# Financial Constraints, Firm Age, and the Labor Market†

JOB MARKET PAPER

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**Abstract**

This paper shows that credit crunches cause labor market effects that are nonlinear over time and heterogeneous by firm age. During the Great Financial Crisis, a credit supply shock caused young firms to reduce employment significantly more than old firms, because the housing bust in 2006 led to a decline in young firms' housing collateral and restricted their ability to borrow. To understand the underlying mechanism, I propose a financial frictions model with an explicit firm age structure. A simultaneous credit crunch and a decline in young firms' net worth can reconcile the model with my empirical results. While old firms switch to equity financing, young firms depend on debt financing and cut labor demand. As young firms disproportionately account for aggregate job growth, my findings explain the sluggish labor market recovery after the Great Financial Crisis. A counterfactual experiment shows that absent the net worth shock, the U.S. unemployment rate would have been back to its pre-crisis level two years quicker.

**JEL classification**: E24, E32, E51, J63.
**Keywords**: Firm Age, Financial Frictions, Labor Market, Credit Supply Shock, TVP-VAR.

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# 1 Introduction

The 2008-2009 Great Financial Crisis (GFC) was different compared to previous recessions in the United States. The crisis was triggered by a bust in house prices that was followed by a considerable credit crunch. The impact on the labor market was substantial. Between 2006 and 2009, net job creation dropped by 30 percent,[1] and the unemployment rate doubled and remained persistently high. One quarter of the decrease in net job creation can be attributed to start-ups and young firms up to the age of five years.[2]

Against this background, I study how financial constraints affect firms' employment decisions over time and by firm age. To answer this question, I proceed in three steps. First, I take a time-varying, macroeconomic perspective and apply a structural time-varying parameter vector-autoregression (TVP-VAR) model with stochastic volatility. My approach is complementary to existing empirical contributions focusing either on the microeconomic perspective[3] or on time-invariant effects of credit crunches.[4] I provide evidence that the effects of credit supply shocks vary over time and by firm age. Second, using cross-regional variation, I identify housing net worth of young business owners as an important driver for differences by age. Third, I build a firm dynamics model with financial frictions to understand the underlying mechanism. The model allows to investigate the interaction between the credit supply channel, the (housing) net worth channel, and firms' labor demand.

I obtain two key results in my structural empirical analysis. In response to credit crunches, labor market reactions are (i) nonlinear over time and (ii) heterogeneous by firm age. I perform a historical shock decomposition and detect a structural break: Since the late 1990s, credit supply shocks are an important driver of U.S. unemployment and output dynamics but were statistically and economically unimportant before. During the GFC, credit supply disturbances accounted for 60% of the variance of the U.S. unemployment rate. Furthermore, I estimate the employment reactions of young and old firms in response to an exogenous tightening of credit supply. With the onset of the Great Financial Crisis, young firms reacted significantly stronger in response to credit supply shocks, whereas I find no systematic difference along the firm size dimension. This is in line with the body of literature arguing that age is the relevant proxy for financially constrained firms (e.g. Cloyne, Ferreira, Froemel, and Surico, 2019 and Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova, 2018).[5]

In the first step of my analysis, I apply a time-varying parameters vector-autoregression (TVP-VAR) with stochastic volatility to estimate the net job creation rate (NJCR) and employment reactions in response to a credit supply shock.[6] The advantage of this methodology is its flexibility. A TVP-VAR with stochastic volatility allows for a different set of coefficients and a differ-

[1] Data source: Business Dynamics Statistics.

[2] Considering establishments instead of firms, the contribution of young establishments to the decrease in net job creation amounts to around one half.

[3] see Chodorow-Reich, 2014, Chodorow-Reich and Falato, 2018, Gilchrist, Siemer, and Zakrajsek, 2018, and Siemer, 2019.

[4] see Gilchrist and Zakrajšek, 2012, Bassett, Chosak, Driscoll, and Zakrajšek, 2014, Barnichon, Matthes, and Ziegenbein, forthcoming. Note that Barnichon et al. (forthcoming) consider asymmetric effects of credit supply shocks in a time-invariant vector moving-average model.

[5] I discuss the difference between firm age and firm size in detail in Subsection 4.2.

[6] See Primiceri (2005) and Cogley and Sargent (2005) for seminal contributions regarding a TVP-VAR.

ent variance-covariance matrix at every point in time.[7] This is important for two reasons. First, the effects of financial shocks may vary over time. Potential reasons for time variation can be structural (e.g. deregulation) or cyclical (stronger effects in recessions compared to booms) and can arise due to different shock sizes or from changes in the transmission mechanism. Second, compared to other classes of nonlinear VARs, this methodology does not hinge on any imposed threshold or a specific switching variable that dictates changes in parameters.[8]

Descriptively, the diverging of employment responses by firm age coincide with the bust in house prices in 2006. As house price growth was picking up again, young firms' employment reactions became less pronounced. In addition, evidence based on the 'Survey of Business Owners' illustrates the increased importance of private real estate collateral for start-ups. In the second step of my analysis, I investigate whether changes in house prices explain the stronger employment reaction of young firms. I use cross-regional variation at the metropolitan statistical area (MSA) level and find that in areas with a larger decline in house prices, job creation of young firms is significantly more sensitive to local credit conditions. This result points towards an important role of housing net worth for the hiring decisions of young firms, which is in line with recent literature stressing the importance of the housing collateral channel for young firms and start-ups (see Adelino, Schoar, and Severino, 2015, Kaas, Pintus, and Ray, 2016, Bahaj, Foulis, and Pinter, 2020, and Davis and Haltiwanger, 2019). The housing net worth channel offers also one potential explanation of why financial market shocks gained importance since the late 1990s. At this time, U.S. financial markets were deregulated. Financial deregulation led to a rise in securitization and mortgage-backed securities. This was followed by a surge in house prices (see e.g. Favara and Imbs, 2015). In combination with the relaxation of credit standards and a shift in beliefs regarding future housing demand (see Kaplan, Mitman, and Violante, 2020), the level of household debt increased substantially. Given the importance of real estate collateral for young business owners, these developments strengthened the linkage between financial market conditions and labor market dynamics.

As a third step, I uncover the underlying mechanism and build a quantitative general equilibrium model that features endogenous firm entry and aging firm cohorts. At the model's core is a financial contract between lenders and heterogeneous borrowers. Asymmetric information between the financial intermediary and entrepreneurs who require loans to finance their risky operations gives rise to a financial friction. I extend the financial accelerator model of Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1999) with costly-state-verification in the spirit of Townsend (1979) along two dimension. First, I add endogenous entry of entrepreneurs and a detailed entrepreneurial age structure. Second, I allow entrepreneurs to raise equity from households and pay out dividends. The latter extension accounts for the empirical fact that the structure of firm financing varies over the business cycle and depends on firm age and size (see Covas and Den Haan, 2011 and Begenau and Salomao, 2018). I follow Bernanke and Gertler (1989) and define net worth as collateralizable assets (such as buildings, land etc.) which reflect the possibility of self-financing. In the model, households provide entrants with starting net

[7] As such, it captures both possible structural changes as well as state-dependent effects (e.g. different effects in recessions compared to expansions).

[8] This is the case for threshold or smooth-transition VARs.

worth. As entrepreneurs grow older, they accumulate net worth. Thus, the younger a firm, the lower is its net worth and the higher are the agency costs (in terms of information asymmetry) which is reflected in a higher external finance premium (i.e. the costs of external relative to internal funds). This is consistent with empirical evidence that new businesses face more difficulties in accessing credit markets.[9]

After parameterizing the model to match the relative firm age distribution, I simulate a credit crunch and a decline in young firms' net worth. A credit supply shock leads to an initial, but short-lived drop in labor demand for all firms. As young firms face higher financing costs, their amount borrowed declines and they reduce economic activity. The effect on young firms' labor demand is stronger compared to old firms but not large enough to explain the diverging employment reactions by age found in the empirical analysis. Adding a decline in the value of young firms' collateralizable net worth reconciles the model with my empirical results. As young firms' balance sheets have deteriorated, lenders demand a higher compensation for the rise in agency costs, making borrowing even more costly. Due to their restricted access to credit, young firms' economic activity drops persistently which further depresses net worth. Thus, the contractionary effect on young firms is amplified via a financial accelerator mechanism: the endogenous link between the external finance premium and borrowers' net worth amplifies the impact of the shock. A persistent decline in the labor demand of young firms is the result. In contrast, the effect on old firms is only temporary. They have higher net worth, face low agency costs, and, in response to the credit crunch, households are willing to provide them with equity. Their ability to substitute between internal and external finance dampens the impact of the shock.

Overall, I find that the persistence in young firms' employment reaction is caused by the decline in their net worth and resulting higher borrowing costs. A counterfactual exercise shows that absent the housing net worth channel, young firms would have resumed job creation earlier and the pre-crisis U.S. unemployment rate would have been reached two years earlier. This translates on average to a two percentage points lower unemployment rate between 2012 and 2016.

The contribution of my paper is threefold. First, I establish empirically the differential employment responses of credit supply shocks by firm age and over time. I document the divergence of employment responses between young and old firms since the onset of the Great Financial Crisis. Housing net worth for young firms and the bust in house prices bust can explain this divergence. Second, I show that since the late 1990s, credit supply shocks are an important driver of unemployment dynamics but were not important before. Third, I propose a theoretical model that sheds light on the economic mechanism. The model disentangles the relative contribution of the credit supply and the net worth channels, which jointly led to diverging employment responses by firm age. My findings point towards an important role for firm age in the amplification and propagation of aggregate macroeconomic shocks.

**Relation to the literature:** I add to the empirical literature that analyzes the effects of credit supply shocks on labor market reactions of young and old firms. Chodorow-Reich (2014), Gilchrist

[9] I provide survey evidence based on the Kauffman Firm Survey. In the year 2007, a large fraction of businesses with a rejected loan application reported that the main reason for denial was insufficient collateral (44%) or 'Not being in business long enough'(35%), multiple answers possible. For details see Table 5 in Appendix A.

et al. (2018), and Siemer (2019) use either worker- or firm-level data to document that credit supply shocks account for a large share of the employment decline during the Great Financial Crisis. The role of firm age in explaining these employment dynamics has been stressed by Davis, Haltiwanger, and Schuh (1996), Haltiwanger, Jarmin, and Miranda (2013), and Dinlersoz et al. (2018). Results from microeconometric approaches at the firm level show that especially young firms reduce employment in response to credit contractions (see among others Duygan-Bump, Levkov, and Montoriol-Garriga, 2015, Chodorow-Reich, 2014 and Siemer, 2019). These papers study the effects of credit supply shocks from a microeconomic perspective. Complementary to them, I take the macroeconometric perspective and estimate the potential time-varying effects of credit supply shocks on employment by firm age.

Second, my paper provides a new empirical contribution on the effect of credit supply shocks on the macroeconomy. Gilchrist and Zakrajšek (2012) and Bassett et al. (2014) use linear vector-autoregressions (VARs) to study the consequences of credit tightening, whereas Barnichon et al. (forthcoming) focus on the asymmetric effects. I add to this literature by taking time-variation and firm heterogeneity into account.

Third, I contribute to the literature on the role of housing for start-ups and young firms. Davis and Haltiwanger (2019) show that the share of young firms' activity depends on local credit supply and local house price changes. Given that their analysis focuses on the relative distribution of employment between young and mature firms, my work is complementary to theirs as I investigate the time-varying diverging reaction by firm age.[10] My paper further relates to Kaas et al. (2016) who show in a model with collateral constraints à la Kiyotaki and Moore (1997) and labor market frictions that shocks to firms' land collateral lead to empirically relevant labor market dynamics. Their analysis abstracts from the firm age dimension. Complementary to Schott (2015), who also connects the decline in house prices to persistent high unemployment rates and low job creation of start-ups, I provide detailed empirical evidence. In addition, while he builds a model with labor market frictions, the mechanism in my theoretical framework works via financial frictions.

Fourth, I contribute to the theoretical literature on financial constraints by introducing heterogeneity in the age of firms. Cooley and Quadrini (2001) and Khan and Thomas (2013) show that financial frictions can explain why firms' borrowing structure differs by the size or age of a firm. In addition, Begenau and Salomao (2018) and Covas and Den Haan (2011) have documented that firms' financing structure varies over the business cycle and is size-dependent. Consistent with my theoretical framework, Begenau and Salomao (2018) find that only large firms substitute between debt and equity financing and small firms maintain a procyclical financing structure.[11] Further, Cloyne et al. (2019) document that young, non-dividend-paying firms make the largest capital adjustments after an aggregate shock.

The discussion whether the *age or size* of a firm is the relevant dimension of heterogeneity when analyzing financial constraints is still ongoing. Focusing on firm size, Covas and Den Haan (2011)

[10] Further research on the macroeconomic impact of fluctuations in the housing market includes Mian and Sufi (2009), Mian and Sufi (2011), Mian, Rao, and Sufi (2013), Giroud and Mueller (2017), Justiniano, Primiceri, and Tambalotti (2019), and Bahaj et al. (2020).

[11] Begenau and Salomao (2018) find a similar pattern in a robustness check with age.

and Begenau and Salomao (2018) study debt versus equity issuance over the business cycle. Related to that, Crouzet and Mehrotra (2020) study the cyclicality of small and large firms. Another strand of literature (see Davis et al., 1996, Haltiwanger et al., 2013, and Dinlersoz et al., 2018) stresses the importance of firm age for explaining business cycle dynamics. Recent contributions argue that firms who face financial constraints are those who show the strongest business cycle reactions. Financially constrained firms, however, are difficult to identify in the data. Cloyne et al. (2019) tackle this issue and show that young, non-dividend-paying firms serve as a good proxy for financially constrained firms. Against this background, I focus my analysis on the employment reaction by firm age instead of size for three reasons. First, age is a clear, rank invariant measure because firm age does not vary due to changes in employment (as opposed to size).[12] Second, young firms show the highest growth potential and are therefore more likely to be financially constrained (see Haltiwanger, Jarmin, Kulick, and Miranda, 2016, Sedláček and Sterk, 2017, and Pugsley and Şahin, 2018). Third, young firms have a short business history that leads to information asymmetries between borrowers and lenders. This makes external finance more costly for young firms.

**Structure of the paper:** Section 2 presents descriptive evidence motivating the focus on firm's job creation by age. Section 3 introduces the structural empirical approach and Section 4 presents the empirical results. I discuss the role of housing net worth in Section 5. The theoretical model is laid out in Section 6, Section 7 introduces the calibration and Section 8 presents the simulation results. Section 9 concludes.

## 2 Stylized Facts

This section presents stylized facts on the correlation between the U.S. credit and labor market and motivates my focus on the role of heterogeneity by firm age.

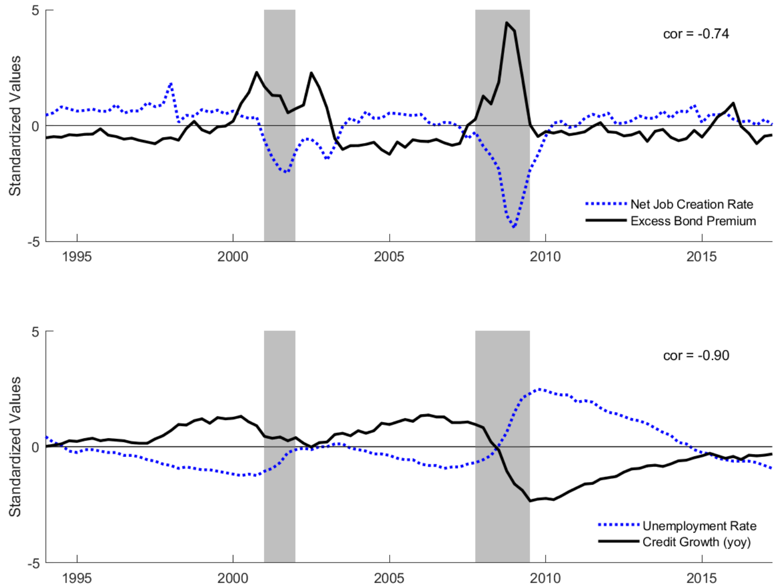
**The Credit and the Labor Market:** Figure 1 shows a strong negative correlation between U.S. labor market and financial variables for the time span 1993Q3 to 2016Q4. For improved visibility, I show standardized values (i.e. the data is demeaned and divided by its standard deviation). The upper panel of Figure 1 illustrates the strong negative correlation (-0.74) between the Excess Bond Premium and firms' net job creation rate, where the net job creation rate (NJCR) is defined as (job creation - job destruction)/employment. The Excess Bond Premium (EBP) is based on Gilchrist and Zakrajšek (2012) and captures credit supply conditions as the part of the corporate credit spread which is not due to firms' expected default risk. As such the EBP can be interpreted as a measure of lenders' risk attitude and, thus, credit supply conditions. See Section 3.2 for details. The lower panel of Figure 1 documents the strong negative relationship between U.S. credit growth and the unemployment rate in the US which amounts to -0.9.[13]

**Young vs. Old:** There exists considerable heterogeneity in net job creation rates by firm age. Figure 2 depicts quarterly net job creation rates from 1993Q3 to 2016Q4 based on the Quarterly

[12] see Cloyne et al. (2019) for a similar argument.

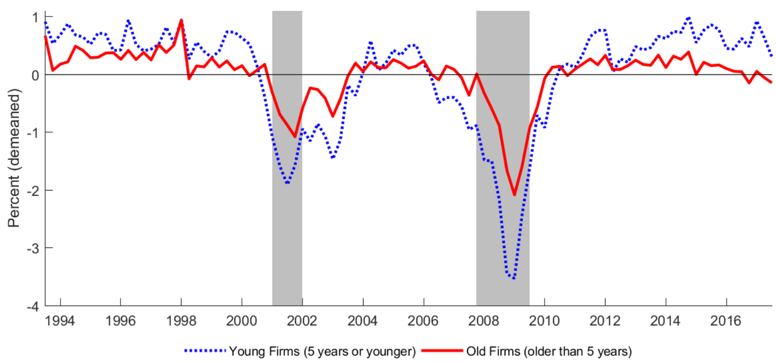
[13] I use data on net job creation from the Quarterly Workforce Indicator (QWI) which restricts the sample period to the illustrated time span. For increased comparability, I choose the same time span for credit growth and unemployment. Note, however, that the negative correlation between credit growth and the unemployment rate was less pronounced before the 1990s.

