Start-ups, Credit, and the Jobless Recovery

- Job Market Paper -

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Start-ups and young firms play a crucial role for job creation in the US: they grow faster and create more net jobs than older, incumbent firms. The number of start-ups in the US has declined by over 20% since 2007. Young firm's below-trend job creation can account for almost all of the persistently high unemployment rate. In this paper I claim that this fact is related to the unprecedented fall in the value of real estate. 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, firm heterogeneity, labor adjustment costs, and aggregate shocks. It generates a jobless recovery and is able to explain over 80% of the increase and persistence in unemployment during the recession.

JEL classificatons: L26; E24; E51; J23; J64

Keywords: Labor search; Adjustment Costs; Employment; Start-ups; Credit Friction; Jobless Recovery

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1 Introduction

In this paper I argue that jobless recoveries can be explained through lower job creation by start-ups (firms of age zero). Figure 1 shows the result of a simple counterfactual exercise. Had employment by start-ups and young firms been equal to its pre-crisis trend, the unemployment rate at the end of 2011 would have been as low as 6.5% instead of 8.5%. The Figure also shows that changes in job *destruction* were not driving the jobless recovery. Even with pre-crisis levels of job destruction the unemployment rate would have been almost as high as it was. There has been a renewed interest in jobless recoveries due to the slow recovery of the US labor market following the 'Great Recession': Although the US economy has shown positive GDP growth rates since the third quarter of 2009, employment has been slow to follow. Only in the first quarter of 2011 did the unemployment rate fall below its end-of-recession level.[1] In the first quarter of 2013, the unemployment rate stands at 7.7%, compared to the 4.8% unemployment rate in the last quarter prior to the recession (Q42007). And employment relative to the working age population in May 2013 was lower than at the height of the financial crisis.

Relatively little is known about who creates - and who destroys - jobs.[2] 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.[3] At the heart of these dynamics lie start-ups and young firms. Successful start-ups become vibrant young firms which make up the lion's share of net job creation. A consequence of the prominent role of start-ups is that whenever the *inflow* of new firms into the economy is interrupted, this can have long-lasting adverse effects on job creation and result in a jobless recovery. I will argue that the 'credit crunch' and the fall in house prices associated to the recent economic crisis has created such an event.

To this end I develop a quantitative model of heterogeneous firms that operate in a frictional labor market. Firms must post vacancies that are filled with endogenous probability. Wages are determined through bargaining between workers and firms. Unproductive firms may exit the economy, while new firms can enter. During recessions firms shed workers and post fewer vacancies, generating a Beveridge-curve relationship. Entering firms require a one-period loan to finance start-up costs. They obtain this loan from the bank and may put down their home as collateral. Because new entrepreneurs may strategically default, the risk neutral bank efficiently prices interest rates by charg-

[1] Throughout this paper I use the NBER recession dates for my business cycle classifications.

[2] The most common misperception regards the role small firms play for aggregate job creation. As Haltiwanger *et al.* (2010) point out, the relationship between size and growth vanishes once age is controlled for.

[3] Over the last 35 years the average number of gross jobs created was around 16 million per year, while 14.4 million jobs per year were destroyed. This respectively corresponds to 17% and 15% of the entire labor force. In other words, over 30% of the labor force is reallocated in a given year.

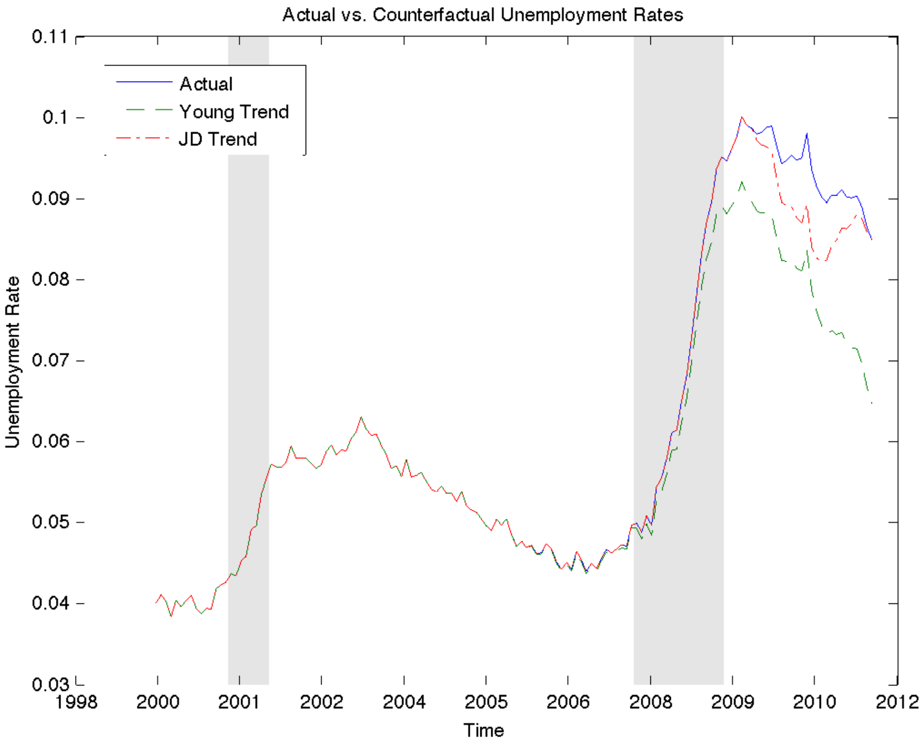

Figure 1: The actual unemployment rate is plotted in as the solid line. The remaining lines show the counterfactual unemployment rates for the following experiments: The dashed line labeled 'Young Trend' shows unemployment if gross job creation by young firms (age 5 or below) had been equal to its pre-2006 HP-trend. For the dashdotted line 'Trend JD' I set gross job destruction (JD) equal to its pre-2006 HP-trend. Source: Census, BLS, own computations

ing a default premium to compensate itself for expected losses. In this way changes in the value of collateral feed back to the entry costs of new firms. Adverse conditions on the housing market can constrain the number of start-ups that enter during a recovery. This link between house prices and firm entry can explain why job creation by start-ups already decreased *before* the beginning of the recession in 2007, a fact that previous models were unable to address. My model generates jobless recoveries if even after aggregate profitability has recovered the value of collateral continues to be depressed. Since start-ups have hiring rates over-proportional to their share of output, this channel breaks the strong correlation between output and unemployment observed in other models. Additional propagation comes through labor adjustment costs which are chosen to match key moments of the employment change distribution.

Standard models of the labor market are unable to generate jobless recoveries and sufficient volatility in unemployment and vacancies. The RBC model cannot generate jobless recoveries because shocks are only to aggregate TFP. After a negative shock the reversion to the unconditional mean of TFP increases the marginal benefit of all factor inputs. The Mortensen and Pissarides (1994) search model suffers from the same shortcomings. Furthermore, as pointed out by Shimer (2005) it is unable to generate the volatility in unemployment and vacancies we observe in the data. The competitive industry model (Hopenhayn (1992); Hopenhayn and Rogerson (1993)) introduces entry of new firms. This is a frictionless model in which a market-clearing wage is found via the free-entry condition. The general equilibrium effects induced by this condition are quite powerful in this environment, virtually eliminating any selection effects that could result from the composition of entering and exiting firms (see e.g. Lee and Mukoyama (2012)). I base my model on the framework developed by Hopenhayn (1992). This framework appears as a natural starting point for studying the effects of entry. I depart from the basic model in the following respects. First, I add aggregate shocks to the model since I am interested in the business cycle implications of the model. Second, I add a search-and-matching framework where firms post vacancies and the wage is determined through bargaining between workers and entrepreneurs. This is done in order to study the implications of the model for unemployment and vacancies. Third, labor adjustment costs are added to the model in order to match the employment change distribution. Finally, I assume that start-ups must borrow the costs of entry. Potential entrepreneurs use housing to collateralize a fraction of the loan. As the value of housing falls, the interest rate they pay on the loan increases. This raises their costs of entry and deters some entrepreneurs from entering. Making entry a function of house prices has several advantages. First, there is empirical evidence on the sensitivity of young firms' hiring behavior with respect to conditions on the credit market. Secondly, a model with a standard free-entry condition generates entry rates which are much too volatile with respect to the data. The additional dependence on a slow-moving process such as the value of collateral is succesful in generating a realistic entry sensitivity.

My model is then calibrated to match certain cross-sectional data moments, such as the unemployment-vacancy ratio and the firm age distribution. I estimate firm-level labor adjustment costs via a simulated method of moments (SMM) approach. The stationary version of the calibrated can replicate the average life cycle of firms, the positive correlation between productivity and age and the negative correlation between employment growth and size observed in the data. I find that the model with financial friction significantly outperforms alternative specifications. The model generates jobless recoveries and can explain over 80% of the increase and persistence in unemployment since the end of 2007.

This paper contributes to the literature on jobless recoveries, firm dynamics and the role of start-ups over the business cycle. At the basis of the model lies a heterogeneous-firm framework as in Hopenhayn (1992) and Hopenhayn and Rogerson (1993) - henceforth HR -, to which I propose several extensions. One is a search-and-matching strucutre as in Mortensen and Pissarides (1994). An important distinction with respect to the standard search and matching model is that in my model the economy is populated by a mass of heterogeneous firms which differ in idiosyncratic profitability and age. The search-and-matching framework has been combined with a heterogenous firm environment by Cooper *et al.* (2007). More recently Kaas and Kircher (2011), Schaal (2011), Elsby and Michaels (2013), Moscarini and Postel-Vinay (2013), and Acemoglu and Hawkins (n.d.) have extended the search and matching framework to include multi-worker firms. Cooper *et al.* (2007) estimate labor adjustment costs in a heterogeneous firm model with search frictions but their framework does not allow for entry and exit. Kaas and Kircher (2011) augment the HR framework with a competitive search framework. Their model can generate sluggish movements of unemployment following a boom but they rely crucially on a time-varying entry cost and the convexity parameter of the recruiting costs. Schaal (2011) shows that volatility shocks can significantly improve the explanatory power of search models in terms of a lagged response of employment. Elsby and Michaels (2013) introduce the Stole and Zwiebel (1996) bargaining framework to the multi-worker firm environment but do not study entry. Moscarini and Postel-Vinay (2013) provide a theoretical model for the empirical finding that large employers have more cyclical job creation. Their focus is on job flows between firms of different size. Contributions that have focused particularly on the importance of start-ups include Haltiwanger *et al.* (2010), Clementi and Palazzo (2010), Coles and Kelishomi (2011), Lee and Mukoyama (2012), Schmalz *et al.* (2013)and Fort *et al.* (2013). The contributions by Haltiwanger *et al.* (2010) and Fort *et al.* (2013) are empirical and show that by controlling for firm age there remains no systematic relationship between firm size and growth. Fort *et al.* (2013) focus on cyclical dynamics of firms of different age. They estimate a VAR and conclude that the collapse in housing prices accounts for a significant part of the large decline in job creation by young firms during the recent recession. Schmalz *et al.* (2013) empirically link home ownership to entrepreneurial activity. Coles and Kelishomi (2011) study single-worker firms with a two-stage entry process. They show that thus replacing the free entry condition in the standard matching framework significantly enhances the aggregate properties of the model. Lee and Mukoyama (2012) study the cyclical properties of entrants vs. exiters. Clementi and Palazzo (2010) replace the free entry condition of a standard competitive industry model with a fixed mass of potential entrants and show that entry and exit can propagate the effects of aggregate shocks. Using a free-entry conditionHawkins (2011) finds the opposite result, however, he overstates the cyclicality of entry. To the best of my knowledge the previous literature on heterogeneous firms has not been succesful in finding a specification for time-varying entry costs that allows for cyclicality in start-up job creation but does not overstate its cyclicality (see e.g. Clementi and Palazzo (2010), Hawkins (2011), Lee and Mukoyama (2012), Berger (2012)).[4]

In my model start-ups need to borrow in order to pay the entry costs, making firm entry a function of credit conditions. Following the seminal publications by Kiyotaki and Moore (1997) and Bernanke *et al.* (1999) there now exists a vast theoretical literature on the linkages between the financial sector and the real economy. Jermann and Quadrini (2012) and Gilchrist and Zakrajšek (2012) study feedback effects of credit shocks onto the real economy but do not study entry and exit. Financial constraints have been introduced into heterogeneous firm models by Midrigan and Xu (2010) and Khan and Thomas (2011).[5] In their models, firm can save and tend to outgrow the financial constraints. Recent theoretical studies demonstrating the real effects of a decrease in credit supply include Clementi and Hopenhayn (2006), Campello *et al.* (2010), and Bassett *et al.* (2012). Credit constraints in a standard search-and-matching framework were studied by Dromel *et al.* (2010) and Petrosky-Nadeau (forthcoming), who find that the presence of constraints can impact both the level and the persistence of unemployment. Recent contributions that link shocks in the real estate and land markets to corporate investment and unemployment are Chaney *et al.* (2012), Liu *et al.* (2013*b*) and Liu *et al.* (2013*a*). An entrepreneurial choice models that studies the effect on those shocks on entrepreneurship is Corradin and Popov (2013).

Recent contributions to the jobless recovery literature are Galí *et al.* (2012), Drautzburg (2013), Bachmann (2011), and Berger (2012). In Berger's model firms lay off unproductive workers during recessions. This mechanism is able to generate acyclical ALP together with jobless recoveries. Differently from my paper, the focus of Berger (2012) is on the intensive margin of job creation. In the baseline results free entry is assumed thus generating entry rates that are too volatile with respect to the data. While the mechanism is otherwise complementary to Berger's, I show that introducing financing costs for entrants can not only generate jobless recoveries, it also significantly contributes to limiting the volatility of the entry rate. Drautzburg's focus lies on entrepreneur's ex-ante risk. His is an occupational choice model which he uses to estimate that approximately one third of the change in start-up job creation following the recent recession can be

[4] An example with one-worker firms where the value of a vacancy is endogenously varying is Shao and Silos (2013). Another paper worth mentioning is Sedlacek (2011) who uses a reduced form specification of the free-entry condition.

[5] Kerr and Nanda (2010) and Abo-Zaid (2013) also study interactions between job creation and credit availability. Kerr and Nanda (2010) find that US banking deregulation has had no significant effect on the size of entrants. Abo-Zaid (2013) argues that credit conditions of firms play an important role in shaping labor market outcomes after a recession. Macnamara (2012) also finds that entry and exit rates are more sensitive to financial shocks than output and employment. There is also an occupational choice literature which has studied links between entrepreneurship and credit constraints. References include Evans and Jovanovic (1989), Cagetti and Nardi (2006), Fonseca *et al.* (2001), and Buera (2008).

attributed to higher risk. Bachmann (2011) explains the jobless recovery through a combination of adjustment costs which generate a jobless recovery after a short and shaloow recession. For more severe recession episodes such as the 2008/09 case the model cannot reproduce the observed dynamics, however. Galí *et al.* (2012) argue that the 2008/09 downturn only produced a *quantitative* change in the relation between GDP and employment. Figure 11 in Appendix A.1 shows the trajectories of GDP, unemployment, job destruction, and start-up job creation for different recession episodes. We see that the employment series differ substantially compared to the other post-1980 recessions, particulary for start-ups. Additional support for the idea that 2008/09 was *different* comes from Figure (12) in Appendix A.1, which compares the cyclical component of the Case-Shiller Home Price Index (HPI) across recession episodes.

2 Facts

This section presents some of the stylized facts from the data on job destruction and job creation, enterprise dynamics, firm survival, and the link between credit conditions and start-ups. Throughout this paper I will refer to firms of age zero as start-ups or entrants, while firms aged one to five years will be referred to as young firms. All firms are employer 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) data base. Details regarding all the data used in this paper can be found in the Data Appendix.

