

Startups, Credit, and the Jobless Recovery

Immo Schott*

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Job creation depends on a firm's age. Startups (firms of age zero) and young firms play a crucial role for job creation: they grow faster and create more net jobs than older incumbent firms. During the 2008-2009 recession the jobs created by those firms declined considerably, adversely affecting aggregate employment figures. While net job creation by existing firms is beginning to recover, job creation by startups in 2010 was at its lowest point since 1983 and continues to be at historically low levels. This paper argues that the conditions on the credit market are linked to the 'jobless recovery' phenomenon. Especially young and small firms are still finding it difficult to obtain credit, limiting their growth prospects and job creation. The paper links regional conditions in the US housing market to state-level data on job creation by startups. I then estimate a search model augmented with heterogeneous firms, entry and exit, and financial frictions. This model is able to match key moments of the firm distribution and employment at the micro- and macrolevel. In the context of this model I analyze the effects of a 'credit crunch' and consider possible policies to boost job creation by startups.

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

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1 Introduction

The importance of understanding job creation can hardly be overestimated. Battling persistently high unemployment rates plays a crucial role in bringing the economy back

*Phd candidate, European University Institute, Florence. Special thanks to my supervisor Russell Cooper, as well as Simon Gilchrist who provided me with valuable advice during my stay at BU. I would furthermore like to thank Michael Elsby for a helpful discussion on a related project as well as Rick Clayton of the BLS for pointing out additional data sources for me.

onto a path of economic growth. Yet while the latest unemployment figures are amongst the most anticipated and disseminated economic statistics, relatively little is known about who creates - and who destroys - jobs.¹ Several recent studies have focused on the importance of startups (e.g. Haltiwanger *et al.* (2010), Coles and Kelishomi (2011), and Stangler and Litan (2009)). Every year several hundred thousand new firms are created, providing work for millions of people. 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 economy's firm dynamics: Successful startups become vibrant young firms that together make up the lion's share of net job creation. A consequence of the prominent role of startups is that whenever the creation of new firms in the economy is interrupted, this can have long-lasting adverse effects on job creation and even lead to a jobless recovery. In this paper I will argue that the 'credit crunch' associated to the recent economic crisis has created such an event.

2 Firm Dynamics

The labor market is characterized by extraordinary dynamics, resulting from persistent and large heterogeneity across firms. While some firms are expanding others are contracting, firms are born and firms die. 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. This 'churning' of labor across firms is the result of expansions and contractions in existing firms, as well as of entry and exit. This section points out the main driving forces of the economy's dynamics: startups and young firms.² The next section will then take a closer look at what happened during the recent recession. For this purpose, I use the annual Business Dynamics Statistics (BDS) dataset. A unique feature of the BDS is its longitudinal source data that permit tracking establishments and firms over time. In addition it allows me - other than Hopenhayn and Rogerson (1993) and more recently Lee and Mukoyama (2008) - to not only focus exclusively on the manufacturing sector, but to consider the entire universe of firms and establishments in the US economy.

The importance of startups Startups play a crucial role for at least two reasons. One is their independent importance for net job creation. Figure 1 plots an updated version of a graph used in Coles and Kelishomi (2011). It shows net job creation by startups and incumbent firms and clearly highlights that except in periods of very strong job growth, the contribution of incumbents firms to net job creation is typically negative, while startups create around three million new jobs each year. Whereas incumbents

¹The 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.

²Throughout this paper I will refer to firms of age zero as startups, while firms aged one to five years will be referred to as young firms. All firms are employer firms.

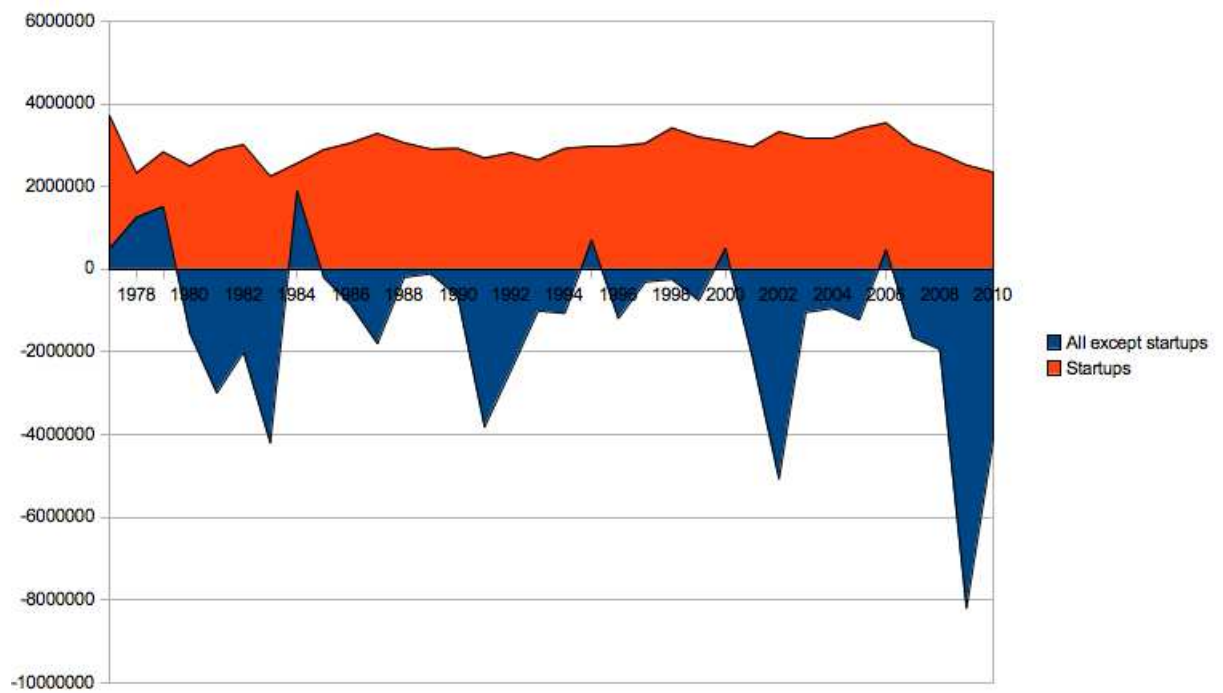


Figure 1: Net job creation by startups vs. incumbents. Source: Census, Longitudinal Business Database

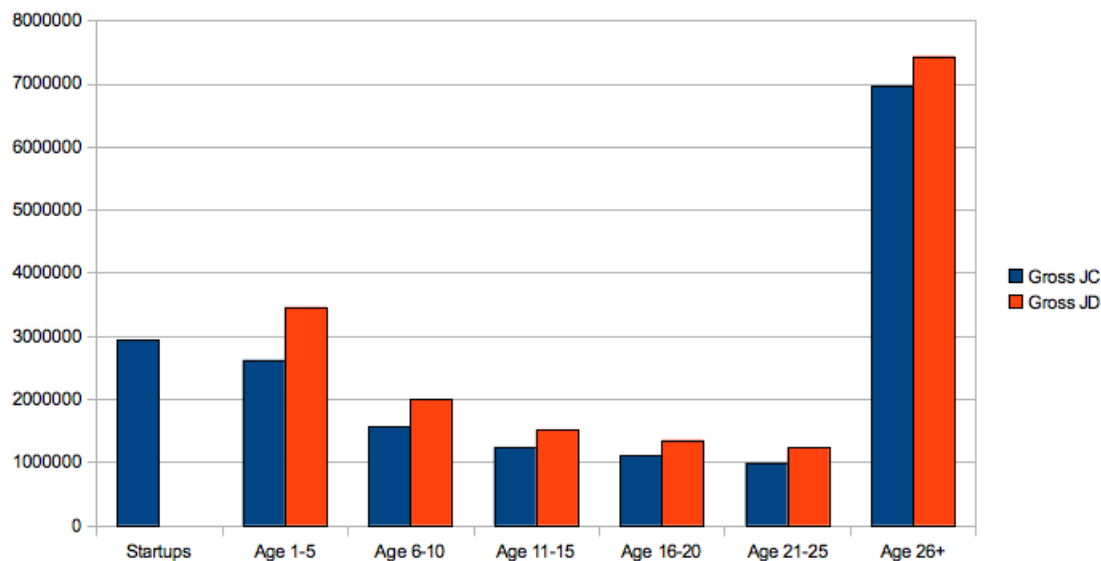


Figure 2: Gross Job Creation and Job Destruction by age. Averages. Source: Census.

show a pronounced cyclical pattern in net job creation patterns, job creation by startups has been much less volatile. However, the recent crisis has clearly left its mark: While net job creation by existing firms is beginning to recover, job creation by startups is at its lowest point since 1983.

The second reason startups are important is linked to what Haltiwanger *et al.* (2010) have labeled 'up or out' dynamics: Conditional on survival, young firms grow faster than their mature counterparts. However, young firms also show very high exit rates. The US Census Business Dynamics Statistics (BDS) data tells us that only 77.36% of all startups are still operating after one year. And only 46.6% of the same cohort are still in business after five years. Figures 2 and 3 sum this up nicely. In Figure 2 we see that young firms aged 1-5 have both higher job creation and job destruction rates than older firms with the exception of the age group 26+, which is right-censored. Job creation essentially comes from startups, young firms aged 1-5 as well as mature firms. Figure 3 highlights the heterogeneity within the group of young firms. While successful businesses expand and show strong job creation, exit is prevalent among their less successful counterparts. On the contrary, downsizing rather than exit plays the dominant role for job destruction later during a firm's life cycle. Taken together, these facts imply that those startups that do survive become extraordinary contributors to job creation during the first years of their life.

Taken together, startups emerge as decisive in the continuous process of labor reallocation in the economy. First, they constitute the single largest contributor to job creation. Secondly, a vital part of the economy's labor market dynamics is spurred by the up or out behavior of startups during the first years of their existence.

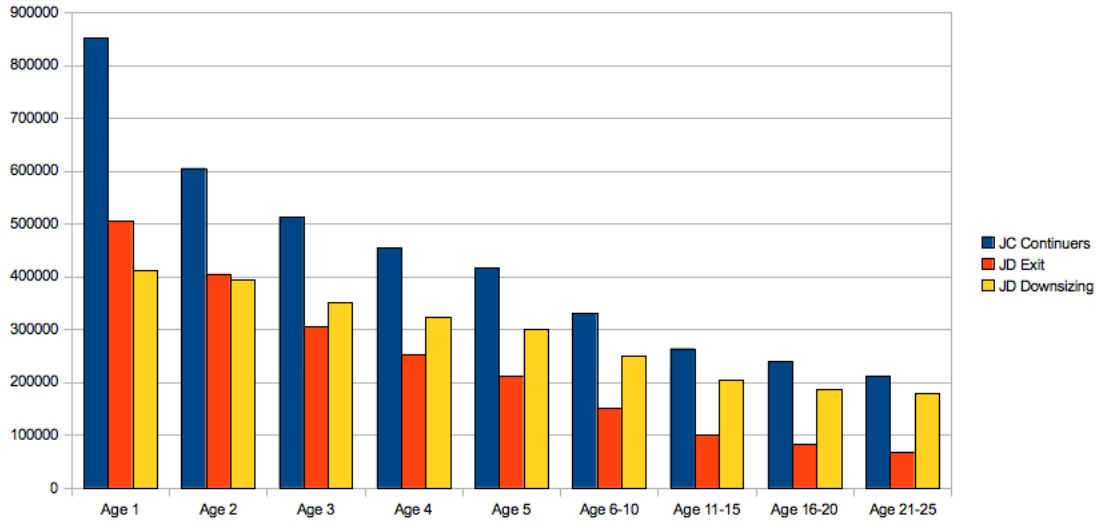


Figure 3: Gross Job Creation and Job Destruction from Exit and Downsizing by age.
Source: Census. Own computations.

