces a costly state-verification problem. In my model state-verification is costless but in case of default the bank can only recuperate the collateral.

[13] If the value of real-estate is high enough so that $p^h h_{W,-1} \geq RF_e$ we obtain $q = RF_e$ from (11) and $R = r$ from (12).

aggregate profitability. Within a period the worker statically decides how to allocate available wealth between consumption and housing. The value of being unemployed is

$$W^u(a, h_{-1}) = \max_{c^u, h^u} Z(c^u, h^u) + \beta E[\phi(\theta) W^e(a', h) + (1 - \phi(\theta)) W^u(a', h)], \tag{15}$$

The unemployed worker's state vector consists of aggregate profitability a and the stock of housing inherited from the previous period. The continuation value is a weighted-average of being employed or unemployed next period. With probability $\phi(\theta)$ an unemployed worker is able to find a job, with the counter-probability he remains unemployed. Similarly, the value of being employed is

$$W^e(a, h_{-1}) = \max_{c^e, h^e} Z(c^e, h^e) + \beta E[(1 - \delta) W^e(a', h) + \delta W^u(a', h)]. \tag{16}$$

With (endogenous) probability δ an employed worker loses his job and receives the value of unemployment $W^u(a', h)$ next period. With the counter-probability he continues to be employed. Now the state-contingent contract which determines an employed workers' income is described.

The Wage Contract The optimal wage contract between workers and entrepreneurs specifies $w(S)$, the compensation for a worker in a firm with state S, where $S = (\varepsilon, e; a, H)$ is the firm's updated state vector after it has decided how many workers to employ. As in Cooper *et al.* (2007) entrepreneurs are able to make take-it-or-leave-it offers, i.e. the workers have zero bargaining power. The firm thus chooses the wage subject to the worker's participation constraint:[14]

$$W^e(a, h_{-1}) \geq W^u(a, h_{-1}) \tag{17}$$

In equilibrium the participation constraint will hold with equality, implying

$$Z(c^e, h^e) = Z(c^u, h^u) \tag{18}$$

$$w(S) = b(a). \tag{19}$$

The contract stipulates that the wage offered by the firm is always equal to the state-dependent outside option.[15] This is a simple way in which the model generates movements in the wage without the complexity of adding aggregate labor demand as an additional state variable. Since workers of both types i make identical consumption and housing choices the superscript i is now dropped.

2.5 Equilibrium

I now describe the distribution of firms, the laws of motion for the exogenous and endogenous processes, and define equilibrium.

[14] Formally, the profit maximizing contract results from the following optimization problem: $\hat{\pi}(a, \varepsilon, e) = \max_{w(S)} a\varepsilon F(e) - ew(S)$ subject to $W^e(a, h_{-1}) \geq W^u(a, h_{-1})$.

[15] See Appendix for details.

Distribution of Firms The joint distribution of incumbent firms over employment and productivity is denoted $\lambda_t(e, x)$.[16] In the absence of aggregate shocks it is possible to solve for the stationary distribution λ^*. The transition from λ to λ' can be written as $\lambda' = T(\lambda, M)$, where the operator T is linearly homogeneous in λ and M jointly. This implies that if one were to double the amount of firms in this economy and doubled the amount of entrants the resulting distribution would be unchanged. For any set $(e\ x)' \in E \times X$, where E and X respectively denote the employment and profitability space we can now define T. Assuming that some initial distribution λ_0 exists and given the policy functions for employment and exit, the operator T is defined by

$$\begin{aligned}\lambda'((e\ x)' \in E \times X) = &\int_{x \in x'} \int_{E \times X} (1-\delta_x) \times 1_{\{\phi_e(x,e;H) \in e'\}} \times F(dx'|x)\lambda(dex) \\ &+ M \times \int_{x \in x'} \int_{0 \times X} (1-\delta_x) \times 1_{\{\phi_e(x,0;H) \in e'\}} \times F(dx'|x)\nu(dx). \quad (20)\end{aligned}$$

Exogenous shocks I now define the exogenous and endogenous processes for the non-stationary economy with aggregate fluctuations. The logarithm of the idiosyncratic productivity shock ε follows an autoregressive process.

$$\ln \varepsilon_t = \rho_\varepsilon \ln \varepsilon_{t-1} + v_{\varepsilon,t}\ ,\ v_\varepsilon \sim N(0, \sigma_\varepsilon) \quad (21)$$

The initial productivity of entrants is determined by a draw from $v_\nu \sim N(0, \sigma_\nu)$ and then evolves according to (21). The two exogenous aggregate state variables (a, p^h) evolve jointly according to an unrestricted VAR(1) process with normal innovations that have zero mean and covariance matrix Σ.

$$\begin{pmatrix} a' \\ p^{h\prime} \end{pmatrix} = \rho \begin{pmatrix} a \\ p^h \end{pmatrix} + u, \qquad \mathbf{cov}(u) = \Sigma \quad (22)$$

with ρ and $\Sigma \in \mathbb{R}^{2\times2}$. The shocks to the aggregate variables are orthogonal to the shocks from the idiosyncratic productivity shocks. For the model simulation the above process is discretized using a joint Markov chain. The law of motion for the (endogenous) vacancy filling rate H is given by

$$H' = \mathbb{F}(a, a', \lambda). \quad (23)$$

The knowledge of $\mathbb{F}$ requires the joint distribution over employment and idiosyncratic profitability, which is (theoretically) infinitely-dimensional. I follow the approach developed by Krusell and Smith (1998). It consists of postulating a functional form for $\mathbb{F}$ which entrepreneurs use to make their optimal decisions. From a subsequent simulation of the model one can check the consistency between the actual law of motion of H and the one predicted by the guess of $\mathbb{F}$. The resulting equilibrium must be such that $\mathbb{F}$ must track the evolution of H very accurately. This is explained in detail in the Appendix.

[16] I define $x \in X$ as the firm's combined idiosyncratic and aggregate profitability state (ε, a).

2.5.1 Definition of Equilibrium

For a given initial distribution λ_0 a recursive competitive equilibrium consists of (i) value functions $V^i(s)$ and $V^e(a,H)$, (ii) a policy function $\phi^e(s)$, (iii) bounded sequences of non-negative negotiated wages $\{w_t\}_{t=0}^{\infty}$ and interest rates $\{R_t\}_{t=0}^{\infty}$, unemployment $\{U_t\}_{t=0}^{\infty}$, vacancies $\{V_t\}_{t=0}^{\infty}$, incumbent measures $\{\lambda_t\}_{t=0}^{\infty}$ and entrant measures $\{M_t\}_{t=0}^{\infty}$ such that (1) $V^i(s)$ and $\phi^e(s)$ solve the incumbent's problem, (2) $\{w_t\}_{t=0}^{\infty}$ satisfies the worker's participation constraint, and $\{R_t\}_{t=0}^{\infty}$ is determined by the bank's zero-profit condition, (3) the measure of entrants is given by the free-entry condition (10), and (4) λ_t evolves according to (20). The law of motion of H is taken as given by agents and is consistent with their aggregate behavior.

3 Results

Since the models' non-linearities do not allow a closed-form solution I now present quantitative results. The model is calibrated to salient features of the US economy. Using the stationary version of the model without aggregate shocks I show how parameter choices map into data moments. After describing the calibration, I evaluate the performance of the stationary model and then discuss the results of the model with aggregate shocks.

3.1 Calibration

I calibrate the model at monthly frequency.[17] The calibration is summarized in Table 1. I set the discount factor β to correspond to an annual interest rate of $r^{ann} = 4\%$. The curvature of the production function is set to α to 0.6. The matching function is $m = \mu U^{\gamma} V^{1-\gamma}$. It has two parameters, the match efficiency μ and the elasticity γ. The latter is set to 0.60 following Pissarides and Petrongolo (2001). I follow Den Haan *et al.* (2000) and target an average quarterly vacancy filling probability of 0.71, which implies a monthly probability of $H = 0.3381$. Together with an average unemployment rate over the time of my sample (1977-2012) of 6.4% this pins down the values for μ and the steady-state value for θ.[18] Following Cooper *et al.* (2007) the workers' outside option takes the functional form $b(a) = b_0 a^{b_1}$. Given the nature of the wage contract the parameter b_0 plays the role of a base wage, while b_1 governs the wage's sensitivity to the aggregate profitability state. I normalize $b_0 = 0.5$. To estimate b_1 I use (HP-filtered, seasonally adjusted) average weekly wages from the Quarterly Census of Employment and Wages (QCEW) between 2001 and 2011. The correlation between the cyclical component of this series and GDP is 0.49, which is very close to the value used in Cooper *et al.* (2007). The rate of exogenous quits is set to 0.019, which corresponds to 5.7% per quarter. The firm exit rate δ_x is chosen to match the annual exit rate from the BDS data.

[17] I choose this frequency because at a lower frequency the job-finding and vacancy-filling probabilities can become larger than 1. Where required, the simulated firm-level moments are computed using time-aggregation so they can be compared to the data counterparts.

[18] See Appendix A.2.5 for details.

Parameters	Symbol	Value	Source
Discount Factor	β	0.9967	$r = 4\%$
Curvature of profit function	α	0.60	Cooper *et al.* (2007)
Matching elasticity	γ	0.6	Pissarides and Petrongolo (2001)
Match efficiency	μ	0.2567	eq. (63)
Base wage	b_0	0.5	normalized
Elasticity of wage	b_1	0.49	QCEW
Quit rate	q	0.019	BLS
Firm exit rate	δ_x	0.0087	Annual Firm Exit Rate 10%
Aggregate shocks	ρ, Σ	eq. (27)	US data 1977-2011
Mean of (log) ε	μ_ε	1.0111	Firm Employment Distribution
Autocorrelation of ε	ρ_ε	0.9920	Firm Size Distribution
Standard deviation of ε	σ_ε	0.0761	Firm Size Distribution
Disruption adjustment cost	ξ	0.0699	Inaction in Δe
Quadratic costs vacancies	c_v	0.0243	Share of small Start-ups
Quadratic costs firing	c_f	0.0131	"–"
Start-up productivity	σ_ν	1.9933	Start-up Fraction of JC = 18.6%

Table 1: Parameter Values. The first block consists of calibrated parameters, the parameters in the second block were estimated via SMM.