**Figure 1:** The U.S. Credit and Labor Market




Notes: Upper Panel: The Net Job Creation Rate is defined as (job creation - job destruction)/employment. The Excess Bond Premium (EBP) is a measure of credit supply (see main text for details). Grey-shaded areas denote NBER recession periods. Lower Panel: Credit growth refers to total credit to private non-financial sector. All data series are demeaned and divided by their standard deviation. Sample period is 1993Q3 to 2016Q4. Appendix F provides details on data sources.

**Figure 2:** Net Job Creation Rates by Firm Age




Notes: Grey-shaded areas denote NBER recession periods. The data is demeaned and divided by its standard deviation. Data source: Quarterly Workforce Indicator (QWI).

Workforce Indicator (QWI). During the two recessions in the sample, the net job creation rate dropped strongly. Unsurprisingly, the fall in net job creation rates was strongest during the Great Financial Crisis. Young firms' net job creation rate (i.e. firms up to the age of five) drops considerably stronger compared to old firms.

**Quantitative Importance:** It is well-known that young firms and especially start-ups are an important engine for job growth in the United States. As has been stressed by Fort, Haltiwanger, Jarmin, and Miranda (2013), young firms account disproportionately to the decline in employment growth between 2006 and 2009. Table 1 shows that firms up to the age of five contribute to 13.5% of overall employment but more than one quarter of the aggregate drop in net job creation can be attributed to them. Extending the definition of young firms up to age 10 (as do Haltiwanger et al., 2013 and Foster, Haltiwanger, and Syverson, 2016), who account for 23.3% of total employment but for 36.7% of the fall in net job creation, the disproportionate contribution of young firms persists. This stresses the quantitative importance of young firms for aggregate employment dynamics.

**Table 1:** Contribution of Young Firms

| | 0-5 years | 0-10 years |
|---|---|---|
| Employment Share | 13.5% | 23.3% |
| Contribution to drop in NJC | 26.4% | 36.7% |

Notes: NJC denotes absolute net job creation, the drop is calculated between the years 2006 and 2009, employment shares are based on the year 2006. Data Source: Business Dynamics Statistics (BDS).

# 3 Structural Empirical Analysis

## 3.1 A Time-Varying Parameter VAR with Stochastic Volatility

I estimate a time-varying parameter vector-autoregression model (TVP-VAR) with stochastic volatility (as in Primiceri, 2005 and Cogley and Sargent, 2005). The choice for this empirical model is based on its flexibility. In contrast to a threshold VAR or a smooth transition VAR, it is not required to specify a switching variable or to impose a certain threshold. This is especially important against the background of diverging views in the the existing literature on on whether *young or old firms* react stronger in response to aggregate shocks. Fort et al. (2013) find that young/small firms showed the strongest employment reaction during the Great Financial Crisis. This stands in contrast to Moscarini and Postel-Vinay (2012) who find that net job destruction of large firms is proportionally higher relative to small firms if unemployment is above trend. According to Chari, Christiano, and Kehoe (2013) and Fort et al. (2013), the disagreement stems from different sample periods and underlying cyclical indicators. This stresses the advantage of my TVP-VAR approach, which does not hinge on any imposed business cycle indicator. A further advantage is that I can look at the effects at a specific point in time as the coefficients are allowed to change every quarter. Hence, the coefficients capture possible changes in the lag structure of the model due to nonlinearities or state-dependency. Furthermore, allowing for stochastic volatility is crucial if one aims to capture changing shock sizes as well as time-variation in the contemporaneous relationship between variables.

Formally, the TVP-VAR(p) model can be written as

$$y_t = B_{1,t}\, y_{t-1} + \cdots + B_{p,t}\, y_{t-p} + \epsilon_t = X_t' \theta_t + \epsilon_t, \tag{3.1}$$

where the time-varying coefficients $B_{1,t \cdots p,t}$ are stacked in $\theta_t$ and $X_t$ contains the lags of all endogenous variables $y_t$. The error term $\epsilon_t$ is normally distributed with mean zero and a covariance matrix $\Omega_t$ that varies over time.[14] $\Omega_t$ can be decomposed into

$$\Omega_t = A_t^{-1} H_t (A_t^{-1})'$$

where $A_t$ is a lower triangular matrix that contains the time-varying contemporaneous relationships among endogenous variables. $H_t$ contains the stochastic volatilities.

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{t,21} & 1 & 0 & 0 \\ \alpha_{t,31} & \alpha_{t,32} & 1 & 0 \\ \alpha_{t,41} & \alpha_{t,42} & \alpha_{t,43} & 1 \end{bmatrix} \qquad H_t = \begin{bmatrix} h_{t,1} & 0 & 0 & 0 \\ 0 & h_{t,2} & 0 & 0 \\ 0 & 0 & h_{t,3} & 0 \\ 0 & 0 & 0 & h_{t,4} \end{bmatrix}.$$

Let $\alpha_t = (\alpha_{t,21}, \alpha_{t,31}, \ldots, \alpha_{t,43})$ be the vector of unrestricted (non-zero and non-one) elements of $A_t$ and $h_t$ a vector containing nonzero elements of $H_t$, the state equations are given by

$$\theta_t = \theta_{t-1} + \nu_t, \qquad \nu_t \sim N(0, Q) \tag{3.2}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t, \qquad \zeta_t \sim N(0, S) \tag{3.3}$$

$$ln\ h_{i,t} = ln\ h_{i,t-1}, + \sigma_i \eta_{i,t} \qquad \eta_t \sim N(0, 1). \tag{3.4}$$

Hence, $\theta_t$ and $\alpha_t$ follow random walks and the stochastic volatilities $h_t$ are geometric random walks. $Q$ denotes the covariance of $\theta_t$, $S$ is the covariance of $\alpha_t$. I assume that the innovations of the model equation and the three state equations are jointly normally distributed. Following Primiceri (2005) and Baumeister and Peersman (2013), I assume that the coefficients of the contemporaneous relations are uncorrelated across equations. This simplifies inference and increases the efficiency of the estimation. Technically this imposes that $S$ is block diagonal with blocks corresponding to the equations of the system (see Kilian and Lütkepohl, 2017). I estimate the model with Bayesian methods using an Markov Chain Monte Carlo (MCMC) algorithm with Gibbs Sampling.[15] My estimation algorithm follows Baumeister and Peersman (2013). I draw sequentially from the conditional posterior distributions of the set of parameters (i.e. the unobservable states of coefficients $\theta_t$, contemporaneous relations $\alpha_t$, variances $H_t$ and the hyperparameters of the variance-covariance matrices ($Q$, $S$ and $\sigma_i^2$).[16]

## 3.2 Data

To conduct my baseline empirical analysis, I use data on employment and net job creation rates by firm age from the Quarterly Workforce Indicators (QWI) based on the Longitudinal Employer-Household Dynamics (LEHD) data. I use the effective federal funds rate (FFR) to control for the monetary policy stance. For the post-2008 period, I use the shadow federal funds rate of Wu

[14] See Kilian and Lütkepohl (2017) for details.

[15] I follow Baumeister and Peersman (2013) and check the convergence of the Markov chain by computing the inefficiency factors of the draws, which is the inverse of the numerical efficiency measure as proposed by Geweke (1992).

[16] For details on the estimation algorithm and the choice of priors, see Appendix B.

and Xia (2016).[17] To measure credit supply conditions, I use the Excess Bond Premium (EBP) as introduced by Gilchrist and Zakrajšek (2012). Gilchrist and Zakrajšek (2012) construct a corporate bond spread ('GZ spread') which is representative of both maturity and credit quality in the corporate cash market for a specific month. They use a micro-level data set of secondary market prices of outstanding senior unsecured bonds issued by US non-financial corporations. In a second step, they decompose this aggregate corporate bond spread into a component of firm-specific default risk and firm-specific bond characteristics and a residual component, the excess bond premium (EBP). Thus, the EBP is the part of the corporate bond credit spread that is cleared of firms' default risk. Gilchrist and Zakrajšek (2012) argue that as such, the EBP reflects the *'effective risk-bearing capacity of the financial sector'* (Gilchrist and Zakrajšek, 2012, p. 1693) and, as a result, credit supply conditions. Furthermore, Figure 19 in Appendix A shows that the EBP and bank tightening standards for small firms are highly correlated. As such, the EBP serves as a proxy for bank lending standards.
The frequency of my data is quarterly. I estimate two empirical models that differ in their estimation period. The first model differentiates by firm age and the estimation period ranges from 1994Q1 to 2017Q4, where the first five years are used as a training sample to obtain priors. Hence, the sample starts in 1999Q1. In the second specification, the sample ranges from 1973Q1 to 2019Q2. I use the first seven years as a training sample, thus, the estimation starts in 1980Q3.[18]

### 3.3 The Empirical Model

The baseline empirical specification is

$$y_t = [LM_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t] \tag{3.5}$$

where $INT_t$ refers to the interest rate (i.e. the shadow rate) and $LM_t^j$ denotes the following sequentially entering labor market variables by age group $j \in$ (young, old):

$$[log(NJCR_t^j); \quad log(EMP_t^j)]$$

where $NJCR_t^j$ refers to the net job creation rate and $EMP_t^j$ denotes the total employment stock by firm age category.[19] I set the lag length $p$ to 2 and demean all variables prior to estimation.[20]

[17] Based on the observed Treasury yield curve, Wu and Xia (2016) construct a federal funds rate that is not constrained at zero.

[18] The chosen sample periods are based on data availability restrictions of the QWI data (short sample) and the Excess Bond Premium (long sample). Due to the chosen lag length of $\rho = 2$, I lose two more periods.

[19] Note that each specification includes one labor market variable (one element of $LM_t^j$) while the remaining variables always enter the model.

[20] I demean all variables because I estimate the model without an intercept.

### 3.4 Identification

After estimating the reduced form Equation 3.1, I am interested in the structural interpretation of shocks. Given the structural representation of the TVP-VAR

$$y_t = X_t'\theta_t + A_t^{-1}u_t, \tag{3.6}$$

where $X_t$ contains the lags of all endogenous variables $y_t$, $\theta_t$ denote the time-varying parameters and $u_t = A_t\epsilon_t$ are the structural shocks. $A_t$ is a lower triangular matrix containing the time-varying contemporaneous relationships among endogenous variables.[21] Generally, the TVP-VAR is identified if I impose $\frac{n(n-1)}{2}$ restrictions where $n$ denotes the number of elements in vector $y_t$. To obtain the restrictions, I apply a Cholesky decomposition and, hence, impose that $A_t, t = 1,\dots,T$ is lower triangular. While I maintain the same recursive identification strategy for all $t = 1,\dots,T$, the contemporaneous reaction is time variant.

Theoretically, these restrictions can be justified by the temporal reaction of the variables in $y_t$. Due to the lower triangular structure, the ordering of variables is crucial. Note that I order the corresponding labor market variable first and the measure for credit supply (the excess bond premium, EBP) last. Therefore, I impose the assumption that the labor market responds only with a lag of one quarter to shocks in credit supply (EBP). Only the excess bond premium itself reacts on impact to a shock in credit supply. As a result, the ordering of variables is from 'slow-moving' to 'fast-moving' variables (see e.g. Bernanke et al., 1999). This identification strategy in the context of credit supply shocks is well-established in existing literature. Among others, Lown and Morgan, 2006, Gilchrist and Zakrajšek, 2012,Bassett et al., 2014, and Barnichon et al., forthcoming impose a recursive ordering between macroeconomic and financial variables. One potential drawback of the recursive identification strategy is its sensitivity to the ordering of variables. To address this issue, I perform a robustness analysis regarding the ordering of variables (see Section 4.3).

## 4 Empirical Results

This section presents the results of the structural empirical analysis. First, I present the impulse response analysis of a credit supply shock on young and old firms' labor market variables. Then, I show results on the time-variation of employment responses by firm age. I provide several extensions and robustness checks in Subsection 4.3. In Subsection 4.4, I analyze the importance of credit supply shock since the early 1980s.

### 4.1 Results by Firm Age

One advantage of a TVP-VAR is that it allows computing generalized impulse response functions (GIRFs) for every point in time. Figure 3 depicts the GIRFs in response to a credit supply shock over all periods and the entire impulse response horizon in a three-dimensional manner. Figure 4 illustrates the results with a rotated view. Thus, Figure 3 allows inspecting the effects over

[21] For a detailed description of the TVP-VAR with stochastic volatility, see Appendix B.

time and the rotated view in Figure 4 visualizes the effects over the impulse response horizon. To ensure comparability over time, I normalize the shock size to one in every period. The upper two panels in both figures illustrate median responses of firms' net job creation rate (NJCR), with young firms on the left (in green/blue) and old firms to the right (in yellow/orange).[22] Figure 3 shows that all firms faced a decline in net job creation rates in recessionary periods. However, especially during the GFC, the reaction of young firms was stronger relative to old firms. In addition, the contraction of young firms' NJCR lasted until the year 2012 and, thus, longer compared to old firms. The rotated view in the upper panel of Figure 4 gives further insights on the persistence of the effects. Old firms experience only a short-lived decline in the NJCR, whereas the effect on young firms is highly persistent.

The lower two panels in Figures 3 and 4 depict the employment reaction by firm age. Regarding, employment, the differences over time and the impulse response horizon by age are even stronger compared to the net job creation rate. During the 2001 recession, young and old firms showed similar employment responses in response to a credit supply contraction. However, this similarity vanishes over time and starting in the mid-2000s, young firms show a considerably stronger employment response if credit supply tightens.[23] Young firms' responses were not only more pronounced but also much more persistent compared to old firms (see the lower panel of Figure 4 for a rotated view). Old firms' response dampened soon after the Great Financial Crisis in 2009, whereas young firms faced the strongest employment reaction after the crisis around the year 2012.

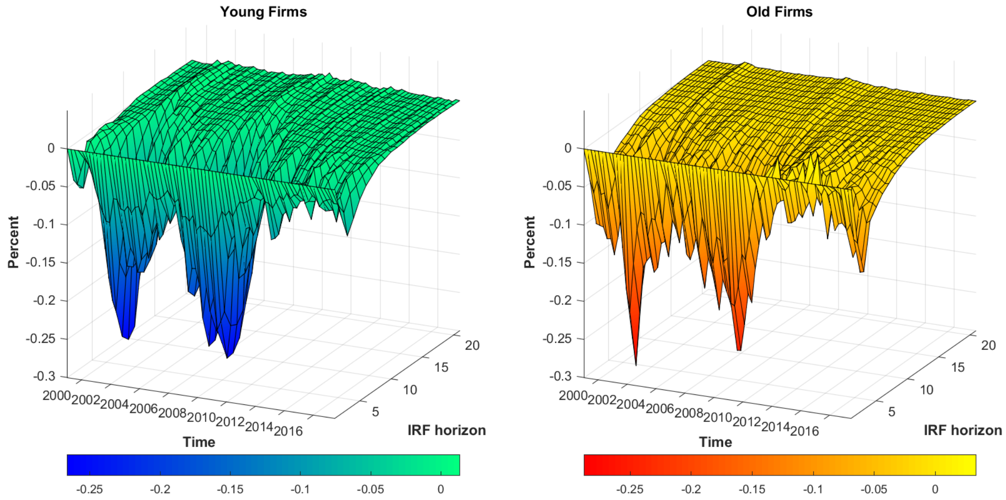
Next, I analyze the time-variation of the labor market effects in response to a credit supply shock. For this purpose, I consider the reaction six quarters after the shock over the entire estimation period (from 1999Q1 to 2017Q4). I choose the sixth quarter after the shock because it takes several quarters until the shock materializes and a clear picture emerges. However, results are similar for slightly different periods.[24] Figure 5 illustrates the responses of the net job creation rate of young (blue line) and old firms (red line) over time in response to a credit supply shock. The findings can be summarized as follows: The NJCR of young firms reacts stronger in recessions (as defined by the NBER and illustrated as grey-shaded areas) whereas in expansions the effects are similar and negligible. The reaction of young firms comes with higher estimation uncertainty. Regarding the timing of effects, young firms' median NJCR responds earlier compared to old firms. Starting around 2006, the median responses of young and old firms start to diverge and young firms' reaction gets much stronger. Similarly, Figure 6 illustrates the effects of employment by firm age in response to a credit supply shock over time. Again, the reaction of young firms comes with higher estimation uncertainty. Until the year 2006, median employment responses are almost identical by firm age. This picture changes in a statistically significant way with the Great Financial Crisis. Young firms start to respond significantly stronger to a decrease in credit supply, whereas old firms' reaction remains relatively constant. Even though, since 2011 the employment response of young firms is on an upward-trending path again, there is still a (weakly significant) level dif-

[22] The color scale illustrates the effects in response to a credit supply shock in percent. The darker the color (red or blue), the stronger is the effect.

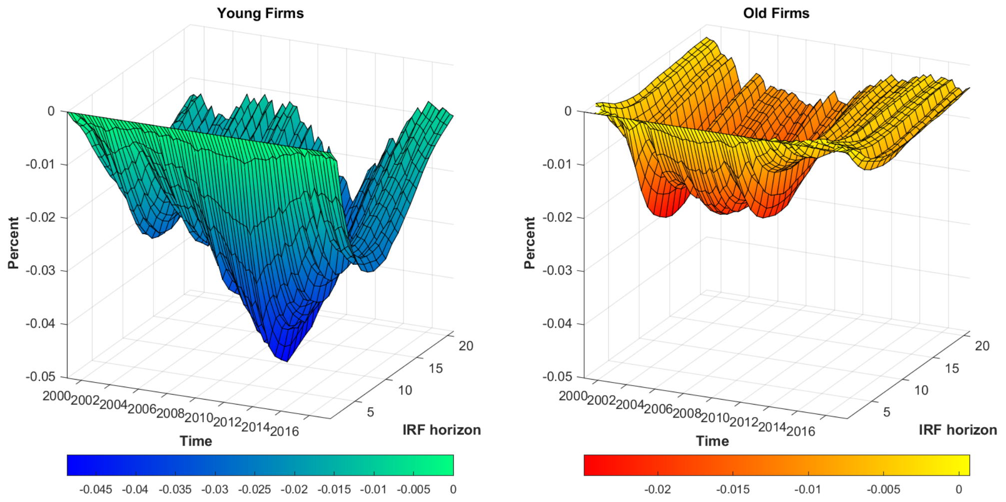
[23] Figure 23 in Appendix C compares the IRFs in recessionary periods and the Great Financial Crisis only.

[24] See Figures 20 to 22 in Appendix C for an illustration of all endogenous variables and a cross-section of generalized impulse responses one period, 6 periods, and 12 periods after the shock in the specification with employment.