The importance of young firms Let us now take a closer look at the early years in a firm's life. I want to show that whenever startup activity is low, this has long-lasting consequences for the economy. Both startups and young firms are marked by overproportional employment growth. In any given year, around 3% of the US workforce is employed in startups. This figure becomes substantial in the light of an average annual net employment growth of 1.62% since 1977. Furthermore, as we saw above startups account for virtually all net job creation, and for about 18.5% of gross job creation. The picture for young firms looks similar. While on average 13.5% of the labor force are employed in those firms, they contribute 21.2% of all gross job creation.

To show the long-run consequences of low job creation by startups for the economy, I return to the Census BDS data. This data permits me to study the life cycle of different cohorts of startups.³ Specifically, I am interested in whether the initial employment level of a cohort is a good predictor for employment levels at a later point in time. The answer to this question turns out to be yes. I perform an analysis similar to Reedy and Litan (2011): The size (number of firms) and employment level of each cohort is normalized to 100. Then I compare the largest 20% of cohorts at birth (both in terms of employment and number of firms) to the remaining cohorts.⁴ Table 1 summarizes the results. The 20% of cohorts that started out with the highest absolute initial employment levels (row 1) show on average a five percent increase in employment during the first year. The remaining cohorts (row 2) show an average two percent decline. At ages three and five the cohorts with a high initial levels of employment still retained a larger fraction of their

³For what follows I use only those years where data for the first five years is available, i.e. 1977-2005.

The recent crisis is dealt with in a separate section below.

⁴Changing this margin to anything between 10 and 30% does not alter the results much.

Employment			
	After 1 year	After 3 years	After 5 years
Top 20% initial emp. cohorts	105	90	82
All remaining cohorts	98	85	77
	After 1 year	After 3 years	After 5 years
Top 20% initial # of firms cohorts	100	90	81
Remaining cohorts	102	87	81
Number of firms			
	After 1 year	After 3 years	After 5 years
Top 20% initial # of firms cohorts	77	57	45
Remaining cohorts	78	58	47

Table 1: Employment and number of firms after 1, 3, 5 years. Initial values normalized to 100 in all cases. Source: Census BDS, own computations

initial workforce. The correlation between employment at birth and employment at year 1 (years 3 & 5) is .78 (.82 & .74). This goes against the idea that cohorts *catch up* on employment growth later during their life when initial conditions were unfavorable for large employment levels. This results from the firm dynamics which I described above. The early years of a firm's life are decisive in determining its employment life cycle. We can perform a similar analysis based on the number of firms in a given cohort but this factor seems to be of less importance. A clear systematic relationship is missing between the initial number of firms in a cohort and its employment level over time (rows 3-4). Furthermore, the number of firms in a given cohort evolves very similarly among large and small cohorts (rows 5-6). This implies that a good indicator for large job creation by a cohort is its initial employment level, not simply the number of startups.⁵

Size and Age-Size Distribution There is one other feature of the Census data which should be highlighted. The BDS provides data by firm age and size, as well as by firm age and initial firm size, which we will come back to below. This aspect of studying age and size jointly has received relatively little attention in the literature so far but holds some illuminating insights about job creation and will be important for the calibration of my model later on. It also underlines the importance of heterogeneity among startups and young firms. For this part of the analysis I create four size categories, 1-19, 20-99, 100-499, or 500+ employees.⁶ The distribution of firms over size categories is given in Table 2. The fact that the distribution over establishments differs from the distribution

⁵The absence of 'catch-up growth' among firms can be interpreted in different ways. One way that fits the modeling approach quite well is that firms enjoy a certain productivity level for rather short amounts of time. This can be seen as a limited amount of time to establish a product or to remain at the technological frontier.

⁶One 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

	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%

Table 2: Size Distribution. Source: Census/BDS. Employment is calculated using the DHS-denominator.

	1-19	20-99	100-499	500-999
Number of Startups	98.1%	1.75%	0.14%	0.01%
Startup Employment	69.36%	20.90%	8.26%	1.47%

Table 3: Distribution of startups by number of firms and initial employment.

over firms reflects the fact that small firms often consist of a single establishment, while large firms are frequently composed of several establishments. The average firm size is 21.43 workers, while the average establishment size is 16.99 workers. We can devise a similar table for the distribution of startups (Table 3). It shows that the majority of startups starts with less than 19 employees. Larger startups are rarer, but contribute overproportionally to employment growth.⁷ The distribution of firm ages is given in Table

Comparing Recessions 1977-present We can compare different recession periods and the ways in which GDP, the unemployment rate, the HPI (after 1991), and employment by different categories of firms moved together. For this exercise I first remove a time

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.

⁷In practise, firms that show up in the CES or comparable surveys as being both young and large should be treated with caution, as they are often temporary entities that get folded into other firms.

	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5
Firms	11.18%	8.62%	7.28%	6.32%	5.57%	4.97%
Employment	3.19%	3.18%	2.90%	2.71%	2.56%	2.43%
	Age 6-10	Age 11-15	Age 16-20	Age 21-25	Age 26+	
Firms						
Employment	18.69%	12.91%	9.44%	7.15%	7.88%	

Table 4: Age Distribution. Source: Census/BDS. Employment is calculated using the DHS-denominator.

trend (where warranted) and then compute percentage deviations from the trend.⁸ Figures 15 - 18 (in the Appendix) compare four different recession episodes since 1977, the beginning of the BDS data. This exercise highlights four points. First, the different recession episodes had different consequences on the employment of startups. Second, the behavior of startups is almost entirely driven by those with initially under 100 employees. Third, the HPI and startup activity appear to be linked. And finally, it is not very revealing to focus solely on 'small' or 'large' firms.

I treat the time between 1980 and 1982 as a single recession episode. We see (Figure 15) that while the time series for small and large firms move almost in sync with GDP, startups show more volatility. This observation holds for all the recession episodes. After an initial decrease in startup employment the series recovers and then decreases again. GDP, the unemployment rate, and startup employment start recovering in 1983 (the recession officially ended in November 1982).

Between July 1990 and March 1991 the US economy was in a recession and startup employment fell (Figure 16). Similarly to the previous recession episode there was a short recovery followed by a second decline in startup employment which was only stopped several years after the recession was officially over. Again, we notice that the unemployment rate started decreasing at the same time that startup employment began to rebound.

The 2001 recession (Figure 17) led to a decline in startup employment, which, however, remained at all times above trend. Despite the decline in GDP job creation by startups was back to high levels in 2002. The growth rates of the HPI showed almost no variation during the crisis.

The recent crisis (Figure 18) will be the topic of the following section. It presents us with a slightly different picture. Together with the decline in house prices there was a sharp decrease in startup employment. Again this was mainly caused by small startups. Simply looking at different firm sizes shows no comparable trend. The rebound in HPI that started in 2011 (not shown) can be seen as a positive signal for startup employment.

To sum up this section I produce several cross-correlations functions (shown in the Appendix). These show that over the entire time period covered by the data, startup employment tends to precede GDP, while the HPI precedes startup employment (Figure 19). Secondly, Figure 20 shows that the cross-correlations of the unemployment rate with startup employment behaves very differently from that with small or large firms (the latter is not shown). While increases in startup employment are negative correlated with the unemployment rate at lag zero to four, an increase in small firm employment is positively correlated with the unemployment rate at lag zero. This highlights that while startups mostly start small, it is not small firms *per se* that are engines of employment growth (as in Haltiwanger *et al.* (2010)).

⁸Where no significant time trend was found I computed percentage deviations from the mean. There was a statistically significant time trend in GDP and in the employment time series of different size categories. There was no trend in the overall startup employment series nor in the size-categories except for the 100-499 and 500-999 series. The unemployment rate is plotted in percentage points. The HPI is plotted in yearly growth rates.

2.1 Employment Dynamics during the 2008 crisis

The 2008-09 crisis has been labeled the 'Great Recession'. This is not only due to its magnitude but also because the US-recovery from the recession which officially ended in June 2009 (NBER) is still sluggish: Although the economy has shown positive growth rates since the third quarter of 2009 the unemployment rate remains at a high level. It has come down from its peak of 10% in the fall of 2009 to 8.2% in May 2012, which is still very high compared to historical averages and the 5% unemployment rate in 2007 prior to the recession. Employment relative to the working age population was lower in September 2012 than at the height of the financial crisis. These phenomena have received wide public attention under the name of 'jobless recovery'. This term lacks a clear definition but is commonly employed to describe periods of GDP growth with underproportional or no decline in the unemployment rate. A crisis on the labor market can have various reasons. I proceed by analyzing the most recent data from various sources like the US Census and the Bureau of Labor Statistics (BLS).⁹ Many previous studies often focus on the subset of manufacturing firms or data derived from survey data. My research question centers on the role of startups for job creation. I investigate the effect of a tightening of credit supply for new firms and want to gain insights into the interaction of credit market imperfections and labor market rigidities. As a first step I take a broad look at the data to determine some characteristics of the recent crisis that I believe to be important for the economic model. Then I focus more on the role of startups and young firms during the recent downturn.

Figure 4 plots gross job creation (JC) and job destruction (JD) from 1977 to 2010. We see that in boom times JC is above JD, representing employment growth.¹⁰ During recession times - at the beginning of the 1980s, the early 1990s, 2001 and 2008/09 - job destruction surpasses job creation and the economy loses jobs. The recent recession episode is noteworthy in several aspects. One is that the gap between gross job creation and gross job destruction was considerably larger than in previous recessions. This was the result of both an increase in gross job destruction and a decrease in gross job creation. However, the change in the decrease in job creation was considerably larger than the change in the increase in job destruction, especially compared to previous recession episodes.

We can consider the two time series in more detail. Let us first direct our attention to job destruction. Although job destruction increased, it did so far less than during the

⁹For this and most of the following figures I use the Census' BDS data. 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. 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 the results for the BDS data. 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.

¹⁰I use the NBER recession dates for my classifications.

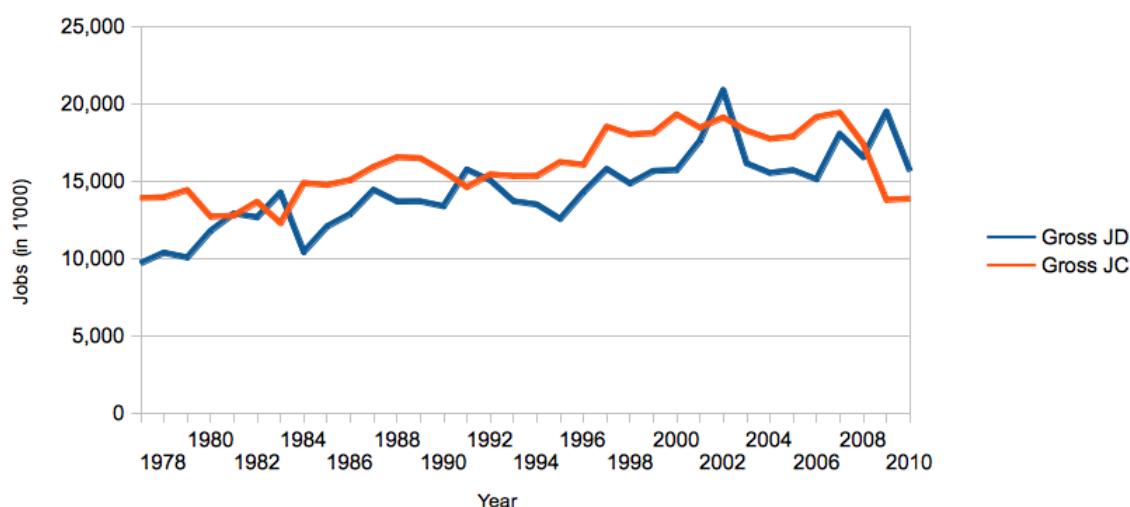


Figure 4: Gross job creation and destruction 1977-2010. Source: Census, BDS

previous recession in 2001. Most job destruction took place on the intensive margin, that is through downsizings of existing establishments. Establishment deaths contributed to less than 30% of all job destruction since 2009 (average since 1977: 35%). The recent crisis was not marked by a high number of exits, nor, by historical standards, by extraordinary levels of job destruction.