The entry costs and workers' preference parameter are derived from the stationary economy. Without aggregate shocks the demand for housing is $h_W = \varphi \frac{b_0}{p^h}$ and the value of real estate held by incumbent workers is thus $p^h h_W = \varphi b_0$. In the Appendix I derive the price of real estate in the stationary economy. I target a value-to-loan ratio of 0.7 for the start-up loans. This implies that $p^h h_W = 0.7 F_e$. Combining this with the expression for the start-up costs F_e from the bank's break-even condition (12) and the free-entry condition (10) I obtain

$$q(S) = \min\left\{\tilde{F}_e, \pi(\varepsilon_0) + 0.7\frac{V_e}{R}\right\} \tag{24}$$

and R as the fixed point of

$$R = \frac{(r - 0.7\delta_x)V_e}{(1-\delta_x)\int_{-\infty}^{\infty} q(S)\nu(\varepsilon)d\varepsilon}. \tag{25}$$

From this expression I can then back out F_e and the utility parameter φ which governs the workers' preference for housing.

$$\varphi = \frac{0.7F_e}{b_0}. \tag{26}$$

Adjustment costs Labor adjustment costs are parameterized in a way that includes fixed and variable costs. Both types of adjustment costs are common in the literature (see e.g. Cooper *et al.* (2007) and Bloom (2009)).

$$\mathbb{C}(a,H;e,e_{-1}) = \begin{cases} a\varepsilon F(e)\cdot\xi + c_v\left(\frac{e-(1-\chi)e_{-1}}{H}\right)^2\cdot\omega(a) & \text{if } e > (1-\chi)e_{-1} \\ a\varepsilon F(e)\cdot\xi + c_f\left(e-(1-\chi)e_{-1}\right)^2\cdot\omega(a) & \text{if } e < (1-\chi)e_{-1} \end{cases}$$

There are two types of costs connected to adjusting labor. The first one, ξ, is a disruption-style adjustment cost. A fixed fraction of output is lost due to the adjustment process. For example, adding or removing workers may require fixed costs of advertising, interviewing, training, or shutting down parts of the production process. This type of cost generates a region of inactivity in which the firm does not adjust its employment level.[19] The second type of adjustment cost is captured by c_v and c_f and represents a quadratic cost to adjustment for each vacancy posted and each unit of labor fired. This captures the idea that more rapid adjustments are more costly. The firm does not pay adjustment costs for exogenous quits. Without labor adjustment costs the value of entry would only depend on aggregate profitability and there would be no mechanism to equalize the cost and benefits of entering.

SMM The remaining parameters are consistently estimated via simulated method of moments (SMM). They include the labor adjustment costs (ξ,c_v), the idiosyncratic profitability shocks (ρ_ε, σ_ε, μ_ε), and the profitability distribution of start-ups (σ_ν).[20] The SMM procedure finds the vector of structural parameters $\Theta = (\xi, c_v, \sigma_\nu, \mu_\varepsilon, \sigma_\varepsilon, \rho_\varepsilon)$ which minimizes the (weighted) distance $L(\Theta)$ between data moments and model moments. The distance is defined as

$$L(\Theta) = \left(\Gamma^D - \Gamma^M(\Theta)\right)\Xi\left(\Gamma^D - \Gamma^M(\Theta)\right)',$$

where Γ^D are data moments and $\Gamma^M(\Theta)$ are moments from a simulation of the model, given parameters Θ. The weighting matrix is Ξ. I solve the dynamic programming problem and generate policy functions given a parameter vector Θ. From the simulation of the model I then obtain $\Gamma^M(\Theta)$. The SMM algorithm finds the parameter vector Θ which minimizes $L(\Theta)$.

I now describe the moments used to identify the parameters in Θ.[21] Table 2 summarizes the results. The disruption costs of employment adjustment generate inactivity. I therefore use the fraction of establishments with no changes in employment as a target for ξ. This fraction is equal to 0.38, which suggests that fixed costs of labor adjustment are important. The scale parameter σ_ν determines the size-distribution of start-ups. I

[19] I found a disruption-style cost to deliver better results than a simple fixed cost of adjustment, because the latter leads to more inactivity among smaller firms.

[20] I restrict adjustment costs to be symmetric for hiring and firing, such that $c_f = c_v$.

[21] Note that no direct mapping between the moments and the parameters exist, all moments in Θ influence all the data moments in Γ^D. The moments were chosen because they are informative about the respective parameter. The choice was motivated by Cooper *et al.* (2012) and Berger (2012). The data on (net) employment changes were derived from continuing establishments using annual Census BDS data between 1985-1999.

use the rate of gross job creation through firm birth from the BDS to identify this parameter. Start-ups contribute to 18.6% of gross job creation. In addition, the quadratic adjustment cost parameter c_v is identified using the fraction of *small* start-ups. If c_v is low, start-ups become large quickly, which skews the distribution of start-ups towards larger firms. Finally, I use the firm size and firm employment distributions to identify the parameters μ_ε, σ_ε, and ρ_ε. I target the fraction of small firms, their employment share, and the fraction of large firms in the economy. Table 2 shows the fit of the targeted moments. All model moments are close to their data counterparts. The fraction of job creation by entrants and the average firm size are easier to match than the employment change distribution. The fit of the inaction and "small adjustment" is high, but the model slightly overestimates large labor adjustments of over 30%, which constitute 29% of adjustments in the data, but 35% in the model. The results for the adjustment costs imply that firms pay 3.04% of their revenues as adjustment costs.[22]

For the idiosyncratic profitability process I choose the parameters, $\rho_\varepsilon = 0.97$, which implies an annual persistence of 0.7, and $\sigma_\varepsilon = 0.086$, which implies an annual standard deviation of 0.3. Together, they are important for the size distribution of firms and I picked them to approximately match the share of large firms in the economy.

An entrant's initial productivity draw is taken from the distribution ν, which is defined over the same domain as incumbents' productivity. To reduce the number of parameters that need to be calibrated I choose to model ν as a Pareto distribution with scale parameter σ_ν. This value is chosen to generate the same amount of gross job creation by start-ups as in the BDS data.

Moment	**Data**	**Model**	**Parameter**
$\Delta e = 0$	0.38	0.42	ξ
Start-up JC	0.19	0.17	σ_ν
Employment in small Start-Ups	0.54	0.34	c_v, c_f
Fraction of Small Firms	0.76	0.72	σ_ε
Employment in Small Firms	0.12	0.12	μ_ε
Employment in Large Firms	0.69	0.58	ρ_ε

Table 2: Data Moments and SMM estimates. The last column shows the parameter associated to each moment. Adjustment costs are symmetric for hiring and firing. The employment change numbers are taken from Berger (2012) who uses LBD averages between 1985-1999.

3.2 Results of the Stationary model

I now discuss some features of the stationary model In particular, I look at the size distribution of all firms and start-ups, as well as the joint distributions of size, age, and employment.

[22]This figure is line with previous results, i.e. Bachmann (2012) estimates adjustment costs to be 2% of output, while in Siemer (2013) adjustment costs account for 5% of GDP.

The size and employment distribution of firms is shown in Table 3. The upper part of the table shows the size distribution, the lower part shows the employment distribution. The model is able to match this distribution very well. Small firms make up 3/4 of all firms, but employ only 1/8 of the workforce. On the other hand, large firms have a largely over-proportional employment share. The model lacks some of the extremely large firms observed in the data and thus generates a smaller employment share of the largest firms compared to the data.[23]

Firm Size	1-9	10-19	20-49	50+
	Size Distribution			
Data	0.76	0.12	0.07	0.04
Model	0.72	0.12	0.08	0.08
	Employment Distribution			
Data	0.12	0.08	0.11	0.69
Model	0.12	0.12	0.17	0.58

Table 3: The Size and Employment Distribution of all Firms.

Although not specifically targeted, the age-distribution of firms generated by the model is very close to the data counterpart. It is plotted in Figure 5. The model gives slightly too much weight to firms in the middle of the distribution, but the overall fit is very good. Start-ups make up around 10% of all firms. Their share of employment is 3%, exactly as in the data. Their share of job-creation is 17%, compared to 18.5% in the data.

3.3 Results with Aggregate Shocks

I now add aggregate shocks to the model in order to assess its business cycle properties and evaluate its quantitative performance. The two exogenous aggregate state variables (a, p^h) evolve according to the VAR in (22). I use monthly US data from 1992-2014 to estimate this process. The results are:

$$\rho = \begin{pmatrix} .699^{***} & .095^{***} \\ -.078^{**} & .956^{***} \end{pmatrix}, \qquad \Sigma = \begin{pmatrix} 2.476e-05 & -1.725e-06 \\ -1.725e-06 & 1.340e-05 \end{pmatrix} \tag{27}$$

To show the effect of shocks to aggregate productivity and the HPI, impulse response functions are generated. I then test alternative model specifications without variations in house prices and with a fixed number of entrants. Finally, I show a policy experiment in which I back out the effects of the decrease in house prices on the increase and persistence of unemployment during and after the Great Recession. I find that this decrease was important in generating the observed dynamics.

[23]In Table 9 in the Appendix I replicate Table 3 for Start-Ups. It shows that the vast majority of start-ups are small, a fact the model matches very well. The model slightly overemphasizes the share of large firms. This is also reflected in the largest start-ups' employment share, as is shown in the lower half of the table.

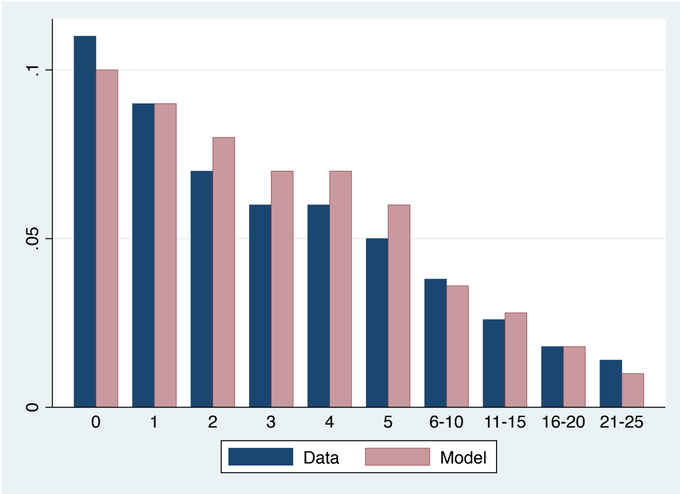


Figure 5: Age distribution of firms. The blue bar on the left shows the data, the light red bar on the right shows the model moment. Averages shown for ages above five years.

3.3.1 Impulse Response Functions

Figure 6 shows a negative shock to aggregate profitability of one standard deviation.[24] The first panel plots A and shows that it is a mean-reverting process. Unemployment and GDP are shown in the second panel. As A falls, output decreases and unemployment increases. The third panel shows the vacancy filling probability $H(\theta)$. As A decreases, the value of entry V^e falls, while the cost of entry has not changed. To restore equality between the costs and benefits of entry, $H(\theta)$ must rise to adjust V^e back to the level of $\tilde{F}_e$ so that (10) holds. This implies that fewer new firms enter the economy, as can be seen in the last panel. It shows the number of start-ups as well as gross job destruction by incumbents.[25] The number of start-ups falls in reaction to the drop in profitability, despite the increase in $H(\theta)$. As A begins to revert back towards its pre-shock mean, the number of start-ups increases, even overshooting in order to replenish the now lower stock of firms. Incumbent firms' net job creation is influenced by two factors: The decrease in A lowers profitability and leads to less net job creation. The increase in $H(\theta)$ makes it less costly to fill vacancies, thus partly offsetting the negative effects of a decrease in A. Taken together, the effect of a drop in A is a fall in incumbents' job creation.

Figure 7 shows results for a fall in house prices p^h. The four panels are constructed in the same way as before. The first panel shows the fall and subsequent mean reversion of p^h. The second panel shows the decrease in GDP and the increase in the unemployment

[24] All impulse responses were created by simulating the economy for a large number of periods and then averaging over all the periods that followed the shock of interest. The series are all normalized to their pre-shock values.

[25] As in the data, start-ups are firms that are less than one year old.