**Figure 3:** Median Generalized Impulse Response Functions (GIRFs) by Firm Age over Time and the IRF-horizon.



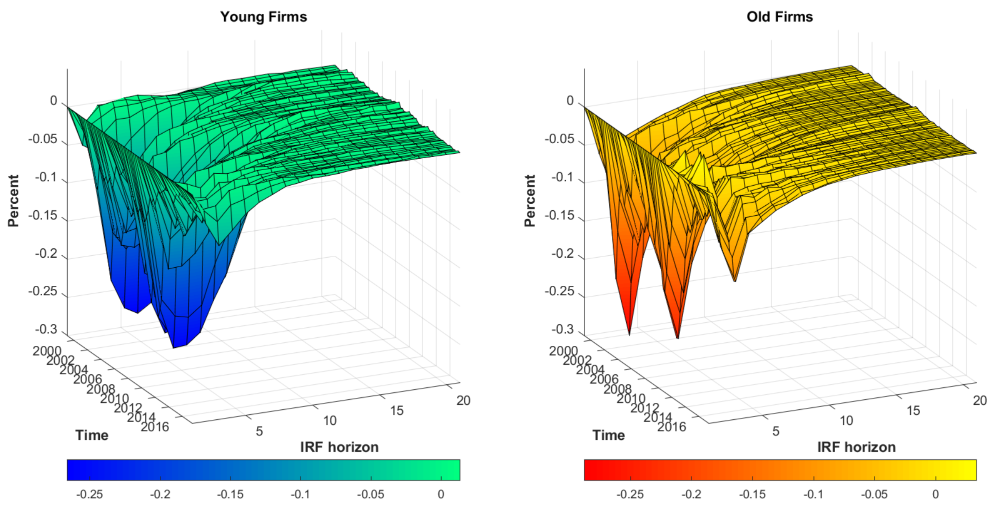

**(a)** Net Job Creation Rate Response over Time and IRF- horizon



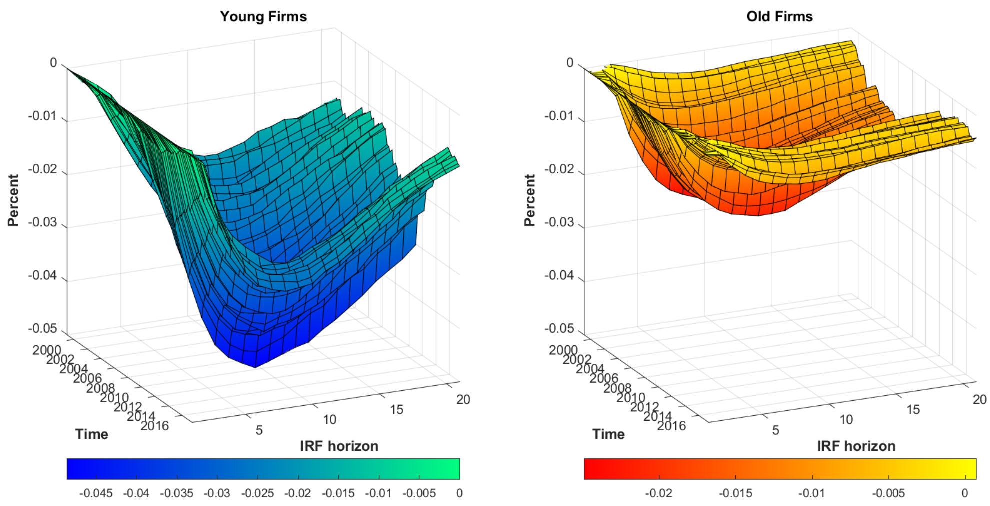

**(b)** Employment Response over Time and IRF-horizon

Notes: Median responses to a 1 std. EBP shock (normalized to one), young firms are depicted in blue, old firms in red. The response over time is depicted on the x-axis, the IRF-horizon is on the y-axis.

**Figure 4:** Median Generalized Impulse Response Functions (GIRFs) by Firm Age over Time and the IRF-horizon (rotated view).



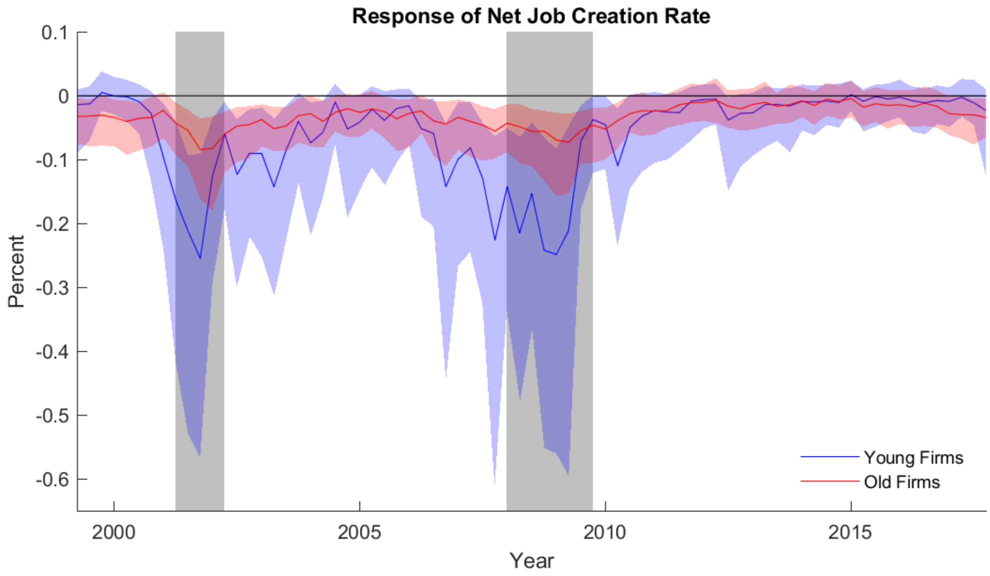

**(a)** Net Job Creation Rate Response over Time and IRF horizon




**(b)** Employment Response over Time and IRF horizon

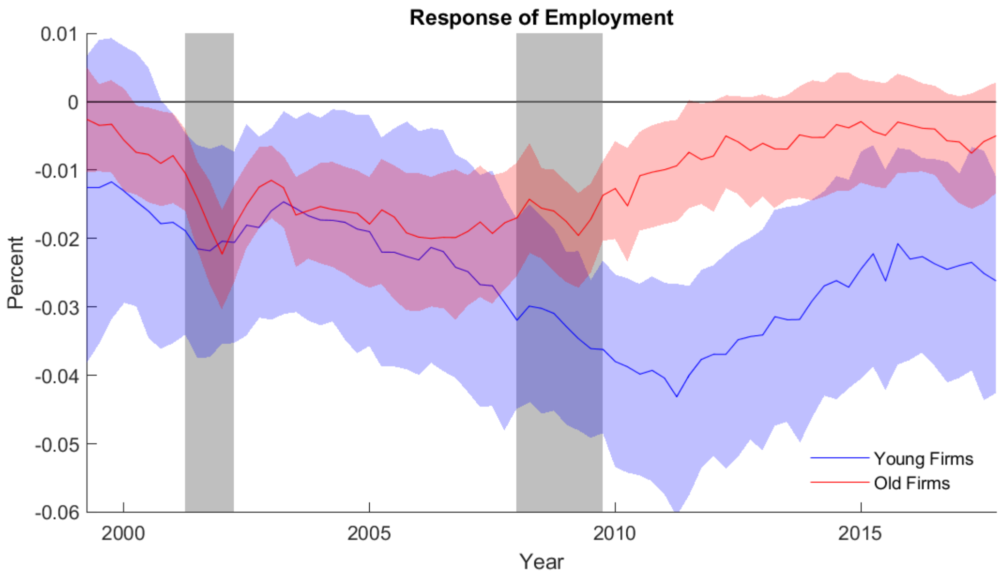
Notes: Median responses to a 1 std. EBP shock (normalized to one), young firms are depicted in blue, old firms in red. The response over time is depicted on the x-axis, the IRF horizon is on the y-axis.

**Figure 5:** Responses of the Net Job Creation Rate by Firm Age over Time




Notes: The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior distribution for young (old) firms. Grey shaded areas denote NBER recession periods.

**Figure 6:** Responses of Employment by Firm Age over Time




Notes: The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior distribution for young (old) firms. Grey shaded areas denote NBER recession periods.

ference between their median responses.

## 4.2 Age vs. Size

I focus on the role of firm age and not size for three reasons. First, age is a clear measure and a good proxy for financially constrained firms. Second, young firms show the highest growth potential and are likely to face financial constraints when they want to expand. Third, the younger a firm, the noisier its signal to lenders on the financial market. This asymmetric information makes borrowing more costly for young firms. In this subsection, I discuss these reasons in more detail and present empirical TVP-VAR results considering the distinction by size.

**Measurement:** I would like to distinguish clearly financially constrained from unconstrained firms. However, as there is no reliable measure of financial constraints in the data, I have to use a proxy. As discussed in Cloyne et al. (2019), one important advantage of the age proxy is rank invariance. This is especially relevant given that I focus on the effects over time and the business cycle. If size is measured along the employment or asset dimension, an individual firm may change size classes over the business cycle (e.g. as they adapt along the employment margin).[25]

**Growth Potential and Credit Constraints:** Young firms tend to be small, but not all small firms are young. Figure 7 depicts the average size distribution of young and old firms for the years 2000 to 2014. Around 50 percent of young firms have less than 20 employees and only a few young firms are relatively large. Old firms tend to be large, but there is also a considerable fraction (around 23 %) of small old firms. Old, small firms are less likely to show high growth rates and are less dependent on debt financing. I am mainly interested in young, small firms. Unfortunately, this distinction is not available at the QWI. Therefore, I focus on young firms in general. Table 2 shows the share of absolute job creation in an age/size matrix. The share of job creation of small, young firms is 2.5 times relative to their employment share. Similarly, the job creation share of young, large firms is twice as high compared to their employment share. However, there is only a small number of young, large firms. Thus, they are quantitatively unimportant. This is consistent with the recent literature documenting that young firms have the highest growth potential (see Haltiwanger et al., 2016, Sedláček and Sterk, 2017, and Pugsley and Şahin, 2018).

**Table 2:** Job Creation Shares by Age and Size

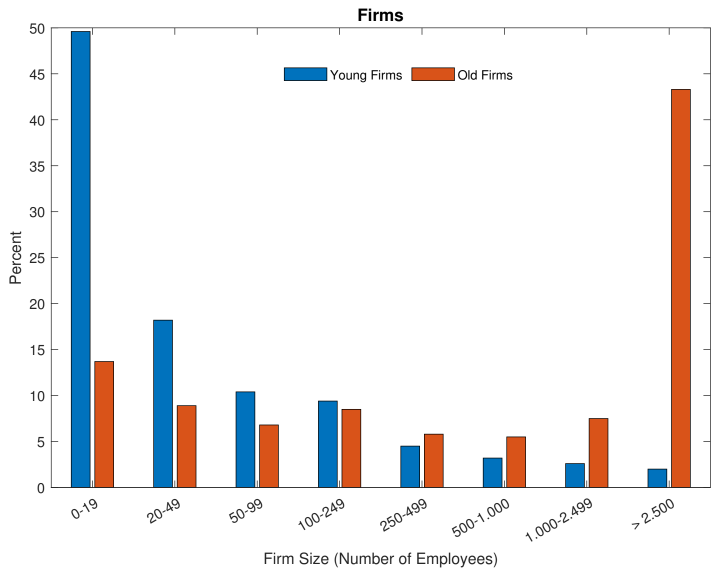
| | Small Firms | Large Firms | All by Age |
|---|---|---|---|
| Young Firms | 22.2% | 8.6% | 30.8% |
| Relative to Employment Share | 2.48 | 2.02 | 2.33 |
| Old Firms | 14.8% | 54.4% | 69.2% |
| Relative to Employment Share | 0.76 | 0.81 | 0.80 |
| All by Size | 37.0% | 63.0% | 100.0% |

Notes: Young firms are defined as up to five years old and small firms are defined with less than 50 employees. Data Source: BDS, averages over the time span 2000-2014.

**Asymmetric Information:** For lenders, a firms' short credit history is a noisy signal. Young firms show a high idiosyncratic risk of defaulting. As the lender cannot observe the firms' productivity,

[25] There is a large corporate finance literature on identifying proxies for financial constraints, however, the debate on the validity of these proxies is still ongoing, see among others Farre-Mensa and Ljungqvist (2016) and Crouzet and Mehrotra (2020).

**Figure 7:** Size Distribution by Firm Age




Notes: Average size distribution of young and old firms for the years 2000 to 2014. Young firms are defined as being up to five years old. Data source: Business Dynamics Statistics (BDS).

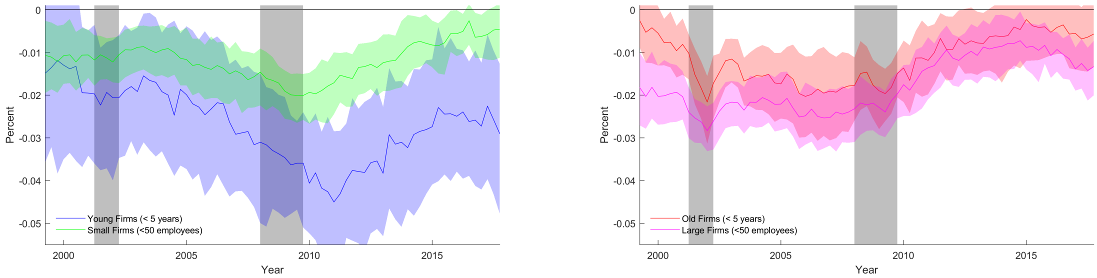
especially young firms are prone to run into financial constraints due to asymmetric information between borrowers and lenders. Micro-level evidence based on the Kauffmann Firm Survey confirms that this is a relevant reason: In 2007, 35% of firms who had a loan application rejected reported that the reason for the denial was that their business was too new.[26]

**TVP-VAR Evidence:** To understand the differences of a credit supply shock by age versus size, I estimate the empirical model with small and large firms and compare the corresponding employment responses. I define a small firm having up to 50 employees and a large firms with more than 50 employees. Figure 8 compares the results of my baseline estimation with firm age to the results by firm size. The right panel illustrates the effects over time 6 quarter after the shock for young (blue shaded area) and small (green shaded area) firms. The left panel of Figure 8 compares the corresponding results for old firms (red shaded area) to large firms (pink shaded area). During the GFC, the employment response of young firms is significantly more pronounced compared to small firms. In contrast, the employment reactions of old and large firms are identical. This finding is independent of different definitions of small vs. large.[27] Hence, credit tightening shocks have a stronger impact on young firms than on small firms. The effect was particularly strong during and after the GFC. This confirms my choice of using firm age as the relevant proxy for a financially constraint firm. I interpret this result as evidence for stronger external financing needs of young firms and the existence of a higher degree of information asymmetries between financial intermediaries and young firms. Financial frictions that arise due to asymmetric information affect young firms stronger than small firms (see Gertler

[26] This was the third most important reason for credit application denial after 'personal credit history' (45%) and 'insufficient collateral' (44%) (see Table 5 in Appendix C for details). The Kauffmann Firm Survey is a panel of newly founded businesses in 2004 who are tracked over time. The sample size is 2.907 observations.

[27] I estimate the TVP-VAR for different thresholds of small and large firms (20 and 250 employees respectively) which does not alter the results.

**Figure 8:** Employment Effects of a Credit Supply Shock, Age vs. Size




**(a)** Young vs. Small

**(b)** Old vs. Large

Notes: Baseline GIRFs of employment by firm age and GIRFs of employment based on two four-variable TVP-VAR estimation with small (<50 employees) and large firms respectively. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods

and Gilchrist, 1994 for a discussion).

### 4.3 Robustness and Extensions

This subsection presents several extensions and robustness checks on the empirical findings.

**Firm Entry and Exit:** In principle, the different reactions by young and old firms in response to a credit supply shock could be driven by firm entry and firm exit.[28] To check for this, I perform the following two robustness checks: First, I add the number of destroyed jobs by exiting firms as a fifth endogenous variable to the estimation.[29] Figure 24a in Appendix A illustrates the median employment responses six quarters after the shock over the estimation sample. The estimation uncertainty for young firms increases, but the main result, the significantly stronger employment reaction of young firms, still holds. Second, to test whether these results are driven by start-ups only, I re-estimate the baseline specification (see Equation 3.5) without the youngest age group, those who are younger than two years. Figure 24b in the Appendix depicts the resulting median employment responses over time. The result remains robust to the exclusion of start-ups and very young firms.

**Measure of Credit Supply:** The EBP is based on a credit spread of corporate bonds issued by a representative sample of U.S. non-financial firms. Whereas corporate bonds are an important financing instrument, it might not be the most prevalent financing option for start-ups and young firms. Figure 19 in Appendix A depicts the EBP and banks tightening standards for loans to small firms. The two measures of credit supply are highly correlated. Therefore, the EBP serves as a proxy for bank lending standards for small firms. As a robustness check, I use banks tightening standards instead of the EBP in my TVP-VAR estimation. For young firms, I use the banks tightening standards for commercial and industrial loans to small firms, whereas for old firms I use banks tightening standards for large firms. The results are illustrated in Figure 26a in Appendix C. The use of banks tightening standards leads to an even more pronounced difference between young and old firms with young firms responding significantly stronger already in the

[28] Pugsley and Şahin (2018) document a decline in start-ups and establish a link to the jobless recovery in the U.S.

[29] Maintaining the assumption that macro variables respond with a lag of one quarter to movements on the financial market, I order the number of destroyed jobs by exiting firms second in the estimation.

early 2000s.

**Definition of Young Firms:** If I consider a firm up to the age of ten years to be a young firm (see panel b of Figure 26b), the divergence in employment reactions is less pronounced. Employment of young firms up to the age of ten years reacts stronger in recessionary phases, but the difference by age is much less pronounced. Immediately after the Great Financial Crisis, median employment responses overlap again. This indicates that the difference by age is only relevant up to a threshold of around five years. This finding is consistent with the observed up-or-out dynamics of young businesses (see Haltiwanger et al., 2013 or Haltiwanger et al., 2016): Firms who survive the first five years in business have a low probability of failure thereafter. According to the BDS, the annual exit rate of firms up to five years is around 70 percent higher than the exit rate for firms between 6 and 10 years.[30] Higher survival rates alleviate financial frictions in two ways: First, firms have accumulated higher net worth over the years and, as a result, have more collateral. In addition, they have to rely less on their own house as a source of collateral. Second, the informational asymmetry between borrowers and lenders is smaller.