If we now turn to the job creation series, we find that the sharp drop in job creation was what made this crisis particularly severe. It achieved a record low in 2009 and continued on this low level into 2010. The years 2009 and 2008 marked the first and second largest decreases in gross job creation in the entire Census data. This is summarized in the following observation.

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

I want to reinforce this point by considering an alternative data set. This is warranted because in the literature there has been a controversy about the relative importance of an increased hazard of entering unemployment during recessions versus a decrease in the unemployment exit probability. 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 (2005a), Hall (2005b), and Shimer (2012) have made the claim that modern recessions do not share this feature and are characterized by acyclical inflow rates. Using a methodology developed in Elsby *et al.* (2009) I decompose changes in the unemployment rate into changes due to variations in the inflow rate and changes

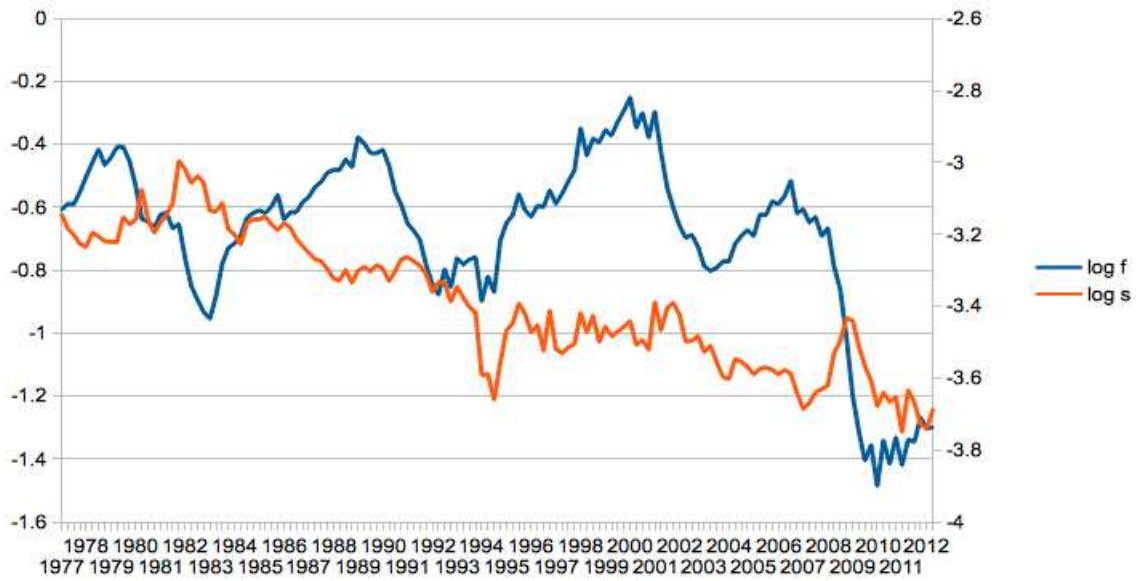


Figure 5: Log inflow hazard rate s (blue, right scale) and log outflow hazard rate f (orange, left scale)

due to variations in the outflow rate of unemployment. 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 $d \log u_t \approx (1 - u_t)[d \log s_t - d \log f_t]$.¹¹ Using this decomposition Elsby *et al.* (2009) and Elsby *et al.* (2010) have shown that the inflow rate is not acyclical, but continues to play a role for increases in the unemployment rate. Using the most recent BLS-CPS data (Q3 2012) I confirm their argument that the inflow rate is not completely acyclical. However, there is a clear picture emerging that the increase in the unemployment rate was mostly a result of decreases in the *outflow* from unemployment. Figure 5 plots the log variation in the inflow and outflow rates. Furthermore, the low outflow rates continue to adversely affect the economy and are the key to understanding the 'jobless recovery' phenomenon. While the inflow rate increased at the onset of the recent recession, its cyclicity is dwarfed by that of the decrease in the outflow rate. Notably, the outflow rate continues to be depressed. Figure 6 directly plots the changes in the decomposition of the unemployment rate. The changes are plotted with respect to start-of-recession values.¹² The same picture emerges: 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 obtained

¹¹See Elsby *et al.* (2009) for further details.

¹²I follow Elsby *et al.* (2009) in choosing the starting dates which slightly differ from the NBER cycles dates. For the 2008/09 recession changes are plotted with respect to the second quarter of 2007.

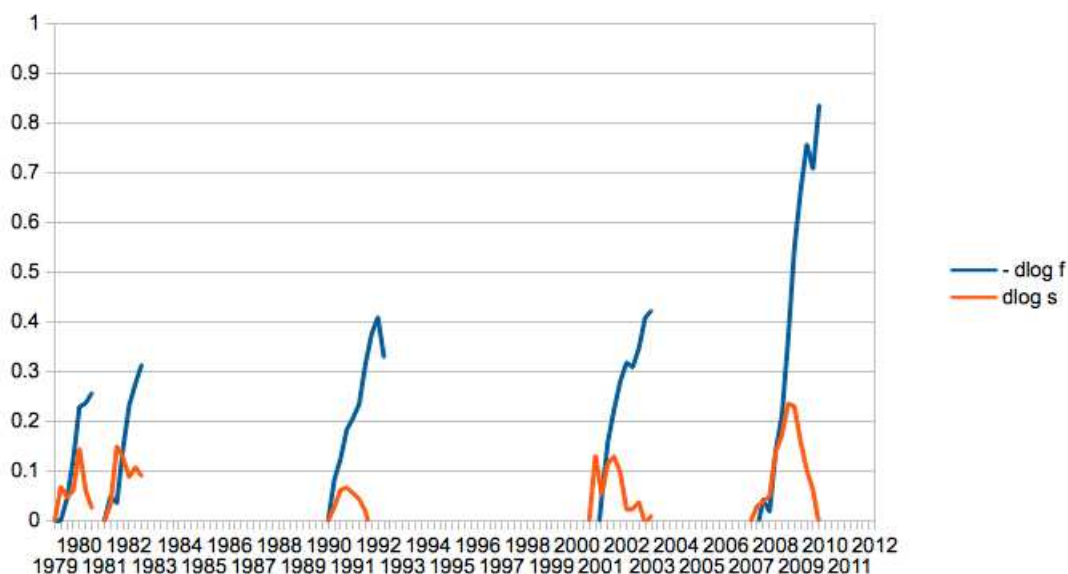


Figure 6: Changes in log inflow and log outflow rates by recession

from studying the BDS data that low job creation made the last recession particularly severe.

The next logical question to ask, then, is what type of firms drove low net job creation. Figure 7 makes a first stab at an answer. The figure plots changes in gross job creation by age firm age relative to a base year 2007.¹³ We see that the largest decrease in gross job creation occurred in the group of startups, followed by the youngest firms. All age groups except the group 26+ saw decreases in gross job creation in all three years covered by the data since 2007. For the 2001 recession the picture looks different. While startup job creation also declined, it did so much less (both in absolute and relative terms) than other age groups and gross job creation in startups quickly rebounded to above its pre-recession level (see Figure 14 in the Appendix). Another noteworthy aspect of Figure 7 is that while most age groups saw a recovery of gross job creation, we observe an ongoing decline for startups and one-year old firms in 2010. Given the firm dynamics described above this is an indicator of continuously low job growth in the future.

Observation 2: *The decrease in gross job creation was to a large part due to lower job creation by startups and young firms.*

¹³Choosing another base year, e.g. 2006 or 2002 leaves results virtually unchanged. The same is true for plotting percentage deviations from pre-recession levels. The graph is omitting the left-censored group of firms because this group is constantly shrinking by definition. That group also shows a drop in gross job creation since 2007.

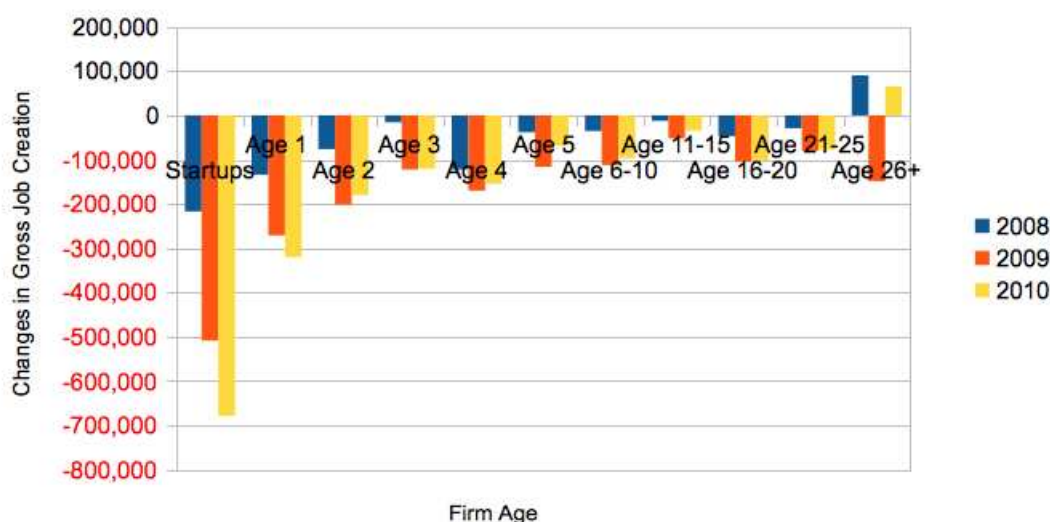


Figure 7: Changes in gross job creation relative to base year 2007. For age group bins averages are shown. Source: BLS, Business Employment Dynamics, own computation

Sanchez and Liborio, 2012 use BED data to point out that the number of startups in the last quarter of 2010 were still 6.2% below the pre-recession peak, while Haltiwanger *et al.* (2012) remark that the decline in startup employment is ubiquitous across states. They also note, however, that states that were hit hardest by the crisis suffered larger decreases in startup employment, a point that I will take up further below because it hints at a link between startup creation and credit availability. Furthermore, the data shows that the decline in startup job creation was common to all sectors.¹⁴

It is interesting to note that the average size of a startup has virtually remained unchanged over the years at around 6 employees. Also the ratio of gross job creation from expansions of existing establishments vs. new establishment entry shows relatively little time series variation and has hardly been affected by the recent crisis.

Age and Initial Size We can now come back to the size-age categories of firms. As a result of the 2008 recession there was a pronounced decrease in the number of startups. This naturally affected all firm size categories, yet the number of firms that started out with less than 100 employees were most markedly affected. The number of startups with 1-19 employees was as of 2009 over 15% below trend, the number of startups starting with 20-99 employees was at around 18% below trend. In the same year employment in startups sized 1-19 (20-99) was 20.09% (18.43%) below trend. Negative employment

¹⁴While the 2001 downturn mostly affected Manufacturing, Trade and Transportation, Communication, and Public Utilities, the recent recession affected the sectors Mining, Construction, Manufacturing, and Finance, Insurance, and Real Estate the most in terms of employment by startups.