2.1 Firm Dynamics

The 2008/09 recession episode produced the largest drop in employment since the beginning of the Census' BDS database in 1977. This was the result of both an increase in gross job destruction and a decrease in gross job creation. I will argue below that persistently low job creation rates are what made the recovery 'jobless'. In 2008/09 fewer jobs were destroyed than during the 2001 recession.[6] Most of it took place on the intensive margin, that is through downsizings of existing firms. Firm deaths only contributed to around 18% of all gross job destruction since 2008.[7] On the other hand, the years 2008 and 2009 marked the largest decreases in gross job creation in the entire Census data. This leads to *Observation* 1:

Observation 1: ***The Great Recession was mainly a crisis of low job creation.***

This *Observation* is robust to employing alternative data sources. Following the methodology developed in Elsby *et al.* (2009) I use data from the Bureau of Labor

[6] This holds both in absolute numbers and for the HP-filtered cyclical component. See Figure 13 in Appendix 1 for details.

[7] The average since 1977 was 17.66%. A similar point can be made for establishment deaths. The fraction of gross JD from establishment deaths since 2008 was 30.53%, the average since 1977 was 35.38%.

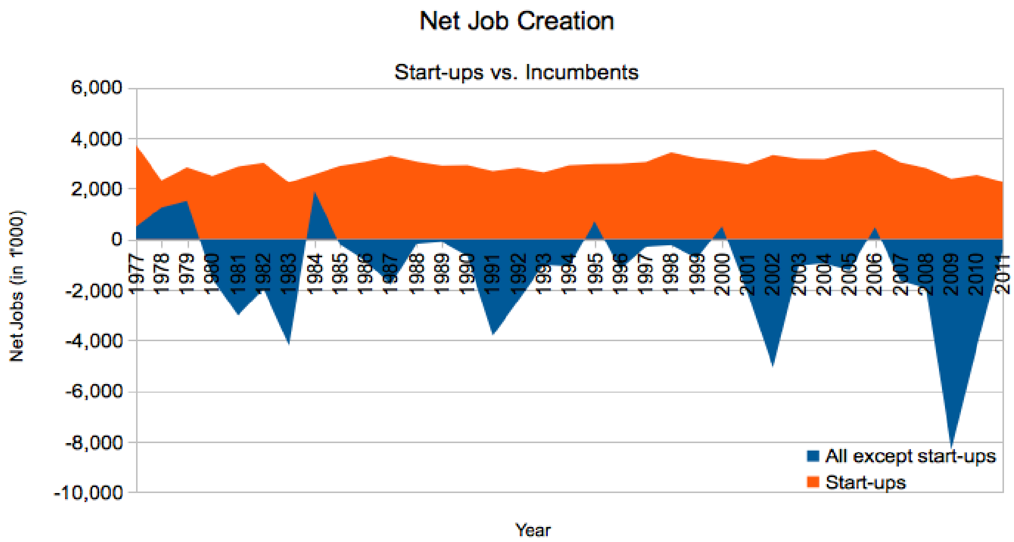

Figure 2: Net job creation by start-ups vs. incumbents. Source: Census, BDS

Statistics (BLS) and decompose changes in the unemployment rate into changes due to variations in the inflow rate and changes due to variations in the outflow rate of unemployment. The data shows that the increase in the unemployment rate was mainly due to decreases in the *outflow* from unemployment, i.e. lower hiring.[8]

Start-ups play a crucial role for the US economy. The main reason is their contribution to net job creation. Figure 2 plots an updated version of a graph used in Coles and Kelishomi (2011). It shows net job creation by start-ups and incumbent firms. While start-ups create around three million new jobs each year the net contribution of incumbents firms is typically negative. While the cyclicality of net job creation by start-ups is dwarfed by that of incumbents firms it nevertheless shows considerable variation over the business cycle. The fraction of total hires that can be attributed to start-ups is procyclical since the early 1990s. The recent recession has left its mark: While net job creation by incumbent firms quickly recovered, job creation by start-ups in 2011 was at its lowest point since the beginning of the Census BDS series in 1977.[9] At the same time the average size of a start-up has virtually remained unchanged. This suggests an important extensive margin effect, causing fewer entrepreneurs to start a business. The drop in start-up hiring is the main factor behind low gross job creation since 2008 (*Ob-*

[8]Additional Figures and details can be found in Appendix A.1.

[9]This result is ubiquitous across regions and sectors. Haltiwanger *et al.* (2012) also find that the decline in startup employment can be found across states. They also note, however, that states that were hit hardest by the financial crisis suffered larger decreases in startup employment, a point that I will take up further below. Others, such as Sanchez and Liborio (2012) have used alternative data sources such as the Business Employment Dynamics (BED) from the BLS to show the decline in startup activity.

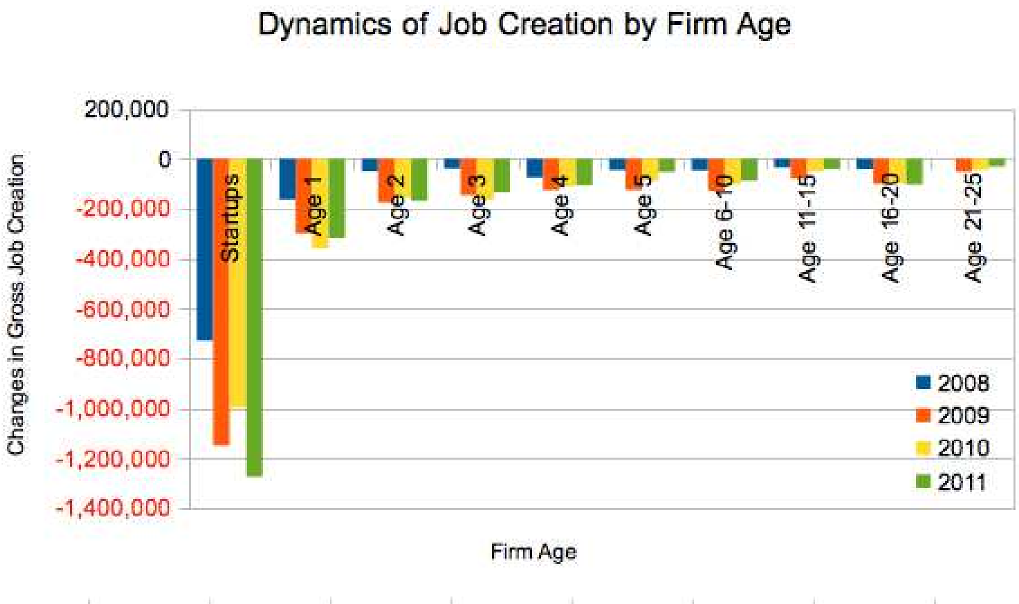

Figure 3: Changes in gross job creation relative to pre-recession year 2006. For aggregated age groups averages are shown. Source: BLS, Business Employment Dynamics, own computations

servation 1) as Figure 3 shows. The figure plots changes in absolute gross job creation by firm age relative to the pre-recession year 2006.[10] The graph shows that e.g. in 2011 start-ups created about 1'200'000 fewer new jobs than in 2006. The largest decreases in gross job creation occured in the group of start-ups, followed by the youngest firms.

A fact that stands out is that for all firm ages gross job creation remains low even after the recession trough. This is a feature of the 'Great Recession' we do not observe to this extent for the 1980 and 2001 recessions. During the 2001 recession employment in start-ups decreased but quickly rebounded in 2002. A further difference was that firms aged 2 and 3 saw an increase in job creation even during the recession. During the 1980s recession data availability is limited but start-up hiring actually increased, both in absolute numbers and a fraction of total hires. The recession in the early 1990s bears more similarity to the 'Great Recession' in that hiring by start-ups decreased slightly prior to the recession and remained on a low level until several years after the recession trough. Figure 14 in Appendix A.1 graphically compares the different recession episodes. This subsection is summarized in *Observation* 2:

[10] Choosing another base year, e.g. 2007 leaves results virtually unchanged. Figure 3 does not show the age group 26+, because it is not possible to compute averages here. On average, this age group showed positive job creation with respect to 2007. Furthermore, qualitatively identical results can be obtained by plotting job creation *rates* or the cohort's fraction of total job creation (both available upon request).

	1-19	20-99	100-499	500+
Firms	88.4%	9.66%	1.54%	0.35%
Establishments	71.32%	10.48%	4.66%	13.54%
Employment	20.14%	18.02%	13.93%	47.90%
Number of Start-ups	98.1%	1.75%	0.14%	0.01%
Startup Employment	69.36%	20.90%	8.26%	1.47%

Table 1: Size- and Employment Distributions. Source: Census/BDS. Employment is calculated using the DHS-denominator.

Observation 2: ***The decrease in gross job creation was largely due to lower job creation by start-ups and young firms.***

I divide firms into four size categories, 1-19, 20-99, 100-499, or 500+ employees.[11] The size distribution of firms and establishments is given in the first two rows of Table 1. The fact that the distribution over establishments differs from the distribution over firms reflects the fact that small firms often consist of a single establishment, while large firms are frequently composed of several establishments. The distribution of employment is given in the third row. It highlights that while over 95% of firms have less than 100 employees, it is large firms that employ almost half of the workforce. The average firm size is 21.43 workers, while the average establishment size is 16.99 workers. The last two rows show the distribution of start-ups. The table shows that the vast majority of start-ups (98.1%) are small firms with less than 20 employees.[12][13] The age distribution of firms is shown in Table 2 . The BDS data exhibits the 'up or out dynamics' first described by Haltiwanger *et al.* (2010). They show that conditional on survival, young firms grow considerably faster than their mature counterparts. In the BDS data start-ups and young firms show overproportional employment growth: On average start-ups employ around 3% of the labor force, yet their job creation corresponds to 18.7% of the total. The group of firms between age one and five is the second biggest group of gross job creators. With 13.5% of the labor force employed in young firms, they contribute 21.2% of all gross job creation. On the other hand, young firms show higher-than-average

[11] One shortcoming regarding the Census data is that for discretionary reasons there are many NAs in the time series for large firms' employment jointly by age and size. I therefore make only general statements about those size categories and limit the data analysis to size categories without any NAs. No NAs appear in the size categories up to 999 employees. The time series of firms size 1000+ contains NAs for the employment series and are omitted from those statistics. Where available, the numbers change only marginally. In the tables I state whether I used the 500+ or the 500-999 category.

[12] Very large start-ups are rare and should be treated with caution, as practise shows they are often temporary entities that get folded into other firms later on.

[13] Many other studies confirm the fact that young firms are also small, but not necessarily vice versa. Studies such as Ibsen and Westergard-Nielsen (2011) and Halabisky (2006) confirm the results found in Haltiwanger *et al.* (2010) for Denmark and Canada. Neumark *et al.* (2011) discuss the inverse relationship between size and growth and Ayyagari *et al.* (2011) underline the higher job creation and destruction rates by small and young firms.

	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5
Firms	11.09%	8.54%	7.22%	6.29%	5.55%	4.97%
Employment	3.16%	3.15%	2.87%	2.68%	2.53%	2.42%
	Age 6-10	Age 11-15	Age 16-20	Age 21-25	Age 26+	
Firms	18.67%	12.91%	9.42%	7.18%	8.16%	
Employment	10.36%	8.89%	8.14%	7.94%	47.87%	

Table 2: Firm- and Employment distributions by age. Source: Census, BDS.

rates of job destruction. A significant fraction of which is the result of firm exit. Older firms shed workers mostly through downsizing, with firm exit being the exception.

2.2 Housing and Credit supply

Data on business lending is notoriously difficult to obtain but certain key facts can readily be established.[14] In the wake of the financial crisis there have been numerous initiatives to monitor credit conditions for small business.[15] This section will show that after 2007 start-ups have been finding it more difficult to obtain credit. This is important because besides personal wealth banks are the most important source of funding for start-ups (see also Foundation (2013)). For example Dennis Jr. (2011) report surveyresuls showng that small firms employing 10 or more people almost universally use one or more types of credit from a financial institution. I make use of the fact established above that young firms are a subset of small firms, for which data availability is better. I then go own to show that the difficulty to obtain credit was the result of illiquid funding markets faced by commercial banks, declines in bank profitability and a sharp drop in the value of real estate, which is frequently used as collateral for business loans.

As a result of the 2008/09 recession there was a pronounced drop in commercial and industrial (C&I) loans commercial banks extended to firms (see Figures 15 and 16 in Appendix A.1 for details). By the end of 2009 both the dollar amount and the number of loans had decreased to around 80% of their pre-recession peaks. While the total volume of C&I loans surpassed the pre-crisis level in the last quarter of 2012, small loans (i.e. loans under $1 Million) only show a very tentative recovery. At the end of the first quarter of 2013 their volume was only 84.84% of that before the recession. The effect on

[14] See e.g. Bassett *et al.* (2011) for a discussion of the data and http://www.federalreserve.gov/events/conferences/2010/sbc/agenda.htm for a forum on this topic organized by the Federal Reserve in July 2010.

[15] Those include the reports issued by the Congressional Oversight Panel for the 'Troubled Asset Relief Program' (TARP) ({United States Congressional Oversight Panel} (2010) and {United States Congressional Oversight Panel} (2011)), surveys by the National Federation of Independent Business (NFIB) summarized in Dennis Jr. (2010), Dennis Jr. (2011), and Dennis Jr. (2012), and the proceedings of the annual conference of the US Securities and Exchange Commission (SEC) on 'Small Business Capital Formation' (2009), which can be found at http://www.sec.gov/info/smallbus/sbforum.shtml. Furthermore the Federal Deposit Insurance Corporation (FDIC) has increased the periodicity of its 'Quarterly Banking Profile'.

business credit was the most severe for recipients of small loans. The share of small loans as a fraction of all C&I loans dropped from a pre-crisis average of 32.33% to 22.39% in the first quarter of 2013. At the same time there was a sharp increase in the interest rate spread between C&I loans and the federal funds rate, again, especially for smaller and riskier loans. The spreads have remained high even after the official end of the recession.

In this paper I highlight the employment effects of decreased credit supply for young firms.[16] The Federal Reserve's 'Senior Loan Officer Opinion Survey on Bank Lending Practices' shows that besides a decrease in credit demand perceived by banks there occured a tightening of credit standards which preceded the fall in demand (see Bassett *et al.* (2012) who also use this survey). Results are shown in Figure 4 By the end of 2008, 69.2% of banks reported that they had tightened credit standards, especially for firms with annual sales less than $50 million for whom the figure is almost 80%. Other than in the 2001 recession bank profitability declined considerably throughout the 2008/09 recession. The percentage of institutions reporting negative quarterly net income increased to over 30% in 2009 (the average between 1990 and 2006 was 8.39%).[17] Banks whose balance sheets have been more severely affected by increased loan defaults may either have insufficient capital to make additional loans, or may choose to conserve capital instead of making loans to entrepreneurs ({United States Congressional Oversight Panel}, 2011, 2010).