**Identification Strategy:** To analyze the sensitivity of the results to the chosen identification strategy, I change the ordering of the variables in the baseline estimation. First, I interchange the ordering of the last two variables, hence, the excess bond premium is ordered third and the federal funds rate fourth.[31] This addresses the imposed restriction that a financial shock does not affect the federal funds rate contemporaneously. The results on the employment reaction by firm age remain robust (see Figure 27 in the Appendix). Second, I set aside the assumption that aggregate variables (i.e. employment and GDP) respond with a lag of one quarter to credit supply shock. Instead, I allow for immediate reactions of employment in response to an increase in the EBP. This corresponds to the following ordering of variables: $Y_t = [EBP_t \;\; INT_t \;\; log(EMP_t^j) \;\; log(GDP_t)]$. The results for the employment reaction of young compared to old firms under different timing assumptions of the endogenous variables are illustrated in Figure 27 in the Appendix. Again, the results remain robust, although less pronounced in the specification with the EBP ordered first.

### 4.4 Taking a Historical Perspective

How important have credit supply shocks been in the past 40 years? To answer this question, I estimate a different empirical model. Due to data limitations, I cannot perform the following analysis for young and old firms separately.[32] For this reason, I estimate the following empirical model

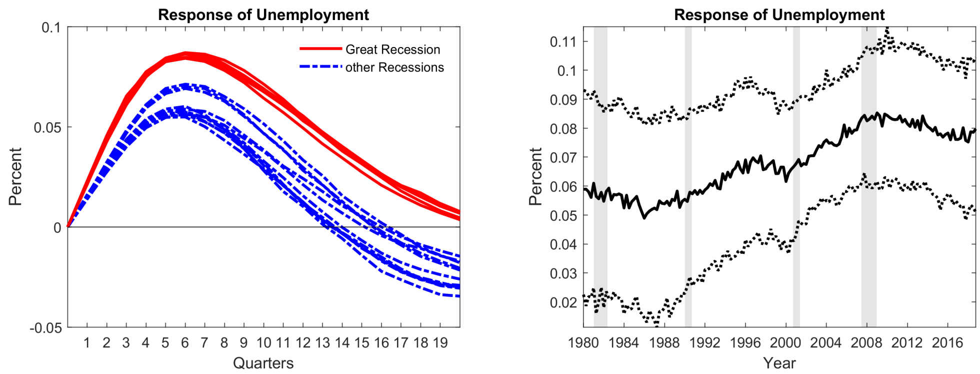
$$Y_t = [log(\text{unemp}_t) \;\; \Delta GDP_t \;\; INT_t \;\; EBP_t].$$

[30] Source: own calculations based on average establishment exit rates by firm age from the BDS between 1999 and 2014. The exit rate for young firms is weighted by their corresponding shares. See also the Section 7 for details.

[31] Note that from 2008 onward the series corresponds to the shadow rate. Using the federal funds rate for the entire period does not change the results.

[32] The Quarterly Workforce Indicator is only available from 1993 onward and data from the Business Dynamics Statistics is in annual frequency.

**Figure 9:** GIRFs of Unemployment in Response to a Credit Supply Shock (Long Horizon). Recessionary Periods and over Time.




Notes: Left Panel: GIRFs of Unemployment in response to a negative credit supply shock in NBER recession periods except the Great Recession (blue) and the Great Recession (red). Right Panel: Cross-section of unemployment responses over time. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), dashed lines denote 16-th and 84-th percentiles of the posterior distribution. Grey shaded areas denote NBER recession periods.

where $\text{unemp}_t$ is the unemployment rate and $\Delta GDP_t$ denotes GDP growth.[33] The estimation period stretches from 1980Q3 to 2019Q2.[34] As a robustness check, I estimate the same model with employment instead of unemployment. The corresponding results are illustrated in Appendix C (Figure 30).

**Reaction over Time:** The left panel of Figure 9 depicts the GIRFs of a credit supply contraction on unemployment in the Great Recession (red lines) and all other NBER recession period (dashed, blue lines). The reaction during the Great Recession was markedly stronger compared to previous NBER recessions. If we consider the cross-section of all unemployment reactions six quarters after the shock since 1980 (right panel of Figure 9), we observe that the unemployment response got stronger over time, peaking after the Great Financial Crisis. Thus, the difference over time thus not emerge from stronger reactions in recessions compared to expansions, but from an overall trend of a stronger unemployment reaction over time. In the specification with employment (see Figure 30 in Appendix C), a similar (inverse) picture emerges.

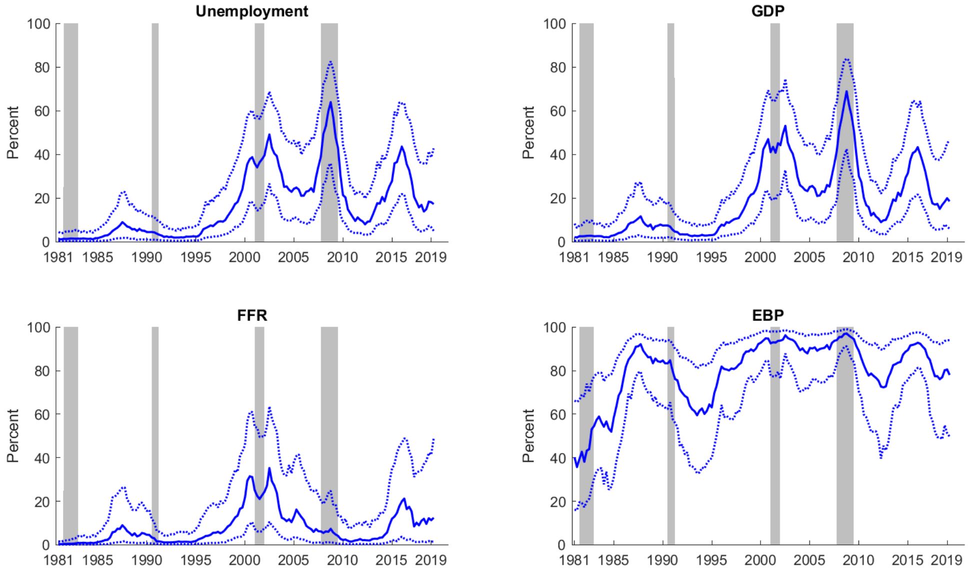
**Forecast Error Variance Decomposition:** Figure 10 depicts the forecast error variance of all four endogenous variables six quarters after the shock with sixteenth and eighty-fourth percentiles of the posterior distribution. The share of unemployment and GDP growth volatility caused by a credit supply shock varies strongly over time. Before the late 1990s a credit supply shock had almost no contribution to the volatility of unemployment and GDP. Since then, changes in credit supply conditions gained importance in explaining the volatility of macroeconomic variables. During the recession in the early 2000s, financial conditions accounted for around 40 percent of the unemployment volatility and around 60 percent during the GFC.

**Historical Decomposition:** Figure 11 displays the historical contribution of credit supply shocks

[33] I use year-on-year GDP growth rates in the specification for the long horizon to ensure stationarity of the model. This is necessary to perform a historical decomposition.

[34] The data sample ranges from 1973Q1 to 2019Q2. I use the first seven years as a training sample.

**Figure 10:** Forecast Error Variance Contribution of Credit Supply Shocks




Notes: The solid line depicts the median of the contribution of credit supply shocks to the forecast error variance of all four endogenous variables 6 quarters after the shock. The dashed lines illustrate the 16th and 84th percentiles of the posterior distribution. FFR refers to the effective federal funds rate with the shadow rate between 2008 and 2015. EBP refers to the Excess Bond Premium. Gray-shaded areas denote NBER recession periods.

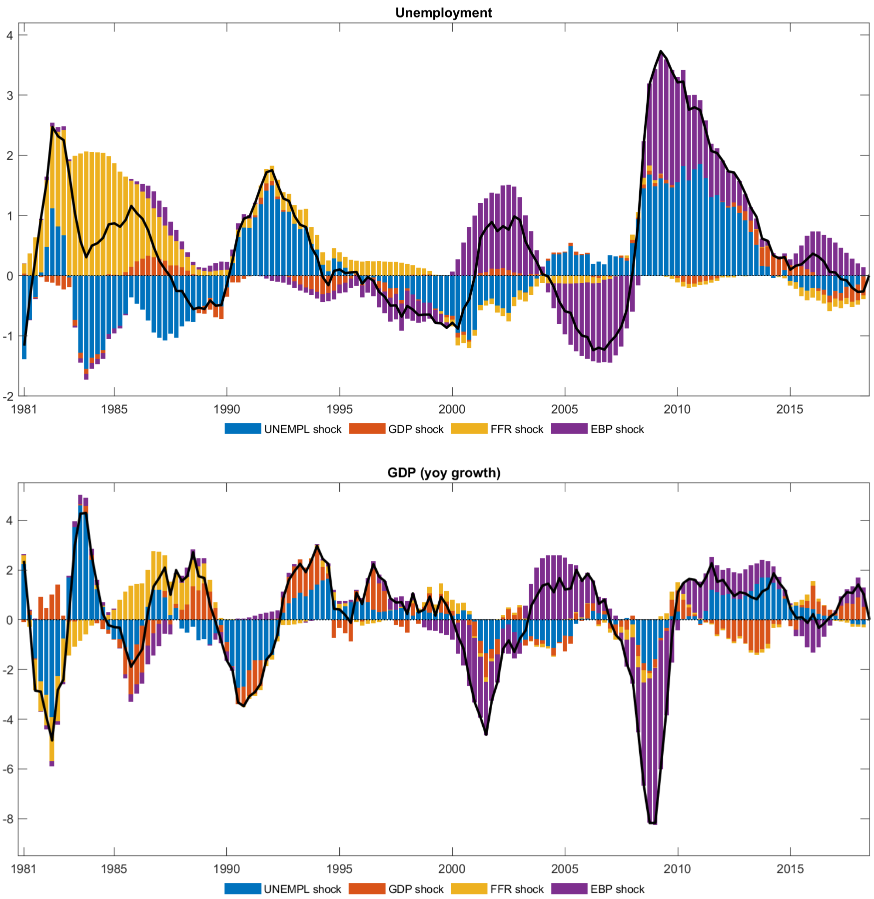
on unemployment (upper panel) and year-on-year GDP growth (lower panel). In the early 1980s monetary policy shocks (shocks to the interest rate) and labor market shocks itself (shocks to the unemployment rate) were important in explaining unemployment dynamics. However, starting in 2000, credit supply shocks explain a large fraction of unemployment developments. In my empirical model, exogenous increases in the EBP explain almost entirely the rise in unemployment during the recession in 2001. Around 40 percent of the rise in unemployment during the Great Recession can be attributed to credit supply shocks. The remaining part originated from the labor market itself. Regarding GDP, credit supply shocks also started to become important in the late 1990s, but can explain an even larger fraction of variations in GDP.

**The Role of Financial Deregulation:** What caused the shift in the contribution of economic shocks to unemployment and GDP growth dynamics? The declining importance of monetary policy shocks (i.e. shocks to the FFR) in the early 80s can be explained by the 'Great Moderation' and the change in monetary policy during the Volcker chairmanship of the FED.[35] Since the late 1990s, financial conditions are an important driving force for unemployment and output dynamics. At the same time, U.S. financial markets underwent strong deregulation.[36] The subsequent rise in securitization changed the nature of housing finance. Securitization caused lenders in the mortgage market to lower their bar on down payments and screening practices (Keys, Seru, and Vig, 2012). Between the years 2000 and 2006, the issuance of U.S. private mortgage backed securities increased tenfold. Favara and Imbs (2015) establish a causal link between

[35] See e.g. Clarida, Galí, and Gertler (2000) for a discussion.

[36] It is a common belief that the e.g. 'Financial Services Modernization Act' of 1999 fostered greater risk-taking behavior of financial firms which led to the rise of new financial products, hedge funds, and securitization of loan obligations.

**Figure 11:** Historical Decomposition of Unemployment and GDP growth.




Notes: The black solid line represents the actual data. Unemployment is demeaned for the baseline forecast.

financial deregulation in the 1990s on the supply of mortgage credit and the U.S. house price boom. In addition, optimism about future housing demand heated-up house prices (see Kaplan et al., 2020).

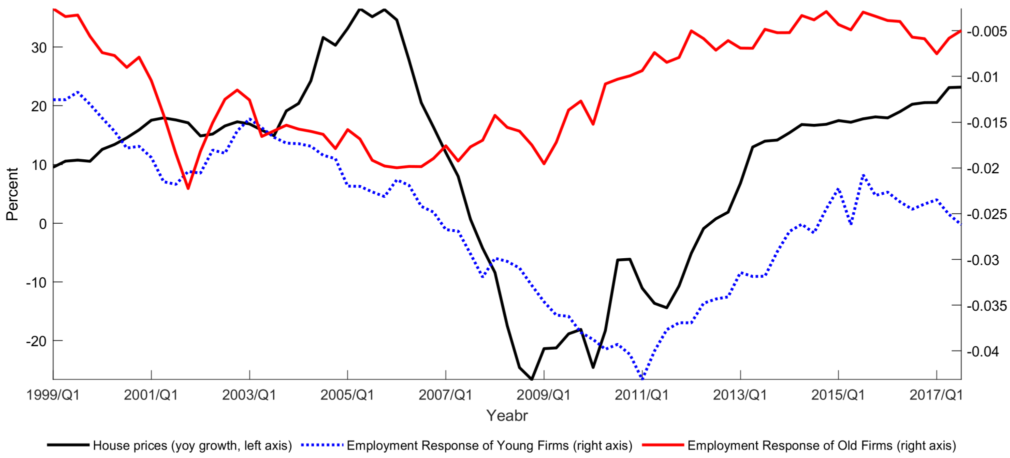
How is financial deregulation and securitization related to firms' employment reaction? The mechanism works via a the role of housing net worth as collateral and starting capital for young firms. The surge in house prices led to an appreciation of housing net worth. In combination with a relaxation of credit standards, owners of young businesses could borrow a high amount of debt. This allowed them to expand their activity. However, as house prices collapsed, they were highly leveraged due to the depreciation of their housing net worth. In the next section, I provide a detailed discussion on the role of house prices in explaining the difference in employment dynamics by age.

## 5 The Role of House Prices

The empirical analysis of Section 4 highlights that with the onset of the GFC, employment reactions by firm age were diverging in response to a credit supply shock. This section investigates the role of house prices for these developments.

**Descriptive Evidence:** Figure 12 displays year-on-year growth rates of U.S. house prices (left axis) and the median employment responses for young and old firms (right axis) The Figure reveals that the timing of the divergence of employment responses coincides with the collapse of U.S. house prices. In the second quarter of 2006, the growth of U.S. house prices fell by 20% compared to the previous year. At the same time, in response to a credit supply shock, young firms started to adapt much stronger along the employment margin, whereas the response of old firms remained stable. Only in 2011, when house prices started to pick up again, the young firms' employment response got weaker.

**Figure 12:** U.S. House Price Growth (yoy) and Median Employment Responses to a Credit Supply Shock by Firm Age




Notes: The solid black line illustrates the year-on-year growth rate of 'All-Transactions House Price Index for the United States' (Data Source: U.S. Federal Housing Finance Agency). The dashed blue (dotted red) line are the median employment responses after 6 quarters to a 1 std. EBP shock (normalized to one).

**House Prices as Endogenous Variable** As a next step, I investigate the employment responses by firm age in the TVP-VAR setting while controlling for house price growth as a fifth endogenous variable in the estimation.[37] The corresponding employment reactions are illustrated in Figure 28 of Appendix C and show that the difference by age is considerable less pronounced. Hence, controlling for the endogenous interaction between employment and house prices in response to a credit crunch explains a significant fraction of the diverging reaction by age. However, the employment reaction of young firms is still significantly more pronounced compared to old firms.

**Collateral for Start-ups:** Why is the value of households' private home relevant to firms' job creation?[38] A considerable fraction of start-ups and young firms use their private home as start-up capital and collateral for business loans. Evidence based on the *Survey of Business Owners*

[37] The ordering of the extended VAR is $y_t = [LM_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t \Delta HP_t]$. Thus, I allow for a contemporaneous effect of financial shocks on house prices.

[38] Several papers attribute (a large fraction of) the employment drop during and after the Great Financial Crisis to the deterioration of households' balance sheet via a housing channel (see e.g. Mian and Sufi, 2014). In a structural model with housing, Kaplan et al. (2020) find that house prices affect credit conditions via changes in household leverage.

**Table 3:** Sources of Start-up Capital by Year of Business Formation in Percent

| | Perc. Change 90s to 2006 | 2007 Start-ups | 2006 1 year | 2005 2 years | 2004 3 years | 2003 4 years | 2000-2002 5-7 years | 1990-1999 8-17 years |
|---|---|---|---|---|---|---|---|---|
| Personal savings of owner(s) | -4.04 | 56.14 | 62.88 | 64.88 | 66.16 | 65.85 | 65.70 | 65.53 |
| Personal/family assets other than savings | -6.73 | 6.58 | 8.90 | 9.40 | 9.51 | 9.85 | 9.57 | 9.54 |
| Bank Loan | -37.00 | 6.58 | 9.87 | 11.22 | 12.31 | 12.97 | 13.48 | 15.67 |
| Personal home equity loan | 36.03 | 5.37 | 8.44 | 9.03 | 9.10 | 9.11 | 7.53 | 6.20 |
| Personal/business credit card(s) | 36.02 | 12.07 | 15.27 | 15.42 | 14.93 | 15.56 | 14.08 | 11.23 |
| Business loan/investment from family/friends | -22.38 | 2.03 | 2.80 | 3.13 | 3.17 | 3.48 | 3.23 | 3.61 |
| Govt. Loan | -39.00 | 0.43 | 0.65 | 0.86 | 0.89 | 0.91 | 0.95 | 1.07 |
| Govt. Guarantee | -30.96 | 0.53 | 0.85 | 0.99 | 1.07 | 1.20 | 1.10 | 1.23 |
| Venture Capital | -13.91 | 0.35 | 0.61 | 0.57 | 0.70 | 0.67 | 0.71 | 0.70 |
| Grant | -1.24 | 0.21 | 0.21 | 0.26 | 0.29 | 0.30 | 0.28 | 0.22 |
| Other Sources | 10.75 | 2.08 | 2.55 | 2.42 | 2.65 | 2.39 | 2.40 | 2.30 |
| Unknown | -52.50 | 1.90 | 2.04 | 2.26 | 2.52 | 2.77 | 2.93 | 4.30 |
| None needed | 45.50 | 29.97 | 19.72 | 17.28 | 15.26 | 15.28 | 15.32 | 13.55 |

Notes: Share of Business Owners who used the corresponding source(s) of start-up or acquisition capital by the year the business was established. The first column refers to the change between businesses established between 1990 to 1999 and 2006. Data Source: 2007 Survey of Business Owners (SBO) Public Use Microdata Sample (PUMS). Totals may sum to more than 100 because of multiple answers.

illustrated in Table 3 shows that the share of owners who have used a personal home equity loan has increased from 6.2 percent (in the 1990s) to more than 9 percent. For businesses established in the year 2006, the importance of home equity as source of start-up capital has increased by more than 36% compared to the 1990s. In the year 2007 (as house prices collapsed), the share of business owners using personal home equity loans decreased considerably.