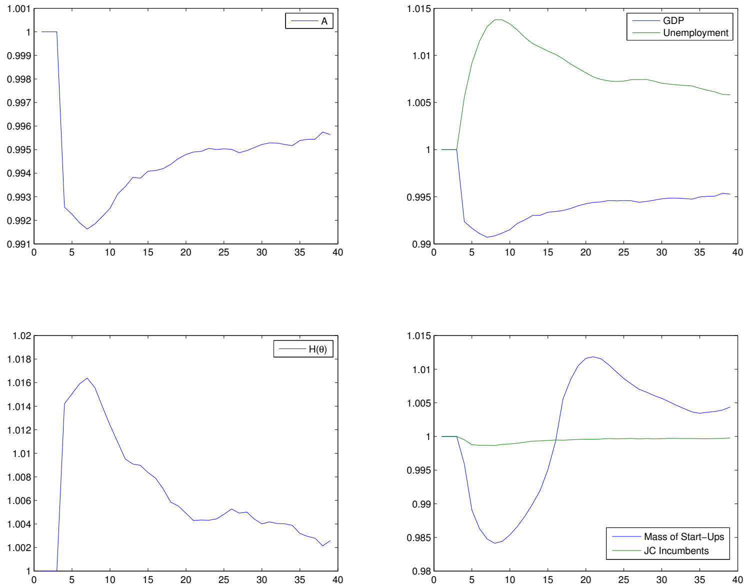


Figure 6: Impulse Response Functions for a shock to A.

rate. A fall in house prices leads to an increase in unemployment and a fall in GDP. Compared to Figure 6 the correlation between the exogenous shock, GDP, and unemployment is lower. Regarding the magnitudes of the effects the shocks to p^h generate larger increases in unemployment compared to the declines in GDP. When house prices fall, the costs of entry rise (Proposition **??**). For the free-entry condition to hold, the value of entry must also go up. This is achieved by an increase in $H(\theta)$ (panel 3). This implies that even for a given level of hiring by incumbent firms, fewer new firms are needed to generate the required number of vacancies to make the free-entry condition hold. Furthermore, the increase in $H(\theta)$ leads to an increase in hiring by firms that expand their workforce. Taken together, job creation by incumbents increases. This result comes from the fact that house prices only indirectly affected incumbent firms through an increase in the job-finding probability. After a few period incumbents' job creation falls, as the (smaller) cohorts of new firms enter the pool of incumbent firms. The last panel further shows that the number of entrants falls in reaction to a drop in house prices. In contrast to a negative profitability shock the number of start-ups does not overshoot by nearly as much once house prices begin to recover. This is a result of the fact that entry costs are still elevated and a large part of the labor market is picked up by incumbent firms, which benefit from lower vacancy creation costs.

From the impulse response functions we can see what is required from the model in order to generate a jobless recovery. A fall in profitability decreases GDP, increases unemployment and produces a drop in the number of start-ups. However, the recovery is

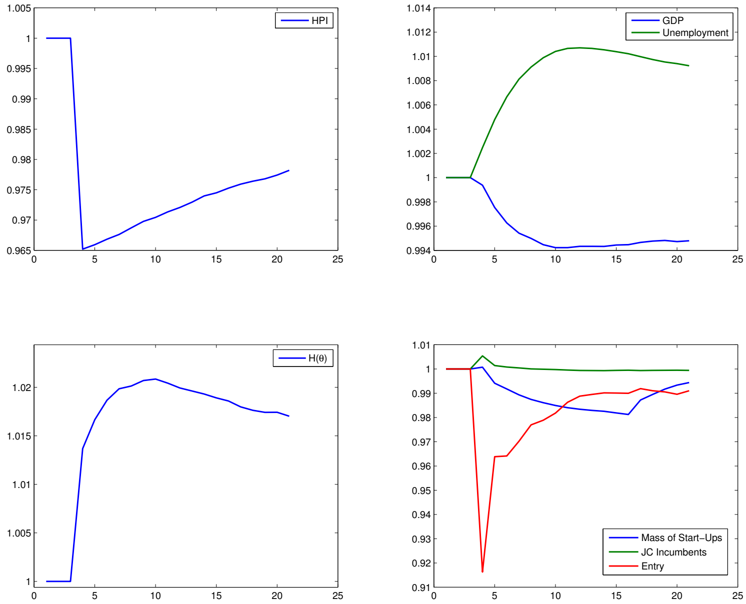


Figure 7: Impulse Response Functions for a shock to p^h.

characterized by a very high correlation between GDP and unemployment. Furthermore, entry overshoots, contrary to what we observed in the data. This is why a shock to A by itself cannot generate a jobless recovery. The fall in HPI on the other hand produces an over-proportional increase in unemployment and a large and persistent fall in the number of start-ups which does not overshoot as conditions converge back to normal. The ability of the model with shocks to A and p^h to generate jobless recoveries thus stems from the effect of house prices on the start-up process. By directly impacting entry, a decrease in p^h has a large effect on start-up activity, and thus on unemployment. The fraction of total hiring by start-ups is over-proportional to their share of total output. Therefore, if the number of start-ups decreases, the effect on unemployment is larger than the effect on GDP.

3.3.2 Business Cycle Statistics

The benchmark model includes shocks to A and p^h. It is able to match several key statistics of the US labor market regarding unemployment, vacancies, and the cyclicality of entry. Table 4 shows the results. The first three columns show the autocorrelation of unemployment, vacancies, and labor market tightness. The fourth column shows the correlation between unemployment and vacancies. Columns five and six report the correlation between the number of start-ups and GDP respectively HPI.

The benchmark model slightly overstates the persistence of U, V, and hence θ. The

	ρ_U	ρ_V	ρ_θ	$\rho_{U,V}$	$\rho(Y,M)$	$\rho(p^h,M)$
US Data	0.944	0.787	0.919	-0.826	0.695	0.581
Benchmark Model	0.987	0.932	0.961	-0.929	0.366	0.534
Only A	0.908	0.504	0.666	-0.744	0.214	-
Only p^h	0.991	0.965	0.978	-0.946	0.523	0.660

Table 4: Business Cycle Statistics of the Model. Source: FRED (2000M12-2015M1) and BDS (1977-2012). All series are log deviations from trend. ρ denotes the autocorrelation of unemployment (U), vacancies (V), and labor market tightness (θ). $\rho_{U,V}$ is the correlation between unemployment and vacancies and $\rho(\cdot, M)$ between GDP/HPI and the number of start-ups. The BDS data is annual and the corresponding model moments have been produced using time aggregation.

	$\rho(Y,N^E)$	$\rho(Y,N^I)$	$\sigma(c/t)^E$	$\sigma(c/t)^I$
US Data	0.35	0.76	0.10	0.07
Benchmark Model	0.34	0.65	0.20	0.07
constant q^h	0.60	0.79	0.30	0.07
constant a	0.06	0.13	0.08	0.06

Table 5: Data and Model Moments. Source: BDS 1977-2011. The resulting model moments have been computed using time aggregation. Data and model moments have been computed as log deviations from mean/trend. $\rho(Y,N^E)$ and $\rho(Y,N^I)$ show the correlation between GDP and gross job creation by entrants and incumbents. The standard deviation of the cyclical over the trend component of job creation by start-ups are ($\sigma(c/t)^E$) and $\sigma(c/t)$ for incumbent firms.

correlation between unemployment and vacancies is strongly negative, as in the data. The US data shows a strong positive correlation between both GDP and HPI and the number of start-ups. The model can replicate both of these positive correlations. Given that it was not calibrated to generate these moments the fit can be considered a success of the calibration strategy.

We can now compare the benchmark results to those of the model without variations in house prices and without shocks to aggregate profitability. The results are summarized in the last two rows of Tables 4 and 5. Table 4 shows that the business cycle statistics of the model without the financial friction are similar to the benchmark model. The volatility of unemployment and vacancies, as well as the correlation between the two is slightly overstated. Furthermore, θ is more volatile than in the data. The fact that the model produces similar moments as the benchmark model is not very surprising given the similarity of the model without the financial friction to Cooper *et al.* (2007), who find similar results. The model without shocks to a, on the other hand, is unable to capture some of the key US business cycle statistics. In particular, the model does not generate enough variation in unemployment and vacancies. The reason is that variations

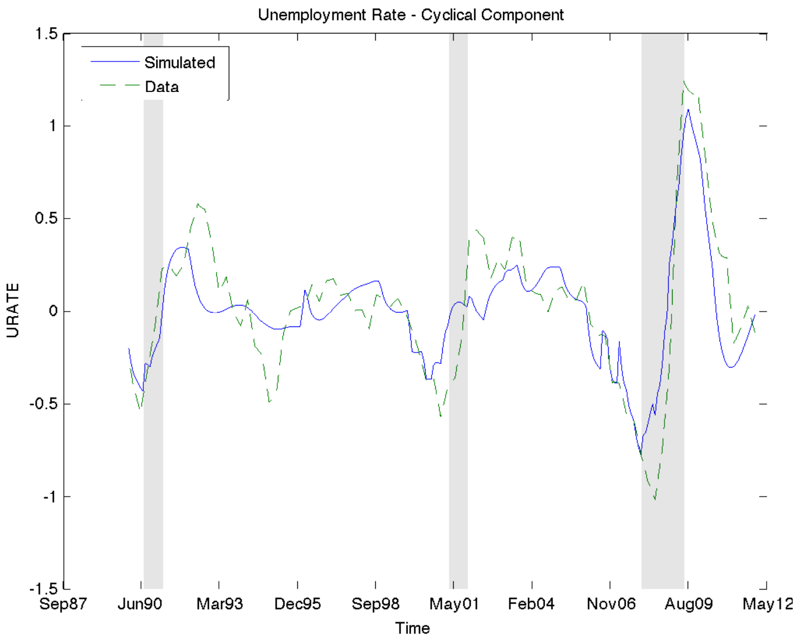


Figure 8: Cyclical component of the unemployment rate. Data vs. simulation using estimated processes for a and q^h between 1990 and 2011. Shaded areas correspond to NBER recession dates.

in q^h have a strong effect on start-ups but only an indirect effect (through labor market tightness) on incumbent firms. The movements in θ generated by changes in p^h are by themselves not sufficient to generate the observed time-series volatility. Table 5 shows the model performance regarding job creation by entrants and incumbents.

Business cycle statistics are summarized in Tables 4. Table 5 shows the correlation of the number of new and incumbent firms, as well as their standard deviation for the various models.

3.3.3 Policy Experiment

Tables 4 and 5 showed that the model is able to match they key properties of the US labor market as well the cyclicality and volatility of job creation by entrants and incumbent firms. I now test in how far the model can replicate the relationship between the cyclical components of GDP growth and unemployment during the *Great Recession*. I evaluate the model's performance by feeding the observed house price index between 1990Q1 and 2013Q1 into the model. Furthermore, I pick the sequence of aggregate productivity shocks to match the cyclical component of GDP over the same period. I begin the simulation from the unconditional means of A and p^h. The results are presented in Figure 8.