Obtaining an initial loan requires collateral for which home equity has been increasingly used prior to the recession (Dennis Jr. (2010)).[18] One of the main concerns expressed in the *Small Business Forum's Report to the President* (2009) was that "[h]ome equity extraction is no longer available for owner's investment" (p. 45). Figure 5 shows that net mortgage equity extraction dropped from around 8% of disposable personal income at the end of 2006 to around -6% at the end of 2010, the lowest value since the beginning of the time series in 1980.[19] This 'deleveraging' by households that accompanied the dramatic decline in household net worth implies that the amount of equity

[16]A large number of recent studies that highlights the role of supply-side factors in the the decline in business lending, e.g. Puri *et al.* (2011), Bassett *et al.* (2011) and ({United States Congressional Oversight Panel}, 2011). Puri *et al.* (2011) use data on loan applications and loans granted from Germany to show that the financial crisis led to a contraction in retail lending as a result of a decreased loan supply by banks. Many reports and surveys also focus on loans to 'small businesses'. Since the fourth quarter of 2010 the Small Business Administration (SBA) conducts a firm survey showing that obtaining credit remains one of the largest problems for small businesses (see http://www.sba.gov/advocacy/10871/29971). The Federal Reserve Bank of Atlanta explicitly addresses financing conditions for young businesses in its survey (see http://www.frbatlanta.org/research/smallbusiness/sbresearch/). The '2012 Small Business Borrowers Poll' and the '2010 Small Business Financing Poll' by the Federal Reserve Bank of New York take the same line. They show that young firms generally rely heavily on bank credit products but that between 2008 and 2010 the use of business loans and credit cards for financing decreased for firms aged 0-5. The common point made in all these reports is that young firms face a different initial lending environment and more challenges than mature firms in obtaining credit.

[17]Based on FDIC data. During 2001 and 2002 the highest percentage was 14.87%. See also Figure 16 where the increase in interest rates was much less pronounced during 2001 than 2008.

[18]Note that C&I are by definition not secured by real estate.

[19]This graph was created using the methodology proposed in **?** for updating the estimates presented inGreenspan and Kennedy (2005). Thanks to Bill McBride for providing me with his estimates.

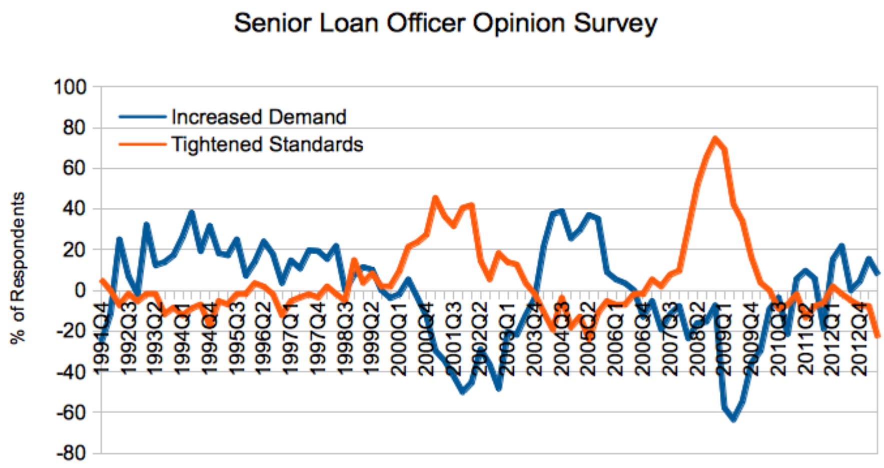

Figure 4: Results from 'Senior Loan Officer Opinion Survey on Bank Lending Practices'. The blue line plots the net percentage of banks reporting tightening standards for C&I loans to firms with annual sales of less than $50 million. The organge line plots the net percentage of banks reporting stronger demand for C&I loans from those same firms. Source: Federal Reserve.

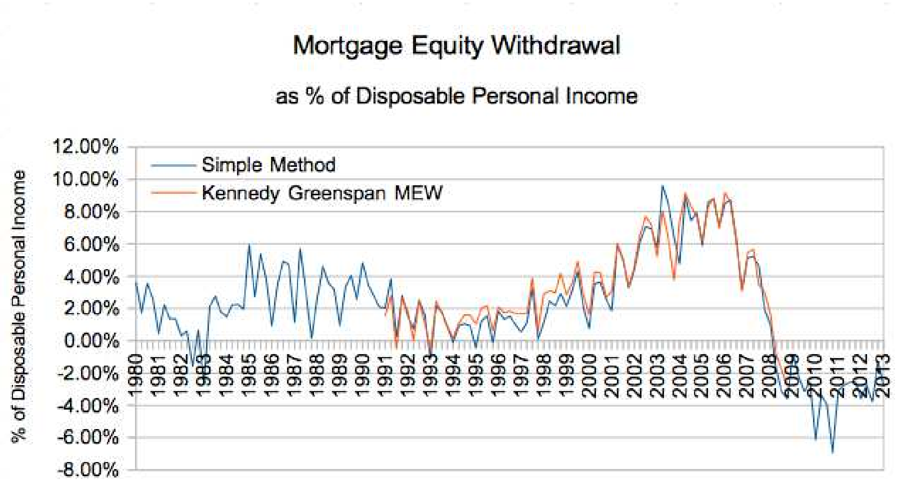

Figure 5: Net equity extraction, or mortgage equity withdrawal (MEW) using the Flow of Funds and BEA data. For comparison the original Kennedy-Greenspan method is plotted as well. Both data are not seasonally adjusted. Sources: Federal Reserve and BEA.

available for start-up equity has been severely curtailed. A reduction of credit supply also played a significant role here as can be seen using FDIC data on used and unused home equity lines which I produce in Figure 17 in Appendix A.1. While unused commitments typically exceed outstanding home equity loans, the 2008/09 recession generated an earlier and steeper decline in unused equity lines. While part of this decline reflects drawdowns of existing lines a large portion represents a reduction of the credit supply by banks, as Bassett *et al.* (2011) argue in a similar context.

State-level HPI and Employment by new Establishments A direct link between housing wealth and the labor market can be established by combining state-level data on house prices and job creation by new establishments.[20] Table 3 shows various state-level regressions. I use employment via establishment births (in 1'000) from the BLS' Business Employment Dynamics (BDM) as the dependent variable. Although this data has several shortcoming (discussed in the Appendix A.0) its main advantage is its quarterly frequency. This variable will be denoted EMP. The main explanatory variable is the state-level HPI, which comes from the Federal Housing Finance Agency (FHFA). As additional controls I use two alternative cyclical indicators: the state-level unemployment rate (UE) and state-level personal income (PI). The reason I use personal income as a cyclical indicator is that state-level GDP is only available on an annual basis. I am controlling for year effects in all the regressions and use cluster-robust standard errors.[21] Summary statistics for all variables can be found in Appendix A.0.

The first column in Table 3 shows a simple regression of EMP on HPI. Controlling for year- and state-effects, the HPI is positively correlated with job creation by new establishments on the state-level. This relationship is robust to controlling for cyclical indicators. Column (2) controls for personal income, which has the expected positive sign and is highly significant. Column (3) controls for both UE and PI. The state-level unemployment rate is not significant but has the expected negative sign. Columns (4) and (5) repeat the regressions in columns (3) and (4) with a fixed-effect estimator, which leaves the results almost unchanged. The results suggest that a one point increase in the cyclical component of a state's HPI is correlated with an increase in the cyclical component of job openings by new establishments of 10'000-12'000 jobs. This positive relationship is largely driven by the years after the 2001 recession. This is not surprising as Figure 5 shows that years following the 2001 recession saw the largest rates of mortgage equity withdrawal.

Observation 3: ***An important feature of the 2008/09 recession is a dete-***

[20] Also Fort *et al.* (2013) and Blanchflower and Oswald (2013) have recently studied links between home ownership and employment. Adelino *et al.* (2012) highlight the positive link between easier access to credit and house prices, and Dell Ariccia *et al.* (2012) link the subprime mortgage crisis to a decline in overall lending.

[21] I removed the states AK, DC, DE, HI, ND, SD, VT, WV, and WY from the analysis because of an FHFA warning. The HPI from those states have been derived from fewer than 15'000 transactions over the last ten years.

Table 3: Descriptive Regressions at the state level

	(1)	(2)	(3)	(4)	(5)
hpi	25.8739*	12.1014^{+}	10.4400^{+}	12.1581^{+}	10.4808^{+}
	(2.17)	(1.87)	(1.68)	(1.88)	(1.68)
pi		0.0839***	0.0831***	0.0842***	0.0833***
		(6.94)	(7.28)	(6.94)	(7.28)
ue			-117.6072		-118.6663
			(-0.57)		(-0.57)
_cons	736.5904***	646.5852***	595.4824***	646.3114***	-164.4027
	(5.11)	(4.77)	(4.22)	(4.84)	(-0.53)
N	3276	3276	3276	3276	3276

Source: BLS, FHFA, BEA. All series are quarterly and have been HP-filtered with $\lambda = 1600$.
All regression include year- and state dummies.
t statistics in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

rioration of the financing environment for start-ups. Credit supply by commerical banks decreased, and real estate values fell.

This section has produced three stylized facts about job creation and destruction. One, high unemployment is mainly driven by low job creation figures. Two, a large part of the decrease in job creation was due to the behavior of the youngest firms. Start-ups constitute the single largest contributor to job creation. Job creation by start-ups has taken a prolonged dive since the onset of the recent crisis. Three, there was a decrease in the availability of external finance for start-ups. Credit supply by commercial banks dropped during the 2008/09 recession, partly because declining property values diminished the value of collateral. The model presented in the following section will essentially take the third *Observation* as given and use it to explain *Observations* 1 and 2.

3 The Model

The economy consists of two types of agents (workers and entrepreneurs) plus a bank which provides start-up financing and is jointly owned by all agents in the economy. Each worker and each entrepreneur owns one unit of housing h, the price of which is q^h. For simplicity the only purpose of housing is to serve as collateral when financing start-up loans. Workers can supply labor and consume their income, either from wages or home production. Entrepreneurs own the production process which utilizes labor to generate a single consumption good. Output is a function of labor and two types of profitability: idiosyncratic and aggregate. Shocks to profitability can be interpreted as changes in productivity or demand. Both types of profitability evolve persistently over time. Time is discrete and a period refers to one month.

The labor market is frictional. To hire unemployed workers firms must post vacancies which are filled with endogenous probability. Following the standard search and matching literature I employ a matching function to capture those frictions. It is denoted as $m(U, V)$. Its inputs are the unemployment rate U and the vacancy rate V. Vacancies posted by firms are filled with probability $H(U, V) = m/V$. An unemployed worker finds a job with probability $\phi(U, V) = m/U$. The ratio $\theta \equiv V/U$ is a sufficient labor market statistic to compute the vacancy-filling and job-finding rates in this economy. Employed workers may lose their job if the entrepreneur they are matched to exits or decides to reduce employment in his production site. The worker takes both the job-finding rate and the job-destruction rate as exogenous. The workers' compensation for their labor input is specified in a state-contingent contract. This contract is the result of a bargaining process between the entrepreneur and the worker. For the simple model I assume that workers have no bargaining power.

A fixed cost to production guarantees that firms exit when they receive a sufficiently low profitability draw. New firms that enter the economy can do so at an exogenous start-up cost c_e, which has to be paid up front, before profits are realized. To finance c_e, new firms obtain an intra-period bank loan. As in the data, a fraction of the loan can be secured by collateral (housing). Changes in the value of collateral lead to variations in the effective price of entry $\tilde{c}_e$ and hence in the number of firms that enter the economy.

The timing of events in my model is based on the setup in Hopenhayn and Rogerson (1993): At the end of a period, before the realizations of new aggregate and idiosyncratic shocks, incumbent firms decide whether to continue operating or exit. Then the aggregate state realizes and new firms enter the economy based without knowing their idiosyncratic productivity draw. The idiosyncratic shocks realize and all firms decide on their desired employment level. Bargaining takes place between workers and entrepreneurs, after which production occurs, and compensations are paid. Finally, intra-period loans are either paid back or defaulted on.[22] The model is now explained in more detail.

3.1 Workers

Workers can either be employed or unemployed. When they are unemployed they receive an outside option $b(a)$, which can vary with the aggregate state a. This ouside option reflects the returns to home production. With probability $\phi(U, V)$ an unemployed worker is able to find a job, thus becoming employed next period. We can write the value of being unemployed as

[22] A difference in the timing of my model compared to Cooper *et al.* (2007) is that in their model the employment decision is made without knowing the current realization of the idiosyncratic productivity state. This is done in order to give meaning to the hours adjustment margin. Since in my model all employment adjustment comes through employment, not hours, I do not make this assumption. The fact that incumbent firms do not observe the aggregate productivity state before making their exit decision is not important and could be relaxed.

$$W^u(a) = Z(b(a) + \pi^b) + \beta E_{a'|a}[\phi(U,V)W^e(a') + (1 - \phi(U,V))W^u(a')], \quad (1)$$

where $Z(\cdot)$ describes the worker's utility from consumption and profits made by the bank π^b. Workers get no utility from housing. The discount factor is β, and $\phi(\cdot)$ is the job finding rate which depends on the current unemployment rate U as well as the number of vacancies V. The utility function $Z(\cdot)$ is assumed to be strictly increasing and concave. For simplicity I assume that there is no disutility from labor. The expectations operator in (1) is taken over the future values of unemployment and unemployment.

By constrast, when a worker is currently employed he receives a compensation ω as defined by the state-contingent contract. With (endogenous) probability δ the worker loses his job and receives the value of unemployment $W^u(a')$ next period. With the remaining probability he continues to be employed.

$$W^e(a) = Z(\omega(a) + \pi^b) + \beta E_{a'|a}[(1 - \delta)W^e(a') + \delta W^u(a')] \quad (2)$$

3.2 Entrepreneurs

Entrepreneurs own the production process. Income from firms constitutes the entrepreneurs' only source of income and they consume all profits within the period.[23] Entrepreneurs have the same utility function as workers, denoted $Z(\cdot)$.[24] They produce using a production technology $F(e)$, where e represents the number of workers. The production function has the properites $F_e(e) > 0$ and $F_{ee}(e) < 0$, meaning it exhibits decreasing returns to labor, which might arise from fixed factors such as capital or materials, from imperfect substitutability for consumers of the goods produced by different firms or from managerial span-of-control as in Lucas (1978). At the end of a period entrepreneurs decide whether to continue operation or exit, based on their expectation of future shocks.[25] At the same time new entrepreneurs enter the economy. After the realization of uncertainty, entrepreneurs make hiring and firing decisions. A fraction q of the workforce is separated exogenously (quits) each period. Given the state vector the entrepreneurs and the workers bargain over a compensation $\omega(a, \epsilon, e)$. The firm's state vector at time t is (a, ϵ, e, θ), where θ reflects labor market tightness, as explained in more detail below. The profit function is given by

$$\pi(a, \epsilon, e) = a\epsilon F(n) - e\omega(a, \epsilon, e) - \mathbb{C}. \quad (3)$$

Output is affected by two multiplicative profitability shocks a, and ϵ. While the former is an aggregate shock, the latter affects only idiosyncratic profitability. The term $\mathbb{C}$ defines

[23] See e.g. evidence in Moskowitz and Vissing-Jorgensen (2002)

[24] For the baseline model I will assume that entrepreneurs be risk-neutral. This formulation is simply chosen to keep the problem as general as possible. As for the workers, I assume that entrepreneurs obtain no utility from housing.

[25] As in Hopenhayn and Rogerson (1993), since there is no additional information gained between periods, the exit decision is taken at the end of a period. This is mainly a computational convenience. Since I have one-period loans in my model the end-of-period exit decision is necessary to obtain default in the same period the loan was issued.

a cost function given by

$$\mathbb{C} \equiv F - F_v \mathbf{1}^+ - C_v v^2 \mathbf{1}^+ - F_f \mathbf{1}^- - C_f f^2 \mathbf{1}^-.$$

The indicator function $\mathbf{1}^+$ is equal to one if the firm is hiring and equal to $\mathbf{1}^-$ if the firm is firing. The term F is a fixed cost of operation to induce exit in low profitability states. There are two types of costs connected to hiring. One is a fixed cost F_v. The other is a quadratic cost C_v.[26] The respective cost associated to firing are given by F_f and C_f. All costs are denominated in wage units. Define $Z(\pi(a, \epsilon, e)) \equiv Z(\pi(a, \epsilon, e) + \pi^b)$ as the utility from firm plus bank profits for notational convenience.