The role of housing collateral for young firms and start-ups is emphasized in a recent paper by Bahaj et al. (2020). They use U.K. firm-level data to show that 70% of loans to small- and medium-sized enterprises use real estate as collateral. Regarding the United States, the picture is similar: According to the analysis in Meisenzahl (2014), who uses the Federal Reserve Board's Survey of Small Business Finances for the years 1998 and 2003, more than 50 percent of firms reported that collateral was required to receive a loan, 54 percent of credits were secured by personal guarantees of the owner and 30 percent of businesses provided both.[39]

Hence, if housing serves as an important source of collateral for young firms and start-ups, a decline in the value of housing makes borrowing more costly. Given that young firms depend stronger on external finance compared to old firms (see Begenau and Salomao, 2018 for descriptive evidence), a contraction of credit supply hits young firms harder. The contractionary response is further amplified if their housing net worth loses value.[40]

**Cross-Regional Evidence:** In the next step, I perform cross-regional estimations at the metropolitan statistical area (MSA) level to analyze the role of house prices on the employment reaction of young firms. My empirical long-difference approach builds on Giroud and Mueller (2017). I regress the change in young firms' employment (and job creation as well as job destruction) on an interaction term of the change in the number (and amount) of small business loans and the change in local MSA-level house prices. The approach is described in detail in Appendix D and the results are presented in Table 6 in the Appendix. The cross-regional regres-

[39] A personal guarantee means that business owners pledge their own (personal) assets to repay debt.

[40] This is also in line with Chaney, Sraer, and Thesmar (2012) who show that there is a strong link between fluctuations in real estate prices and investment. Liu, Miao, and Zha (2016) focus on the interaction of real estate prices and the labor market and find that a shock to house prices leads to an increase in unemployment.

sion results indicate that areas with a stronger decline in house prices exhibit a larger elasticity of young firms' job creation with respect to small business loans.[41] This points towards an important role of the housing net worth (i.e. collateral) channel for young firms' access to credit and their hiring decisions. Although these results cannot be interpreted causally, they provide an interpretation for my key empirical results: First, financial deregulation in the late 1990s led to an increase in home ownership rates and a surge in house prices. Young firms could take on high debt using their housing net worth as collateral. This led to a tighter linkage between credit conditions, house prices, and labor market dynamics (see also Mian and Sufi, 2014) and explains the empirically detected structural break (see Figure 11). However, the bust in house prices led to a depreciation of business owners' housing net worth (and as such their collateral). Along with more restrictive credit conditions imposed by lenders, young firms reacted significantly stronger in response to financial market shocks compared to old firms. The theoretical model outlined in Section 6 allows for a combination of a credit supply shock and a decline in firms' net worth and provides an in-depth discussion of the transmission channel.

# 6 The Quantitative Model

The model economy is populated by households, financial intermediaries, and an entrepreneurial sector that consists of entrepreneurs in different age cohorts (entrants, young cohorts of age one to $J$ and the cohort of old entrepreneurs), capital goods producers, and output goods producers. Households, capital good producers as well as output good producers are described in detail in Appendix E.

Entrepreneurs endogenously enter the market. Upon entry, they operate in the cohort of entrants and, if they do not default or exit exogenously, they move to the next age cohort. Besides the entrants, there exist $K-1$ more cohorts of young firms and old entrepreneurs. Let us assume that each age cohort $j \in (E, 1, \cdots, K, O)$ consists of a continuum of risk-neutral entrepreneurs $i$. Each period, every age cohort pools their earnings which allows cohort-wise aggregation.[42] Except for the entrants (start-ups), every age cohort has two financing channels, external finance (via debt) and internal finance. Internal finance refers to paying out dividends to households, or, if dividends are negative, raising equity from households. I assume that start-ups are equipped with some initial net worth from households and cannot pay out dividends yet.

All entrepreneurs require loans from a financial intermediary to finance their risky operations. They are subject to idiosyncratic productivity shocks $\omega^{i,j}$ which follow a log-normal distribution and determine whether they remain in business or declare bankruptcy.[43] Similar to Bernanke et al. (1999) bankruptcy is endogenous and determines the end of period net worth of each age cohort. In addition some exogenous fraction of each age cohort dies every period with probability $1-\gamma^j$ where $j \in (E, 1, \cdots, K, O)$ denote the age cohorts.[44] The final goods producer rents

[41] Section D in Appendix D provides a detailed discussion of the results.

[42] In addition, they operate under constant returns to scale which makes aggregation within age cohorts straightforward.

[43] Note that $\omega^{i,j}$ is iid across entrepreneurs and time, where the cumulative distribution function $F(\omega)$ is continuous and twice differentiable. As in Bernanke et al. (1999), I assume that $ln(\omega) \sim N(-\frac{1}{2}\sigma^2, \sigma^2)$ and $E(\omega) = 1$.

[44] This implies that the total number of exiting entrepreneurs by cohort is the sum of those exogenously dying and

capital from entrepreneurs and hires labor. Figure 31 in Appendix E gives an overview of the basic model framework. Financial intermediaries collect deposits from households. They keep some exogenous fraction $r$ as reserves and use the remaining fraction of deposits to give out loans to entrepreneurs. The credit supply shock hits the financial intermediaries and increases the fraction of reserves they hold.

In the financial market, a friction arises between the financial intermediary and the entrepreneurial sector due to asymmetric information. Banks have to pay monitoring costs to observe the realization of the entrepreneur's productivity shock $\omega^{i,j}$. This corresponds to the costly state verification (CSV) contract analyzed in Townsend (1979), Gale and Hellwig (1985) and Bernanke et al. (1999).

**Timing of Events:** Households decide how much they want to consume, save in the form of risk-free deposits at banks, and how many equity shares they buy from entrepreneurs. Potential entrants decide upon entry. Those who enter the market receive an exogenous amount of starting net worth from households. Given their beginning of period net worth, entrepreneurs of each cohort $j$ select the optimal loan contract given the available menu of contracts offered by the financial intermediary (i.e. they decide on the amount of capital to purchase for use in the next period and the optimal expected default threshold $\bar{\omega}^j$). The cohort-specific capital goods producer makes an investment decision subject to adjustment costs and sells capital to the entrepreneur. The cohort-specific final goods producer rents capital from entrepreneurs and hires labor. As all final goods producers pay the same wage, members of the representative household are indifferent for which cohort-specific final goods producer they work. At the beginning of the next period, entrepreneurs observe the realization of their idiosyncratic productivity. Final goods producers pay the rental rate for capital $R^{k,j}$ to entrepreneurs, and make wage payments to households. Entrepreneurs sell the non-depreciated capital back to the capital goods producer and pay off their debt to the financial intermediary. The intermediary pays monitoring costs and seizes the wealth of bankrupt entrepreneurs of all age cohorts. In each cohort, a fraction $(1-\gamma^j)$ of entrepreneurs die exogenously.[45] Note that age cohorts differ in their survival rate $\gamma^j$ which increases by age. Finally, all cohorts except the entrants decide on how much dividends they want to pay out to households (if dividends are negative, the amount of equity they want to raise). This determines their end-of-period net worth and they move deterministically to the next age cohort.

### 6.1 The Financial Intermediary

The financial intermediary collects deposits from households and supplies loans to entrepreneurs. He holds an exogenous fraction $r_t$ of deposits as reserves. Therefore, the total loan amount in the economy is given by

$$B_t = (1 - r_t) D_t, \tag{6.1}$$

entrepreneurs going bankrupt (i.e. those with idiosyncratic productivity shocks below the cutoff).

[45] Their net worth is destroyed and enters the resource constraint.

where $r_t$ is an AR(1)-shock process

$$r_t = \rho^r r_{t-1} + (1-\rho^r) r_{SS} + \epsilon_t^r, \tag{6.2}$$

with $\rho^r$ denoting the autocorrelation of the shock process, $r_{SS}$ the steady-state value of $r_t$ and $\epsilon_t^r$ an exogenous innovation. An exogenous increase in the fraction of deposits that have to be held by the bank decreases the amount of credit in the model economy. As an exogenous increase in $r_t$ leads to a reduction in the overall amount of loans in the economy, I interpret this as credit supply shock.

The financial intermediary is only willing to enter a contract with an entrepreneur in age cohort $j$ if the bank's expected return on a loan is greater or equal the risk-free return that the bank has promised households on their deposits. The bankruptcy rate $F(\bar{\omega}^j)$ is given by the cumulative distribution function (CDF) at the cutoff point (derived below) and the fraction of bankrupt entrepreneurs of age $j \in (E, 1, \cdots, K, O)$ as

$$G(\bar{\omega}_t^{i,j}) = \int_0^{\bar{\omega}_t^{i,j}} \omega dF(\omega).$$

The fraction of entrepreneurs above the cutoff is given by $1 - F(\bar{\omega})$. Furthermore, the expected fraction of entrepreneurial earnings going to lenders can be written as

$$\Gamma(\bar{\omega}_t^{i,j}) = \bar{\omega}_t^{i,j} \left[1 - F(\bar{\omega}_t{}^{i,j})\right] + G(\bar{\omega}_t^{i,j}).$$

The share of earnings net of monitoring costs can be expressed as

$$\Gamma(\bar{\omega}_t^{i,j}) - \mu G(\bar{\omega}_t^{i,j}),$$

where $1 - \Gamma(\bar{\omega}_t^{i,j})$ denotes the fraction of earnings kept by the entrepreneur.

The financial intermediary receives the non-default loan rate for borrowing $Z_t^{i,j}$. The total price of a loan $Z_t^{i,j} B_t^{i,j}$ must equal the expected revenue of an entrepreneur's risky operation $E_t \left\{R_{t+1}^{k,j}\right\} Q_t^{i,j} K_t^{i,j}$ at the cutoff $E_t \left\{\bar{\omega}_{t+1}^{i,j}\right\}$.[46] The entrepreneurs' expected gross return of holding one unit of capital is given by

$$R_t^{k,j} = \frac{r_t^{k,j} + (1-\delta) Q_t^j}{Q_{t-1}^j}, \tag{6.3}$$

which depends on the capital rental rate $r_t^{k,j}$ (i.e. the marginal product of capital) and the intraperiod gain from selling non-depreciated capital $(1-\delta)Q_t^j$ back to the capital goods producer. The ex-post cutoff is given by

$$E_t \left\{\bar{\omega}_{t+1}^{i,j}\right\} = \frac{Z_t^{i,j} B_t^{i,j}}{E_t \left\{R_{t+1}^{k,j}\right\} Q_t^{i,j} K_t^{i,j}}. \tag{6.4}$$

[46] Under aggregate uncertainty, the aggregate return on capital $R_{t+1}^{k,E}$ is ex ante unknown, which makes $\bar{\omega}_{t+1}^{i,E}$ dependent on the ex-post realization of the return on capital.

The entrepreneur repays the lender the amount $E_t\left\{\bar{\omega}^{i,j}_{t+1}R^{k,j}_{t+1}\right\}Q^{i,j}_t K^{i,j}_t$. In case $E_t\left\{\omega^{i,j}_{t+1}\right\} > E_t\left\{\bar{\omega}^{i,j}_{t+1}\right\}$, the entrepreneur keeps the remaining profits $E_t\left\{(\omega^{i,j}_{t+1}-\bar{\omega}^{i,j}_{t+1})R^{k,j}_{t+1}\right\}Q^{i,j}_t K^{i,j}_t$. If $E_t\left\{\omega^{i,j}_{t+1}\right\} < E_t\left\{\bar{\omega}^{i,j}_{t+1}\right\}$, the financial intermediary pays monitoring costs and seizes the remainder of the profits $E_t\left\{(1-\mu)\omega^{i,j}_{t+1}R^{k,j}_{t+1}\right\}Q^{i,j}_t K^{i,j}_t$. In this case, the entrepreneur declares bankruptcy and receives nothing.

After dropping the superscript $i$ for notational convenience, the lender's participation constraint can be written as

$$\underbrace{E_t\left\{[\Gamma^j(\bar{\omega}^j_{t+1})-\mu^j G^j(\bar{\omega}^j_{t+1})]R^{K,j}_{t+1}Q^j_t K^j_t\right\}}_{\text{Loan repayment of non-defaulting entrepreneurs net of monitoring costs}} = \underbrace{R^n_t \frac{B^j_t}{(1-r_t)}}_{\text{Riskless return on deposits}} \tag{6.5}$$

The financial intermediary has a different participation constraint for each age cohort. It states that the expected loan repayment by every cohort has to equal the risk-free return on the amount of household deposits used to give out the loan $B^j_t$.[47] It holds that the economy-wide loan amount $B_t$ equals the sum over all cohorts $\sum_{j=E}^{O} B^j_t$ for $j \in (E,1,\cdots,K,O)$ such that Equation 6.1 holds.

Total monitoring costs per entrepreneurial cohort are given by

$$\mathrm{m}^j_t = \mu^j E_t\left\{\int_0^{\bar{\omega}^j_{t+1}} \omega\, dF(\omega) R^{k,j}_{t+1}\right\}Q^j_t K^j_t. \tag{6.6}$$

## 6.2 The Entrepreneurial Sector

The entrepreneurial sector consists of entrepreneurs in different age cohorts $j \in (E,1,\cdots,K,O)$. The model features an endogenous entry decision. Upon entry, entrepreneurs are denoted entrants ($j = E$). Those who do not go bankrupt or die exogenously at the end of the period, move to the next age cohort ($j = 1$). The amount of each age cohorts' end-of-period net worth depends on the corresponding endogenous bankruptcy rates. At the beginning of the next period, the predetermined net worth and the amount of capital purchased jointly pin down the required loan amount.

The individual entrepreneur $i$ of cohort $j$ transforms the purchased capital into effective capital and rents it to output goods producers.[48] The return per unit of capital is given by the realization of the idiosyncratic productivity times the aggregate return on capital, $\omega^{i,j}_{t+1}R^{k,j}_{t+1}$.

**Age cohort E (Start-ups):**

Entrepreneurs decide to enter the market if the expected average profit for a non-defaulting entrepreneur is higher than the fixed entry costs $F^e$.[49] Households equip entrants with exogenous starting net worth $N^{ST}$. Within the entrant cohorts, entrepreneurs purchase capital $K^E_t$ at the price $Q^E_t$ for use in $t+1$. They finance these purchases with the starting net worth and the loan

[47] Following Bernanke et al. (1999), I assume that the participation constraint of lenders has to be fulfilled ex post. This implies that the entrepreneur bears all the aggregate risk.

[48] Note that the assumption of constant returns to scale makes the distribution of net worth $N^{i,E}_t$ and capital $K^{i,E}_t$ across entrepreneurs *within* the cohort irrelevant.

[49] Note that the entrant's case is closest to the standard CSV-debt contract described in Bernanke et al. (1999) as the only source of financing is debt. The entry decision is described in more detail in Subsection 6.3.

from the financial intermediary $B_t^E$. This results in the aggregate balance sheet constraint of the start-up cohort

$$Q_t^E K_t^E = B_t^E + N^{ST}. \tag{6.7}$$

Aggregating over the entire start-up cohort, their maximization problem can be rewritten

$$\max_{\{K_t^E, \bar{\omega}_{t+1}^E\}} E_t \left\{(1-\Gamma(\bar{\omega}_{t+1}^E))R_{t+1}^{k,E}\right\} Q_t^E K_t^E$$

subject to the participation constraint of lenders (equation 6.5) and the balance sheet constraint (equation 6.7).[50] The end-of-period net worth of age cohort $E$ amounts to the profit of surviving firms that do not go bankrupt.

$$N_t^E = \gamma^E (1-\Gamma(\bar{\omega}_t^E))R_t^{k,E} Q_{t-1}^E K_{t-1}^E. \tag{6.8}$$

At the end of the period, entrepreneurs of cohort $j = E$ transfer their net worth $N_t^E$ to the next period, where it is used to take out a new loan, now for age cohort $j = 1$.

**Entrepreneurs of Age Cohort $j \geq 1$**

Among age cohort $j$, we can differentiate between three types of cohorts. First, cohort 1, that is last period's start-up cohort. Second, the remaining young cohorts 2 to $K$, and third, the old cohort $O$. An entrepreneur of cohort $j$ takes her net worth as given and requires the loan amount $B_t^j$ to finance his capital purchases $Q_t^E K_t^j$. This results in the following balance sheet identities:

$$B_t^j = \begin{cases} Q_t^j K_t^j - N_t^E & \text{if } j = 1 \\ Q_t^j K_t^j - N^{j-1} & \text{if } j \in (2, \cdots, K) \\ Q_t^j K_t^j - N_t^j & \text{if } j = O. \end{cases} \tag{6.9}$$

All entrepreneurs of age cohort $j = 1$ onward, have the option to pay out dividends and, in case these dividends are negative, to raise equity from households. This corresponds to the internal financing channel.

However, internal financing is costly (see Jermann and Quadrini, 2012). As a result, the actual cost for the entrepreneurial age cohort $j \in (1, \cdots, K, O)$ are total dividends paid/equity raised plus costs:

$$\varphi(d_t^j) = d_t^j + \kappa^d (d_t^j - d_{SS}^j)^2, \tag{6.10}$$

where $\kappa^d > 0$ and $d_{SS}^j$ denotes the steady state value of dividends for the corresponding age cohort. These adjustment costs on equity payouts capture the idea that firms incur costs when changing their source of funds and that there exist motives for dividend smoothing.