The co-movement of the two time series is extremely strong, particularly during the

Great Recession, indicated by the third shaded area. The simulated data is able to explain 72.23% of the variation of the unemployment rate observed in the data. For the period starting in 2006 the simulated data can even explain 84.66% of the movement in the unemployment rate. The recovery is 'jobless' because of the ongoing negative influence of the low HPI on start-up job creation. Like in the data this leads to high levels of unemployment even after the official recession end. Net job creation by incumbents begins to recover before job creation by start-ups. This is the case because at the end of the recession incumbent firms take advantage of the high vacancy filling probability, while entry remains low. What the model is unable to match is the time lag in the respective troughs of the HPI and job creation by start-ups. In the simulation job-creation by start-ups coincides with the trough in the HPI series, while in the data job creation by start-ups was lower in 2011 than in 2009.

4 Discussion of Results using Microdata

This section serves to re-evaluate the results of the quantitative part in the light of the data. First, I use information at the Metropolitan Statistical Area (MSA) level to quantify the impact of changes in house prices on business formation. Then I examine the Survey of Consumer Finances (SCF) and the Survey of Business Owners (SBO) to show that personal wealth is a key factor in start-up capital. All the data is described in detail in the Appendix.

4.1 MSA-level data

The previous section has shown the results and policy implications of the model. This section revisits the data. I use MSA-level data on house prices and firm dynamics to test some of the model's predictions. If the house-price channel is as important as the model suggests, one should observe that

1. Employment in start-ups and young firms has fallen more in areas with large house price declines relative to areas with small or no house price declines. This relationship does not exist for older firms.

2. In areas with larger drops in GDP, employment in firms of *all ages* have seen relatively larger declines.

3. HPI growth has a significant positive effect on employment in start-ups and young firms. It has no significant effect on employment in old firms.

4. The *recovery* of the labor market in MSAs with large HPI declines during the crisis was slower.

This is precisely what I find in the data. Figure 9 shows employment in young firms before and after the 2007-09 recession, divided by location. The left (right) graph divides firms by whether or not house prices (GDP) in their MSA showed small or large declines.[26] The left graph shows that prior to the recession no discernible difference between young firms existed. However, starting in 2007 there is a significant gap depending on whether or not a large drop in house prices occurred. This gap is big and persistent. The graph on the right shows employment in young firms by GDP growth of the MSA. There is a stronger increase of employment in young firms prior to the recession and a consequently larger fall, but beginning in 2008 the differences are not significant.

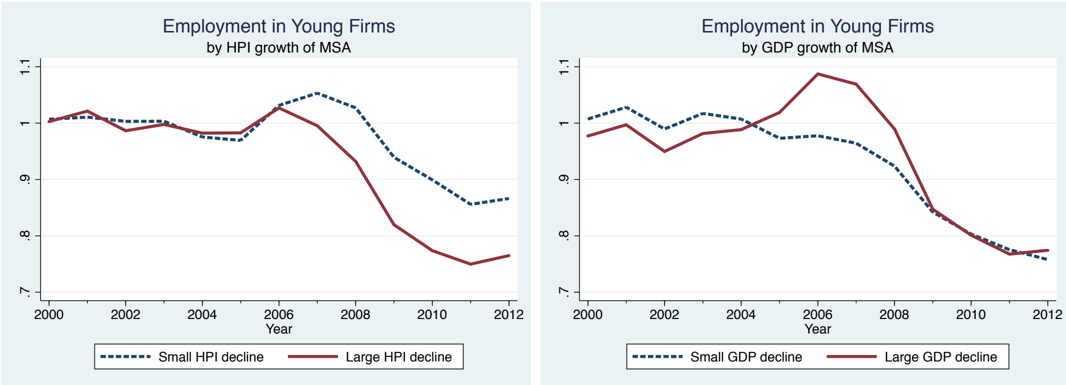


Figure 9: Employment Decline during the 2007-09 recession. MSAs with large (small) HPI or GDP declines are represented by the solid red (dashed blue) line. Series are indexed to their mean 2000-2007 values.

The impact of large declines in house prices on employment Table 6 shows the corresponding regression results using MSA level data. The idea behind this empirical strategy is that the effects of declines in house prices are potentially non-linear, with large declines having stronger effects than small declines. An alternative approach is to use changes in the continuous variable HPI to identify changes in employment in start-ups and young firms. That approach is pursued below. For a MSA i in year t the specification is a variant of:

$$Y_{i,t}^{\tau} = \alpha_0 + \alpha_H HPI_i^{-} + \alpha_P Post_t + \beta_H HPI_i^{-} \times Post_t + \alpha_X X_{i,t} + \varepsilon_{i,t} \tag{28}$$

The main explanatory variables are indicator variables, or interactions of indicator variables. The indicator variable HPI_i^{-} is equal to one $\forall t$ if and only if the change in house prices between 2006 and 2009 was among the lowest 20% and equal to zero if the change was among the highest 20%.[27] $Post_t$ is equal to 1 if and only if $2007 \leq t \leq 2010$, the years of the correction in house prices. $X_{i,t}$ is a vector of additional control variables. The dependent variable is total employment at firms of age τ in MSA i at time t.[28] The

[26]Following Mian and Sufi (2014) I define MSA with "large" or "small" declines as those in the top or bottom 20% of the change in the HPI (GDP) between 2006 and 2009. All the graphs start in the year 2000 because that is the first year where GDP data by MSA is available.

[27]Qualitatively the results remain unchanged when moving the cutoff or setting the dummy equal to zero if a MSA was not in the bottom 20% of house price changes.

[28]Results do not change qualitatively by using the number of firms as the dependent variable.

main coefficient of interest is β_H, which estimates the average change in $Y^{\tau}_{i,t}$ after the year 2006 specific to firms in MSAs with large HPI declines. Additionally, I test the effects of a large decline in GDP by estimating

$$Y^{\tau}_{i,t} = \alpha_0 + \alpha_G GDP^{-}_i + \alpha_P Post_t + \beta_G GDP^{-}_i \times Post_t + \alpha_X X_{i,t} + u_{i,t} \tag{29}$$

The indicator variable GDP^{-}_i is defined in the same manner as HPI^{-}, applied to GDP changes between 2006 and 2009. We are now mainly interested in the coefficient β_G. Results for $\tau = 0$, $\tau \leq 5$, and $\tau > 15$ i.e. employment in start-ups, young, and old firms are shown in Table 6. For each value of τ I estimate the two models, (28) and (29). The first row of Table 6 shows the estimated coefficients for $\hat{\beta}_H$. For start-ups and young firms it is negative and significant. For old firms, the estimated $\hat{\beta}_H$ is positive and insignificant at the 10% level. Overall, the results confirm that in MSAs with large house price declines start-ups and young firms employed significantly fewer people than in MSA with small or no house price declines. Specifically, the results suggest that when $HPI^{-}_i \times Post_t$ switches from zero to one, the effect on start-up job creation is a decline of 6.8%.[29] For young firms the effect is a decline of 4.4%.

Columns 4-6 of Table 6 show the results of large declines in GDP. As expected, the coefficient of interest, $\hat{\beta}_G$, is negative. Furthermore, it becomes smaller with τ. While for employment in start-ups and young firms the effect of switching $GDP^{-}_i \times Post_t$ from zero to one is estimated with -9.9% and -7.7%, the effect for old firms is -3.9%.

I have performed a large number of alternative specifications of (28). As robustness checks, I find that the results obtained in Table 6 are not sensitive to using firm-age specific employment trends, using linear time trends instead of year dummies, restricting the analysis to specific years, and creating a 'placebo' dummy for the time of the recession.

As a final exercise, I create a new indicator variable, HPI^{+}, which takes a value of one for those MSAs that saw the 20% largest HPI *increases* after the year 2009, and zero for the 20% smallest increases. I want to test whether a rebounding of house prices had positive effects on employment of firms at various ages. The specification I use is

$$Y^{\tau}_{i,t} = \alpha_0 + \alpha_H HPI^{+}_i + \alpha Post_t + \beta_H HPI^{+}_i \times Post_t + \alpha_X X_{i,t} + \varepsilon_{i,t}, \tag{30}$$

where $Post$ is equal to one if and only if $t > 2009$. Results are presented in Table 10 in the Appendix. I find that a strong recovery in the HPI is positively correlated with higher employment in start-ups and young firms (both +6.3%) after controlling for GDP. For old firms the coefficient of interest is negative, but not significant.

The impact of house prices on employment An alternative identification strategy that uses the MSA-level data to estimate the effect of house prices on start-up activity treats all changes in HPI equally. It consists of estimating the following model:

$$\mathrm{Y_{i,t}}^{\tau} = \beta_0 + \beta_H \Delta HPI_{i,t} + \beta_G \Delta GDP_{i,t} + \beta_U U_{i,t} + \beta_X X_{i,t} + \varepsilon_{i,t} \tag{31}$$

[29]Since $\exp(-0.0706) - 1 = -0.068$.

	(1) Start-ups	(2) Young Firms	(3) Old Firms	(4) Start-ups	(5) Young Firms	(6) Old Firms
HPI$^-$× Post	-0.0706***	-0.0454**	0.00923			
	(-2.78)	(-2.42)	(0.54)			
GDP$^-$× Post				-0.104***	-0.0800***	-0.0401**
				(-3.09)	(-2.63)	(-2.04)
HPI$^-$	0.0890***	0.142***	-0.199***			
	(9.58)	(16.52)	(-26.17)			
GDP$^-$				0.762***	0.843***	1.124***
				(159.75)	(193.22)	(134.29)
Post	-0.0934***	-0.125***	-0.178***	-0.257***	-0.212***	-0.192***
	(-2.88)	(-5.57)	(-7.90)	(-5.55)	(-5.92)	(-7.34)
GDPr	0.700***	0.658***	0.417***			
	(5.92)	(7.47)	(3.57)			
HPIr				0.431***	0.454***	0.102
				(7.36)	(7.92)	(1.61)
Constant	3.947***	5.475***	4.401***	-1.210***	0.294	2.030***
	(6.41)	(11.96)	(7.22)	(-4.24)	(1.07)	(6.36)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
MSA dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.347	0.494	0.387	0.266	0.295	0.352
N	1675	1680	1540	3709	3712	1529

Table 6: The impact of HPI price declines on employment.

Notes: The dependent variable is log employment of firms. Young firms are maximum five years old, old firms are older than 15 years, excluding right-censored firms. HPI^- is equal to 1 (0) for MSA i at time t if the change in HPI between 2006 and 2009 was among the lowest (highest) 20%. GDP^- is defined in the same manner for GDP, where GDP has been normalized to its 2005 value. *Post* takes a value of one between 2007 and 2010. $GDPr$ is log real GDP and $HPIr$ is log real HPI. All regressions include year and MSA dummies and errors are clustered at the MSA level. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) start-ups	(2) start-ups	(3) Young Firms	(4) Young Firms	(5) Old Firms	(6) Old Firms
ΔHPI	0.538***	0.281**	0.415***	0.145*	-0.00313	-0.0675
	(8.77)	(2.86)	(8.35)	(2.36)	(-0.04)	(-0.75)
ΔGDP		0.115		0.0545		0.0595
		(0.77)		(0.61)		(0.80)
U		-0.0940*		-0.134***		-0.0592
		(-2.06)		(-3.97)		(-1.43)
Constant	7.457***	7.547***	8.930***	9.196***	9.148***	9.238***
	(234.21)	(108.35)	(404.02)	(183.55)	(937.84)	(143.01)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
MSA dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.245	0.394	0.289	0.566	0.376	0.384
N	10355	3811	9872	3811	3938	3815

Table 7: Panel Regressions at the MSA level. The effect of house prices on employment.