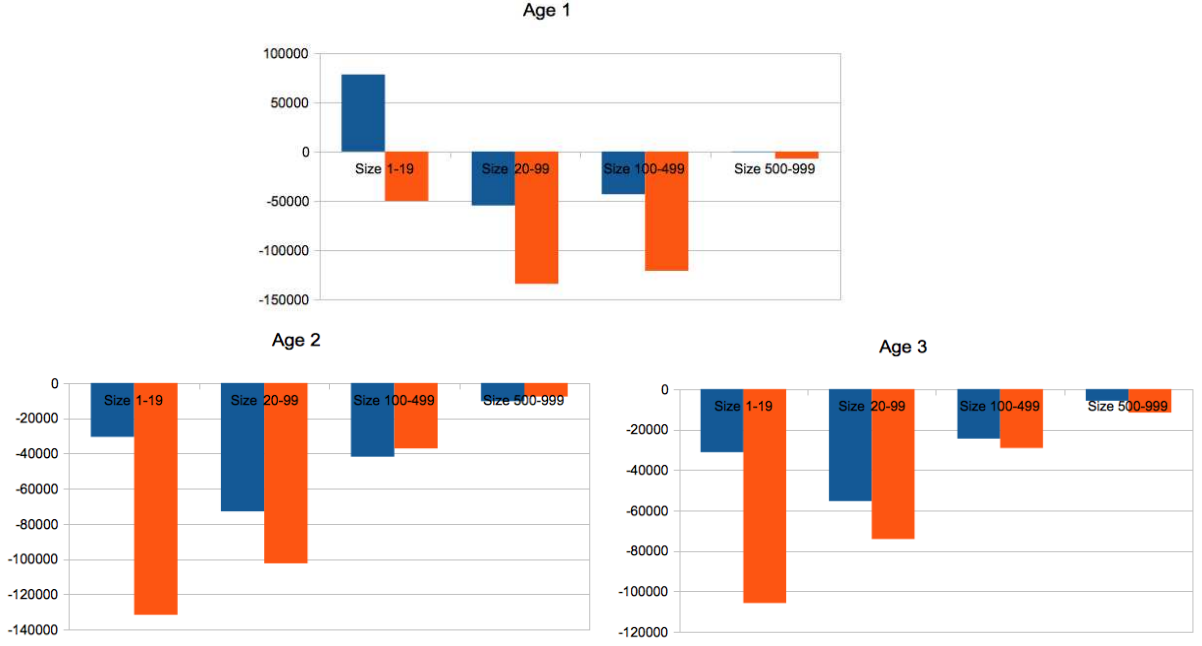


Figure 8: Net Job Creation before and during the recent crisis by initial firm size for Age 1,2, and 3. Source: BDS, own computations

growth rates during the 2001 recession were much below these numbers. All this suggests that founders of small and medium sized startups experienced the crisis differently from those founding initially larger firms.¹⁵

Let us turn to firm dynamics during the first years of their lives. The Census BDS data by age and *initial* size allows us to track a cohort of establishments over time, given their initial employment level. Figure 8 plots net job creation by different classes of age and initial size. The graph shows net job creation before and during the recent crisis and illustrates that it was mainly small young firms that showed lower job creation. In fact, by comparing the years 2008 (2009) with the pre-crisis year 2007, we see that 60.06% (70.48%) of the overall decrease in gross job creation by startups was due to the decrease in small startups (1-19 employees).

2.2 Summing up

Before we turn to the question of credit availability, let us sum up some preliminary results. Based on the above discussion, my proposed view of the recent crisis is closely tight to the understanding of firm dynamics. First, I have argued that startups are a crucial component of job creation. The relatively invariant job creation rates of startups

¹⁵The time series for larger firms are much more volatile due to the lower number of firms. In addition, I do not make any statements here about startups with more than 1000 employees at birth because these are often entities that get folded into other firms later on.

described in Coles and Kelishomi (2011) have taken a prolonged dive since the onset of the recent crisis. There have never been as few startups than in 2010. Furthermore, those 395'000 startups that entered in 2010 created a historically low number of jobs.¹⁶ For the first time in Census BDS data records has the employment created by startups decreased four consecutive years (in 2010). In a second step I argued that startups also matter because they turn into young firms who are another key driver of job creation. However, similarly to startups young firms have been hit especially hard by the crisis. Gross job creation by firms aged 1-5 is only at 58% of its 2000 level, compared to 75% by old firms (aged 6 and older). Next I argued that firm cohorts that start out with little employment as startups tend to have lower employment levels later on. This implies a rather pessimistic outlook on future job creation. The section concluded by stating that small young firms were hit especially hard by the recent crisis, in ways not seen for example in the 2001 recession. I will now argue that the low availability of credit for young firms is the key to understanding low job creation figures.

3 Startup Financing and Credit supply

I want to convince the reader that adverse conditions in credit supply (or more generally the unavailability of funds) are linked to the fact that fewer jobs are being created by startups.¹⁷ The data shortfall makes it challenging to determine whether the decline in business lending by banks has been driven by demand or supply side factors.¹⁸ In this section I will bring together recent data and previous studies that together lend support my hypothesis. Many of the reports referred to below focus on 'small businesses', not startups per se.¹⁹ However, as I discussed above a vast majority of startups falls into this size category during the early years of its life.

Banks are the most important source of credit for emerging businesses ({United States Congressional Over 2010; Dennis Jr., 2010). The financial crisis and the 2008-09 recession caused bank profitability to decline significantly and produced an increase in commercial and industrial loan rates spreads over intended federal funds rate.²⁰ This is shown in Figure 9. The increases that can be observed after the 2001 recession are markedly smaller. Data from the Federal Deposit Insurance Corporation (FDIC) shows that commercial and industrial lending has decreased during the recent recession (Figure 10). The recovery in business lending is not observable for all loan categories: According to FDIC's quarterly banking profile the amount of small business loans (business loans under \$1 million) has

¹⁶In 2010 there were 2'344'682 jobs created by startups. This figure was only lower in 1978 and 1983, years that followed occurrences of strong job creation.

¹⁷See e.g. Campello *et al.* (2010) or Bassett *et al.* (2012) for studies showing that a decrease in credit supply is likely to have real effects as well as a discussion on how to disentangle demand from supply effects.

¹⁸This data shortfall was highlighted and discussed in a special forum organized by the Federal Reserve in July 2010. See <http://www.federalreserve.gov/events/conferences/2010/sbc/agenda.htm> for details.

¹⁹The definitions of what exactly constitutes a 'small business' vary. For the most part, all businesses with less than 500 employees fall into this category.

²⁰C&I loans may be secured or unsecured but are not secured by real estate.

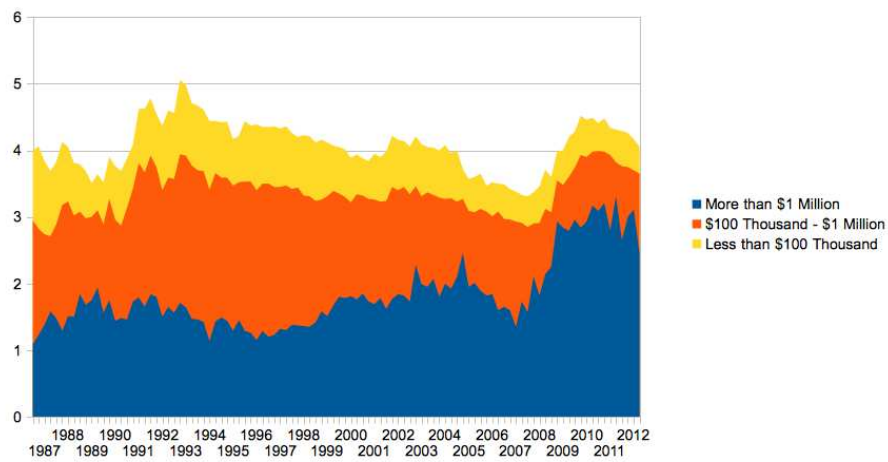


Figure 9: Commercial and Industrial Loan Rates Spreads over intended federal funds rate, by loan size (E2). Source: Federal Reserve

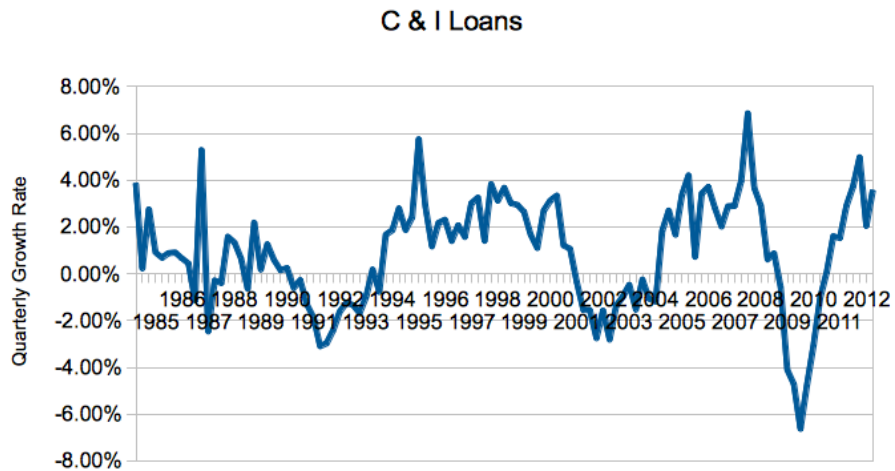


Figure 10: Commercial and industrial loans - Break adjusted quarterly growth rate; All commercial banks, seasonally adjusted. Source: FDIC, own computations

trailed behind and continues to show negative growth rates as of the second quarter of 2012. The decrease in bank lending together with an increase in the price of loans starting in the third quarter of 2008 is indicative of a decrease in the supply of credit by banks. Theoretically, a decrease in business loans can be the result of a decrease in supply and/or a decrease in demand. However, there is a large number of recent studies highlighting the importance of supply-side factors on the credit market in the wake of the 2008/09 recession. In Europe, 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. Similar studies for Spain by Jimenez Porras *et al.* (2012) and the evaluation of surveys such as the ECB's 'Survey on Access to Finance of Small and Medium Enterprises' (SAFE) confirm the importance of supply-side factors driving business lending to SMEs.²¹ Since the fourth quarter of 2010 the Small Business Administration (SBA) conducts a comparable survey with very similar results, stating that obtaining credit remains one of the largest problems for small businesses.²² Many institutions created similar indicators of business financing after the recent recession. The Federal Reserve Bank of Atlanta explicitly addresses financing conditions for young businesses in its 'Small Business Survey'.²³ The report points out that young firms face a different initial lending environment and more challenges than more mature firms in obtaining credit. 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. It shows 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.

What is important for the story I am trying to convince the reader of, is that the reduction in credit to young businesses was not entirely demand-driven. The Federal Reserve's 'Senior Loan Officer Opinion Survey on Bank Lending Practices' is an attempt at disentangling supply- and demand factors on the credit market. The data shows that besides a decrease in credit demand perceived by banks there occurred a tightening of credit standards, especially for firms with annual sales less than \$50 million. By the end of 2008, 69.2% of respondents reported that they had tightened credit standards. And even by the end of 2010 standards for small business lending had remained tight. In line with the FDIC data the survey results show that the mild recovery in lending standards since 2011 was much more pronounced for firms with annual sales of \$50 million or more.

Part of the US government's measures to strengthen the financial sector during 2008 was the 'Troubled Asset Relief Program' (TARP). Part of the TARP's Congressional

²¹The most recent SAFE report states that "According to the survey results, euro area SMEs' external financing needs increased between October 2011 and March 2012. At the same time, the survey results show that access to bank loans continued to deteriorate; on balance, firms reported a worsening in the availability of bank loans (...). Moreover, the survey results point to somewhat higher rejection rates when applying for a loan." See <http://www.ecb.int/press/pr/date/2012/html/pr120427.en.html> for details.