In contrast to entering entrepreneurs, entrepreneurs of age cohort $j$ maximize the stream of

[50] see Appendix E.1 for the corresponding first-order conditions.

dividends

$$\max_{\{d_t^j, K_t^j, \bar{\omega}_{t+1}^j\}} E_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_{t+1}}{\lambda_t} d_t^{j+t}$$

subject to the participation constraint of lenders (equation 6.5), the balance sheet constraints (equation 6.9), and the flow-of-funds constraint which equates this periods' outflows to its inflows:

$$\underbrace{\varphi_t^j + Q_t^j K_t^j}_{\text{Outflow in period t}} = \underbrace{\gamma^{j-1}\left(1-\Gamma(\bar{\omega}_t^{j-1})\right) R_t^{k,j-1} Q_{t-1}^j K_{t-1}^{j-1} + B_t^j}_{\text{Inflow in period t}}, \tag{6.11}$$

where for cohort 1, $j-1$ denotes the start-up cohort.[51] Note that for the flow-of-funds constraint, we require all intra-period flows. As the return on capital and, hence, entrepreneurial earnings materialize only in the next period, last periods' earnings net of monitoring costs $\gamma^{j-1}\left(1-\Gamma\left(\bar{\omega}_t^{j-1}\right)\right) R_t^{k,j-1} Q_{t-1}^{j-1} K_{t-1}^{j-1}$ denoting earnings of the previous age cohort $j-1$ enter the flow-of-funds constraint.

**End-of-Period Net Worth:** The end-of-period net worth of age cohorts $k \in (1, \cdots, K)$ is given by the profits of surviving, non-bankrupt entrepreneurs that have not been paid out as dividends.

$$N_t^k = \text{nw}_t^k \gamma^k (1-\Gamma(\bar{\omega}_t^k)) R_t^{k,k} Q_{t-1}^k K_{t-1}^k - \varphi(d_t^k), \tag{6.12}$$

where $\text{nw}_t^k$ denotes a shock to the net worth of age cohort $k$. The shock process is defined as

$$\text{nw}_t^k = \rho^{nw} \text{nw}_t^k + (1-\rho^{nw}) \text{nw}_{ss}^k + \epsilon_t^{nw}, \tag{6.13}$$

with $\rho^{nw}$ denotes the autocorrelation of the process, $\text{nw}_{ss}$ the steady state value and $\epsilon_t^{nw}$ is an exogenous innovation with $\epsilon_t^{nw} \sim N(0, \sigma^{NW})$. The old entrepreneurs' beginning-of-period net worth consists of the net worth of previously old, surviving and non-bankrupt entrepreneurs and the net worth of entrepreneurs of age cohort $Y_K$ who did not go bankrupt before turning old:

$$N_{t+1}^O = \gamma^o (1-\Gamma(\bar{\omega}_{t+1}^O)) R_{t+1}^{k,O} Q_t^O K_t^O + N_t^K - \varphi(d_t^O). \tag{6.14}$$

Note that the shock process $nw_t$ is only present in the net worth of young cohorts. The shock represents a decline in entrepreneurs' value of housing, which is only for young entrepreneurs a relevant part of the overall net worth (see Section 5).

### 6.3 Endogenous Entry and Age Dynamics

Similar to Bilbiie, Ghironi, and Melitz (2012) potential entrants are identical and face sunk entry costs $F^e$. They are forward-looking and enter the market if the average value of an entrepreneur after entry is at least as large as the entry costs.

The average value of an entrepreneur after entry is given by the fraction of earnings remaining

[51] see Appendix E.1 for the corresponding first-order conditions.

in the age cohort of the entering firms (after payment of monitoring costs to the bank) divided by the number of entrepreneurs above the productivity cutoff $1-G(\bar{\omega}_t^E)$:

$$E_t\left\{\tilde{V}_t^E\right\} = \frac{E_t\left\{\left(1-\Gamma(\bar{\omega}_{t+1}^E)\right)R_{t+1}^{k,E}\right\}Q_t^E K_t^E}{E_t\left\{\left(1-G(\bar{\omega}_{t+1}^E)\right)\right\}}. \tag{6.15}$$

This results in the free entry condition

$$E_t\left\{\tilde{V}_t^E\right\} = F^e. \tag{6.16}$$

The household equips entering firms with an exogenous amount of starting net worth $N_t^{ST}$. The size of the entering age cohort $E$ is denoted $\theta_t^E$. The age cohorts evolve according to

$$\theta_t^1 = \gamma^E \theta_{t-1}^E \tag{6.17}$$

$$\theta_t^k = \gamma^E \theta_{t-1}^{k-1} \tag{6.18}$$

$$\theta_t^O = \gamma^O \theta_{t-1}^O + \gamma^K \theta_{t-1}^K \tag{6.19}$$

with $k \in (2, \cdots, K)$. Age cohort $k = 1$ is given by the number of surviving start-ups, age cohort $k = 2$ by the number of surviving entrepreneurs of age cohort $k = 1$ and so on. Entrepreneurs of age cohort $k = K$ turn old in the subsequent period. As a result, the number of old entrepreneurs $\theta_t^O$ is given by last periods' surviving old entrepreneurs $\theta_{t-1}^O$ and the number of surviving entrepreneurs who turn old ($\gamma^K \theta_{t-1}^K$).
Aggregating over all age cohorts $j \in (E, 1, \cdots, K, O)$ gives the overall number of firms in the economy

$$\theta_t = \sum_{j=E}^{O} \theta_t^j. \tag{6.20}$$

## 6.4 Aggregates and Closing the Model

Aggregate employment, loan amount, capital stock and dividends paid in the economy are

$$L_t = \sum_{j=E}^{O} L_t^j, \quad B_t = \sum_{j=E}^{O} B_t^j, \quad K_t = \sum_{j=E}^{O} K_t^j, \quad d_t = \sum_{k=1}^{O} d_t^k,$$

with $j \in (E, 1, \cdots, K, O)$. Aggregate output, monitoring costs and the consumption of exiting entrepreneurs is weighted by the size of the corresponding age cohort:

$$Y_t = \sum_{j=E}^{O} \theta_t^j Y_t^j, \qquad \mathrm{m}_t = \sum_{j=E}^{O} \theta_t^j \mathrm{m}_t^j, \quad C_t^e = \sum_{j=E}^{O} \theta_t^j C_t^{e,j}.$$

The aggregate economy-wide resource constraint holds:

$$Y_t = C_t + I_t + \mathrm{m}_t + C_t^e. \tag{6.21}$$

# 7 Calibration and Steady State

I calibrate the model to semi-annual frequency. This choice is driven by the deterministic aging structure of firms as it allows me to keep the model (and the number of young entrepreneurial cohorts) tractable. Thus, besides the entrants, my model features $K = 9$ young firm cohorts. By the semi-annual frequency of my model, firms that are at least five years old, are old firms. This age cutoff is consistent with the corresponding definition in my empirical analysis. Hence, with the entering cohort, firms are young for five years before they turn old.

Table 4 gives an overview of all parameter choices of the calibration. Parameter values are identical among age cohorts if not stated otherwise. I target an annualized risk-free interest rate of 3 percent, which results in a semi-annual household discount factor $\beta$ of 0.985. As is standard in the literature, I set the capital depreciation rate $\delta$ to 5 percent and the weight of capital in the production function $\alpha^j$ to 0.33. Productivity is normalized to 1 in steady state. Furthermore, I set the Frisch elasticity of labor supply $\eta^{L,j}$ to 2. After solving for steady state employment for each age cohort and aggregating over all firms, the disutility of labor parameter $\chi^j$ is pinned down endogenously.

In setting the parameters for the optimal debt contract between banks and entrepreneurs, I follow Afanasyeva and Güntner (2020). In steady state, the monitoring costs in case of default are set to $\mu^j = 0.2$ and are within the range of estimates reported in Carlstrom and Fuerst (1997) and Levin, Natalucci, and Zakrajsek (2004). Furthermore, as in Afanasyeva and Güntner (2020), I set the steady state value of the idiosyncratic productivity realization $\bar{\omega}^j$ to 0.35 and assume that these idiosyncratic productivity draws follow a log-normal distribution with unit mean and variance 0.18. The amount of reserves held by financial intermediaries is 20% of household deposits. Regarding the capital goods producer, $\Lambda$ has the functional form

$$\Lambda\left(\frac{I_t}{K_t}\right) = a^K \left(\frac{I_t}{K_t}\right)^{1-\eta^K} + b^K$$

where $\eta^i$ corresponds to the elasticity of the price of capital with respect to the investment rate and $a^K$ and $b^K$ are two additional parameters governing the investment technology. I follow Gertler, Kiyotaki, and Prestipino (2020) and set $\eta^i = 0.25$, a value consistent with panel data estimates. The remaining parameters $a^K$ and $b^K$ are calibrated in order to hit the target of a ratio of semi-annual investment to the capital stock (see Gertler et al., 2020). I further set the parameter of dividend adjustment costs to $\kappa^d = 0.15$, a value close to Jermann and Quadrini (2012). The parameter of wage adjustment costs is set to $\kappa^W = 61.36$ as suggested in Born and Pfeifer (2016).

To pin down the size of the credit supply shock, I extract the structural credit supply shock of my baseline estimation by firm age and calculate the resulting standard deviation of the empirical structural EBP shock. Figure 29 in Appendix C depicts the structural shocks based on the TVP-VAR. The resulting standard deviation is 0.84. Regarding the shock to net worth, I set the size of the shock to the peak-to-trough decline in house prices in the United States between 2007Q1 and 2012Q4. Hence, I target a maximum decline in young firms' net worth of 23%.[52] I set the

[52] This value corresponds to the 'All-Transactions House Price Index' for the United States, not seasonally adjusted.

autocorrelation of both shock processes to 0.8.

Furthermore, I target the average pre-crisis share of young vs. old firms from the BDS (for the period 1990 to 2006). This results in a share of around 63% of old firms. For this target, I set the survival rate of two cohorts of entrepreneurs, the entering cohort ($\gamma^E = 0.855$) and the old cohort ($\gamma^O = 0.954$). The remaining survival rates arise endogenously in steady state. The resulting survival rates are increasing by each young age cohort. In addition to the exogenous exit, entrepreneurs whose idiosyncratic productivity realization is below the cutoff value $\bar{\omega}^j$ exit endogenously. Hence, the total exit of firms by cohort is given by the sum of the endogenous default rate and the exogenous rate of death.[53]

**Table 4:** Calibration and Targets

| | Parameter name | Symbol | Value |
|---|---|---|---|
| **Preferences and Production** | | | |
| | Discount factor | $\beta$ | 0.985 |
| | Risk aversion | $\sigma_c$ | 2.00 |
| | Capital depreciation | $\delta$ | 0.025 |
| | Weight on Capital in Production | $\alpha$ | 0.33 |
| | Productivity (SS) | $a_t^j$ | 1.00 |
| | Frisch elasticity of labor supply | $\eta$ | 2 |
| **Financial Frictions and Policy** | | | |
| | Monitoring costs in case of default | $\mu^j$ | 0.20 |
| | Standard deviation of idiosyncratic realizations | $\sigma^j$ | 0.42 |
| | Idiosyncratic productivity cutoff | $\bar{\omega}^j$ | 0.35 |
| | Reserves (SS) | $r$ | 0.20 |
| | Capital adjustment cost | $\eta^i$ | 0.25 |
| | Wage adjustment cost | $\kappa^W$ | 61.36 |
| | Dividend adjustment cost | $\kappa^d$ | 0.15 |
| **Survival Rates** | | | |
| | Entrants | $\gamma^E$ | 0.855 |
| | Old cohort | $\gamma^O$ | 0.954 |
| **Shocks** | | | |
| | Autocorrelation of credit supply shock process | $\rho^r$ | 0.80 |
| | Standard deviation of credit supply shock process | $\sigma^r$ | 0.84 |
| | Autocorrelation of net worth shock process | $\rho^{nw}$ | 0.80 |
| | Standard deviation of net worth shock process | $\sigma^{nw}$ | 1.45 |

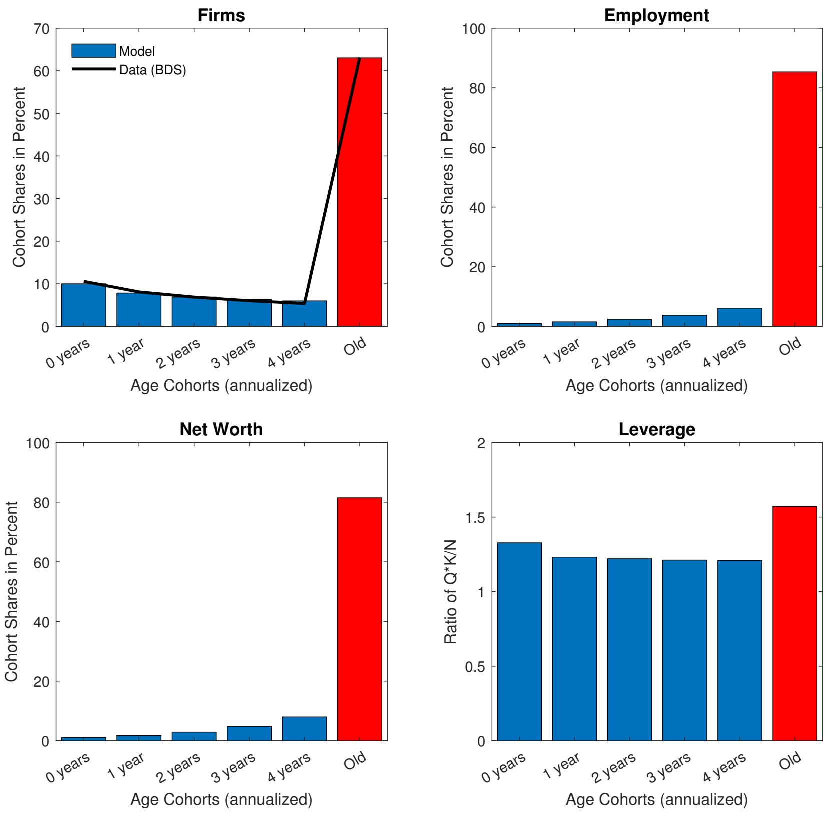
## 7.1 The Model in Steady State

I parameterize the model to match the relative share of young to old firms in steady state. The bars in the upper left panel of Figure 13 depict the models' age distribution of firms in the cross-section compared to the BDS data (solid line). The model captures endogenously a realistic distribution within young firms (i.e. a high share of entrants and a decreasing share of young firms).[54] This is consistent with a higher probability of exit for young entrepreneurs and mimics

[53] Note that the identical calibration over age cohorts regarding the debt contract implies that the endogenous default rate is identical in steady state for all entrepreneurs. However, in response to a shock, bankruptcies evolve differently by cohorts.

[54] Note that only the relative share of young vs. old is a calibration target.

**Figure 13:** Firm Age Distribution in Steady State




Notes: Selected variables by age cohorts in steady state. The upper left panel compares the firm distribution in percent with data from the Business Dynamics Statistics (BDS). Firms, employment and net worth are illustrated as annualized cohort shares (in percent). Leverage is defined as the capital-to-net worth ratio and is depicted for individual cohorts.

the up-or-out dynamics documented in Haltiwanger et al. (2013).

Figure 13 further illustrates the distribution of several variables of interest by age cohort in equilibrium. The left panel depicts employment shares by age cohort. Without this being an explicit target, the model's steady state employment share of old firms amounts to 85.5% which is close to the 85.2% share of old firms in the BDS (again the average share for the years from 1990 to 2006). The middle panel further depicts the share of net worth by age cohort. Net worth increases with age and is concentrated in the old cohort with a share of around 80 percent.

The lower right panel of Figure 13 depicts the leverage (capital-to-net worth ratio) by age cohort. As entrepreneurs grow older and accumulate net worth, they are less leveraged. The old entrepreneurial cohort, however, has the highest leverage ratio. The reason is that an entrepreneur in the old cohort will select the highest possible leverage for a given $\bar{\omega}^j$ that the bank is willing to offer.[55] Put differently, by the participation constraint of lenders (see Equation 6.5), the bank is willing to offer a higher amount of debt for a given idiosyncratic productivity cutoff and net worth. This outcome is broadly consistent with Dinlersoz et al. (2018) who document that publicly-listed firms are highly leveraged as they grow older.

[55] Note that due to data availability, I set the steady state threshold $\bar{\omega}^j$ to 0.35 for all cohorts. A natural extension would be to vary $\bar{\omega}^j$ by age cohort.

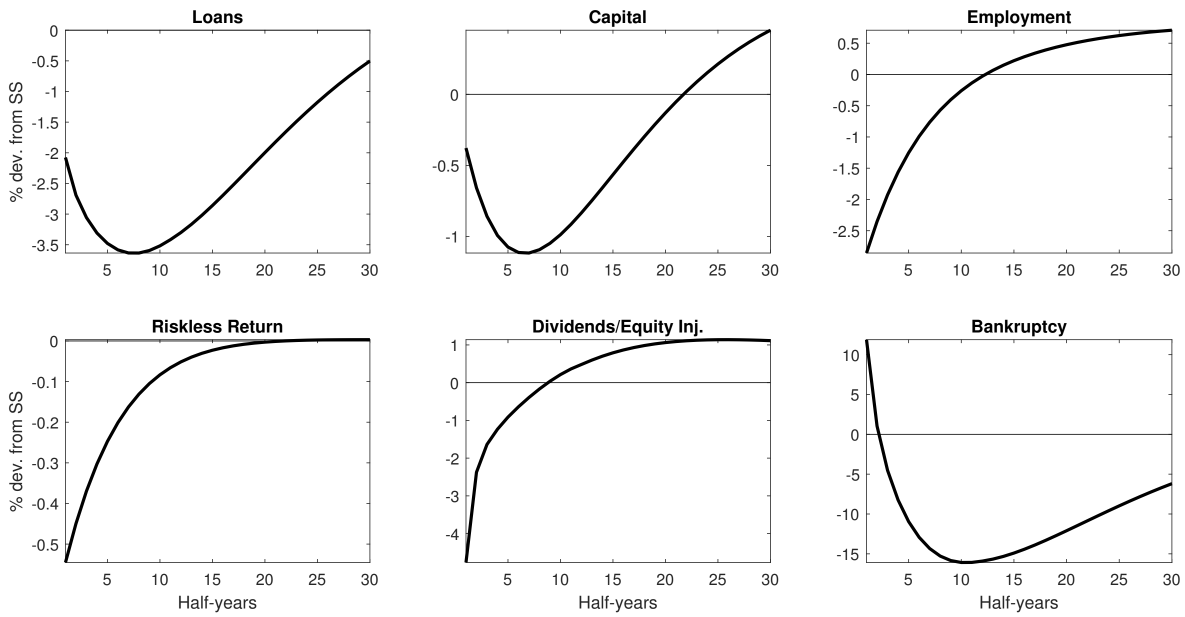
# 8 Effects of Credit Crunches and Declines in Net Worth

This section presents the simulation results in response to a credit tightening shock. First, I discuss the effect on aggregate economic outcomes. Then, I present the effects by firm age. Lastly, I discuss the results if on top of a credit crunch, young firms' net worth experiences an exogenous decrease.