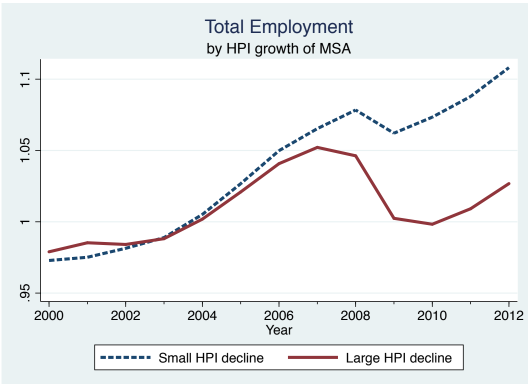
Notes: The dependent variable is log employment of firms. Young firms are maximum five years old, old firms are older than 15 years, excluding right-censored firms. ΔHPI is the first difference of the logarithm of the real HPI. ΔGDP is the first difference of the logarithm of the real GDP. U is the logarithm of the unemployment rate. All regressions include year and MSA dummies and errors are clustered at the MSA level. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The explanatory variables are continuous variables and include the growth in house prices, GDP growth, the unemployment rate, and other covariates, summarized by $X_{i,t}$. The dependent variable, $Y^{\tau}_{i,t}$, is employment at firms of age τ.[30] The key coefficient of interest is β_H, the MSA-level house price at time t. Results are shown in Table 7. I estimate two models for start-ups, young firms, and old firms respectively. The first model is a simple model of HPI growth on firm employment, while the second model controls for changes in GDP and the unemployment rate.

The first row shows the estimates of $\hat{\beta}_H$. It is positive and significant for start-ups and young firms. For old firms, the point estimate is very close to zero and the estimate is not significant at conventional levels. This confirms the results obtained previously: There exists a positive relationship between HPI growth and start-up activity. The signs of $\Delta GDP_{i,t}$ and $U_{i,t}$ enter with the expected sign and decrease the magnitude of $\hat{\beta}_H$. The results with the additional controls suggest that a one percentage point increase in HPI growth increases employment in start-ups by 0.28% and employment in young firms by 0.15%. Given an average annual HPI decline of around 5% during the recession years, this translates into an average start-up employment decrease of 1.4% in each of those years.

[30]Results do not change qualitatively by using the number of firms as the dependent variable. Results available upon request.

The Recovery In the model, a drop in house prices leads to a fall in start-up activity, which can result in a jobless recovery because start-ups and young firms are characterized by their over-proportional job creation rates. We can now use the MSA-level data to test whether the recovery was more ”jobless” in MSAs with large HPI declines. Specifically, I test whether the speed of employment adjustment is a function of the house price decline. Figure 10 plots employment in MSAs by whether or not they had a large decline in HPI or GDP. The variables are created in the same manner as was described above. The left-hand panel shows results by changes in HPI. The difference between the two series are not significantly different from zero before the year 2007. Starting in that year employment in MSAs with large declines in house prices fell more strongly. Furthermore, employment in those MSAs recovered more slowly than in MSAs with low or no HPI declines: In spite of the fact that GDP growth rates were positive in both groups starting in 2010, employment in MSAs with large house price declines was still below its pre-recession value in 2012. As the right-hand panel of Figure 10 shows, a large fall in GDP growth rates alone seems insufficient to predict a slow recovery of employment. The difference between the two series is not significantly different from zero, neither before nor after the start of the recession. There is, however, a significant different in the two years prior to the recession.



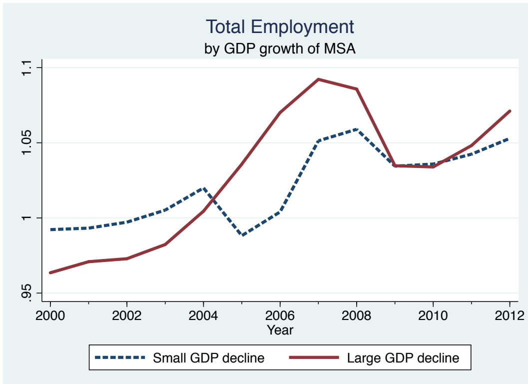


Figure 10: Total Employment during the 2007-09 recession. The left-hand panel shows employment in MSAs with large (small) HPI decline as the red solid (blue dashed) line. The right panel shows employment in MSAs with large (small) GDP growth as the red solid (blue dashed) line. Series are indexed to their mean 2000-2006 values.

To assess the significance of this difference I have run the following regression specification:

$$E_i^* - E_{i,t} = \alpha_0 + \alpha_H HPI_i^- + \alpha_P Post_t + \beta_H HPI_i^- \times Post_t + \alpha_X X_{i,t} + u_{i,t} \quad (32)$$

The variables are defined as above, with the exception of $Post$, which now takes the value of one if and only if $t > 2009$, i.e. after the end of the recession. The dependent variable is the deviation of $E_{i,t}$, log total employment in MSA i at time t, from its linear trend,

$E_{i,t}^*$. The results are shown in Table 11 in the Appendix. They show that being in an MSA with large house price declines increases the gap $E_i^* - E_{i,t}$ by 5.02% after 2009.[31] Furthermore, I test the for speed of employment adjustment back to the linear trend E_i^* depending on whether or not $HPI_i^- = 1$ or $GDP_i^- = 1$. I estimate the following specification:

$$\Delta E_{i,t} = \alpha_0 + \alpha_H HPI_i^- + \beta_g(E_i^* - E_{i,t}) + \beta_{gH}(E_i^* - E_{i,t}) \times HPI_i^- + \alpha_X X_{i,t} + u_{i,t}, \quad (33)$$

and equivalently for GDP^-. The results are shown in Table 12 in the Appendix. They suggest that the adjustment parameter at which the gap $(E_i^* - E_{i,t})$ is closed is around 30% smaller when $HPI_i^- = 1$. The difference is highly significant. This implies that total employment in MSAs with large declines in house prices has been *slower* to recover than in MSAs with small or no house price declines.[32]

4.2 The Importance of Real Estate for Start-ups: Evidence from Survey Data

Start-ups and young firms rely heavily on external liquidity. The initial lending environment they face is different from that of more mature firms, resulting in more challenges in obtaining credit. Young firms do not have an established credit record and typically face restrictions in their access to commercial bonds or other means of financing available to older firms. Entrepreneurs thus often hold highly leveraged equity claims in their firms because their personal assets are regularly used as collateral for their business (Robb and Robinson (2014)).[33] Data availability on newly founded businesses is limited but the Survey of Consumer Finances (SCF) can be used to shed some light on entrepreneurial financing.[34] In 2010, 70% of business owners reported having used personal savings or assets in initiating their business, making this by far the most important funding source of entrepreneurs. By 2013 this figure had dropped to 66.7%. For new firms the numbers are 76.9% in 2010 and 71.8% in 2013.[35] On the other hand, only 14% of owners of new business reported having applied for a business loan in the last five years (10.1% in 2013). Entrepreneurs typically possess a higher value of home equity than non-business owners and are over twice as likely to be borrowing on a credit line that is secured by home equity. Housing wealth constitutes by far the largest asset in households' portfolios. The two graphs in Figure 11 show the use of personal assets as business collateral across time. On the left-hand side is the fraction of business owners that report using personal assets as business collateral. On the right-hand side is the

[31] Being in an MSA with large GDP declines increases the gap by only 2.19% after 2009. Note that the average gap is zero by definition. Results are robust to including additional controls, such as job creation by firm age.

[32] There are no significant differences between MSAs with low vs. high GDP growth. By using only the post-2005 data, the gap term becomes significantly smaller for MSAs with large GDP declines. The differences between HPI^- groups are not significant prior to 2005 (not shown).

[33] According to Avery *et al.* (1998) loans having a personal guarantee account for 55.5% of small business credit dollars.

[34] The SCF is a repeated cross-section. It includes employer firms.

[35] I define a new firm as a business that was created either in the year of the survey or the year before.

average dollar amount that is collateralized. New firms are shown as the blue solid line, incumbent firms are represented as the dashed red line. The fraction of new business owners who collateralize their business has declined since the year 2004, both as a fraction and in the average dollar amount, while the same pattern is not true for incumbent businesses.

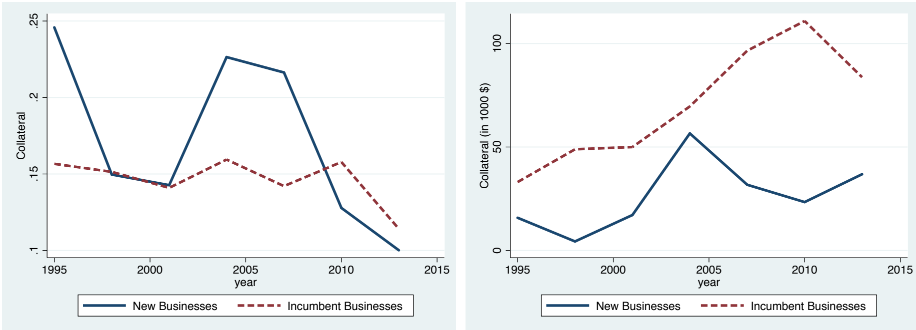


Figure 11: Personal assets as collateral among business owners by business age. The left graphs shows the fraction of business owners that use personal assets as business collateral. The right graph shows the dollar amount that is collateralized (in 2013 dollars). The red dashed lines refer to incumbent businesses. Survey years: 1995, 1998, 2001, 2004, 2007, 2010, 2013. Source: SCF, own calculations

Similar results are obtained from the US Census' 2007 Survey of Business Owners (SBO), which is a single cross-section. Almost 72% of respondents indicated having used personal savings as a source of start-up capital. For start-ups this number is even over 80%. Among start-ups that are employer firms 14.1% reported using housing equity as a source of start-up financing, as opposed to 9.1% among incumbent firms. The importance of bank loans is minor, but increases with the amount of start-up capital. All results are available upon request.

5 Conclusion

Every year several hundred thousand new firms are created, providing millions of new jobs. While not all of those firms succeed, those that do remain strong engines of job growth over the coming years. This highlights the importance of studying the labor market's extraordinary dynamics, resulting from persistent and large heterogeneity across firms: While some firms expand, others contract, firms are born and firms die. At the heart of these dynamics lie start-ups and young firms. Start-ups create around three million new jobs each year. But the recent recession has left its mark: While net job creation by incumbent firms quickly recovered since the end of the recession, job creation by start-ups is at its lowest point since the beginning of the Census BDS series in 1977. At the same time the average size of a start-up has virtually remained unchanged. This suggests an important extensive margin effect: fewer entrepreneurs start a business. In this paper I tried to answer the question why this might be the case.

I focus on the fact that the 2007 recession was accompanied by an unprecedented fall in the value of real estate. As the main channel through which house prices can exert this influence on the unemployment rates I propose the process of lending to new firms. The model captures the idea that start-ups require external financing, for which real estate is used as collateral. As the value of this collateral falls, start-up costs increase and the number of new firms declines.