²²See for example <http://www.sba.gov/advocacy/10871/29971>

²³The Atlanta FED classifies young businesses as those under six years old. The latest report is available from <http://www.frbatlanta.org/research/smallbusiness/sbresearch/>

mandate was to promote growth and create jobs. The Secretary of the Treasury has singled out small businesses lending (under 500 employees) as a means to achieve this.²⁴ Following these increased efforts of reviving small business lending, there was an increased amount of governmental supervision over this aspect of the financial sector which can partly mitigate the above-mentioned shortcoming in data availability. The effectiveness of the measures taken by the US government were regularly summarized and evaluated by a Congressional Oversight Panel. Its 'Final Report' (by statute) was published in March 2011. It describes the financial crisis, summarizes and updates the Panel's prior oversight reports, and evaluates federal financial stabilization initiatives. This report also makes use of the Senior Loan Officer Opinion Survey among other sources to conclude that although a decrease in the demand for small business loans played a role, there was a significant and ongoing decrease in loan supply which was caused by the consequences of the tumultuous events on the financial markets.

Observation 3: *An important feature of the 2008/09 recession is a decrease in credit supply by commercial banks. It appears to have played a less important role during the 2001 recession.*

House Prices and Startup Activity The 'Final Report of the Congressional Oversight Panel' states that many larger banks pulled back from the small business lending market during the crisis ({United States Congressional Oversight Panel}, 2011). Smaller banks on the other hand remained strained by the exposure to commercial real estate and other liabilities. In the following I will use data on house prices to serve as an indicator of credit supply. I assume that on a regional level decreases in house price indexes are negatively correlated to banks' credit supply. The reason behind this is essentially what has been captured by Figures 9 and 10: 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). Decreases in the house price index, I argue, partly capture this channel. A recent paper by Adelino *et al.* (2012) highlights the positive link between easier access to credit and house prices. Dell Ariccia *et al.* (2012) link the subprime mortgage crisis to a decline in overall lending standards. Furthermore, real estate - either the owner's private home or commercial real estate - is commonly used to collateralize commercial credit. The decline of property values may therefore have negative consequences on businesses' ability

²⁴Specifically, through the Capital Purchase Program (CPP), the Community Development Capital Initiative (CDCI) and most famously the Small Business Lending Fund (SBLF) which was enacted into law as part of President Obama's Small Business Jobs Act of 2010. According to the SBLF's June 2012 Cost Report 'on September 27, 2011, the SBLF program's core investment activities were completed. SBLF is now staffed primarily to monitor, manage, and report on these investments and related participant lending and program activities.' By that time banks connected to this program had given out roughly \$4 billion in credit to small businesses (see SBLF Transactions Report as of August 31, 2012).

to obtain the required credit.

If startups do in fact rely on credit for job creation and are susceptible to conditions on the credit market, we are now able to construct at least two testable predictions:

1. The effect on startup activity should be more pronounced in times when banks' credit supply was more adversely affected.
2. The decrease in employment by startups should turn out larger in regions where banks decrease their credit supply further.

I obtain house price data from the Federal Housing Finance Agency, which provides quarterly house price indices (HPI) by state (purchase only) from 1991 until 2011. I average over the quarterly indices to obtain yearly data and recompute the index year to 2007=100. This year immediately preceded the crisis and showed on average the highest values of the index. I will discuss choosing different index years below. Visual inspection as well as the appropriate statistical tests show a time trend in the HPI which I remove.²⁵ What makes it interesting is that different U.S. states were affected very differently by the crisis so that we can combine the information on the severity of the housing crisis with the numbers of employment creation by startups. If we see a high correlation between the decline in house prices and the decrease in startup activity during the recent crisis, this should increase the reader's confidence in my hypothesis that credit supply was and continues to be an important determinant of a firm's initial size.

A first stab at the data reveals that there exists considerable heterogeneity between states: Based on the index year 2007 = 100, in 2010 the HPI had plummeted to under 60 in a number of states, while others saw declines in the index of less than 10 index points. The (non-weighted) average HPI in 2010 was 88.51. The HPI for 2010 is plotted in Figure 11, which shows a map of the states of the United States. A darker blue indicates a larger decrease in the HPI since 2007. Each state falls into one of six equally sized percentile bins. We see that the largest decreases in house prices took place in the west of the US, as well as in some of the eastern states like Florida, Georgia, Michigan, and Maryland.

We can now compare this to the data on employment creation by startups during the same time period. The previously described BDS Census data is available by state which allows me to generate a new map which I plot in Figure 12. There is a remarkable similarity to the previous figure. Mere visual inspection already reveals that those states that saw large decreases in house prices and - thus the argument goes - in supply of bank loans were often the same states in which we observe the biggest decline in job creation by startups. In fact, conditional on registering a below-average HPI for 2010

²⁵In the following I will use the detrended data when discussing implications over longer time horizons. For comparing HPI during the recent recession I use the non-detrended data because it facilitates the comprehension and visual inspection of the data.

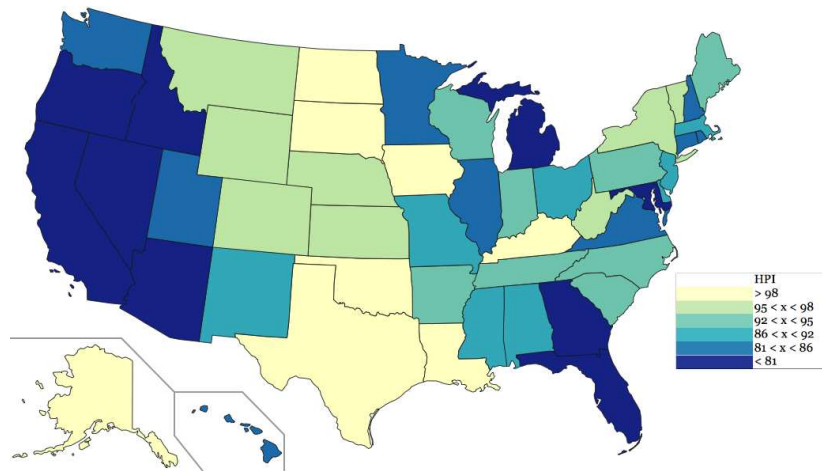


Figure 11: HPI in 2010 (2007 = 100). Data is divided into six evenly spaced percentiles. Source: Federal Housing Finance Agency. Graph created with Python by author.

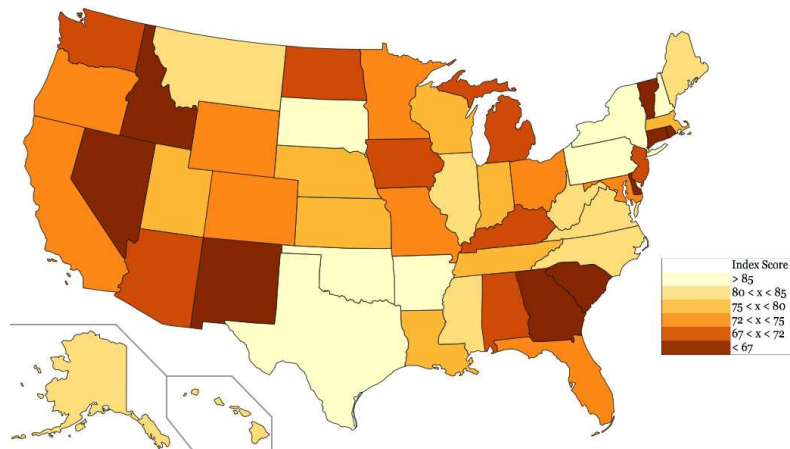


Figure 12: Employment by startups in 2010 (2007 = 100). Data is divided into six evenly spaced percentiles. Source: Federal Housing Finance Agency. Graph created with Python by author.

the probability that the state's job creation index was below average as well was .7895.²⁶

Digging deeper into the data further strengthens the view that the HPI and job creation by startups are linked. Coming back to the first assertion above, the correlation between startup employment and house prices is in fact more tightly connected for periods of negative growth rates of the HPI. The 2001 recession - associated with the "dotcom-bubble" - was not accompanied by large declines in the HPI. As stated in *Observation 3*, a decrease in the supply of bank credit for commercial loans seems much more predominant during the 2008/09 recession. The 2001 recession is not commonly seen as a banking crisis, wherefore it would be surprising if there was a very strong link between state-level changes in the HPI and the employment created by startups.²⁷ On the other hand, the recent financial crisis produced a strong positive correlation between the two time series ($\rho = .74$). This large correlation is not merely driven by a few small states. The five states with the largest startup job creation figures all exhibit this positive correlation.²⁸ If we weight the correlation between the two indices with the fraction of a state's startup job creation of nationwide job creation that year, the overall correlation remains almost unchanged at $\rho = .70$. This confirms the second assertion above. The decrease in employment by startups was larger in regions where banks were more likely to curb credit supply.

Other measures of collateralizable funds and job creation Another possible source of startup finance is personal savings. In the following I plot the total gross savings against the number of startups. The gross savings data comes from the National Income and Product Accounts (NIPA) of the Bureau of Economic Analysis (BEA). Figure 13 shows a strong correlation between the number of startups and gross savings. The BLS data used to create this figure is obtained as part of the CES. This has the disadvantages discussed above, yet this quarterly series has the great advantage of being already available for the second quarter of 2012. A similar figure (available upon request) can be created with the BDS firm data I have used previously and shows the same correlation.

Observation 4: *The decrease in the number of startups is strongly correlated with a decrease in housing wealth and gross savings.*

- here short summary of two above paragraphs. -

²⁶I obtain this number by removing those states for which the Federal Housing Finance Agency issues a warning that fewer than 15'000 transactions have been recorded over the last decade. Those states are: AK, DC, HI, ND, SD, VT, WV, and WY. They are also removed for the figures cited below. Including those states reduces the conditional probability to .75. Using the detrended HPI data this figure falls to .62.

²⁷In fact, for index year 1991 = 100 the correlation between the (detrended) HPI and startup employment is -.23 during the 2001 recession.

²⁸Those states were CA (12.2% of nationwide startup job creation in 2010, correlation $\rho = .32$), TX (9.5%, $\rho = .96$), FL (7.81%, $\rho = .93$), NY (7.38%, $\rho = .40$), and IL (3.99%, $\rho = .96$). Only in two states do we observe a negative correlation between the two indices during the recent crisis (MA: -.09, NH: -.25).

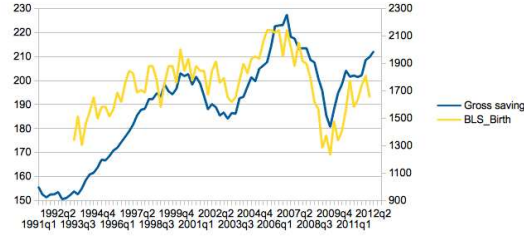


Figure 13: Gross savings (in billions of dollars, seasonally adjusted, source: BEA/NIPA Table 5.1) and private sector establishment births (in thousands, seasonally adjusted, source: CES/BLS Table 9).

4 The Model

I depart from a standard search and matching model to which I add several features. The economy consists of two types of agents, workers and entrepreneurs. An important distinction with respect to the standard search and matching model is that the economy is populated by a mass of heterogeneous firms which differ in their profitability, which reflects both productivity and demand. Profitability evolves persistently over time. Entrepreneurs operate firms that use labor as input and generate a single consumption good as output. In addition to the idiosyncratic variations in profitability, there is an aggregate shock to profitability, which likewise evolves persistently over time. The setup is similar to the model in Cooper *et al.* (2007) henceforth CHW.