The employment decision A firm that is operation at the time its idiosyncratic profitability is realized is called an incumbent, or 'continuing' firm. This firm employed e_{-1} workers last period and faces a shock x, where $x = (a, \epsilon)$, together with aggregate labor market tightness θ. This information is summarized in state $s = (x, e_{-1}; \theta)$. The value function for a continuing firm is denoted $Q^c(s)$. Because there are fixed costs to variations in employment, the entrepreneur faces a discrete choice problem within the period. He can decide between posting vacancies, remaining inactive, and firing workers. Vacancies must be reposted each period. The value $Q^c(s)$ is thus given by the maximum of the values of posting vacancies, firing, and inaction.

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

The three Bellman equations will now be described in turn. The value of posting vacancies Q^v is given by

$$Q^v(s) = \max_v Z(\pi(a, \epsilon, e)) + \beta E_x \max\{Q^c(x', e'; \theta'), Q^x(0, e)\},$$

and the evolution of employment is given by the number of quits and the vacancy filling rate $H(\cdot)$

$$e = e_{-1}(1 - q) + H(U, V)v,$$

The value of firing workers is

$$Q^f(s) = \max_f Z\left(\pi(a, \epsilon, e_{-1}(1 - q) - f)\right) + \beta E_x \max\{Q^c(x', e'; \theta'), Q^x(0, e)\}.$$

Lastly, the value of inaction is given by

$$Q^n(s) = Z\left(\pi(a, \epsilon, e_{-1}(1 - q))\right) + \beta E_x \max\{Q^c(x', e'; \theta'), Q^x(0, e)\}.$$

Here E_x denotes the expectation conditional on the current value of x. The maximum operator nested on the right-hand side of all three Bellman equations reflects the fact that a firm can make a decision about exiting before the next period. Since this is decided before the realization of new information the choice can be made in the current

[26] I abstract from the complex employment adjustment function in Cooper *et al.* (2007).

period. Conditional on this period's employment choice the entrepreneur must evaluate the expected value of being active next period, given by $E_x\left[Q^c(x', e'; \theta')\right]$, and compare this to the present discounted value of exiting, given by $Q^x(0, e)$. This value is defined below. The policy function for employment will be denoted $\phi^e(s)$. The employment policy function will be characterized by different cutoff values in the (x, e_{-1}) space. For a given e_{-1} there exists a region of inaction over the values of the idiosyncratic shock due to the presence of fixed costs. An example is given in Figure 19 in Appendix A.2. For values higher than a cutoff $\bar{x}$, the firm hires new workers, while for values below $\underline{x}$ workers are shed. Note that changes in employment do not take 'time-to-build' because I want to rule this out as a driver of jobless recoveries.

The Optimal Contract We can now define the optimal wage contract between workers and entrepreneurs. As in Cooper *et al.* (2007) a contract is $\Upsilon = w(S)$, where $S = (a, \epsilon, e, \theta)$ is the firm's state vector. The contract specifies the compensation for a worker in a firm with state S. An important assumption is that entrepreneurs are able to make take-it-or-leave-it offers, i.e. the workers have zero bargaining power.[27] While this is not a realistic assumption the dynamics of the model do not depend greatly on wage dynamics. In Appendix ?? I show some intuition for a model with an alternative bargaining rule based on Stole and Zwiebel (1996). A firm thus chooses the contract that maximizes its utility from period profits subject to the condition that the employed workers' outside option must be at least as large as the remuneration offered by the contract. The profit maximizing contract results from the following optimization problem

$$\hat{\pi}(a, \epsilon, e) = \max_{\Upsilon} Z(a\epsilon F(e) - ew(S)) \tag{5}$$

$$\text{s.t. } W^e(a) \geq W^u(a) \tag{6}$$

In equilibrium, the values in (6) will depend only on a, not on labor market tightness θ. Due to the no bargaining power assumption firms are able to reduce the workers' match surplus to zero and their participation constraint in (6) will hold with equality. This implies that $Z(w(S)) = Z(b(a))$, or $w(a) = b(a)$. In this way the model generates movements in the wage without the complexity of adding aggregate labor demand as an additional state variable.

The Exit Decision At the beginning of a period, before any new information about the exogenous shocks arrives, an incumbent entrepreneur has to decide whether he wants to continue operating or exit next period. The exit decision is thus based on the expected future value of x. If the entrepreneur decides to exit, at the beginning of the previous period he will reduce the amount of workers to zero (paying the firing costs for its e_{-1}

[27] As in Cooper *et al.* (2007) and many other papers this assumption is employed to facilitate the computation of the optimal contract. See Elsby and Michaels (2013) and Acemoglu and Hawkins (n.d.)for a different approach based on Stole and Zwiebel (1996). Kaas and Kircher (2011) introduce a competitive search procedure.

remaining workers) and generate zero revenue. However, he avoids paying the fixed cost of operation. Any outstanding debt obligations are defaulted on. The value of exiting is

$$Q^x(0, e_{-1}) = Z\left(0 - F_f - C_f e_{-1}\right) \leq 0. \tag{7}$$

This formulation implies that once a firm has decided to exit, it can not re-enter the market. All future profits are zero. The firm decides to exit whenever

$$E_{a',\epsilon'|a,\epsilon}\left[Q^c(s') - Q^x(0, e)\right] < 0. \tag{8}$$

Since $Q^x(0, e)$ is always non-positive the fixed cost of operation F plays the role of inducing exit. The associated exit policy function will be denoted $\phi^x(s)$ and takes a value of one if the firm exits, and zero otherwise. For any given value of employment it is defined by a threshold productivity level below which a firm exits. The value of exit has the property $Q^x(0, e^i) > Q^x(0, e^j)$ for $e^i < e^j$. This implies that *ceteris paribus* small firms are more likely to exit than large firms.

The Entry Process At the beginning of each period there is a continuum of ex-ante identical potential entrants. The entry decision is made before the idiosyncratic profitability is known. Entrants do not pay a fixed cost of operation in the first period. Instead, to enter potential entrants must pay a start-up cost $\tilde{c}_e$, which they compare to the expected value of entry Q^e. The cost $\tilde{c}_e$ consists of a physical entry cost c_e and possible interest payments to the bank (defined below). If the value function Q^c 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

$$Q^e(a, \epsilon_{i,0}, \theta) = \int_\epsilon Q^c(a, \epsilon_{i,0}, 0, \theta) d\nu.$$

If an entrepreneur has decided to enter he receives an initial profitability draw of $\epsilon_{i,0}$ from a distribution ν, which may differ from the distribution of incumbents productivity draws.[28] After the initial period, profitability evolves identically to that of all other incumbent firms. Firms entering in period t have mass M_t, which is pinned down via a free-entry condition.[29] Free entry requires that the cost of entry be equal to the value of entry.

[28]This modelling choice that the distribution of firm-specific productivity is distributed independently of the number of entrants is supported by the data. Using the BDS data I can show that the initial employment level of a firm cohort is a good predictor for employment levels at a later point in time. This implies that the initial size of a cohort does *not* have a significant effect on the cohort's employment growth, and specifically, that initially small cohorts do not grow faster than initially large cohorts (*cf.* Reedy and Litan (2011)).

[29]In Hopenhayn and Rogerson (1993) the free-entry condition works via the real wage. Additional entrants increase labor demand, and hence the real wage. Since labor supply is strictly decreasing in the real wage this guarantees that a market-clearing $M_t = M^* \; \forall t$ can be found each period. In my model there exist frictions on the labor market and hence the resulting wage is not a market-clearing wage.

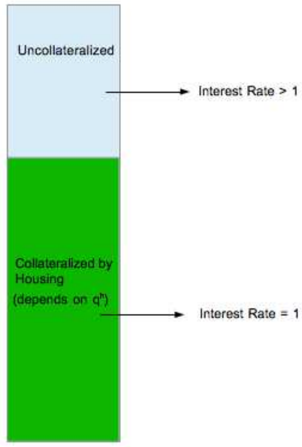

Figure 6: The Intra-period Loan. For the collateralized fraction of the loan an intra-period interest rate of unity is charged. The uncollateralized part includes a positive default risk for which the bank charges a no-default interest rate larger than unity.

$$\tilde{c}_e = Q^e(a, \epsilon_{i,0}, \theta). \tag{9}$$

Note that $\frac{\partial Q^e}{\partial a} > 0$ and $\frac{\partial Q^e}{\partial \theta} < 0$. This implies that entry is procyclical. Additional entry increases the labor market tightness which in turn diminishes the value of entry. New firms enter until the cost of entry is equal to the value of entry.

3.3 The Bank

The bank is owned by all agents in the economy and behaves competitively, i.e. makes zero profits. To pay the entry cost c_e new firms must obtain a loan from the bank. To this end entrepreneurs can use their real estate as collateral to secure part of the loan. This can be thought of as a shortcut for the idea that in reality some loans are completely secured by real estate while others are not. Putting down collateral for a loan is desirable because uncollateralized loans are risky for the bank. A start-up may strategically choose to exit and hence walk from its obligations before the loan has to be repaid. Therefore, the bank efficiently prices interest rates by charging a default premium to the *uncollateralized* fraction of the loan in order to compensate itself for expected losses.[30] The fraction of the loan that can be collateralized depends on the value of real estate q^h. The diagram in Figure 6 illustrates the structure of the loan.

[30]This is similar to the mechanism in 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 defalt the bank is unable to recuperate any fraction of the initial loan because wages are paid before the intra-period loan is reimbursed. I choose this timing of events in order to eliminate the default dimension from the worker-firm bargaining problem.

Interest Rates and Credit Supply The entrepreneur chooses a fraction $0 \leq \mu \leq 1$ of the loan to be secured by collateral.[31] Collateralized loans can always be enforced by the bank in case of default, hence the intra-period interest rate for this part of a loan is equal to 1. This corresponds to the bottom area in Figure 6. Default occurs with positive probability, namely whenever a borrowing firm chooses to exit. In that case the bank claims any collateral used to secure the loan. The remaining fraction $1 - \mu$ of the loan is not secured by collateral and the bank charges a non-default interest rate $\hat{R} \geq 1$ (defined below). Since the price of collateralized loans cannot exceed $\hat{R}$, an entrepreneur will always choose to secure the largest possible fraction of the loan. The value of μ is then pinned down by the collateral constraint

$$\mu \cdot c_e \leq q^h. \tag{10}$$

This constraint says that the value of the secured fraction of the loan, $\mu \cdot c_e$, cannot exceed the value of the collateral. Optimization by the entrepreneur implies that (10) will hold with equality and the choice of μ is given by $\mu = \frac{q^h}{c_e}$. The remaining fraction $(1 - \mu) \cdot c_e$ has to be financed by an uncollateralized loan. As can be seen from (7), profits are non-positive if a firm exits. Therefore the bank will be unable to recuperate an uncollateralized loan to a firm that exits. If the borrowing firm does *not* exit, it pays back $\tilde{c}_e$ at the end of the period and enters the next period as an incumbent firm. Therefore the loan contract for the uncollateralized fraction of the loan is characterized by a non-default interest rate $\hat{R}$ and a threshold value of the idiosyncratic shock, $\bar{\epsilon}_{i,0}$. For any initial productivity draw $\epsilon_{i,0} \leq \bar{\epsilon}_{i,0}$ the entrepreneur will exit and hence default on his loan. The non-default interest rate $\hat{R}$ is given by the bank's zero-profit condition

$$- c_e + \hat{R} \int_0^{\infty} (1 - \phi^x(\epsilon_{i,0}, 0; a, \theta)) \cdot c_e d\nu = -c_e + \hat{R} \int_{\bar{\epsilon}_{i,0}}^{\infty} c_e d\nu = 0 \tag{11}$$

$$\hat{R} = \frac{c_e}{\int_{\bar{\epsilon}_{i,0}}^{\infty} c_e d\nu}. \tag{12}$$

Equation (11) shows the bank's balance sheet for an individual transaction. It pays out a loan c_e to the entrepreneur. If the entrepreneur receives an initial idiosyncratic profitability draw $\epsilon_{i,0}$ above the threshold $\bar{\epsilon}_{i,0}$ he does not default $(\phi^x(\epsilon_{i,0}, 0; a, \theta) = 0)$ and the bank receives $\hat{R} \cdot c_e$. With the counter-probability the firm will exit and the bank receives nothing. The interest rate $\hat{R}$ will be counter-cyclical since lower aggregate profitability induces a higher probability of default. The overall interest rate paid on the loan depends on the fraction μ that is collateralized and is given by

$$\tilde{R} = \mu + (1 - \mu)\hat{R}. \tag{13}$$

[31] The allocation problem gross of period profits is given by $\max_{0 \leq \mu \leq 1} c_e - c_e \cdot 1 \cdot \mu - c_e \cdot \hat{R} \cdot (1 - \mu)$ subject to the collateral constraint (10), where $\hat{R}$ is the non-default interest rate defined in (13).

The Value of Real Estate and Entry The price of housing is given by q^h. Similarly to the aggregate profitability shock a, I calibrate a sequence of q^h to the data and feed it into the model. Changes in the price of housing can have asymetric effects on the cost of entry, depending on whether the change is positive or negative. The effect of changes in q^h on the cost of entry $\tilde{c_e} = c_e \cdot \tilde{R}$ can be seen by rewriting $\tilde{c_e} = q^h[1 - \hat{R}] + \hat{R}$. We have $\frac{\partial \tilde{R}}{\partial q^h} = 1 - \hat{R} < 0$. A positive change in q^h implies that a larger fraction of the loan c_e can be collateralized and the cost of financing falls as long as $q^h \leq c_e$. Once $q^h > c_e$ an increase in the value of real estate will have no further effect on entry since the loan is already fully collateralized. On the other hand, a decrease in q^h always increases the cost of entry as long as $q^h \geq 0$.

3.4 Equilibrium

The distribution over incumbent firms In the absence of aggregate shocks (as in Hopenhayn and Rogerson (1993)) it is possible to solve for a stationary distribution of incumbent firms λ^*. Although my model incorporates aggregate shocks it is useful to spell out the transition of the firm distribution here, since my non-stochastic simulation method is based on (14). The distribution over incumbent firms in period t is given by λ_t. The mass of entering firms shall be denoted M_t. I will drop the time subscripts for notational convenience. The transition from any λ to λ' will be written as $\lambda' = T(\lambda, M)$. The operator T is linearly homogeneous in λ and M jointly. This implies that if we doubled the amount of firms in this economy and doubled the amount of entrants the resulting distribution would be unchanged.

Assuming that some initial distribution λ_0 exists and given the policy functions for employment and exit we can now write the law of motion of the distribution over incumbent firms. For any set $(e\ x)' \in E \times X$, where E and X respectively denote the employment and exogenous shock space the law of motion for λ can be written as

$$\lambda'((e\ x)' \in E \times X) = \int_{x \in x'} \int_{E \times X} (1 - \phi_x(x, e; \theta)) \times 1_{\{\phi_e(x,e;\theta) \in e'\}} \times F(dx'|x)\lambda(dex) \\ + M \times \int_{x \in x'} \int_{0 \times X} \times 1_{\{\phi_e(x,0;\theta) \in e'\}} \times F(dx'|x)\nu(dx). \quad (14)$$

This defines the operator T. For the case $x = \epsilon$ a stationary distribution λ^* exists.[32]

[32]Equation (15) can be most easily read by fixing an exogenous state x', then integrating over the space of incumbents $(E \times X)$ and selecting those for whom the policy function $\phi_e(\cdot)$ prescribes e'. The term $F(dx'|x)$ defines the probability that a firm with current productivity x has productivity x' next period. This is multiplied with λ to obtain the mass of these firms. The second term refers to entrants, who have mass M. Their initial employment is equal to zero and they cannot exit in the same period as they enter, otherwise the structure is identical. The stationary equilibrium with entry and exit is given by $\lambda^* = (I - \pi')^{-1}(\pi' * E)$,where λ is the distribution over incumbents, π is the transition matrix and E is the distribution over entrants.