I calibrate and compute a quantitative competitive industry model with endogenous entry and exit. The model captures the importance of new firms for employment and generates a jobless recovery following a shock to house prices. The model is able to explain over 80% of the increase and persistence in unemployment since 2007. In contrast to previous studies my framework establishes a structural link between house prices, entrepreneurial activity, and the US recovery. This setup is suited to explain why start-up job creation began to decrease *prior*to the recent recession, and why - contrary to older, incumbent firms - it remains at low levels.

I have tested the model implications using data at the MSA-level. The data confirms that movements in house prices are an important predictor for the activity of start-ups and young firms. Specifically, I find that employment in start-ups and young firms has fallen more in areas with large house price declines. Furthermore, the recovery of the labor market was slower. The micro data supports the key findings of the theoretical model and its quantitative implications.

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Appendix

A.1 Data

The main dataset used in this paper is the Business Dynamics Statistics (BDS) dataset published by the Census. This annual dataset is derived from the Longitudinal Business Database (LBD) and covers both firm size, firm age, as well as firm- and establishment level data. A unique feature of the BDS is its longitudinal source data that permit tracking establishments and firms over time. A strength of data is its robustness to ownership changes because the age of a firm is determined by the age of its oldest establishment. The BDS data is publicly available after aggregation at various levels, such as age, sector, size, MSA, and certain combinations thereof.

Virtually all of my qualitative results can also be obtained with the 'Business Employment Dynamics' (BED) series by the Bureau of Labor Statistics (BLS). The BED is derived from a quarterly census of all establishments under state unemployment insurance programs, representing about 98 percent of employment on non-farm payrolls. A caveat is the limited comparability between the age and size series as the age data is based upon establishment-level data, while the size class tabulations use firm-level data instead. For this reason I present most of the trends using the BDS data.

The series for house prices come from the Federal Housing Finance Agency (FHFA), which provides national, state-, and MSA-level house price indices from 1991 onwards. The unemployment rate was obtained from the BLS. Real GDP and the GDP deflator come from the St.Louis Fed. The monthly GDP series was obtained from `www.macroadvisers.com`. The VAR(1) to estimate the joint evolution of GDP and house prices has been estimated using quarterly data from 1975q1 to 2014q3. Both series are in logs and were HP-filtered with a smoothing parameter of 14400. The results are reported in Equation (27).

The data used for the MSA-level regressions is summarized in Table 8.

The Survey of Consumer Finances can be accessed via `http://www.federalreserve.gov/econresdata/scf/scfindex.htm`. I have analyzed the years 1998, 2001, 2004, 2007, 2010 and 2013 using the software *R*. The data is multiply-imputed (meaning that answers to the same question for the same household may vary across implicates) and the analysis must account for this to correctly calculate the statistics and confidence intervals. I have used the scripts available at `https://github.com/ajdamico/usgsd/tree/master/Survey%20of%20Consumer%20Finances`. All remaining errors are my own.

The Survey of Business Owners (SBO) is a cross section of employer and non-employer firms. It is available at `http://www.census.gov/econ/sbo/`.

Variable	Mean	Std. Dev.	Min.	Max.	N
Year	1998.988	7.95	1985	2012	11698
MSA	29197.588	11853.961	870	49740	11698
# of start-ups	1130.467	2952.277	34	43896	10248
# of Young Firms	4518.735	11696.213	181	165186	10248
# of Old Firms	2028.815	4776.705	101	65423	4026
Employment in start-ups	1	1.181	-2.333	5.600	10226
Employment in Young Firms	2.709	1.158	0.018	7.225	10248
Employment in Old Firms	2.852	1.158	0.147	7.125	4026
HPI (real) in logs	5.019	0.199	4.324	5.949	10143
HPI (real) change[a]	-12.909	13.616	-53.555	27.475	10582
GDP (real) in logs	-4.378	1.265	-6.847	2.64	4584
GDP (real) change[b]	-0.071	0.082	-0.452	0.6	10445
Unemployment Rate (in logs)	-2.87	0.436	-4.395	-1.168	8485
Post	0.149	0.356	0	1	11698
$HPI^{-} \times$ Post	0.072	0.259	0	1	4259
$GDP^{-} \times$ Post	0.071	0.257	0	1	4207
Employment (in 1'000)	4.912	1.086	2.73	9.098	8485

All the employment variables are in logs

[a] The change is computed between 2006 and 2009.

[b] The change is computed between 2006 and 2009. For each MSA GDP has been normalized to its 2005 value.

Table 8: Summary statistics

A.2 Model derivations

The Entrepreneur's Problem Entrepreneurs maximize utility subject to the budget constraint (2). Define $\Omega_E = \pi + p^h h_{E,-1}$.

$$\max_{c_E, h_E} c_E + \varphi_E \log(h_E) + \lambda(\Omega_E - c_E - p^h h_E), \tag{34}$$

where λ is the Lagrange multiplier of the budget constraint. The first order conditions with respect to c_E and h_E yield the interior solutions

$$1 = \lambda \tag{35}$$

$$\frac{\varphi_E}{h_E} = \lambda p^h. \tag{36}$$

Together with the budget constraint this implies interior solutions

$$h_E = \frac{\varphi_E}{p^h} \tag{37}$$

and

$$c_E = \Omega_E - \varphi_E. \tag{38}$$

A corner solution occurs when Ω_E is low. The solution is then $h_E = \min\left\{\frac{\varphi_E}{p^h}, \Omega_E\right\}$ and $c_E = \max\{\Omega_E - \varphi_E, 0\}$. To find the minimum amount of Ω_E required to guarantee an interior solution set $c_E = 0$ in the budget constraint:

$$\underline{\pi} + \varphi_E \frac{p^h}{p^h_{-1}} = 0 + \varphi_E \tag{39}$$

$$\underline{\pi} = \varphi_E(1 - \frac{p^h}{p^h_{-1}}) \tag{40}$$

$$\underline{\pi} = -\varphi_E g_{p^h}, \tag{41}$$

where g_{p^h} is the growth rate of the house price. To avoid this corner solution I choose $\varphi_E = 0$.

The Worker's Problem Define $\Omega^i_W = y^i + p^h h^i_{W,-1}$. The worker maximizes

$$\max_{c^i_W, h^i_W} \log(c^i_W) + \varphi \log(h^i_W) + \lambda(\Omega^i_W - c^i_W - p^h h^i_W). \tag{42}$$

The first order conditions with respect to c^i_W and h^i_W yield

$$\frac{1}{c^i_W} = \lambda \tag{43}$$

$$\frac{\varphi}{h^i_W} = \lambda p^h. \tag{44}$$

Together with the budget constraint this implies that interior solutions are

$$h_W^i = \frac{\varphi}{1+\varphi}\frac{\Omega_W^i}{p^h} \tag{45}$$

and

$$c_W^i = \frac{\Omega_W^i}{1+\varphi}. \tag{46}$$

In the stationary economy $h_W^i = h_{W,-1}^i$ and (45) can be written as

$$h_W = \frac{\varphi}{1+\varphi}\frac{y + p^h h_W}{p^h} \tag{47}$$

$$p^h h_W = \frac{\varphi}{1+\varphi}(y + p^h h_W) \tag{48}$$

$$\frac{p^h h_W}{1+\varphi} = \frac{\varphi}{1+\varphi} y \tag{49}$$

$$h_W = \varphi \frac{y}{p^h} \tag{50}$$

Workers' demand for housing comes from existing workers and newborn workers, who replace nascent entrepreneurs. Workers that are turned into new entrepreneurs are replaced by new workers with zero housing wealth. For those workers the demand for housing is given by

$$h_W^0 = \frac{\varphi}{1+\varphi}\frac{y}{p^h}. \tag{51}$$

The optimal contract A worker's utility evaluated at the above solutions for consumption and housing is:

$$Z(c^i, h^i) = \log(\frac{\Omega_W^i}{1+\varphi}) + \varphi \log\left(\frac{\varphi}{1+\varphi}\frac{\Omega_W^i}{p^h}\right) \tag{52}$$

The equality of workers' utilities across types in (18) requires that Ω_W be identical across worker types, which implies (19) because the current price p^h and last period's housing wealth $h_{W,-1}$ are beyond the worker's control when the wage is negotiated. To see this write the previous equation as

$$\begin{aligned} Z(c^i, h^i) &= \log(\Omega_W^i) - \log(1+\varphi) + \varphi\left(\log(\varphi) - \log(1+\varphi) + \log(\Omega_W^i) - \log(p^h)\right) \\ &= (1+\varphi)\log(\Omega_W^i) - (1+\varphi)\log(1+\varphi) + \varphi\log(\varphi) - \varphi\log(p^h) \end{aligned} \tag{53}$$

This expression must be equal across types. The only type-dependent term is Ω_W^i, implying that

$$(1+\varphi)\log(\Omega_W^e) = (1+\varphi)\log(\Omega_W^u) \tag{54}$$

$$\Omega_W^e = \Omega_W^u \tag{55}$$

$$\omega(a) + p^h h_{W,-1}^e = b(a) + p^h h_{W,-1}^u \tag{56}$$

Since all new workers start with $h^i_{W,-1} = 0$ it must be true for all new workers that

$$\omega(a) = b(a). \tag{57}$$

Workers of different types hence make identical choices h_W from (45). The value $h_{W,-1}$ is therefore identical at all times.

The house price The market cleaning condition for housing is given by

$$1 + \int_0^{\bar{\varepsilon}^x_{-1}} h_{E,-1} d\lambda_{-1}(\varepsilon, e) + M_{-1} \int_0^{\bar{\varepsilon}^x_{-1}} h_{E,-1} d\nu + M h_{W,-1} = (1 - M) h_W + M h^0_W + \int_0^{\infty} h_E d\lambda(\varepsilon, e) + M h_E \tag{58}$$

The total supply of housing is on the left-hand side of equation (58). I normalize the available stock of housing in the economy to one. Incumbent and entering firms which exit in $t-1$ sell $h_{E,-1}$. All current entrants sell $h_{W,-1}$. Demand comes from workers, incumbent entrepreneurs and new entrants. Workers demand h_W, while the M newborn workers demand h^0_W. All incumbent entrepreneurs and new entrants demand h_E.