A period refers to one month. Workers and entrepreneurs are matched through a search process. 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. Unemployed workers successfully find a job with a given probability each period. This probability depends on the current unemployment rate and the amount of vacancies created by entrepreneurs. Employed workers may lose their job if the entrepreneur they are matched with 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 timing of events in my model is based on the setup in Hopenhayn and Rogerson (1993): At the beginning of each period, before the realizations of aggregate and idiosyncratic shocks, incumbent firms decide whether to continue operating or exit. At the same time, new firms enter the economy based on expected aggregate conditions. Then production takes place and compensations are paid. One important difference in the timing of my model compared to CHW 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 following sections explain the model in more detail.

4.1 Workers

Workers can be either employed or unemployed. When they are unemployed they receive an outside option $b(a)$, which can vary with the aggregate state a . This outside 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

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

where $Z(\cdot)$ describes the worker's utility from consumption, β the discount factor, and $\phi(\cdot)$ 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 strictly concave. For simplicity I assume that there is no disutility from labor. In (1) the expectations operator is associated to the future values of unemployment and employment.

By contrast, 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.

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

4.2 Entrepreneurs

Entrepreneurs own the production process. They consume all the profits and are risk-neutral. The revenue function is given by $y = ae\epsilon^\alpha$, where e stands for the number of workers and $\alpha < 1$ represents the labor share. This technology 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). Based on the realization of the exogenous states, entrepreneurs make hiring and firing decisions and decide whether to continue operation or exit. A fraction q of the workforce is separated exogenously (quits) each period. Given (a, ϵ) the entrepreneur and the workers bargain over a compensation ω . 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 contract As in CHW 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.²⁹ The profit maximizing contract results from the following optimization problem

²⁹This assumption facilitates the computation of the optimal contract. The same procedure is used in Cooper *et al.* (2007) and Fajgelbaum (2012)???. See Elsby *et al.* (2010) for a different approach based on Stole and Zwiebel (????).

$$\pi(a, \epsilon, e) = \max_{\Upsilon} a\epsilon e^\alpha - ew(S) \quad (3)$$

$$\text{s.t. } W^e(a) \geq W^u(a) \quad (4)$$

In equilibrium, the values in (4) 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 (4) 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 employment decision Vacancies must be reposted each period. The recruiting decision is made knowing $s = (a, \epsilon, e_{-1}, \theta)$. The firm value is $Q^c(s)$, where the c stands for 'continuing'. Because there are fixed costs to variations in employment, the entrepreneur faces a discrete choice problem. He can decide between posting vacancies, remaining inactive and firing workers. The value $Q^c(s)$ is given by the maximum of those values.

$$Q^c(s) = \max\{Q^v(s), Q^n(s), Q^f(s)\} \quad (5)$$

The value of posting vacancies is given by

$$Q^v(s) = \max_v \pi(a, \epsilon, e) - F_v - C_v(v) + \beta E[Q(s')].$$

When posting vacancies

$$e = e_{-1}(1 - q) + H(U, V)v, \quad (6)$$

where q is the quit rate and $H(\cdot)$ is the vacancy filling rate. There are two types of costs connected to hiring. One is a fixed cost F_v . The other is a variable cost C_v .³⁰ Both of these costs are denominated in wage units.

The value of firing workers is

$$Q^f(s) = \max_f \pi(a, \epsilon, e_{-1}(1 - q) - f) - F_f - C_f(f) + \beta E[Q(s')].$$

Similarly to the hiring case, there is both a fixed and a variable cost component to reducing the stock of workers.

Lastly, the value of inaction is given by

$$Q^n(s) = \pi(a, \epsilon, e_{-1}(1 - q)) + \beta E[Q(s')].$$

The policy function for employment will be denoted $\phi^e(s)$.

³⁰I abstract from the complex employment adjustment function in CHW.

Exit Before any exogenous shocks are realized, the entrepreneur has to decide whether he wants to continue operating or exit. The exit decision is thus based on the expected future values of ϵ and a . When exiting a firm reduces the amount of workers to zero (paying the firing costs for doing so) and generates zero revenue. The value of exiting is

$$Q^x(s) = 0 - F_f - C_f e_{-1}.$$

This formulation implies that once a firm has decided to exit, it can not re-enter the market. All future profits are zero. If the firm chooses to continue, the firm faces the same choices as discussed above. The firm decides to exit whenever

$$E_{A', \epsilon' | A, \epsilon} Q^c(s') < Q^x(s). \quad (7)$$

The associated policy function will be denoted $\phi^x(s)$ and takes a value of one if the firm exits, and zero otherwise.

Entry At the beginning of each period there is an infinite mass of potential entrants. Similarly to exit, the entry decision has to be made before any exogenous shocks are realized, *i.e.* in expectation of ϵ and a . The cost of entry is given by c_e , which potential entrants compare to the expected value of entry. After a firm has decided to enter it starts out with an initial employment of zero and an initial profitability draw of $\epsilon_{i,0}$ from a distribution that may differ from the distribution of incumbents productivity draws. After the initial period profitability evolves identically to that of all other incumbent firms. Entering firms have mass M^e . Entrants do not pay a fixed cost of operation in the first period. Note that my setup requires the introduction of an additional parameter in order to pin down M^e . In the work following Hopenhayn and Rogerson (1993) labor demand is strictly increasing in the mass of entrants, while labor supply is strictly decreasing.³¹ This guarantees that a market-clearing M^e can be found. Because the wage in this model of a frictional labor market is the outcome of a bargaining process and hence not a market-clearing wage, another identification method for M^e needs to be applied. I therefore introduce a component of the entry cost which is increasing in the number of firms in the economy. The entry condition now reads as

$$c_e \cdot (N_t + M_t^e)^{\alpha_1} = V^{\text{entry}}, \quad (8)$$

where I define $V^{\text{entry}} \equiv E_{A', \theta' | A, \theta} Q^c(A', \epsilon', 0, \theta')$ as the expected value of entry. Entry occurs until this expression holds with equality. The right hand side of (8) represents the expected value of entry. The left hand side is composed of c_e which is a physical cost of entry (setting up shop, bureaucracy, etc.) and $(N_t + M_t^e)^{\alpha_1}$, where I require that $\alpha_1 > 0$. This latter term captures the idea of a increasing costs of finding appropriate land or office space as well as a market niche. With positive entry, entry costs are increasing both in the number of entrants and in the number of incumbent firms. From a technical

³¹The increase in the mass of entrants increases the wage. Resulting from the assumptions about preferences this results in a decrease in labor supply.

point of view, since the right hand side of (8) is a constant this term guarantees that a positive mass M^e can be found each period. This number is equal to

$$M_t^e = \left(\frac{V^{\text{entry}}}{c_e} \right)^{\frac{1}{\alpha_1}} - N_t. \quad (9)$$

This function has the following important properties: $\frac{\partial M_t^e}{\partial V^{\text{entry}}} > 0$ and $\frac{\partial M_t^e}{\partial N_t} < 0$. The first property simply states that the higher the expected value of entry, the higher the mass of entering firms. The second property states that the higher the mass of incumbents the lower the mass of entries. This condition is required to guarantee that the number of firms does not explode. Appendix A.1 takes another look at entry and shows how entry costs and costs of operation are connected to entry for the case of a simplified version of the model.

Exogenous processes I assume that the logarithms of both a and ϵ follow autoregressive processes.

$$\ln a_t = \rho_a \ln a_{t-1} + v_{a,t}, \quad v_a \sim N(0, \sigma_a) \quad (10)$$

$$\ln \epsilon_t = \rho_\epsilon \ln \epsilon_{t-1} + v_{\epsilon,t}, \quad v_\epsilon \sim N(0, \sigma_\epsilon) \quad (11)$$

4.3 Equilibrium

In equilibrium both workers and firms optimize and all consistency conditions are satisfied. The first part of equilibrium is an optimal contract which determines worker compensation. This contract maximizes (3) subject to the workers' participation constraint (4). Secondly, firms optimally adjust employment (5). Third, workers apply their decision rule whether to accept a contract or not. The mass of entrants is given by M_t and is determined by (8).

In (6) firms need to use the current state of θ in order to 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. In order to have the firms generate consistent forecasts of θ a methodology similar to Krusell and Smith (1998) is applied.

Unemployment follows $U' = (1 - U)\delta(U, V) + (1 - \phi(U, V))U$, where $\delta(U, V)$ is the separation rate (quits + layoffs) and $\phi(U, V)$ describes the job-finding rate.

5 Introducing Financial constraints

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 w 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. $\frac{\partial^2 R}{\partial \xi \partial y} > 0$.³²

Gauging the default risk The bank can only use currently observable information when deciding on a loan application in period t . On an aggregate level this includes the common shock a_t , labor market tightness θ_t , as well as the wage level. On the firm-level the available information is limited to the beginning-of-period level of employment $e_{i,t-1}$, where i denotes a firm-identifier. Specifically, a firm's current productivity draw $\epsilon_{i,t}$ is not observable by the bank. Furthermore the bank knows the distributions and laws of motions for both the aggregate and the idiosyncratic shock processes.

The bank is interested in computing a firm's default risk in order to compute the optimal interest rate. The bank uses the information contained in $e_{i,t-1}$ in order to assess the likelihood that firm i draws an idiosyncratic shock $\epsilon_{i,t}$ that would lead to the decision to exit (and hence renege on the loan), i.e. where $\phi_{i,t}^x = 1$. The employment level $e_{i,t-1}$ was an optimal response of the firm to the state $s_{i,t-1} = (a_{t-1}, \epsilon_{i,t-1}, e_{i,t-2})$. Hence the bank uses the firm's policy function for employment $\phi_i^e(\cdot)$ in order to form a probability distribution over the firm's past idiosyncratic shock $\epsilon_{i,t-1}$, which is in turn used to compute the distribution over the current idiosyncratic shock $\epsilon_{i,t}$ using the known Markov process for ϵ .

³²See appendix for derivations.

It does this by using the firms policy function for employment. The bank backs out a probability distribution over firm i 's idiosyncratic shock $\epsilon_{i,t-1}$. Specifically, the bank computes the probability (REWRITE THIS INTEGRAL)

$$p(\phi_{i,t}^x(s_{i,t})|a_t, e_{i,t-1}) = \int_{\epsilon} \phi_{i,t}^x(a_t, \epsilon_{i,t}, e_{i,t-1}) f(\epsilon) d\epsilon_{i,t}$$

where the firm-specific state vector $s_{i,t} = (a_t, \epsilon_{i,t}, e_{i,t-1})$.

5.1 Credit Crunch

A credit crunch manifests itself through an increase in the banks' risk aversion parameter ξ . This can be thought of banks receiving a negative shock and being closer to their binding capital requirements constraint. This would induce them to hand out less risky loans.

In the appendix I show that $\frac{\partial^2 R}{\partial \xi \partial y} > 0$. This implies that as a credit crunch hits the economy, interest rates increase for all loan sizes. However, the increase will be larger for firms that have a high risk of default, i.e. small and young firms. This mirrors the idea that small and young firms are more severely affected by a worsening of credit conditions than old and large firms.

The intuition is this: For a large, old firm the perceived risk of default may be close to zero. Hence an increase in ξ has little effect on the interest rate. A young firm with a high default risk is much more affected because the increase in risk aversion leads to a larger compensation payment for the bank in order to take on the risk of default.

6 Calibration

All parameter values together with their calibration target are listed in Table 5 in the Appendix. Some of the baseline parameters are not calibrated. Instead I assume values that are common in the literature. These include the discount factor β , the curvature of the profit function α , and the parameters governing the evolution of the aggregate state. For those parameters that are calibrated the goal is to either match steady-state values of the model to values observed in the data.