Endogenous and Exogenous processes Unemployment follows $U' = (1-U)\delta(U,V) + (1-\phi(U,V))U$, where $\delta(U,V)$ is the separation rate and $\phi(U,V)$ describes the job-finding rate. I assume that the logarithms of both a and ϵ, as well as q^h follow autoregressive processes.

$$\ln a_t = \rho_a \ln a_{t-1} + v_{a,t} \ , \ v_a \sim N(0, \sigma_a) \tag{15}$$

$$\ln \epsilon_t = \rho_\epsilon \ln \epsilon_{t-1} + v_{\epsilon,t} \ , \ v_\epsilon \sim N(0, \sigma_\epsilon) \tag{16}$$

$$q_t^h = \rho_q q_{t-1}^h + v_{q,t} \ , \ v_q \sim N(0, \sigma_q) \tag{17}$$

Equilibrium For a given λ_0 a recursive competitive equilibrium consists of (i) value functions $Q^c(a, \epsilon, e_{-1}; \theta)$ and $Q^e(a, \epsilon_{i,0}, \theta)$, (ii) policy functions $\phi^e(a, \epsilon, e_{-1}; \theta)$ and $\phi^x(a, \epsilon, e_{-1}; \theta)$, (iii) bounded sequences of non-negative negotiated wages $\{w_t\}_{t=0}^{\infty}$ and interest rates $\{\tilde{R}_t\}_{t=0}^{\infty}$, 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) $Q^c(a, \epsilon, e_{-1}; \theta)$, $\phi^e(a, \epsilon, e_{-1}; \theta)$, and $\phi^x(a, \epsilon, e_{-1}; \theta)$ solve the incumbent's problem, (2) $\{w_t\}_{t=0}^{\infty}$ satisfies the worker's participation constraint, and $\{\tilde{R}_t\}_{t=0}^{\infty}$ is given by the bank's zero-profit condition, (3) labor market tightness $\{\theta_t\}_{t=0}^{\infty}$ is determined by the ratio of vacancies $\{V_t\}_{t=0}^{\infty}$ over unemployment $\{U_t\}_{t=0}^{\infty}$, (4) the measure of entrants is given by the free-entry condition (9), (5) λ_t evolves according to (14).

4 Computational Strategy

To determine the optimal employment decision firms need to use the current state of θ in order compute the vacancy-filling rate $H(U,V)$. The aggregate variable θ is determined in equilibrium. While firms take this function as given, it must be consistent with the relationship generated by the model. Without the financing friction this does not generate a computational problem since free-entry of new firms makes the tightness parameter θ respond perfectly elastically to changes in the aggregate state a. In that case there is no need for an approximation as in Krusell and Smith (1998). The model generates unrealistically volatile entry rates and basically reduces the model to a function of the aggregate state a, with some propagation through the adjustment costs.

With financial frictions the free-entry condition is given by (9). The labor-market tightness θ is now a slow-moving state variable about which firms must generate consistent forecasts. The solution of this model is non-trivial since firms need to forecast the entire cross-sectional joint distribution of employment and productivity in order to forecast labor market tightness in the following period. In the presence of aggregate shocks, this distribution moves over time and the state-space becomes (theoretically) infinite-dimensional. Following the seminal work of Krusell and Smith (1998) an approximate solution can be found by postulating that firms track only several moments of this joint distribution. The first moments usually turns out to be a sufficient statistic. The word *sufficient* typically means that the forecast generates a high R^2. However, as Den Haan (2010) has shown, it should also be verified that the maximum forecast errors that result from the approximated law of motion are small. In the present framework firms are ultimately interested in forecasting θ', the labor market tightness next period. The perceived law of motion of θ is denoted $\theta' = \mathbb{H}(\theta, A', A)$, where $\mathbb{H}(\cdot)$ is to be determined as part of the solution of the model. Firms make their forecasts of θ' conditional on the current realizations of θ and A, as well as on possible future realizations A'. The solution algorithm first postulates an initial guess for for $\mathbb{H}(\cdot)$. Next, policy functions are computed given the guess. Following a simulation, the parameters of $\mathbb{H}(\cdot)$ are updated. This procedure is repeated until the difference between the current guess and the updated version of $\mathbb{H}(\cdot)$ are sufficiently close, according to a stopping criterion. I guess a log-linear prediction rule for θ'.

$$\log \theta_t = b_0 + b_1 \log \theta_{t-1} + b_2 \log A_t + b_3 \log A_{t-1} + b_4 \cdot I(A_t \neq A_{t-1})$$

The coefficients that minimize the stopping criterion are given by

$$\log \theta_t = -0.0087123 + 0.99391 \cdot \log \theta_{t-1} + 20.996 \cdot \log A_t - 21.095 \cdot b_3 \log A_{t-1} + 0.23266 \cdot I(A_t \neq A_{t-1}).$$

This functinoal form for $\mathbb{H}(\cdot)$ generates an $R^2 = 0.9994$ and a maximum forecast error of 0.005%. The simulation of the model is carried out 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 representing a combination of 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 latter source of error can become important in Krusell-Smith type solution algorithms. The details of this algorithm are laid out in appendix A.3.

5 Calibration and Results

I calibrate the model at a monthly frequency. The steady state equilibrium without aggregate shocks matches US non-farm establishment level data. All paramter values together with their calibration targets are listed in Table 4. The parameters can be divided into two groups. The first group consists of parameters that either taken from the existing literature or backed out given calibration targets. The second group of parameters to here are estimated with a simulated method of moments (SMM) procedure. The first group includes the discount factor β, the curvature of the profit function α, the parameters governing the evolution of the aggregate state, σ_A and ρ_A, as well as the parameters of the matching function. I assume a constant returns to scale matching function which takes the standard form

$$m = \mu U^{\gamma} V^{1-\gamma} = \mu V \theta^{-\gamma},$$

where $\theta \equiv \frac{V}{U}$ measures the labor market tightness. The job-finding rate of a worker is defined as $\phi = m/U$, which given the functional form for the matching function takes the form

$$\phi = \mu\theta^{1-\gamma}.$$

Similarly the vacancy-filling rate for firms, $H = m/V$ takes the form

$$H = \mu\theta^{-\gamma}.$$

Based on BLS data the average unemployment rate over the time of my sample (1977-2010) was 6.3%, which serves as my target for the steady state. I target a monthly job-finding probability of 0.45. This is in line with empirical evidence in Den Haan *et al.* (2000), Pissarides (2009), Shimer (2012), and Elsby and Michaels (2013), but lower than the estimates in Cooper *et al.* (2007) who find 0.61. The same studies suggest a steady-state value of $\theta = 0.70$. Based on a survey by Pissarides and Petrongolo (2001) the matching elasticity γ is set to 0.60.[33] My target for ϕ together with a choice of γ implies a matching efficiency parameter of $\mu = 0.5132$. I follow Cooper *et al.* (2007) and allow the workers' value of leisure to depend on the aggregate state of the economy: $b(a) = b_0 a^{b_1}$. The parameter b_1 measures the sensitivity of the wage rate with respect to the aggregate state and is set to 0.5 as in Cooper *et al.* (2007). The parameter b_0 is calibrated to match an average firm size of 21.43 from the BDS data.

The labor adjustment costs are given by

$$\mathbb{C} \equiv F - F_v \mathbf{1}^+ - C_v v^2 \mathbf{1}^+ - F_f \mathbf{1}^- - C_f f^2 \mathbf{1}^-.$$

As in Cooper and Haltiwanger (2006) this specification allows for different adjustment costs based on whether a firm is hiring or firing workers. The cost parameters are consistently estimated via SMM, which entails finding the vector of structural parameters Θ. This vector is found by minimizing the (weighted) distance $L(\Theta)$. It is defined as

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

where Γ^{D} are data moments and $\Gamma^{\mathrm{M}}(\Theta)$ 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 $\Gamma^{\mathrm{M}}(\Theta)$. The parameter vector is given by $\Theta = (f, c_f, v, c_v, c_o, \rho_\varepsilon, \sigma_\varepsilon)$. The choice of moments is motivated by Cooper *et al.* (2012) and is shown in the first row of Table 5. The moments are derived from the distribution of employment changes for continuing establishments using Census BDS data between 1985-1999. I use the inaction rate as well as the respective fraction of establishments with certain job creation and destruction rates. For example, JD30 stands for job destruction exceeding 30%, while JC1020 stands for job creation rates between 10% and 20%. The fixed costs play an important role for generating inaction, while the quadratic costs are identified through the

[33] While Cooper *et al.* (2007) estimate this parameter to be .36, Hall (2005*b*) finds 0.72.

Calibrated Parameters	**Symbol**	**Value**	**Calibration Target / Source**
Discount Factor	β	.9967	implies $r^{ann} = 4\%$
Curvature of profit function	α	.65	—
Autocorrelation of a	ρ_a	.988	quarterly $\rho_a = 0.95$
Standard deviation of ν_a	σ_a	.0025	—
Autocorrelation of q^h	ρ_q	.9886	HPI Purchase Only 1991-2012
Standard deviation of ν_q	σ_q	.063	HPI Purchase Only 1991-2012
Matching elasticity	γ	.6	Pissarides and Petrongolo (2001)
Match efficiency	μ	.5132	$\phi = 0.45, \theta = 0.7$
Sensitivity of outside option to a	b_1	0.5	Cooper *et al.* (2007)
Estimated Parameters	**Symbol**	**Value**	**Calibration Target / Source**
Fixed costs vacancies	v		Distribution of Δe, JC
Variable costs vacancies	c_v		Distribution of Δe, JC
Fixed costs firing	f		Distribution of Δe, JD
Variable costs firing	c_f		Distribution of Δe, JD
Fixed costs of operation	c_o		Start-ups $\approx 11.09\%$ of all firms
Outside option	b_0	.58	Average firm size 21.43 (BDS)
Autocorrelation of ε	ρ_ε		
Standard deviation of ε	σ_ε		

Table 4: Parameter Values of the Benchmark Model. The first block consists of calibrated parameters , the parameters in the second block consists were estimated via SMM.

	JC30	**JC1020**	**JC10**	**Inaction**	**JD10**	**JD1020**	**JD30**
DATA	0.15	0.07	0.05	0.38	0.04	0.06	0.14
No restrictions	0.18	0.08	0.00	0.35	0.00	0.02	0.10
Symmetric AC	0.15	0.12	0.05	0.35	0.01	0.11	0.00
No firing costs	0.18	0.12	0.05	0.22	0.03	0.07	0.13
No hiring costs	0.39	0.07	0.02	0.23	0.00	0.05	0.12
No AC	0.14	0.18	0	0.2	0	0.16	0.08

Table 5: LBD Micro data and SMM estimates. Row 2 estimates the benchmark model. Row 3 enforces symmetric adjustment costs (AC) for hiring and firing. Row 4 estimates the model without firing costs, row 5 estimates the model without hiring costs. Row 6 estimates a model without adjustment costs. LBD averages 1985-1999 taken from Berger (2012).

small employment changes. In addition to the moments in Table 5 I use the steady state value of θ as a moment. This is done in order to enforce equilibrium, in the sense that the entrepreneur's beliefs about θ are consistent. Rows 2-6 of Table 5 show estimates for five different specifications of the model. Besides the unconstrained ('benchmark') model I estimate a version without firing costs, without hiring costs, and with symmetric adjustment costs, meaning $f = v$ and $c_f = c_v$. The last row presents estimates from a model without labor adjustment costs. I include these alternative specifications as a robustness check for the business cycle properties of the model and in order to highlight the role of adjustment costs for generating jobless recoveries. Table 5 shows that the fit of the benchmark model is good. The model without adjustment costs is unable to generate small employment changes (JC10, JD10) and generates inaction through a high estimate of ρ_ε. (DISCUSS A BIT MORE) The further analysis of the distributional performance of the calibrated benchmark model is relegated to Table 8 in Appendix A.2, which shows the fit of the firm-age distribution.

I use the national purchase-only house price index (HPI) data from the FHFA to calibrate the process of house prices q^h. I HP-filter the quarterly data with a smoothing parameter $\lambda = 1600$ and compute the autocorrelation and the standard deviation of the innovation. The results can be seen in Table 4. For the policy experiment I conduct below I directly feed the cyclical component of the HPI from 1991Q1-2012Q4 into the model.

5.1 Results with Aggregate Shocks

I now add aggregate shocks to the model in order to assess the business cycle properties of the model and evaluate its quantitative performance. To demonstrate the effect of shocks to aggregate productivity and the HPI, impulse repsonse functions are generated. In a policy experiment I then back out the effects of the fall in the HPI on the increase and persistence of unemployment during and after the Great Recession. Finally, I test alternative model specifications without financial frictions and without adjustment costs in order to build some intuition about the respective effects those features on the results. The main results are summarized in Table 6.

5.1.1 Results of the Full Model

This section describes the results of the full model, meaning that it includes shocks to a, the financial frictions q^h, as well as labor adjustment costs.[34] The model is able to match the key statistics of the US labor market. This can be seen by comparing the first two rows of Table 6. The first row was computed using US Data, while the second row reports moments from 500 model simulations of 1000 periods each. All figures are in log deviations from the mean/trend. The model generates realistic amounts of variability and persistence in unemployment, vacancies, and labor market tightness. Additionally,

[34]Unless otherwise stated I am using the adjustment cost calibration without any restrictions.

	σ_U	ρ_U	σ_V	ρ_V	$\rho_{U,V}$	σ_θ	ρ_θ	$\rho(Y, M^E)$
US Data	0.13	0.948	0.16	0.93	-0.896	0.316	0.94	0.09
Benchmark Model	0.13	0.996	0.17	0.91	-0.86	0.303	0.943	0.09
No Financial Friction	0.17	0.995	0.198	0.95	-0.94	0.359	0.984	0.10
No Shocks to a	0.02	0.99	0.02	0.90	-0.89	0.03	0.97	0.07

Table 6: Data and Model Moments. Source: FRED, FHFA, and BLS. Data (1995Q1-2010Q4) and model moments have been computed as log deviations from trend. Vacancy data starts in 2001Q1. σ denotes the standard deviation and ρ the autocorrelation of unemployment (U), vacancies (V), and labor market tightness $\theta = \frac{V}{U}$. The term $\rho_{U,V}$ is the correlation between unemployment and vacancies, while $\rho(Y, M^E)$ is the correlation between GDP and the mass of entrants.

it does a good job at generating the standard deviation and autocorrelation of unemployment and vacancies. The correlation of GDP and the mass of start-ups is excatly as in the data, although even the benchmark model generates burst of entry that are larger than those observed in the data. This good match in the correlation is achieved through the effect of house prices q^h on the entry process as will be explained below. Furthermore, the model replicates the high correlation between GDP and job creation by incumbent firms. This has been an important feature of the recovery after the Great Recession (see Figure 2).

Compare those results to those of the model without financial frictions and without shocks to aggregate productivity. The main results are summarized in the second and third column of Table 6. This model behaves very similarly to the standard HR model. In particular, the free entry condition becomes very important in this environment. It reduces the computational burden because the future value of θ can be computed without a Krusell-Smith type algorithm for the cross-sectional distribution. The reason is that with free entry aggregate labor demand becomes perfectly elastic and for each a there exists one value of θ which is consistent with equilibrium. Figure 20 in the Appendix A.2 plots results for a sample simulation with non-varying value of collateral q^h.[35] Since the mass of entrants in this model is only influenced by a and θ, the time series of entry is roughly two times more volatile than in the data. The model without financial frictions is unable to generate jobless recoveries. An increase in unemployment in this model can only result from a low realization of the aggregate shock a. However, once a returns to its unconditional mean the unemployment rate reverts back to its pre-recession value almost immediately. The high correlation between unemployment and GDP can be seen in the first panel of Figure 20.