In the stationary version of the model, the market clearing condition for housing in (58) can be simplified in the following ways. First, in the stationary economy $\int_0^{\bar{\varepsilon}^x} d\lambda^*(\varepsilon, e) + M \int_0^{\bar{\varepsilon}^x} d\nu = M$, i.e. the total mass of exiting firms equals the mass of new entrants. Second, I replace the expressions for stationary housing demand derived above. Note that in the main text the size of the labor force L is normalized to one.

$$1 = (L - 2 \cdot M) h_W + M h^0_W + h_E \lambda^* \tag{59}$$

$$1 = (L - 2 \cdot M) \varphi \frac{y}{p^h} + M \frac{\varphi}{1 + \varphi} \frac{y}{p^h} + \frac{\varphi_E}{p^h} \lambda^* \tag{60}$$

$$p^h = \varphi y \cdot (L - 2M + \frac{M}{1 + \varphi}) + \varphi_E \lambda^* \tag{61}$$

Pinning down θ and μ By targeting $H = 0.71$ and $u = 0.064$ in the stationary economy one can back out the parameter μ and the stationary value of θ. From $H = \mu\theta^{-\gamma}$ it follows that $\mu = H\theta^{\gamma}$. The stationary unemployment rate follows from its law of motion $u' = (1-u) \cdot \delta(\lambda^*) + u \cdot \phi(\theta)$, where $\delta(\lambda^*)$ defines the separation probability (fires plus quits) in the stationary distribution λ^*. The stationary unemployment rate is $u^* = \frac{\delta(\lambda^*)}{\delta(\lambda^*) + \phi(\theta)}$. Plugging in $\phi(\theta) = \mu\theta^{1-\gamma}$ into this expression and rearranging yields

$$\theta = \frac{\delta(\lambda^*)}{H} \cdot \frac{(1 - u)}{u}. \tag{62}$$

It follows that

$$\mu = H^{1-\gamma} \left(\delta(\lambda^*) \cdot \frac{(1 - u)}{u} \right)^{\gamma} = H^{1-\gamma} \phi^{\gamma} = H \cdot \theta^{\gamma} \tag{63}$$

A.3 Computational Strategy

Forecasting H' Firms need to forecast $H(\theta')$, the expected vacancy-filling rate next period. The labor-market tightness θ, of which H is a function, is determined in equilibrium. While firms take it as given, it must be consistent with the relationship generated by the model. The model with aggregate shocks poses a non-trivial computational problem, because firms need to forecast the entire cross-sectional joint distribution of employment and productivity in order to forecast H in the following period. In the stationary model without aggregate shocks this joint distribution is stable and there exists a steady state value H^*. In the presence of aggregate shocks, the joint distribution moves over time and the state-space becomes (theoretically) infinite-dimensional. I solve this problem using the methodology developed by Krusell and Smith (1998). An approximate solution can be found by postulating that firms track only several moments of this joint distribution. As in most of the literature in the present problem the first moment turns out to be a sufficient statistic. The word *sufficient* means that the forecast generates a high R^2, and - following Den Haan (2010) - a small maximum forecast error.

The perceived law of motion of H is denoted $H' = \mathbb{F}(H, A', A)$, where $\mathbb{F}(\cdot)$ is parameterized as a linear regression. The coefficients are to be determined as part of the solution of the model. Firms make their forecasts of H' conditional on the current realizations of H and A, as well as on possible future realizations A'. The solution algorithm first postulates an initial guess for for $\mathbb{F}(\cdot)$. Next, policy functions are computed given the guess. Following a simulation, the parameters of $\mathbb{F}(\cdot)$ are updated. This procedure is repeated until the current guess and the updated version of $\mathbb{F}(\cdot)$ are sufficiently close (consistency) and until $\mathbb{F}$ tracks the evolution of H with high accuracy. I guess a log-linear prediction rule for H'.

$$\log H_t = b_0 + b_1 \log H_{t-1} + b_2 \log A_t + b_3 \log A_{t-1} + b_4 \cdot I_{A_t \neq A_{t-1}}$$

The last term, $I_{A_t \neq A_{t-1}}$, is an indicator function which takes the value of one if $A_t \neq A_{t-1}$. The coefficients that minimize the stopping criterion are given by

$$\log H_t = -0.0087 + 0.9939 \cdot \log H_{t-1} + 20.996 \cdot \log A_t - 21.095 \cdot b_3 \log A_{t-1} + 0.2327 \cdot I_{A_t \neq A_{t-1}}.$$

This functional form for $\mathbb{F}(\cdot)$ generates an $R^2 = 0.99889$ and a maximum forecast error of 0.00778%. An accuracy plot for a sample simulation of $T = 300$ periods is shown in Figure 12.

Simulation I simulate the model using a non-stochastic simulation technique. The algorithm does *not* draw a random sequence of idiosyncratic shocks for each firm and play out the policy function for a large number of periods. Instead, my algorithm computes the exact mass of firms at each grid point jointly representing idiosyncratic productivity and employment. This solution method is applicable for both the stationary and non-stationary version of the economy. The main advantages of this approach are its speed and the fact that it eliminates sampling error. Den Haan (2010) showed that this

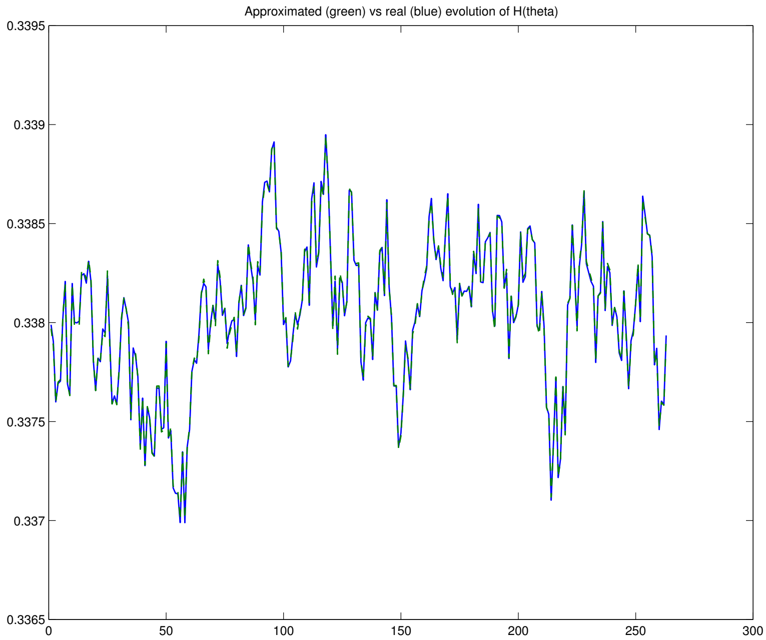

Figure 12: Realized path of $H(\theta)$ (blue, solid) and the forecast (green, dotted).

latter source of error can become important in Krusell-Smith type solution algorithms. This is all the more important in my setup, as the mass of entering firms can be small relative to the mass of incumbents. Therefore sampling uncertainty may bias the results even though the overall number of firms is large.

I create fine grids for e and ε. Denote the number of grid points by $\#_e$ and $\#_\varepsilon$, respectively. I specify an initial distribution over the points $[e_i, \varepsilon_j]$, where $i \in [1, 2, \ldots, \#_e]$ and $j \in [1, 2, \ldots, \#_\varepsilon]$. This determines the mass of firms with employment e_i and productivity ε_j. The simulation then follows this iterative process:

1. The aggregate states of the economy realize.
2. New firms enter based on the free-entry condition (10)
3. The idiosyncratic productivity state evolves according to its law of motion. The employment policy selects a new level of employment, e'. This implies distributing the mass at each point $[e_i, \varepsilon_j]$ to a new point $[e'_i, \varepsilon_k]$, where $k \in [1, 2, \ldots, \#_\varepsilon]$.
4. At each grid point some incumbent firms exit.
5. Go back to step 1.

To find a solution for a fixed aggregate state A, this process simply iterates on a distribution over employment and idiosyncratic productivity, $\lambda(e, \varepsilon)$ and finds its fixed point, where

$$\lambda_{t+1}(\bar{e}_l, \bar{\epsilon}_m) = \sum_{i=1}^{M} \sum_{j=1}^{N} \Pr(\phi_e(\bar{e}_i, \bar{s}_j) = \bar{e}_l | e_t = \bar{e}_i, \epsilon_t = \bar{\epsilon}_j) \pi_{jm} \lambda_t(\bar{e}_i, \bar{\epsilon}_j).$$

The distribution λ has dimensionality $(\#_e \cdot \#_\varepsilon \times 1)$. The law of motion is set up by combining the policy functions and the law of motion for the idiosyncratic state into a large transition matrix Γ, which has dimensionality $(\#_e \cdot \#_\epsilon \times \#_e \cdot \#_\epsilon)$. This transition matrix Γ may vary for incumbents and entering firms, since entrants are allowed to have a different initial transition matrix for the idiosyncratic shock. The non-zeros in the row associated with $\bar{e}_i, \bar{\epsilon}_j$ are then defined as

$$\Gamma((i-1) \cdot \#_\varepsilon + j, (\phi_e(i,j) - 1) \cdot \#\varepsilon + 1 : \phi_e(i,j) \cdot \#_\varepsilon) = \pi_\varepsilon(i,:) \cdot (1 - \phi_x(i,j)).$$

Then we can rewrite the law of motion for λ as

$$\tilde{\lambda}_1 = \tilde{\lambda}_0' \Gamma,$$

and the solution can be found by solving $\tilde{\lambda} = \tilde{\lambda}' \Gamma$, where $\tilde{\lambda}$ is the eigenvector of Γ that is associated with its unitary eigenvalue.

In the presence of a aggregate shocks there exists no stationary distribution. To iterate on the distribution λ, which now has dimensionality $(\#_e \cdot \#_\epsilon \cdot \#_A \cdot \#_H \times 1)$ I use a transition matrix Γ which now has dimensionality $(\#_e \cdot \#_\epsilon \cdot \#_A \cdot \#_H \times \#_e \cdot \#_\epsilon \cdot \#_A \cdot \#_H)$ The simulation then consists of drawing a random sequence of realizations of aggregate shocks and computing $\tilde{\lambda}_1 = \tilde{\lambda}_0' \Gamma$.

Determining the interest rate For a given profitability shock and a house price the solution algorithm determines the interest rate R by using the bank's break-even condition (12). It is computed for each possible realization of H. The value of entry is interpolated at values of H off the grid. The equilibrium value of H_t is the one that equalized the cost and the value of entry.

Determining the number of entrants I then obtain the employment policy functions for that value of H_t. The policy functions determine the number of total vacancies and the total number of fires for that period. I then use the definition of θ to solve for M_t.

$$\theta_t = \frac{V_t}{U_t} = \frac{V_t^{inc} + M_t \cdot V_t^{new}}{F_t^{inc} + M_t F_t^{new} - H_t^{inc} - M_t H_t^{new} + U_{t-1}}, \tag{64}$$

where $V_t^{inc} = \int V(s) d\lambda_t$ are vacancies posted by incumbents and $V_t^{new} = \int V(s) d\nu$ stands for vacancy posting by new firms, $H_t^{inc} = \int H(s) d\lambda_t$, $H_t^{new} = \int H(s) d\nu$ for hiring, and $F_t^{inc} = \int (F(s) + \chi) d\lambda_t$, resp. $F_t^{new} = \int (F(s) + \chi) d\nu$ for the number of endogenous fires plus exogenous quits from incumbent and new firms. I have replaced total vacancies by those created by incumbent firms, summarized in the distribution λ_t, plus those created by new firms, distributed over ν and multiplied with the number of entrants. The unemployment rate has been replaced with its law of motion. Solve the equation for M_t yields:

$$M_t = \frac{\theta_t \left[U_{t-1} + F_t^{inc}\right] - V_t^{inc}(1+\mu\theta_t^{1-\gamma})}{V_t^{new}(1+\mu\theta_t^{1-\gamma}) - \theta_t F_t^{new}}, \tag{65}$$

A.4 Robustness of Empirical Results

Firm Size	1-9	10-19	20-49	50+
	Size Distribution			
Data	0.94	0.03	0.01	0.01
Model	0.93	0.04	0.02	0.01
	Employment Distribution			
Data	0.54	0.14	0.14	0.18
Model	0.34	0.17	0.23	0.26

Table 9: The Size and Employment Distribution of Start-Ups.