## 8.1 Aggregate Effects

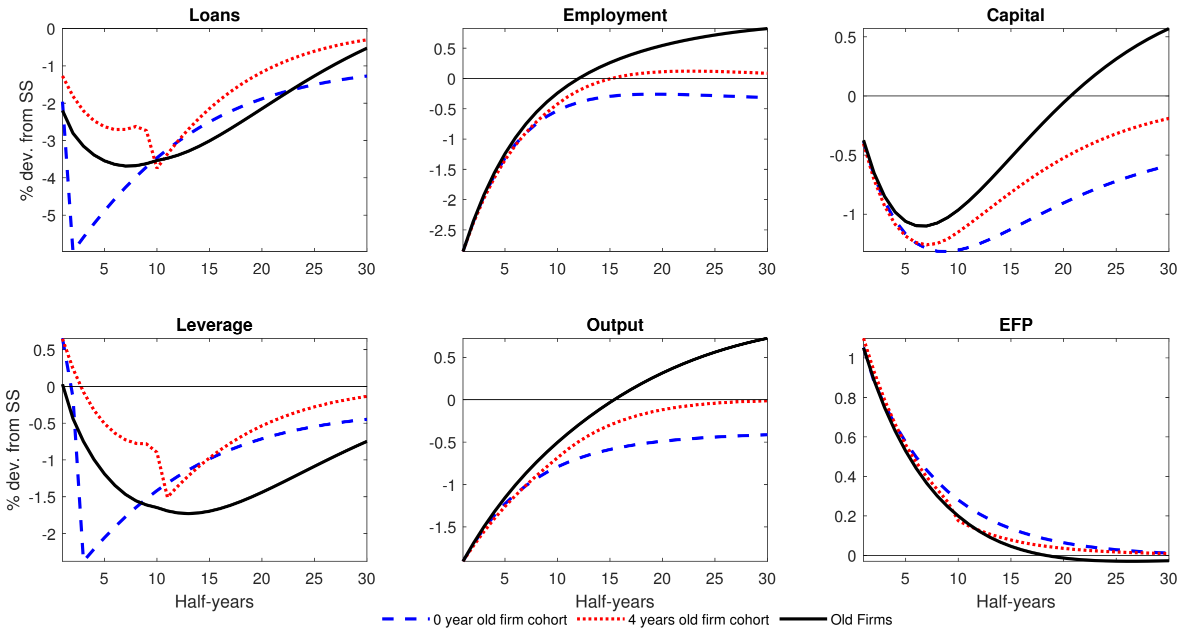
Figure 14 depicts the model's responses to a one standard deviation increase in the reserves financial intermediaries must hold. This leads to a strong decline in the aggregate amount of loans in the economy, and as such, acts as a credit supply shock. Given the balance sheet identity of a firm $Q_t^j K_t^j = N_t^j + B_t^j$, a fall in the loan amount decreases capital demand and leads to a fall in the price of capital $Q_t^j$. The economy-wide capital stock declines slowly as adjusting the capital stock is costly. As firms adapt their capital stock only gradually, aggregate employment drops strongly on impact. As both capital and employment fall, the economy-wide output declines as well. Furthermore, the riskless return on household deposits drops. As a result, households prefer to equip entrepreneurs with equity instead of savings in form of riskless deposits at banks (the drop in dividends corresponds to an equity injection). As the financial intermediary collects fewer deposits, this further exacerbates the decline in credit supply. After an initial spike, bankruptcies decline with a lag because lower credit supply causes entrepreneurs to be less leveraged. Overall, we observe a strong and persistent contraction of the model economy.

**Figure 14:** Responses to a Credit Supply Shock: Aggregate Effects




Notes: Responses to a 1 std contractionary credit supply shock.

**Figure 15:** Responses to a Credit Supply Shock: Young vs. Old Firms




Notes: Responses to a 1 std contractionary credit supply shock.

## 8.2 Effects by Firm Age

A look at the effects by firm age (as depicted in Figure 15), reveals that there is substantial heterogeneity among the responses by age. For expositional clarity, I illustrate the reaction of three different age cohorts: a recent start-up (depicted by the blue, dashed line), the four-year-old firm (depicted by the red, dotted line), and old firms (depicted by the black solid line).

All age cohorts face a strong decline in their loan amount. The immediate reaction is strongest for the youngest age cohort, whereas, for the four-year-old firm, the loan contraction is less severe. Hence, among young cohorts, the youngest one is affected strongest as it is highly leveraged. Even though young firms have access to equity from households, they can raise only a small amount due to the incurred costs. As entrepreneurs grow older and are less leveraged, the reaction of loans is dampened. Old firms also show a strong contraction in the borrowed amount in response to the credit supply shock. They substitute between external and internal finance and reduce the loan amount as they receive equity injections from households. This is consistent with recent empirical evidence from Begenau and Salomao (2018). Old firms can raise equity easily compared to young firms because in steady state, old firms pay out a higher level of dividends $d^O$ compared to young firms with $d^k$ for $k = 1,\ldots,K$ approximately zero. This arises endogenously in steady state as young firms want to accumulate net worth. Due to the underlying cost function, which is identical for young and old firms, raising the same amount of equity comes with a multiple of the costs for young firms.

Even though old firms have a higher debt-to-net worth ratio in steady state, it is the younger firms that are more financially constrained because old firms can switch to internal finance more easily compared to old firms. In that sense, even though in steady state old firms are highly leveraged, they are less impacted by a decline in credit supply. In addition, the household also prefers buying shares from old firms as in expectation the return is higher compared to the now lower risk-free rate offered by banks on deposits.

Even though all age cohorts decrease their demand for capital and labor, the effect is heterogeneous across cohorts. Regarding capital, the initial drop is similar among cohorts, but the persistence differs by firm age. In response to the shock, they face a strong reduction in loans, but unlike old firms cannot easily raise equity from households. As a result, the youngest age cohort faces the most severe and persistent decline in capital. Old firms' demand for capital on the other hand quickly picks up again as they raise equity from households. The capital reaction transmits to the labor market via the Cobb-Douglas production structure. However, the difference across cohorts is less pronounced. Employment at the old firms' cohort recovers quicker compared to young firms. Lower employment and capital at young firms transmits to a decline in output.

A core mechanism of this type of financial friction models is the financial accelerator. Most importantly, the financial accelerator amplifies the effects more for those firms with low net worth (i.e. the young firms). The credit supply shock leads to a rise in the external finance premium (EFP) which slowly return to its initial steady state.[56] For the youngest age cohort, the rise in the EFP is slightly more persistent. A higher EFP further dampens capital demand and depresses net worth. However, an even lower net worth makes young firms' access to external finance more difficult as banks charge a higher loan rate which reduces the borrowed amount even further. Thus, the financial accelerator mechanism amplifies the effects of the credit supply shock heterogeneously among age cohorts. Regarding the response of employment, the model's reaction to a credit tightening does not lead to a persistent divergence by firm age. Next, I investigate the role of a decline in firms' net worth.

### 8.3 A Decline in Young Firms' Net Worth

In this subsection, I study the model's dynamic responses for a simultaneous tightening of credit supply and a decline in firms' net worth. Bernanke and Gertler (1989) define net worth as collateralizable assets. Given that mainly tangible assets (such as buildings and land) can be collateralized, I interpret the shock to young firms' net worth as a house price shock. This interpretation only holds for start-ups and young firms. Therefore, old firms are not directly affected by the net worth shock.[57]

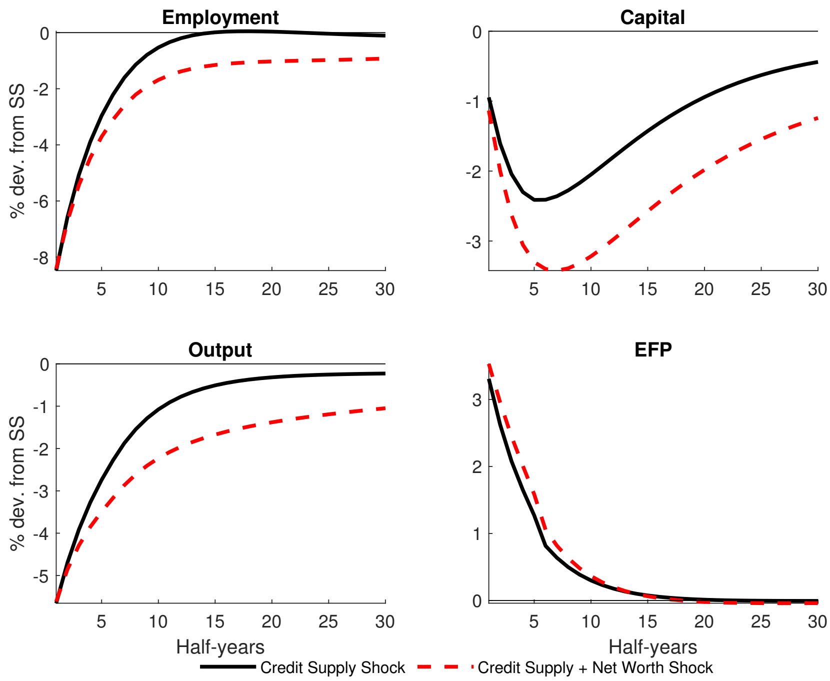
**Shock Sizes:** For the analysis of two simultaneous shocks, the relative magnitude of shock sizes is important. I focus on the period of Great Financial Crisis and use the structural shocks of my empirical TVP-VAR to pin down the shock size for the credit contraction. Figure 29 in Appendix C illustrates the series of structural shocks based on my baseline (long horizon) specification. I pick the structural credit supply shock from the period 2008Q4 which is the largest shock and amounts to a value of 2.55.[58] Regarding the size of the net worth shock, I target the overall decline in young firms' net worth such that it corresponds to the peak-to-trough decline in U.S. house

[56] The EFP is defined as the return of holding one unit of capital over the risk-free rate $R^{k,j}_{t+1}/R^n_t$.

[57] Old firms are indirectly affected via the net worth that aging (formerly) young firms bring to the old cohort.

[58] The empirical model identifies the spike in (perceived) credit risk in response to the collapse of Lehmann Brothers in September 2008.

**Figure 16:** Responses to a Credit Supply and Net Worth Shock: A 2-year old Firm



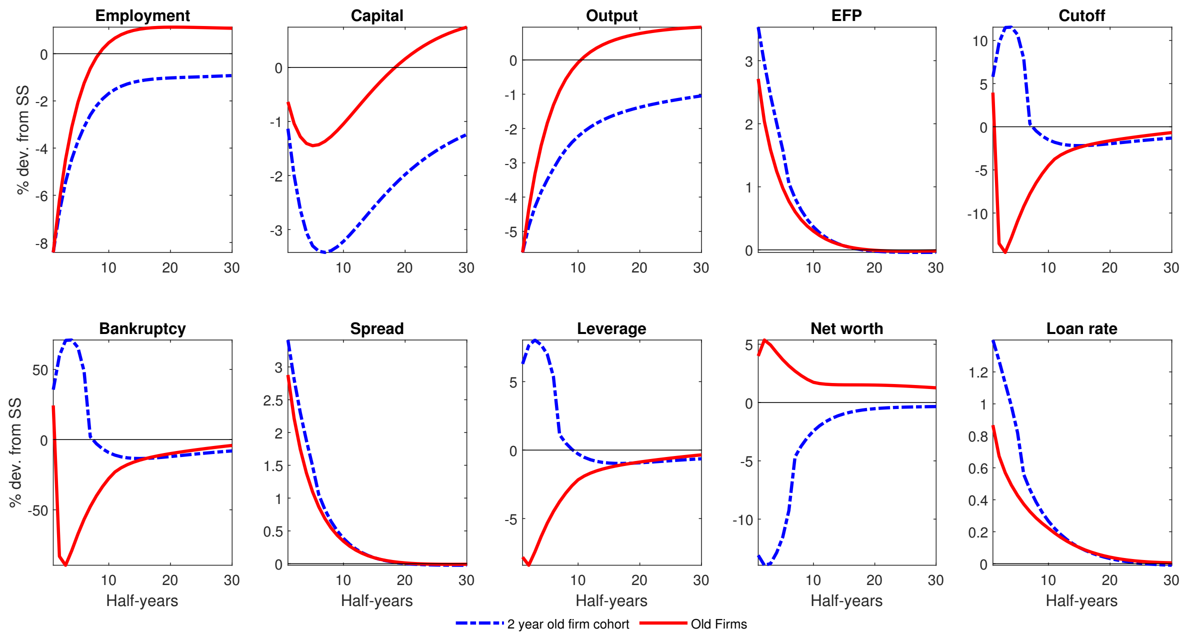

Notes: Responses to a contractionary credit supply shock and net worth shock for a two-year-old firm (age cohort $K = 5$). The black, solid line depicts the credit supply shock only, the red, dashed-line illustrates the model's response if both shocks hit the model economy simultaneously. The size of the credit supply shock is based on the structural shock series from the TVP-VAR and amounts to 2.55. The size of the net worth shock targets a decline in young firms' net worth that is equivalent to the observed peak-to-trough decline in U.S. house prices and amounts to 1.45.

prices between 2007Q1 and 2012Q4 (see also Section 7). This results in a net worth shock of 1.45.

**The Effect on a Young Firm:** Figure 16 illustrates how the model responses change if, on top of the credit supply shock, young firms experience a simultaneous decrease in their net worth. The responses are depicted for a two-year-old firm (representing a typical young firm). The solid black line shows the responses after a credit supply tightening only and the joint responses are illustrated by the dotted red line. The decline in young firms' net worth makes borrowing more costly as can be seen by the more pronounced increase in the EFP (lower right panel). As a result, the demand for capital drops much stronger and more persistently compared to the scenario in which only credit supply tightens. The decline in capital transmits to labor input. The initial reaction of employment is almost identical to the scenario where only the credit supply shock affects the economy, but employment is depressed for a long time and recover only slowly. The contractionary effect on output is more persistent as well. Thus, it takes the combination of lower net worth and tighter credit supply to cause a large and persistent drop in young firms' labor demand.

**The Effect by Firm Age:** The different reaction of young compared to old firms if both shocks hit the model economy at the same time are depicted in Figure 17. The response of a two-year-old firm ($Y_5$ cohort) is illustrated by the dashed blue line, the response of the old cohort by the solid red line. Consistent with the empirical evidence of Section 4, employment responses between young and old firms are diverging after a similar initial drop in employment. This divergence is even stronger for capital. The exogenous decrease in net worth makes young firms more lever-

**Figure 17:** Responses to a Credit Supply and Net Worth Shock: Young vs. Old




Notes: Responses to a contractionary credit supply shock and net worth shock. The red, solid line depicts the response of an old firm. The blue, dashed line illustrates the response of a two-year-old firm (cohort $K = 5$). The size of the credit supply shock is based on the structural shock series from the TVP-VAR and amounts to 2.55. The size of the net worth shock targets a decline in young firms' net worth that is equivalent to the observed peak-to-trough decline in U.S. house prices and amounts to 1.45.

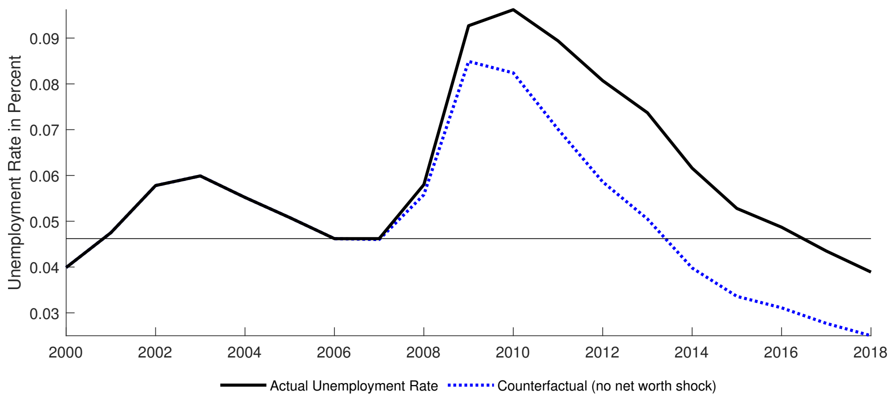
aged which makes additional borrowing more costly and their idiosyncratic productivity cutoff increases. The financial intermediary demands a higher loan rate and the spread for young firms is much higher compared to old firms. The net worth shock affects old firms only via the (lower) net worth of young firms who become old. They can raise equity from households which leads to a higher net worth and lower leverage for them. As a result, their idiosyncratic productivity cutoff and their bankruptcy rate drop. As soon as old firms have raised enough equity from households, their demand for capital and labor picks up quickly after the shock.

My quantitative model highlights the role of the credit supply and net worth shock in explaining the persistent decline of young firms' labor demand during and after the GFC. If the decrease in young firms' net worth coincides with a tightening of credit supply, the model generates an empirically consistent heterogeneous reaction by firm age. The credit contraction leads to the initial drop in employment and the decline in firms' net worth causes the persistent reaction. Young firms have low net worth and depend heavily on external finance. A drop in the value of their net worth intensifies informational asymmetries between borrowers and lenders. As a result, young firms face an increase in the external finance premium. However, to finance their operations, they would require even more loans now. Given that the financial intermediary has tightened credit supply and young firms became riskier (their idiosyncratic productivity cutoff increased), they face a considerable increase in the loan rate and the spread. Now, the financial accelerator mechanism further magnifies and propagates the effects for young firms. Borrowing is even more costly which depresses their demand for capital and labor further.

**The Relative Contribution of Shocks:** How much of the fall in employment can be attributed to the net worth shock? To answer this question, I compute the average relative contribution of the net worth shock to the overall decline in young firms' employment (weighted by their corresponding firm size) over the impulse response horizon.[59] In the first period of the shock, the contribution is slightly negative. This is caused by a temporary capital-labor substitution effect in response to a decline in net worth. Then, the contribution increases sharply and amounts to 50 percent after 8 periods (4 years) and more than 80 percent 12 periods (6 years) after the shock. Figure 32 in Appendix E.5 visualized the relative contribution of the net worth shock to the overall employment reaction of young firms. Thus, the short-run fall in labor demand can be attributed to tighter credit supply, whereas the persistence is caused by the decline in young firms' net worth.

**Counterfactual Experiment:** Given the relative contribution of the net worth shock to the decline in young firms' employment, I can compute the counterfactual development of the U.S. unemployment rate.[60] Figure 18 contrasts the development of the actual U.S. unemployment rate (black, solid line) with the counterfactual development of a scenario in which only the credit crunch hit the economy (dashed, blue line). I find that absent the net worth shock (i.e. the decline in house prices), the U.S. unemployment rate had been back to its pre-crisis level two years earlier. The peak of the unemployment rate would have been one percentage point lower and between the years 2012 to 2016, it would have been on average 2 percentage points lower.