[35] The labor market tightness 'jumps' with the aggregate state. The true and the approximated law of motion are almost indistinguishable. A regression which ignores past realizations of θ produces an $R^2 > 0.99$ and a maximum forecast error of 0.0052%. The R^2 is not equal to 1 because θ influences the interest rate $\hat{R}$ which effects the number of entrants and hence the labor market tightness. Including past realizations of θ into the regression increases the R^2 to over 0.99999999.

The last version of the model to study is the model without labor adjustment costs. Its results are summarized in the last column of Table 6.

The model can generate 'jobless recoveries' through the effect of house prices q^h on the start-up process. Imagine a situation where both aggregate profitability and the HPI are below their unconditional means. Now both shocks start reverting back but - as we will see below - the effects on unemployment and total output of the two shocks differ significantly. Other than the shock to aggregate profitability the shock to q^h exerts only very mild influence on total output. By directly impacting entry, the decrease in q^h has a large effect on hiring by start-ups, and thus on unemployment. The fraction of total hiring by start-ups is overproportional to their share of total output. Therefore, if the number of entrants decreases, the effect on unemployment is larger than the effect on GDP. Incumbent firms are only indirectly affected by the HPI through an effect on θ. On the other hand, shocks to a have the effect that hiring - and most importantly - output by incumbent firms changes. Since the lion's share of total output is produced in incumbent firms, an increase in a after an initial negative shock has an immediate effect on output *and* employment. This is why a shock to a alone cannot generate a jobless recovery. It requires the effect on entry - exerted by shocks to q^h - to make the unemployment rate react sluggishly and uncouple it from the 1:1 movement of GDP. This is what the impulse response functions are going to show.

5.1.2 Impulse Response Functions

In order to disentangle the respective effects of θ and a I show several impulse response functions in Figures 7-9. Figure 7 studies a negative shock to aggregate profitability, Figure 8 shows results for a negative shock to q^h, and in Figure 9 both shocks occur simultaneously. For comparability between the IRFs the size of the (negative) shock to q^h is chosen to generate the same contemporaneous increase in unemployment as a shock to a. The figures are all constructed in the same way: The first panel shows the effect of the shock to the exogenous state. The second panel (clockwise) shows the effects on unemployment and GDP. The third panel plots the labor market tightness θ, while the last panel shows the effect on start-up activity.

I start with Figure 7 where the effects of a drop in a are analyzed. The first panel shows that in period $t = 10$ aggregate profitability falls by 1.22%. This results in an average contemporaneous increase of the unemployment rate by 5.8%, and an average fall in GDP by 1.35%. Labor market tightness falls, both because incumbent firms post fewer vacancies and because there are fewer entrants. The last panel also shows that the mass of entrants quickly rebounds after the initial shock. The reason is that the entrants are facing a trade-off between the lower aggregate profitability and the decreased labor market tightness. The latter has the effect of making it more profitable for potential entrants to start operating. Starting in period $t = 14$ the mass of entrants is above its unconditional mean, beginning to restore the total mass of firms to its pre-recession value.

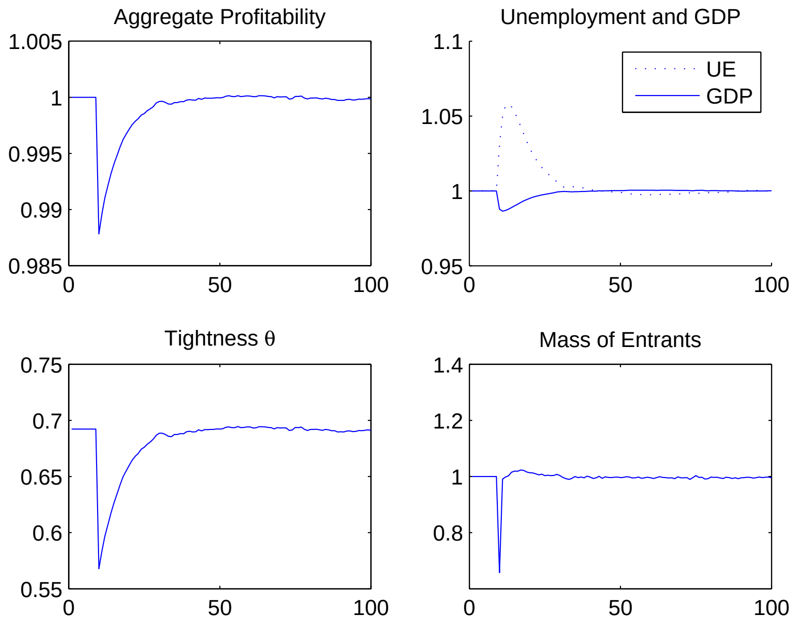

Figure 7: Impulse Response Functions for a shock to a. Simulation results from 10'000 repititions of 200 periods.

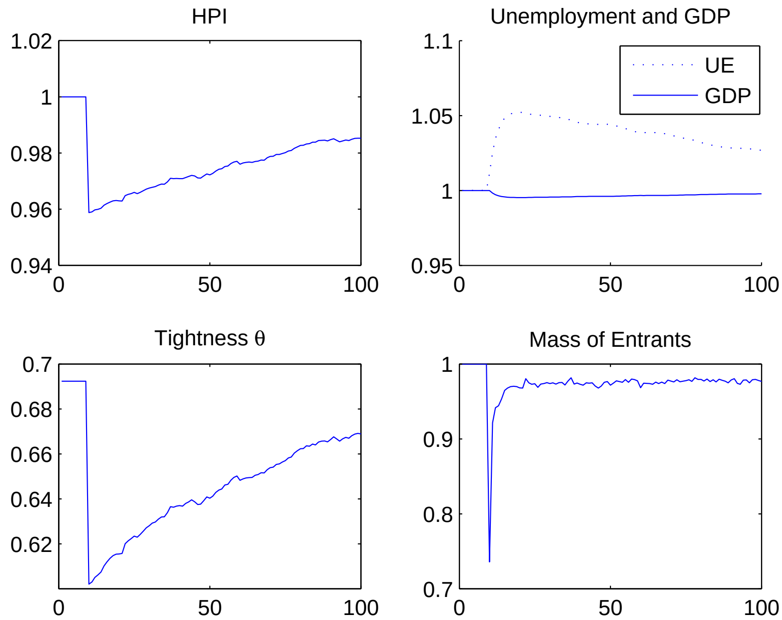

Figure 8: Impulse Response Functions for a shock to q^h. Simulation results from 10'000 repitions of 200 periods.

Now I turn to analyzing the implications of a negative shock to q^h. The first panel of Figure 8 shows that in period $t = 10$ q^h decreases by 4.12%.[36] The shock has been calibrated to generate an average increase in unemployment of 5.80%. This can be seen in the second panel. The shock to q^h produces a smaller decrease in GDP (0.48% on average) than the shock to a. This is because incumbent firms are only indirectly affected by the HPI shock, namely through the effect on θ which is displayed in the third panel. Labor market tightness decreases when the shock occurs and then slowly recovers.[37] The last panel shows the effect on the number of start-ups. The most important difference with respect to the effects of a shock to a is that the mass of entrants is affected both more severely and for a longer period of time. After a rebound to around 92% of its steady-state value in $t = 11$ the entry rate is only gradually moving back towards its unconitional mean. Part of this has to do with the higher persistence of the shock. But note that other than before, there is no 'overshooting' of the entry rate. This is the case in simulations were q^h is reverting to the unconditional mean more quickly than the average. Only as q^h reaches values above 1 does the entry rate exceed unity. The shock

[36]This is a fairly large shock compared to the decrease in the HPI during the Great Recession. The average HPI growth between 2007Q1 and 2011Q1 was -1.46% per quarter, the minimum was -2.88%.

[37]For incumbents firms and hiring entrants this implies that the vacancy-filling probability $H(\theta)$ increases. In the simulation this has the effect that job creation by incumbent firms increases as a result of the shock to q^h (not shown).

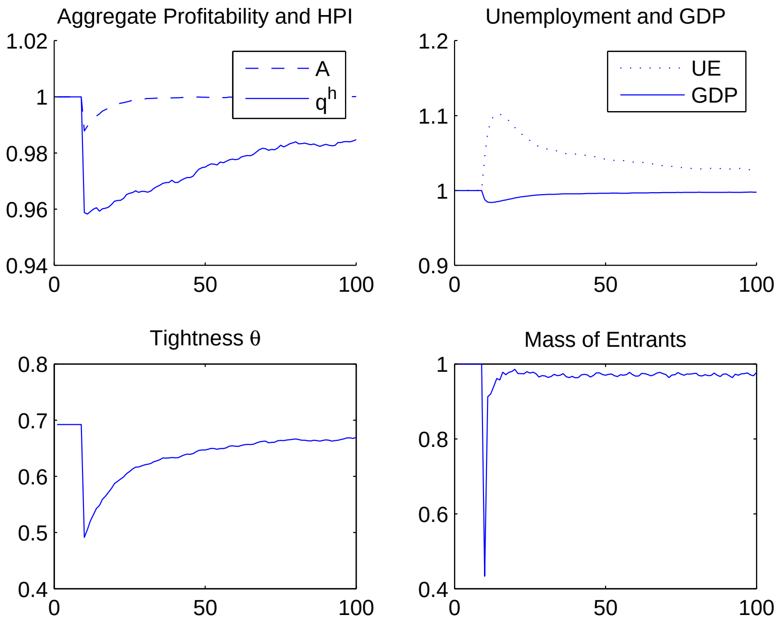

Figure 9: Impulse Response Functions for a shock to a and q^h. Simulation results from 1'000 repititions of 200 periods.

to a generated a tradeoff between lower profitability and lower θ, which induced high entry rates after aggregate productivity had been beginning to recover. The outcome generated by the drop in q^h is different in the sense that the higher entry costs outweigh the effects of the drop in θ for new entrants.[38] This is the main takeaway from Figures 7 and 8: A jobless recovery must be the result of a simultaneous shock to both a and q^h. While the mean reversion of aggregate profitability brings GDP back to its pre-recession value, the slow recovery of the HPI has almost no output effect, but a large positive effect on the unemployment rate. Therefore, although GDP is above its recession trough, the decline in the unemployment rate is strongly underproportional to this decrease.

Figure 9 shows results for a simultaneous shock to a and q^h. The first panel plots the two shock processes. The second panel shows that the average increase in unemployment is 10.2%, while GDP drops by 1.59%, both of which is lower than the sum of the effects of the individual shocks. Both shocks are mean reverting but the persistent q^h shock keeps the unemployment rate high although GDP has practically recovered its pre-shock value (0.9978). The effect on the number of entrants is strong. There is a sharp rebounce in the periods after the initial shock but no overshooting, as the dampening effect of the low q^h prevails over the mean reversion in the shock to a.

[38] In Figure (21) in Appendix A.2 I plot a sample simulation if the only shocks to the economy are to q^h.

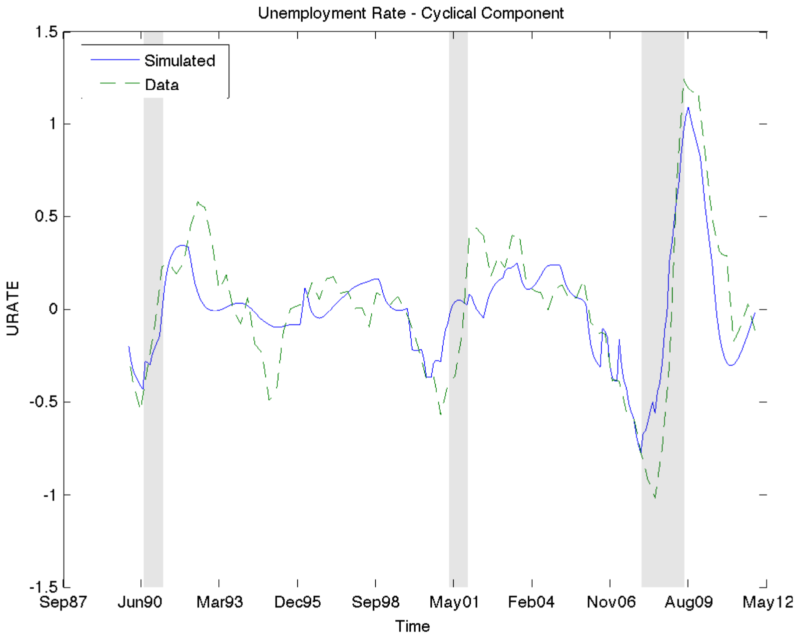

Figure 10: Cyclical component of the unemployment rate. Data vs. simulation using estimated processes for a and q^h between 1990 and 2011. Shaded areas correspond to NBER recession dates.

5.1.3 Policy Experiment

Table 6 showed that the model is able to match they key properties of the US labor market's firm dynamics, as well as movements in unemployment, vacancies, and job creation. The impulse response function were meant to create some intuition about the effect of the two shocks. I now test in how far the model can match the facts which were presented in the introduction and plotted in Figure 11. It showed the relationship between the cyclical components of GDP growth and unemployment during the 'Great Recession': the unemployment rate has remained high even after with positive GDP growth. To evaluate the model's performance in this respect I feed in the observed (HP-filtered) house price index 1990M1 and 2013M3 (see Figure 12). Furthermore, I pick the sequence of aggregate productivity shocks to match the cyclical component of GDP over the same period. I simulate the model for 264 periods after some initial periods for the model to reach the stationary distribution. I choose 264 periods because this corresponds to the monthly data periods between 1990 and 2011.[39] The results are presented in Figure 10. The co-movement of the two time series is extremely strong, particularly during the 'Great Recession', indicated by the shaded area. The simulated data is able to explain 72.23% of the variation of the unemployment rate observed in the

[39]The resulting unemployment series are HP-filtered with $\lambda = 14400$.

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. In Appendix A.2 I repeat this experiment when there are only shocks to a or q^h. Figures 22 and 23 show that although the variation in q^h generates a lot of movement in the unemployment rate it is not enough to reproduce the large increase in unemployment which accompanied the recent recession.[40]

Furthermore, the model is able to reproduce two related facts about the 'Great Recession'. One is that job creation by start-ups decreased prior to the beginning of the recession. The model has this feature simply because the drop in the HPI precedes that in aggregate productivity.[41] The second fact the model can replicate concerns (net) net job creation by incumbent firms vis-à-vis start-ups. Net job creation by incumbents began to recover before job creation by start-ups. In my model this happens because at the end of the recession incumbent firms take advantage of the high vacancy filling probability due to the low θ, while hiring for start-ups remains costly because of the ongoing low q^h which increases the cost for setting up shop. A shortcoming of this is that during the simulation the trough in 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.[42]

6 Conclusion

The recent recession which lasted from the end of 2007 until mid-2009 was severe in many respects. Because the unemployment rate remains far above its pre-crisis level the recovery has been described as jobless. Secondly, the recession was accompanied by an unprecedented fall in the value of real estate. In this paper I claim that these two facts are related. 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 newly entering firms declines.

The number of start-ups in the US has declined by over 20% since 2007. Never since the beginning of the data series in 1977 have there been as few openings of new firms - or as few jobs created by them - than in 2010 and 2011. Young firm's below-trend job creation can account for almost all of the persistently high unemployment rate after the end of the recession.

[40]The q^h shock alone explains about 59.25% and the a shock alone about 56.93% of the variation in unemployment.

[41]The HPI showed negative growth rates as early as Q12006, while the NBER dates the beginning of the recession in Q42007.