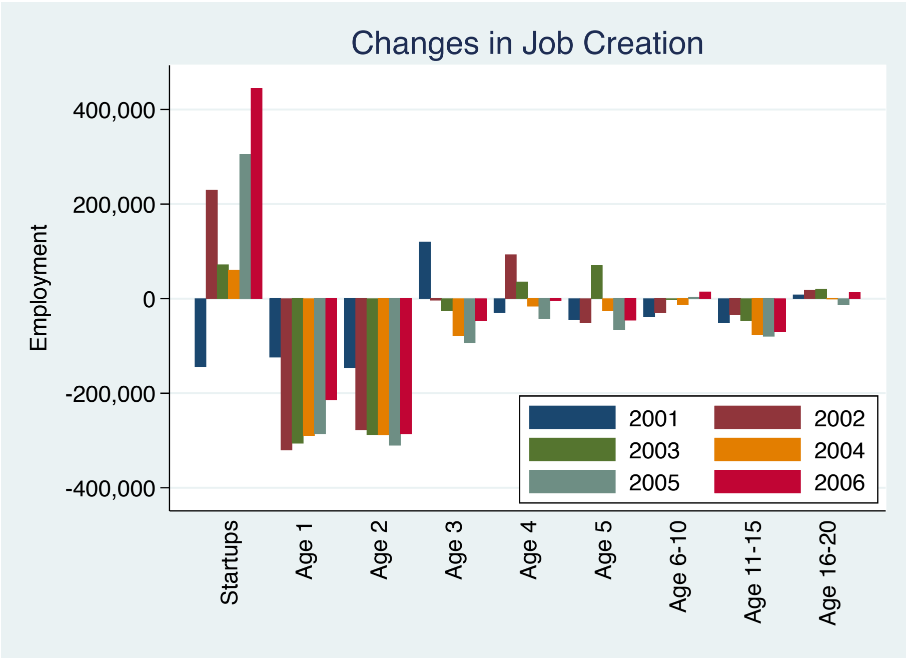

Figure 13: Changes in gross job creation by age with respect to the year 2000. Source: Business Dynamics Statistics (BDS). Age group 21-25 is not defined for these years.

Table 10: The impact of HPI increases on employment.

	(1) start-ups	(2) Young Firms	(3) Old Firms
$\text{HPI}^{+} \times$ Post	0.0606*	0.0606**	-0.0524
	(1.74)	(2.42)	(-1.59)
HPI+	-0.0893***	-0.144***	0.209***
	(-8.00)	(-22.01)	(27.74)
Post	-0.144***	-0.199***	-0.134***
	(-3.73)	(-8.87)	(-4.14)
GDPr	0.782***	0.700***	0.430***
	(6.43)	(8.35)	(3.04)
Constant	4.467***	5.855***	4.266***
	(7.01)	(13.34)	(5.77)
Year dummies	Yes	Yes	Yes
MSA dummies	Yes	Yes	Yes
R^2	0.361	0.541	0.366
N	1641	1644	1507

Notes: The dependent variable is log employment of firms. HPI^{+} is equal to 1 (0) for MSA i if the change in HPI after 2009 was among the highest (lowest) 20%. *Post* takes a value of one after 2009. See notes under Table in main text for details. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11: The Employment Gap after the Recession

	(1)	(2)
	$E^*_{i,t} - E_{i,t}$	$E^*_{i,t} - E_{i,t}$
$\text{HPI}^- \times$ Post	0.0490***	
	(6.60)	
$\text{GDP}^- \times$ Post		0.0216***
		(3.85)
HPI^-	-0.0338***	
	(-16.63)	
GDP^-		-0.00208**
		(-2.84)
Post	0.0353***	0.0285***
	(6.28)	(5.26)
GDPr	-0.207***	
	(-7.25)	
HPIr		-0.130***
		(-11.55)
Constant	-1.089***	0.654***
	(-7.30)	(12.03)
Year dummies	Yes	Yes
MSA dummies	Yes	Yes
R^2	0.672	0.555
N	1680	3158

Notes: The dependent variable is trend employment minus current employment. HPI^- is equal to 1 (0) for MSA i at time t if the change in HPI between 2006 and 2009 was among the lowest (highest) 20%. GDP^- is defined in the same manner for GDP, where GDP has been normalized to its 2005 value. $Post$ takes a value of one after 2009. $GDPr$ is log real GDP and $HPIr$ is log real HPI. All regressions include year and MSA dummies and errors are clustered at the MSA level. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12: Employment Adjustment Speeds

	(1)	(2)	(3)	(4)
	$\Delta E_{i,t}$	$\Delta E_{i,t}$	$\Delta E_{i,t}$	$\Delta E_{i,t}$
$E^*_{i,t} - E_{i,t}$	-0.328***	-0.297***	-0.380***	-0.398***
	(-12.92)	(-16.03)	(-11.03)	(-10.99)
HPI$^-$× Gap	0.110***		0.189***	
	(4.58)		(5.81)	
GDP$^-$× Gap		0.0438		0.178***
		(1.87)		(5.07)
HPI$^-$	0.00685***		0.00338***	
	(9.30)		(9.75)	
GDP$^-$		-0.0160***		-0.0212***
		(-389.31)		(-30.24)
GDPr	-0.0205		-0.0274*	
	(-1.87)		(-2.14)	
HPIr		-0.0351***		-0.0245***
		(-7.55)		(-3.97)
Constant	-0.104	0.182***	-0.125	0.147***
	(-1.82)	(8.01)	(-1.88)	(4.66)
Year dummies	Yes	Yes	Yes	Yes
MSA dummies	Yes	Yes	Yes	Yes
Subset	-	-	2006-2012	2006-2012
R^2	0.523	0.414	0.596	0.603
N	1680	3032	980	973

Notes: The dependent variable is employment change. $E^*_{i,t} - E_{i,t}$ is trend employment minus current employment and is abbreviated as "Gap". HPI^- is equal to 1 (0) for MSA i at time t if the change in HPI between 2006 and 2009 was among the lowest (highest) 20%. GDP^- is defined in the same manner for GDP, where GDP has been normalized to its 2005 value. $Post$ takes a value of one after 2009. $GDPr$ is log real GDP and $HPIr$ is log real HPI. Columns (3) and (4) show results for years 2006-2012. All regressions include year and MSA dummies and errors are clustered at the MSA level. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.5 Alternative Model Specifications

Endogenous p^h In the version of the model laid out in Section 2 the price of real estate p^h is an exogenous object. I have used house price time series to calibrate this process jointly with aggregate TFP. There are at least three reasons for making the house price exogenous. 1) The goal of this paper is not to model house prices and feedback effects from the economy onto house prices. I am interested in the effect house prices have on business formation. 2) The role of house prices in my model is very similar to the role a "recuperation rate" plays in models along the lines of Kiyotaki and Moore (1997). The recuperation rates determines the fraction of a loan that can be recuperated by a lender. Negative shocks to this rate are commonly used to model "financial shocks". While my model could be easily re-written in such terms I believe that the house price channel is preferable. The recuperation rate has no clear real-world counterpart generating enough volatility, while house prices are readily observed. Furthermore the present model generates testable implications (see Section 4.1) which can shed light on its importance. 3) *Some* exogenous driving process is required to generate action on the entry margin. Shocks to aggregate TFP are insufficient to generate the heterogeneous effects on job creation across age cohorts. Given this insight I find it clearest to identify this additional exogenous shock through the channel that I have empirically identified to be the relevant one. An alternative to the current approach is to make the house price endogenous by shocking housing preferences of agents instead of the price directly (see e.g. Justiniano *et al.* (2015)). Such a version of the model is laid out in the Appendix.

Endogenous exit To generate endogenous exit, at the beginning of each new period an incumbent firm must now pay a fixed cost of operation F. The profit function becomes

$$\pi(a, \varepsilon, e) = a\varepsilon F(e) - e\omega(a, \varepsilon, e) - F - \mathbb{C}(a, H; e, e_{-1}). \tag{66}$$

Based on their expected future profitability, entrepreneurs decide whether to continue operation or exit. As in Hopenhayn (1992) no additional information is revealed between the end of period $t-1$ and next period's exit decision. Therefore the firm can determine at the end of period $t-1$ whether it will choose to exit at the beginning of period t. The firm's program can now be written as

$$V^i(s) = \max\{V^v(s), V^f(s), V^n(s)\} \tag{67}$$

as before, with

$$V^v(s) = \max_v \pi(a, \varepsilon, e_{-1}(1-\chi) + Hv) + \beta E \max\{V^i(s'), V^x(s')\} \tag{68}$$

$$V^f(s) = \max_f \pi(a, \varepsilon, e_{-1}(1-\chi) - f) + \beta E \max\{V^i(s'), V^x(s')\} \tag{69}$$

$$V^n(s) = \pi(a, \varepsilon, e_{-1}(1-\chi)) + \beta E \max\{V^i(s'), V^x(s')\} \tag{70}$$

Because the entrepreneur can choose to exit at the beginning of the next period, in (68), (69), and (70) the continuation value is now given by the maximum of the value of an incumbent firm, $V^i(s')$, and the value of exiting, $V^x(s')$. The latter is given by

$$V^x(s) = 0 - \mathbb{C} = -(F_f + c_f e_{-1}^2). \tag{71}$$

Exit decisions are permanent and irrevocable. An exiting entrepreneur reduces employment to zero (paying the adjustment costs for the remaining workers) and generates zero revenue. However, he avoids paying the fixed cost of operation. The firm exits whenever

$$EV^i(s') - V^x(s') < 0. \tag{72}$$

The fixed cost of operation F induces exit for low realizations of ε. Without F the value of continuing would always be positive, while (71) is always non-positive. There exists a threshold productivity level $\bar{\varepsilon}^x$ defined as the lowest realization of ε such that conditional on the current state the firm chooses to continue operation. It is (weakly) decreasing in a and (weakly) increasing in H and e_{-1}.

Definition. The exit threshold

$$\bar{\varepsilon}^x(e_{-1}; a, H) = \begin{cases} \inf\left\{\varepsilon \in S : EV^i(s') \geq V^x(s')\right\} & \text{or} \\ 0 & \text{if this set is empty} \end{cases}$$

The bank's zero-profit condition now reads as

$$R(1 - G(\bar{\varepsilon}^x)) = r.$$

Only the fraction of entrants that receive an initial productivity draw above the exit threshold $\bar{\varepsilon}^x$ will continue operation. We therefore have:

$$R(a, H) = r \cdot \left(\int_{\bar{\varepsilon}^x(0;a,H)}^{\infty} d\nu \right)^{-1}. \tag{73}$$

The law of motion for the distribution of firms is now given by

$$\begin{aligned} \lambda'((e\ x)' \in E \times X) = &\int_{x \in x'} \int_{E \times X} (1 - \phi_x(x, e; H)) \times 1_{\{\phi_e(x,e;H) \in e'\}} \times F(dx'|x)\lambda(dex) \\ &+ M \times \int_{x \in x'} \int_{0 \times X} (1 - \phi_x(x, 0; H) \times 1_{\{\phi_e(x,0;H) \in e'\}} \times F(dx'|x)\nu(dx). \end{aligned} \tag{74}$$