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 data from the Bureau of Labor Statistics the average unemployment rate over the time of my sample (1977-2010) was 6.3%, which serves as my target. As in Elsby *et al.* (2010) I target a monthly job-finding probability of 0.45. This is in line with empirical evidence in Den Haan *et al.* (2000) and Shimer (2012), but slightly higher than the estimates in Cooper *et al.* (2007) who find 0.61. The steady-state ratio of vacancies to unemployment is targeted to be $\theta = 0.72$ as in Pissarides (2009). The matching elasticity γ is assumed to be ???. While Cooper *et al.* (2007) estimate this parameter to be .36, Hall (2005*b*) finds 0.72. My target of the job-finding rate together with a choice of γ implies a matching efficiency parameter of $\mu = .$ ³³

7 Results

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³³This comes from $H = \mu\theta^{-\gamma}$. I obtain $\mu = \frac{0.45}{0.72^{1-\gamma}}$ which gives the value in the text.

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Appendix

A.1 A closer look at entry

Condition (8) pins down the number of entrants each period. In order to understand better, what parameters determine the mass of entrants, consider an abbreviated version of the model without aggregate fluctuations or adjustment costs. In addition, the problem can be simplified by assuming i.i.d. shocks to idiosyncratic productivity and a constant return production function, so that profits are given by $\pi(\epsilon, n) = \epsilon^{1-\alpha} n^\alpha - wn - c_o$. This implies that the expected value of profits is the same for each current value of idiosyncratic productivity and that this productivity pins down the optimal labor demand. Taking the first order condition with respect to labor we get $n = \left(\frac{\alpha}{w}\right)^{\frac{1}{1-\alpha}} \epsilon$. Plugging this expression back into the profit function results in $\pi = \epsilon \cdot \left[\left(\frac{\alpha}{w}\right)^{\frac{\alpha}{1-\alpha}} - w^\alpha \alpha^{\frac{1}{1-\alpha}}\right] - c_o$ or simply $\pi = c(w)n - c_o$, which highlights that profit is linear in labor and premultiplied by a constant which depends on the wage. Potential entrants decide at the beginning of the period whether to enter or not. Given the i.i.d. nature of the shock, there remains no heterogeneity in the firms' decision to continue operation or exit. Hence, there can be no entry in this economy's equilibrium. Equation (8) must hold with equality (assuming indifference leads to no entry) and the term on the right hand side becomes $\sum_{t=1}^{\infty} \beta^{t-1} (\bar{c}(w)n - c_o)$, where $\bar{c}$ is the same as before with the expectation of ϵ , $\bar{\epsilon}$ inside. We can now rewrite equation (8) as

$$c_e (N_t + M_t^e)^{\alpha_1} = \frac{\bar{c}(w)n - c_o}{1 - \beta}.$$

Since no entry occurs in equilibrium $M_t^e = 0 \forall t$ and $N_t = N \forall t$, hence

$$c_e N^{\alpha_1} (1 - \beta) = \bar{c}(w)n - c_o.$$

This highlights how the cost of entry, c_e , is linked to the fixed cost of operation c_o and profits. In this simplified version of the economy it is easy to see that an increase in c_o will imply a reduction in c_e , while an increase in the present-discounted value of profits implies an increase in c_e .

A. 2 Bank's interest rate

Claim: With CRRA utility the bank's interest rate is given by $R = \frac{1}{(1-y)^{\frac{1}{1-\xi}}}$.

Proof. In order to break even in utility terms the bank requires

$$U(c) = y \cdot U(0) + (1 - y) \cdot U(R \cdot c),$$

where y is the default risk, c is the size of the loan and R is the gross interest rate. By assuming a functional form on the utility function we can solve for the interest rate that allows the bank to break even. In the paper I assume CRRA utility and a risk aversion

parameter $-\infty \leq \xi < 1$. This restriction ensures that the utility of zero returns is zero. We obtain:

$$\frac{c^{1-\xi}}{1-\xi} = (1-y) \cdot \frac{(Rc)^{1-\xi}}{1-\xi}$$

$$R = \frac{1}{(1-y)^{\frac{1}{1-\xi}}}$$

□

The effect of an increase in the default probability y is

$$\frac{\partial R}{\partial y} = -\frac{1}{\xi-1} \cdot (1-y)^{\frac{1}{\xi-1}-1} > 0$$

The effect of an increase in the lender's risk aversion is

$$\frac{\partial R}{\partial \xi} = -\frac{(1-y)^{\frac{1}{\xi-1}}}{(\xi-1)^2} \cdot \log(1-y)$$

The denominator is positive, the numerator is positive as well. The log-term is negative since $y < 1$, so the entire expression is positive. An increase in the lender's risk aversion leads to a higher interest rate.

The interesting question is how the interest rate change varies with the default probability of the borrower. We see from

$$\frac{\partial^2 R}{\partial \xi \partial y} = \frac{(1-y)^{\frac{1}{\xi-1}}}{(\xi-1)^3} \cdot \frac{1}{1-y} \cdot \log(1-y) + \frac{(1-y)^{\frac{1}{\xi-1}}}{(\xi-1)^2} \cdot \frac{1}{1-y} > 0$$

that a higher default risk y leads to a stronger effect of variations in the banks' risk aversion on the interest rate R .

A. 3 Non-stochastic simulation method

For the simulation 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 $i \in [1, 2, \dots, \#_n]$ and $j \in [1, 2, \dots, \#_\epsilon]$. This determines the mass of firms with employment n_i and productivity ϵ_j . The simulation then follows this iterative process:

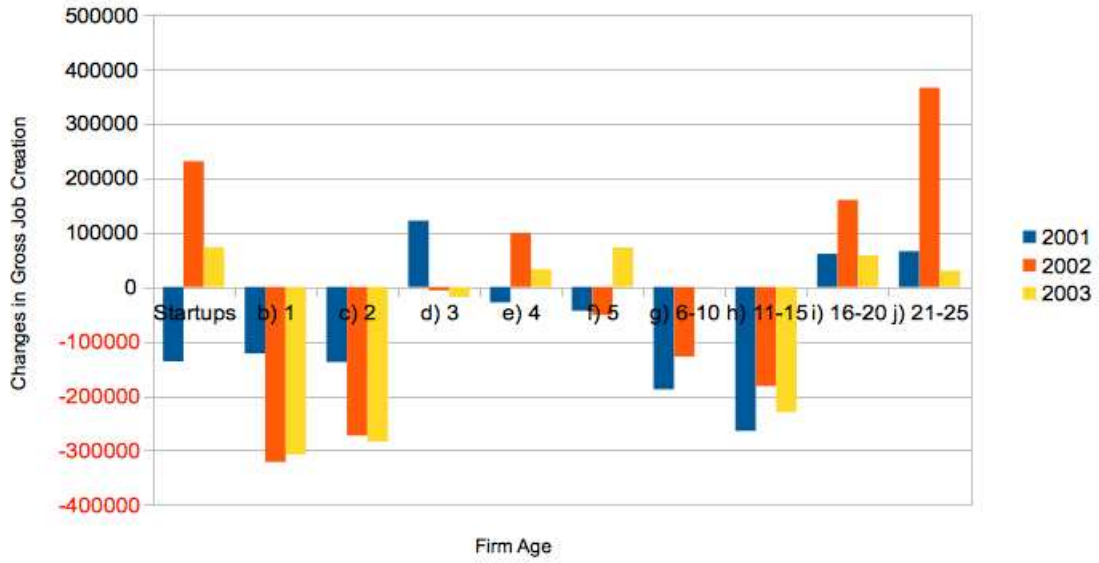


Figure 14: Changes in gross job creation relative to base year 2000. For age group bins averages are shown. Source: BLS, Business Employment Dynamics, own computations. Note that the 26+ category is missing from this graph because no data is available for this group in 2000.

1. At each grid point incumbent firms decide whether to continue operation or exit. The decision is based on equation (7) above.
2. New firms enter based on equation (8)
3. The aggregate productivity state realizes according to its law of motion specified in (10).
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 $k \in [1, 2, \dots, \#_\epsilon]$, according to the law of motion specified in (11).
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 (5).
6. Go back to step 1.

A. 4 Changes in Gross Job Creation During the 2001 recession

A. 5 Data on HPI and Startup Employment by State

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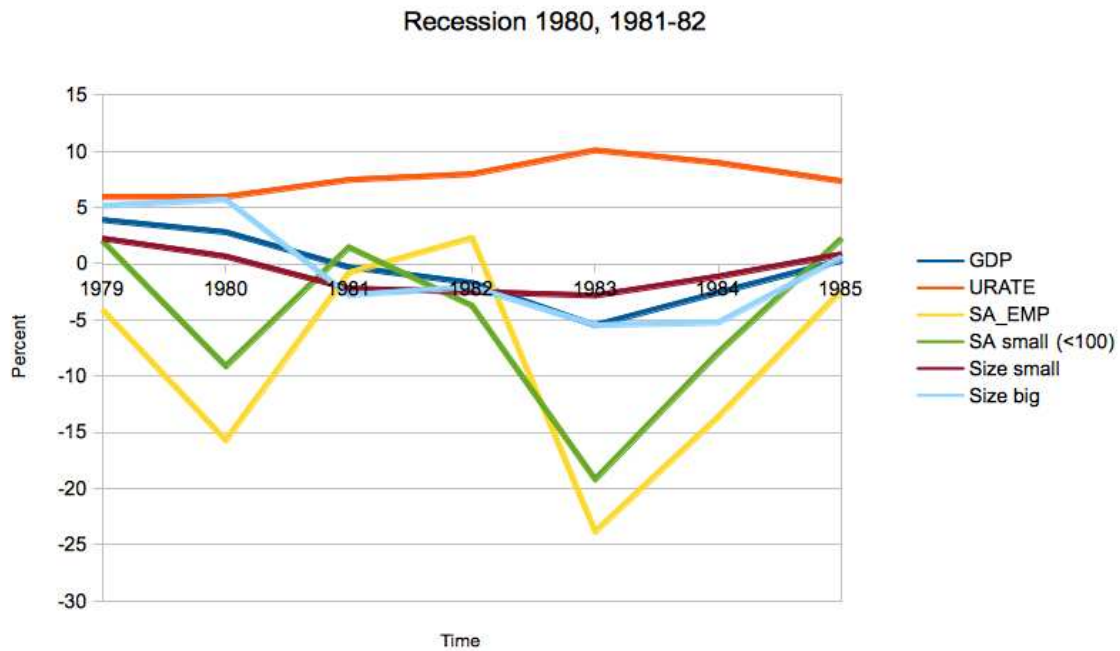


Figure 15: Employment measures, GDP and the unemployment rate during the recession at the beginning of the 1980s. All series except the unemployment rate are in percent deviations from trend. SA_EMP refers to employment in startups, SA_small refers to employment in small startups (<100 employees). Small firms have < 100 employees, big firms have >100 employees. Source: BDS, own computations.

A. 6 Comparing different Recessions using de-trended data

The BDS data are annually collected in March. For this reason I transform the GDP (quarterly) and unemployment (monthly) times series into annual data starting in March 1977. The data was respectively obtained from the Bureau of Economic Analysis (BEA) and the BLS in October 2012.