[42]While the q^h-only model can also replicate these two facts about job creation by start-ups and incumbents, the a-only model fails to do so because the entry rate overshoots after the end of the recession.

I calibrate and compute a quantitative competitive industry model with endogenous entry and exit, firm heterogeneity, labor adjustment costs, and aggregate shocks. This model is able to match key moments of the firm distribution and employment at the micro- and macro-level. It generates a jobless recovery and is able to explain over 80% of the increase and persistence in unemployment since 2007. I find that the effects of a 'technology shock' alone on the unemployment rate are neither strong, nor persistent enough to correspond to the US data. I estimate that absent the deterioration of value of real estate, the increase in the unemployment rate would have been at around 40% of the actual increase..

In contrast to previous studies...

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Appendix

A.0 Data

The main dataset I use for 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.

I complement the analysis by considering alternative data sources obtained from the Bureau of Labor Statistics (BLS). Virtually all of my qualitative results can also be obtained with the 'Business Employment Dynamics' (BED)series by the BLS. The BED is derived from a quarterly census of all establishments under state unemployment insurance programs, representing about 98 percent of employment on nonfarm payrolls. The data frequency is quarterly. It includes data on firm age and firm size. 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.

Another source released by the BLS is the Current Employment Statistics (CES) program. This is a monthly survey of about 145'000 firms and government agencies, representing roughly 557'000 establishments. Despite its high frequency the survey-nature of the CES and its limited representation of the US economy make this data source less useful for the purpose of the present paper.

The series for house prices come from the Federal Housing Finance Agency (FHFA), which provides national and state-level house price indeces from 1991 onwards. The unemployment rate was obtained from the BLS. The quarterly series of state-level personal income was obtained from the Bureau of Economic Analysis (BEA).

Table 7: Summary Statistics for Variables used in Regression

	N	mean	min	p25	p50	p75	max
empc	3,276	-0.000	-4.4e+04	-1.2e+03	-88.366	975.876	8.1e+04
hpi	3,738	-0.000	-34.978	-2.381	-0.210	1.509	48.872
pi	3,738	0.000	-8.4e+04	-1.4e+03	-98.793	1144.323	8.0e+04
ue	3,738	0.011	-2.460	-0.408	-0.025	0.400	4.135
N	3738						

A.1 Additional Figures

This Appendix includes figures referenced to in the main text.

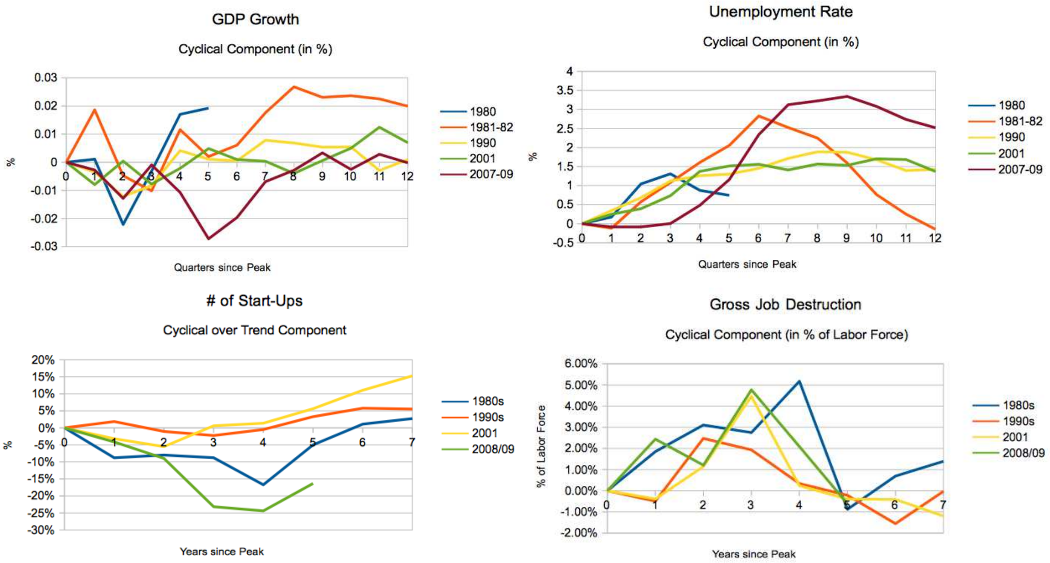


Figure 11: Comparing Recession Episodes: GDP, Unemployment, number of start-ups , and job destruction. GDP and unemployment are quarterly series, start-ups and job destruction are annual. All series are HP-filtered with $\lambda = 100$ for annual and $\lambda = 1600$ for quarterly data. The x-axis shows periods since the respective pre-recession peak, i.e. last period before the official NBER recession date. Employment data comes from the BLS and matches the period of Census data publication. For the annual series I treat the 1980 and 1981/2 recession as a single episode.

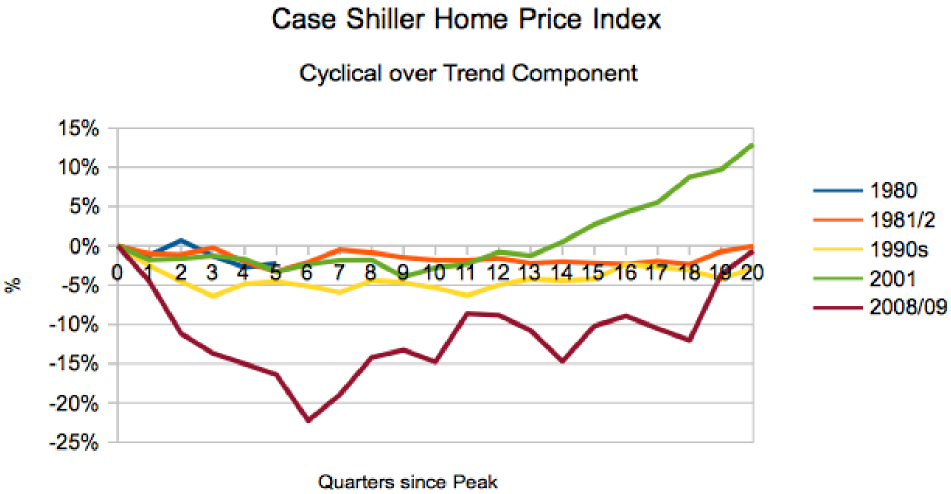


Figure 12: Cash Shiller Home Price Index. HP-filter $\lambda = 1600$. The x-axis shows quarters since the respective pre-recession quarter (based on NBER classification). Inflation-adjusted, not seasonally adjusted. Source: Standard&Poor's. Own computations

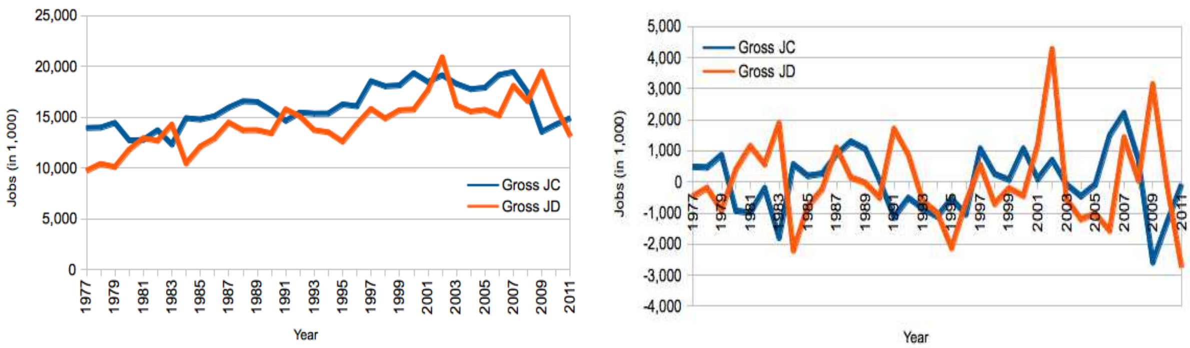


Figure 13: Gross job creation and destruction 1977-2011. The HP-filtered cyclical component is depicted in the right panel. Source: Census, BDS

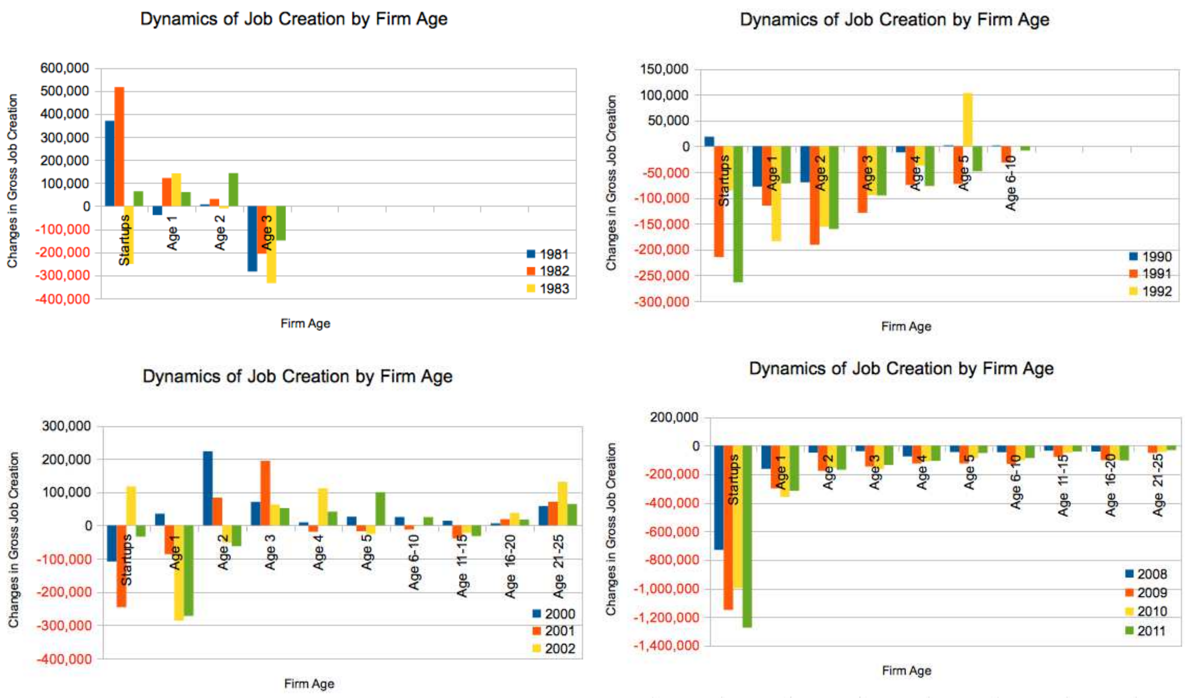


Figure 14: Changes in gross job creation relative to base years 1979, 1989, 1999, and 2006. For age group bins averages are shown. Source: BLS, Business Employment Dynamics, own computations. Note that the 26+ category is missing from this graph because no data is available for this group in 2000.

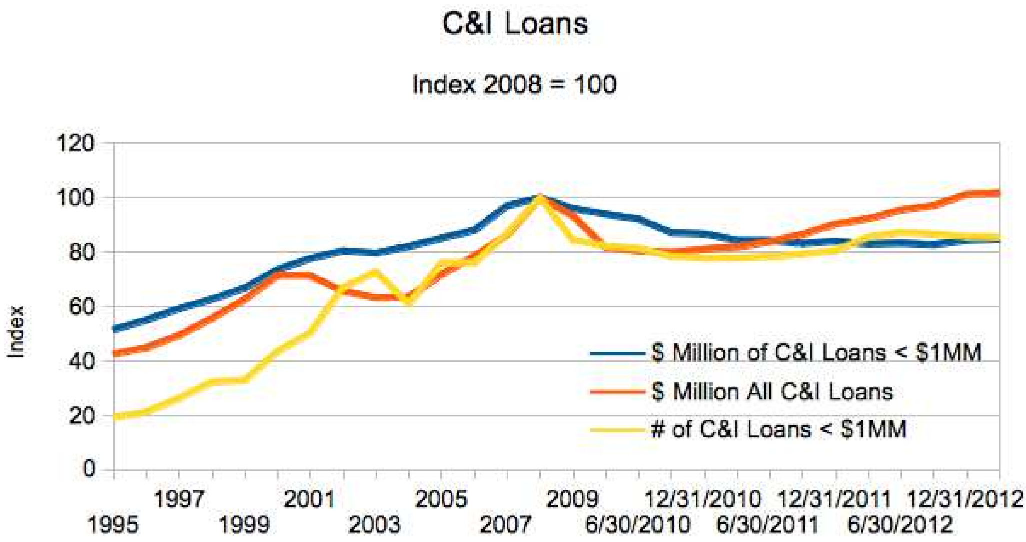
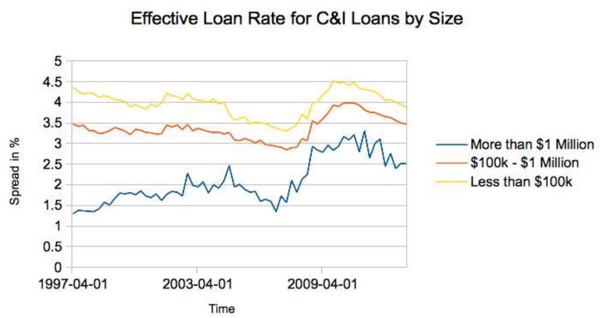


Figure 15: Domestic Commercial and Industrial Loans to U.S. Addressees. Source: FDIC



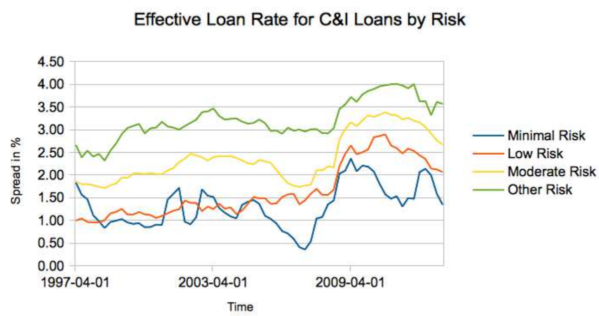


Figure 16: Commercial and Industrial Loan Rates Spreads over intended federal funds rate, by loan sizeand Risk (E2). Source: Federal Reserve

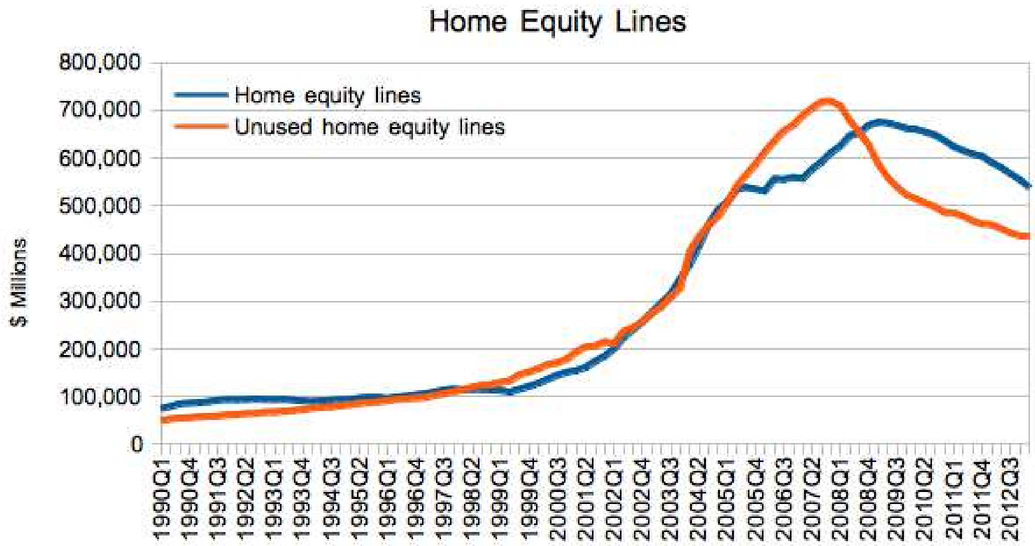


Figure 17: Used and Unused Home Equity Lines. Source: FDIC

Decomposing Changes in the Unemployment Rate Using the formula for the evolution of the steady state unemployment level we can write $u_t = \frac{s_t}{s_t+f_t}$, where s_t and f_t describe the unemployment inflow and outflow hazard rates. Log differentiation of this expression then yields $d\log u_t \approx (1-u_t)[d\log s_t - d\log f_t]$. See Elsby *et al.* (2009) for further details. An increased entry hazard would speak for higher rates of job destruction through layoffs and quits, while a decreased exit probability is related to stalling job creation and/or decreased efficiency of the matching process. While early papers such as Darby *et al.* (1986) suggested that increases in unemployment during recessions are mainly due to increasing number of inflows, the more recent literature has taken the opposite stand. Hall (2005*a*), Hall (2005*b*), and Shimer (2012) have made the claim that modern recessions do not share this feature and are characterized by acylcical inflow rates. I use the Q2 2013 Current Population Survey (CPS) by the Bureau of Labor Statistics (BLS). The left panel of Figure 18 plots the log variation in the inflow *(s)* and outflow rates *(f)*. While the inflow rate increased at the onset of the recent recession, its cyclicality is dwarfed by that of the decrease in the outflow rate. The right panel of the same figure plots the changes in the decomposition of the unemployment rate and leads to the same conclusion: the decreases in the unemployment exit hazard has been the major contributing factor to the continuingly high unemployment rate we observe today. This result strengthens the conclusion summarized in *Observation 1.*

A.2 Model Properties

This Appendix includes derivations and details about the properties and fit of the model.

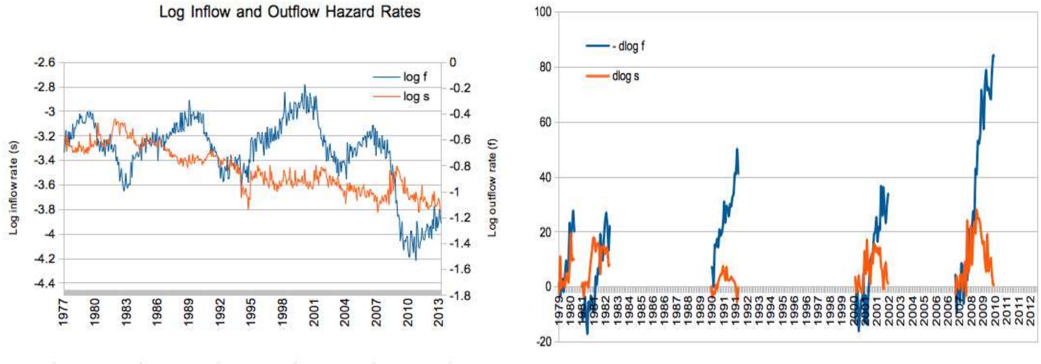


Figure 18: Left: Log inflow hazard rate s (orange, left scale) and log outflow hazard rate f (blue, right scale). Right: Changes in log inflow rates s and log outflow rates f by recession. Changes are shown with respect to start-of-recession values. I follow Elsby *et al.* (2009) in choosing the starting dates as the respective minimum and maximum unemployment rates preceding and following the NBER recession dates. Source: BLS, CPS, own computations.

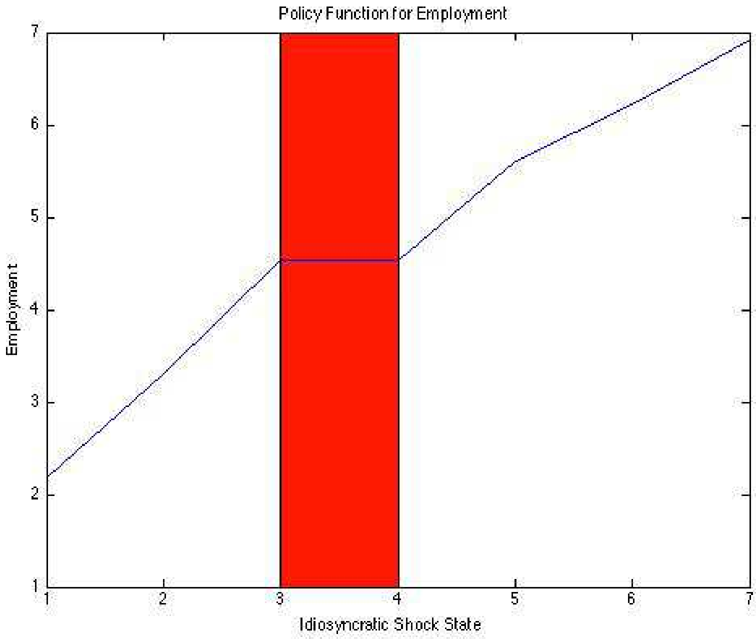


Figure 19: Policy Function for Employment given a value for e_{-1}. The inactivity region is highlighted.

	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5
DATA	11.09%	8.54%	7.22%	6.29%	5.55%	4.97%
Model	11.86%	9.89%	8.83%	7.91%	7.07%	6.29%
	Age 6-10	Age 11-15	Age 16-20	Age 21-25	Age 26+	
DATA	18.67%	12.91%	9.42%	7.18%	8.16%	
Model	18.82%	13.59%	7.30%	3.91%	4.52%	

Table 8: Census BDS data (own calculations) and SMM estimates using the benchmark model.

Figure 20: Sample simulation when the only shocks are to aggregate profitability. The last panel shows the true and approximated values of θ. The series are almost indistinguishable, the prediction produces an $R^2 > 0.998$. The correlation between a and M^E is 0.23 in this simulation. The coefficient of variation of M^E is equal to 0.11 (US Data: 0.0746).

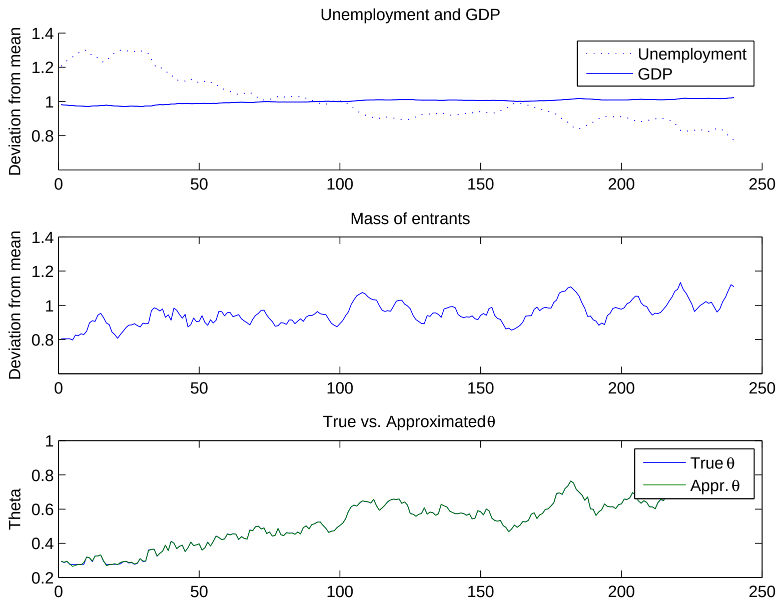


Figure 21: Sample simulation when the only shocks are to HPI. We see in the first panel that the unemployment rate reacts much more strongly to the shocks than GDP. The last panel shows the true and approximated values of θ. The series are almost indistinguishable, the prediction produces an $R^2 > 0.996$. The correlation between q^h and M^E is 0.6239 in this simulation. The coefficient of variation of M^E is equal to 0.0957 (US Data: 0.0746).

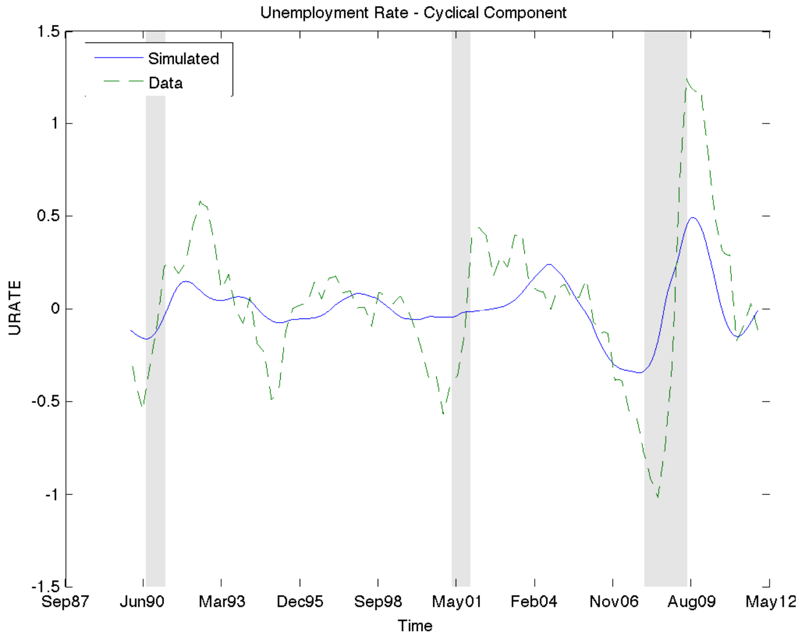


Figure 22: Cyclical component of the unemployment rate. Data vs. simulation using estimated processes only for q^h between 1990 and 2011. Shaded areas correspond to NBER recession dates.

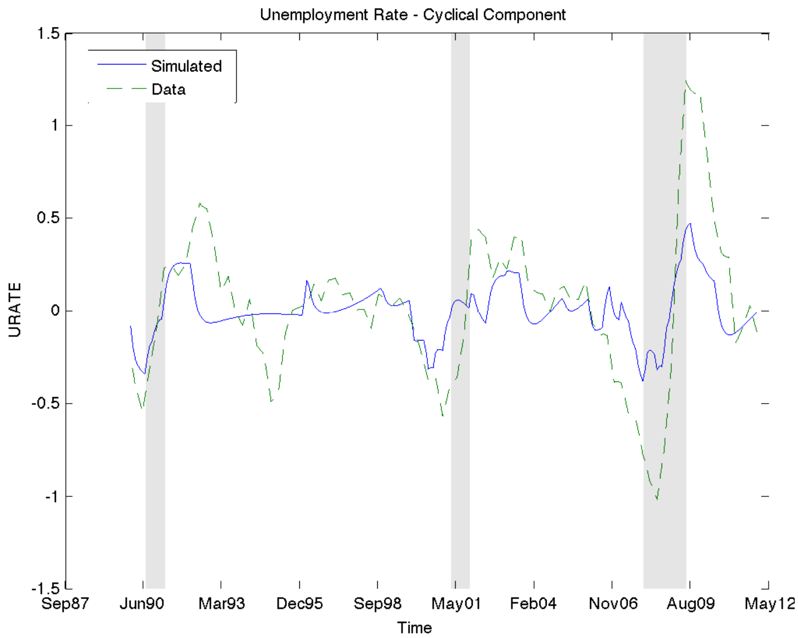


Figure 23: Cyclical component of the unemployment rate. Data vs. simulation using estimated processes only for a between 1990 and 2011. Shaded areas correspond to NBER recession dates.

A.3 Computational Strategy

For the solution of the model I use a non-stochastic grid method. While this method requires finer grids for firm-specific labor and productivity it has the great advantage of eliminating sampling error. As Den Haan (2010) shows, sampling error can lead to severe distortions in the model's results. 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.

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

1. At each grid point incumbent firms decide whether to continue operation or exit. The decision is based on equation (8) above.
2. New firms enter based on equation (9)
3. The aggregate productivity state realizes according to its law of motion specified in (15).
4. The idiosyncratic productivity state realizes. This implies distributing the mass at each point $[n_i, \epsilon_j]$ to a new point $[n_i, \epsilon_k]$, where $k \in [1, 2, \ldots, \#_\epsilon]$, according to the law of motion specified in (16).
5. Apply the employment policy function. This involves distributing the mass at each point $[n_i, \epsilon_k]$ to $[n_i', \epsilon_k]$, where n_i' is given by the firm's policy rule resulting from the maximization of (4).
6. Go back to step 1.

The simulation algorithm takes as given the policy functions for employment (hires, fires, and inaction) ϕ_e, and exit, as well as the laws of motion of all exogenous states, π_ϵ and π_A. To find a solution for a given aggregate state A, it iterates on a distribution over emplyment and idiosyncratic productivity, $\lambda(e, \epsilon)$ 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 $(\#_e \cdot \#_\epsilon \times 1)$, where $\#_e$ and $\#_\epsilon$ respectively refer to the number of grid points for employment and the idiosyncratic shock. In practise 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

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

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 iteration or 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 an aggregate shock the algorithm can obviously not be used to compute a stationary distribution. But the same logic applies and a distribution λ, which then has dimensionality $(\#_e \cdot \#_\epsilon \cdot \#_A \times 1)$ and a transition matrix Γ which then has dimensionality $(\#_e \cdot \#_\epsilon \cdot \#_A \times \#_e \cdot \#_\epsilon \cdot \#_A)$ can be set up. The simulation then consists of drawing a random sequence of realizations of the aggregate shock and computing $\tilde{\lambda}_1 = \tilde{\lambda}_0'\Gamma$. The code is available upon request.

A.Extensions - work in progress

Introducing Financial constraints for all firms I assume that firms are prohibited from accumulating savings.

I introduce a working-capital assumption into the model. Firms have to pay a fraction λ of their period expenses at the beginning of the period. Those expenses include the wage bill we and adjustment costs. To finance those costs, firms borrow from a banking sector. The banking sector is perfectly competitive and provides unlimited funds to entrepreneurs. All bankers share a common discounting and risk-aversion parameter. The utility function is CRRA. At the end of the period, once profits are realized, the entrepreneur pays back the loan to the bank. I assume that an entrepreneur is unable to lie about his end-of-period profit realization.

The price of a loan is negotiated before an entrepreneur's idiosyncratic productivity ϵ is realized. The interest rate is thus determined in expectation of current period productivity. I assume that a bank can perfectly observe ϵ_{-1} (because it can observe employment and profits) and can thus hand out loans at potentially different interest rates, depending on a firm's value of ϵ_{-1}.

The price of a loan is determined by the probability of repayment. In a model without exit and default, the probability of repayment is one and hence all loans have a real interest rate of zero, or $R = 1$. The interest charged by the bank is $R = \frac{1}{(1-y)^{\frac{1}{1-\xi}}}$, where y stands for the risk of default and $-\infty \leq \xi < 1$ represents the banks' risk-aversion parameter. The derivation can be found in the appendix. In the benchmark case where banks are perfectly risk-neutral, i.e. $\xi = 0$, the interest rate is simply $R = \frac{1}{1-y}$. Loans that are being repaid exactly cover the banks' losses from firms that default. Notice the following properties of the optimal interest rate: $\frac{\partial R}{\partial \xi} > 0$, $\frac{\partial R}{\partial y} > 0$, and $\frac{\partial^2 R}{\partial \xi \partial y} > 0$. R is increasing in both y and ξ. Importantly, an increase in ξ will have a larger positive effect on the interest rate for high values of y, i.e. $\frac{\partial^2 R}{\partial \xi \partial y} > 0$.

Alternative wage setting: applying Stole and Zwiebel (1996) To apply the Stole and Zwiebel (1996) framework I assume that the agent's utility function be $Z(c) = c$. As in Elsby and Michaels (2013) this is done to obtain a closed form solution for the problem.