A. 7 Cross-Correlation Functions

A. 8 Calibration of Model Parameters

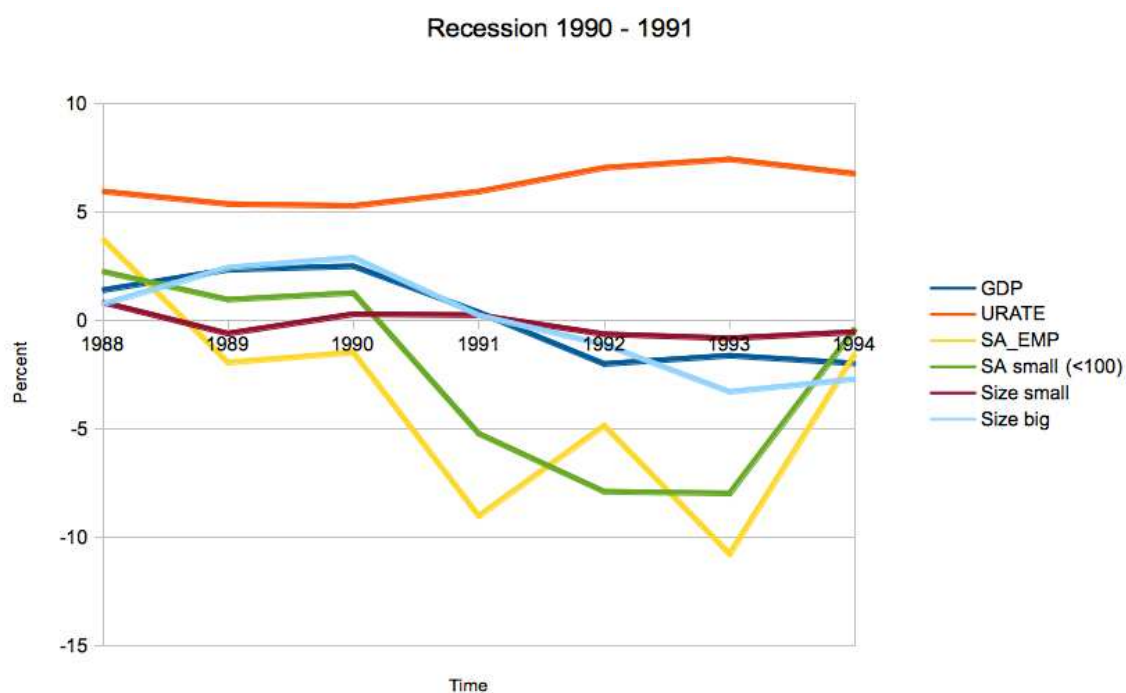


Figure 16: Employment measures, GDP and the unemployment rate during the recession at the beginning of the 1990s. All series except the unemployment rate are in percent deviations from trend. SA_EMP refers to employment in startups, SA_small refers to employment in small startups (<100 employees). Small firms have < 100 employees, big firms have >100 employees. Source: BDS, own computations.

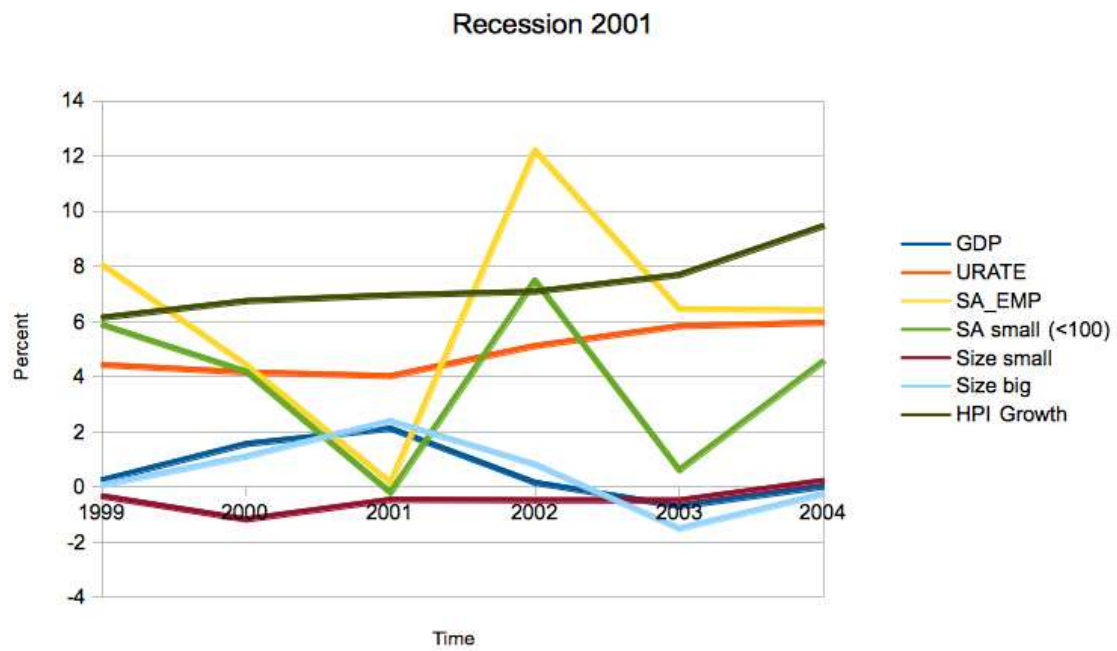


Figure 17: Employment measures, GDP and the unemployment rate during the 2001 recession. All series except the unemployment rate are in percent deviations from trend. SA_EMP refers to employment in startups, SA_small refers to employment in small startups (<100 employees). Small firms have < 100 employees, big firms have >100 employees. Source: BDS, own computations.

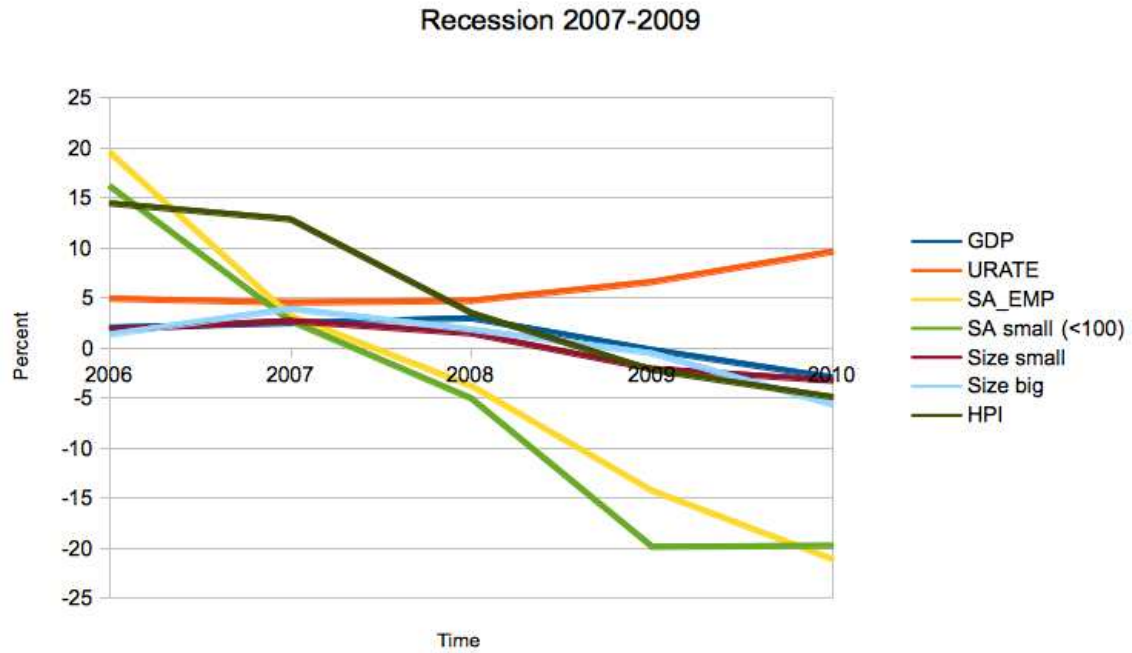


Figure 18: Employment measures, GDP and the unemployment rate during the recent financial crisis. All series except the unemployment rate are in percent deviations from trend. SA_EMP refers to employment in startups, SA_small refers to employment in small startups (<100 employees). Small firms have < 100 employees, big firms have >100 employees. Source: BDS, own computations.

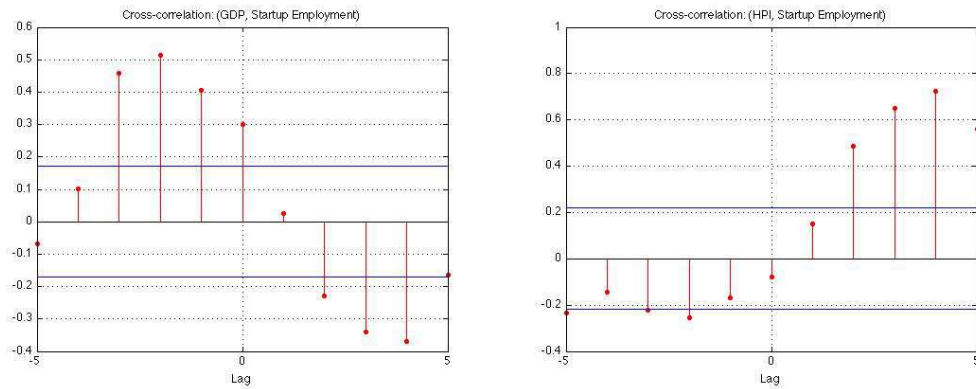


Figure 19: Cross-correlation between GDP and Employment in startups (left). Cross-correlation between HPI and Employment in startups (right). Confidence bands show one standard deviation.

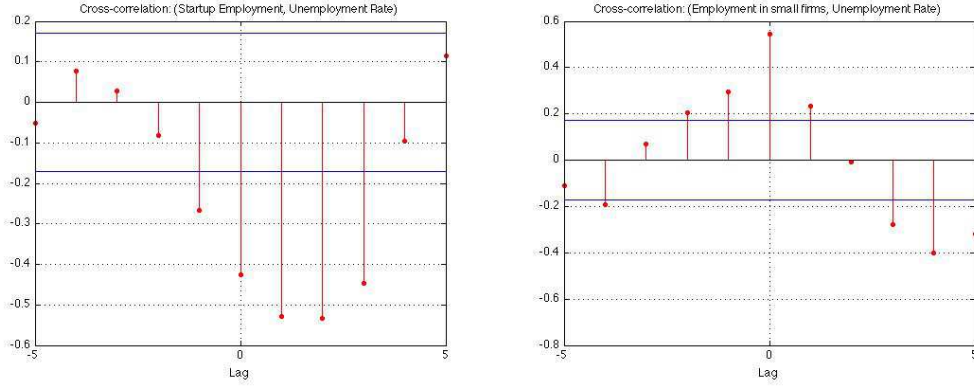


Figure 20: Cross-correlation between Employment in startups and the Unemployment Rate (left). Cross-correlation between Employment in small firms (<100 employees) and the Unemployment Rate (right). Confidence bands show one standard deviation.

Parameter		Value	Calibration Target / Source
Discount Factor	β	.98	
Curvature of profit function	α	.65	Cooper <i>et al.</i> (2007)
Autocorrelation of agg. shock	ρ_A	.95	
Standard deviation of agg. shock	σ_A	0.02	
Match efficiency	μ		$\phi = 0.45$
Matching elasticity	γ		either CHW or Hall
Job finding rate	ϕ	.45	Shimer (2012), Den Haan <i>et al.</i> (2000)
			U=6.3%, (BLS 1977-2010)
Fixed costs vacancies	v		Cooper <i>et al.</i> (2007)
Variable costs vacancies	c_v		Cooper <i>et al.</i> (2007)
Fixed costs firing	f		Cooper <i>et al.</i> (2007)
Variable costs firing	c_f		Cooper <i>et al.</i> (2007)
Fixed costs of operation	c_o		Cooper <i>et al.</i> (2007)
Outside option	b_0	1.12	Cooper <i>et al.</i> (2007)
Sensitivity of outside option to agg. shock	b_1	0.5	Cooper <i>et al.</i> (2007)

Table 5: Parameter Values