**Figure 18:** Counterfactual Unemployment Rate




Notes: The solid line illustrates the actual U.S. unemployment rate, the dashed, blue line depicts the counterfactual unemployment rate absent the net worth shock. The horizontal line depicts the pre-crisis unemployment rate.

# 9 Conclusion

Given the disproportionate contribution of young firms for job growth, it is crucial for economists and policymakers to understand the reasons and channels that prevent them from resuming job creation after a downturn. A key candidate factor is young firms' access to credit

[59] I calculate the difference of the employment reaction in response to both shocks compared to the response with the net worth shock turned off.

[60] I calculate the absolute annual reduction in employment of young firms due to the net worth shock in the years during and after the GFC compared to the pre-crisis year 2006. I use BDS data by firm age, see https://www.census.gov/data/tables/time-series/econ/bds/bds-tables.html.

as they are riskier, have typically low net worth, and a short business history. While the literature has focused either on the microeconomic effects of credit crunches or has imposed assumptions on linear effects over time, my paper fills a gap by studying the non-linear labor market impact of financial market shocks by firm age and over time from a macroeconomic perspective.

I apply a time-varying parameter vector-autoregression with stochastic volatility and find that since the GFC, credit supply shocks lead to stronger employment reactions for young firms compared to old firms. My analysis at the cross-regional MSA-level shows that this difference by age can be explained by the role of housing net worth for young business owners and the house price bust in 2006. Through the lens of my model, the link between firms' net worth and the costs of raising external finance triggers a financial accelerator mechanism that is stronger for young firms with low net worth. Thus, young firms were exposed to two types of shocks: a decline in their value of collateral and a contraction of credit supply. The interaction of those two disturbances forced them to cut labor demand strongly and persistently. In contrast, old firms were not affected by the house price bust and can – if credit supply tightens – switch to other financing channels.

I find that the decline in young firms' net worth, and, as such, their possibility of self-financing caused their persistent decline in labor demand. A counterfactual exercise shows that absent the house price bust in 2006, the U.S unemployment rate would have been back at its pre-crisis level two years quicker and in the aftermath of the GFC, unemployment would have been 2 percentage points lower. Thus, the decline in young firms' net worth can explain the sluggish recovery of the U.S. labor market after the GFC.

Which policy implications can we draw from this findings? First, to prevent long-term scars on the labor market, policy makers need to break the link between housing net worth and young firms' access to external finance. This stresses the importance of a careful design of macroprudential policy to prevent housing boom-bust cycles. Second, firms that show the highest growth (and job creation) potential should be identified and receive support in accessing external financing.[61]

There are several additional open questions on the interaction of credit and labor markets to tackle. First, my analysis focuses on the borrower's balance sheet. However, a shock to house prices can also work via the bank balance sheet channel. If a collapse in house prices leads to a peak of mortgage delinquencies, considerable losses for banks are the result. In response, the lenders' balance sheet deteriorates and they reduce their credit supply. This is especially relevant if firms borrow predominantly at local banks.[62] Extending the framework to account for the transmission mechanism via the bank's balance sheet channel would give further insights on the interaction between the housing net worth channel and young firms' labor market reaction. Second, adding a frictional labor market would allow a more thorough analysis of the general-equilibrium feedback effects between credit and labor markets.[63] I leave this for future research.

[61] The identification of these firms could be pinned down by criteria such as the sector they operate in or whether they were expanding in terms of new establishments.

[62] See Davis and Haltiwanger (2019) for a similar argument.

[63] This type of question has been addressed by Wasmer and Weil (2004) in a model with credit and labor market imperfections that abstracts from heterogeneity.

## References


ADELINO, M., A. SCHOAR, AND F. SEVERINO (2015): "House Prices, Collateral, and Self-employment," *Journal of Financial Economics*, 117, 288–306.

AFANASYEVA, E. AND J. GÜNTNER (2020): "Bank Market Power and the Risk Channel of Monetary Policy," *Journal of Monetary Economics*, 111, 118–134.

BAHAJ, S., A. FOULIS, AND G. PINTER (2020): "Home Values and Firm Behavior," *American Economic Review*, 110, 2225–70.

BARNICHON, R., C. MATTHES, AND A. ZIEGENBEIN (forthcoming): "Are the Effects of Financial Market Disruptions Big or Small?" *Review of Economics and Statistics*, to appear.

BASSETT, W. F., M. B. CHOSAK, J. C. DRISCOLL, AND E. ZAKRAJŠEK (2014): "Changes in bank lending standards and the macroeconomy," *Journal of Monetary Economics*, 62, 23 – 40.

BAUMEISTER, C. AND G. PEERSMAN (2013): "Time-Varying Effects of Oil Supply Shocks on the US Economy," *American Economic Journal: Macroeconomics*, 5, 1–28.

BEGENAU, J. AND J. SALOMAO (2018): "Firm Financing over the Business Cycle," *The Review of Financial Studies*, 32, 1235–1274.

BENATI, L. AND H. MUMTAZ (2007): "U.S. Evolving Macroeconomic Dynamics: A Structural Investigation," Working Paper Series 746, European Central Bank.

BERNANKE, B. AND M. GERTLER (1989): "Agency Costs, Net Worth, and Business Fluctuations," *American Economic Review*, 79, 14–31.

BERNANKE, B., M. GERTLER, AND S. GILCHRIST (1999): "The Financial Accelerator in a Quantitative Business Cycle Framework," in *Handbook of Macroeconomics*, ed. by J. B. Taylor and M. Woodford, Elsevier, vol. 1, Part C, chap. 21, 1341–1393, 1 ed.

BILBIIE, F. O., F. GHIRONI, AND M. J. MELITZ (2012): "Endogenous Entry, Product Variety, and Business Cycles," *Journal of Political Economy*, 120, 304–345.

BORN, B. AND J. PFEIFER (2016): "The New Keynesian Wage Phillips Curve: Calvo vs. Rotemberg," Dynare Working Paper no. 51.

CARLSTROM, C. T. AND T. S. FUERST (1997): "Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis," *American Economic Review*, 87, 893–910.

CARTER, C. K. AND R. KOHN (1994): "On Gibbs Sampling for State Space Models," *Biometrika*, 81, 541–553.

CHANEY, T., D. SRAER, AND D. THESMAR (2012): "The Collateral Channel: How Real Estate Shocks Affect Corporate Investment," *American Economic Review*, 102, 2381–2409.

CHARI, V., L. CHRISTIANO, AND P. KEHOE (2013): "The Gertler-Gilchrist Evidence on Small and Large Firm Sales," Mimeo.

CHODOROW-REICH, G. (2014): " The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008–9 Financial Crisis," *The Quarterly Journal of Economics*, 129, 1–59.

CHODOROW-REICH, G. AND A. FALATO (2018): "The Loan Covenant Channel: How Bank Health Transmits to the Real Economy," Tech. rep., mimeo.

CLARIDA, R., J. GALÍ, AND M. GERTLER (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *The Quarterly Journal of Economics*, 115, 147–180.

CLOYNE, J., C. FERREIRA, M. FROEMEL, AND P. SURICO (2019): "Monetary Policy, Corporate Finance and Investment," Working Papers 1911, Banco de España.

COGLEY, T. AND T. J. SARGENT (2005): "Drift and Volatilities: Monetary Policies and Outcomes in the Post WWII U.S," *Review of Economic Dynamics*, 8, 262–302.

COOLEY, T. F. AND V. QUADRINI (2001): "Financial Markets and Firm Dynamics," *American Economic Review*, 91, 1286–1310.

COVAS, F. AND W. J. DEN HAAN (2011): "The Cyclical Behavior of Debt and Equity Finance," *American Economic Review*, 101, 877–99.

CROUZET, N. AND N. R. MEHROTRA (2020): “Small and Large Firms over the Business Cycle,” *American Economic Review*, 110, 3549–3601.

DAVIS, S. J., J. HALTIWANGER, AND S. SCHUH (1996): “Small Business and Job Creation: Dissecting the Myth and Reassessing the Facts,” *Small Business Economics*, 8, 297–315.

DAVIS, S. J. AND J. C. HALTIWANGER (2019): “Dynamism Diminished: The Role of Housing Markets and Credit Conditions,” Working Paper 25466, National Bureau of Economic Research.

DINLERSOZ, E., S. KALEMLI-OZCAN, H. HYATT, AND V. PENCIAKOVA (2018): “Leverage over the Life Cycle and Implications for Firm Growth and Shock Responsiveness,” NBER Working Papers 25226, National Bureau of Economic Research, Inc.

DUYGAN-BUMP, B., A. LEVKOV, AND J. MONTORIOL-GARRIGA (2015): “Financing Constraints and Unemployment: Evidence from the Great Recession,” *Journal of Monetary Economics*, 75, 89 – 105.

FARRE-MENSA, J. AND A. LJUNGQVIST (2016): “Do Measures of Financial Constraints Measure Financial Constraints?” *Review of Financial Studies*, 29, 271–308.

FAVARA, G., S. GILCHRIST, K. F. LEWIS, AND E. ZAKRAJSEK (2016): “Recession Risk and the Excess Bond Premium,” FEDS Notes.

FAVARA, G. AND J. IMBS (2015): “Credit Supply and the Price of Housing,” *American Economic Review*, 105, 958–92.

FORT, T., J. HALTIWANGER, R. JARMIN, AND J. MIRANDA (2013): “How Firms Respond to Business Cycles: The Role of Firm Age and Firm Size,” *IMF Economic Review*, 61, 520–559.

FOSTER, L., J. HALTIWANGER, AND C. SYVERSON (2016): “The Slow Growth of New Plants: Learning about Demand?” *Economica*, 83, 91–129.

GALE, D. AND M. HELLWIG (1985): “Incentive-Compatible Debt Contracts: The One-Period Problem,” *Review of Economic Studies*, 52, 647–663.

GERTLER, M. AND S. GILCHRIST (1994): “Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms,” *The Quarterly Journal of Economics*, 109, 309–340.

GERTLER, M., N. KIYOTAKI, AND A. PRESTIPINO (2020): “A Macroeconomic Model with Financial Panics,” *Review of Economic Studies*, 87, 240–288.

GEWEKE, J. (1992): “Evaluating the Accuracy of Sampling-Based Approaches to the Calculation of Posterior Moments.” in *Bayesian Statistics*, ed. by J. M. Bernardo, J. O. Berger, A. P. Dawid, , and A. F. M. Smith, Oxford University Press, vol. 4, 169–93.

GILCHRIST, S., M. SIEMER, AND E. ZAKRAJSEK (2018): “The Real Effects of Credit Booms and Busts: A County-Level Analysis,” Tech. rep., mimeo.

GILCHRIST, S. AND E. ZAKRAJŠEK (2012): “Credit Spreads and Business Cycle Fluctuations,” *American Economic Review*, 102, 1692–1720.

GIROUD, X. AND H. M. MUELLER (2017): “Firm Leverage, Consumer Demand, and Employment Losses During the Great Recession,” *The Quarterly Journal of Economics*, 132, 271–316.

HALTIWANGER, J., R. JARMIN, AND J. MIRANDA (2013): “Who Creates Jobs? Small versus Large versus Young,” *The Review of Economics and Statistics*, 95, 347–361.

HALTIWANGER, J., R. S. JARMIN, R. KULICK, AND J. MIRANDA (2016): “High Growth Young Firms: Contribution to Job, Output, and Productivity Growth,” in *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, National Bureau of Economic Research, Inc, NBER Chapters, 11–62.

JACQUIER, E., N. G. POLSON, AND P. E. ROSSI (1994): “Bayesian Analysis of Stochastic Volatility Models,” *Journal of Business & Economic Statistics*, 12, 371–389.

JERMANN, U. AND V. QUADRINI (2012): “Macroeconomic Effects of Financial Shocks,” *American Economic Review*, 102, 238–271.

JUSTINIANO, A., G. E. PRIMICERI, AND A. TAMBALOTTI (2019): “Credit Supply and the Housing Boom,” *Journal of Political Economy*, 127, 1317–1350.

KAAS, L., P. A. PINTUS, AND S. RAY (2016): “Land Collateral and Labor Market Dynamics in France,” *European Economic Review*, 84, 202–218.

KAPLAN, G., K. MITMAN, AND G. L. VIOLANTE (2020): "The Housing Boom and Bust: Model Meets Evidence," *Journal of Political Economy*, 128, in press.

KEYS, B. J., A. SERU, AND V. VIG (2012): "Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets," *The Review of Financial Studies*, 25, 2071–2108.

KHAN, A. AND J. THOMAS (2013): "Credit Shocks and Aggregate Fluctuations in an Economy with Production Heterogeneity," *Journal of Political Economy*, 121, 1055 – 1107.

KILIAN, L. AND H. LÜTKEPOHL (2017): *Structural Vector Autoregressive Analysis*, Themes in Modern Econometrics, Cambridge University Press.

KIYOTAKI, N. AND J. MOORE (1997): "Credit Cycles," *Journal of Political Economy*, 105, 211–248.

LEVIN, A. T., F. M. NATALUCCI, AND E. ZAKRAJSEK (2004): "The Magnitude and Cyclical Behavior of Financial Market Frictions," Finance and Economics Discussion Series 2004-70, Board of Governors of the Federal Reserve System (US).

LIU, Z., J. MIAO, AND T. ZHA (2016): "Land Prices and Unemployment," *Journal of Monetary Economics*, 80, 86–105.

LOWN, C. AND D. P. MORGAN (2006): "The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey," *Journal of Money, Credit and Banking*, 38, 1575–1597.

MEISENZAHL, R. R. (2014): "Verifying the State of Financing Constraints: Evidence from U.S. Business Credit Contracts," *Journal of Economic Dynamics and Control*, 43, 58–77.

MIAN, A., K. RAO, AND A. SUFI (2013): "Household Balance Sheets, Consumption, and the Economic Slump," *The Quarterly Journal of Economics*, 128, 1687–1726.

MIAN, A. AND A. SUFI (2009): "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis," *The Quarterly Journal of Economics*, 124, 1449–1496.

——— (2011): "House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis," *American Economic Review*, 101, 2132–56.

——— (2014): "What Explains the 2007 – 2009 Drop in Employment?" *Econometrica*, 82, 2197–2223.

MOSCARINI, G. AND F. POSTEL-VINAY (2012): "The Contribution of Large and Small Employers to Job Creation in Times of High and Low Unemployment," *American Economic Review*, 102, 2509–39.

PRIMICERI, G. (2005): "Time Varying Structural Vector Autoregressions and Monetary Policy," *Review of Economic Studies*, 72, 821–852.

PUGSLEY, B. W. AND A. ŞAHIN (2018): "Grown-up Business Cycles," *The Review of Financial Studies*, 32, 1102–1147.

SCHOTT, I. (2015): "Start-ups, House Prices, and the US Recovery," Tech. rep., Department of Economics. Université de Montréal.

SEDLÁČEK, P. AND V. STERK (2017): "The Growth Potential of Startups over the Business Cycle," *American Economic Review*, 107, 3182–3210.

SIEMER, M. (2019): "Employment Effects of Financial Constraints during the Great Recession," *The Review of Economics and Statistics*, 101, 16–29.

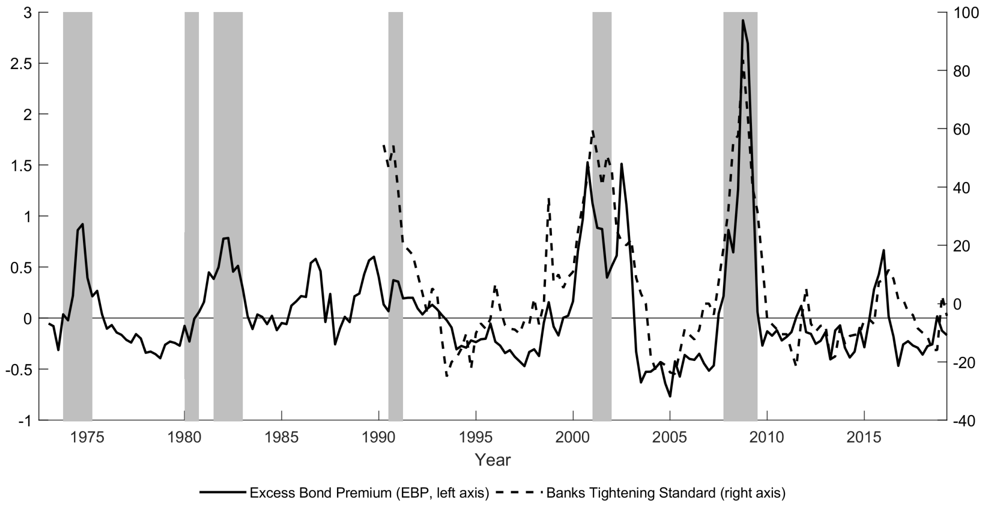
TOWNSEND, R. M. (1979): "Optimal Contracts and Competitive Markets with Costly State Verification," *Journal of Economic Theory*, 21, 265–293.

WASMER, E. AND P. WEIL (2004): "The Macroeconomics of Labor and Credit Market Imperfections," *American Economic Review*, 94, 944–963.

WU, J. C. AND F. D. XIA (2016): "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound," *Journal of Money, Credit and Banking*, 48, 253–291.

# A More Descriptive Evidence

**Figure 19:** Excess Bond Premium vs. Bank Tightening Standards (Small Firms)




Notes: Excess Bond Premium and Net Percentage of Domestic Banks Tightening Standards for Commercial and Industrial Loans to Small Firms. Data Source: Gilchrist and Zakrajšek (2012) and Board of Governors of the Federal Reserve System (US).

**Table 5:** Firm-level Survey Evidence on Loan Applications, 2007-2011

| | | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|
| **Applied for Loan** | | 12% | 13% | 13% | 11% | 11% |
| **Outcome of Loan Application** | | | | | | |
| | Always denied | 11% | 15% | 19% | 20% | 19% |
| | Sometimes denied | 17% | 17% | 16% | 15% | 11% |
| | Always approved | 72% | 68% | 65% | 65% | 71% |
| **Reason for denial** | | | | | | |
| | Personal credit history | 45% | 46% | 39% | 33% | 40% |
| | Insufficient collateral | 44% | 42% | 40% | 40% | 30% |
| | Not being in business long enough | 35% | 15% | 12% | 9% | 11% |
| | Business credit history | 32% | 34% | 30% | 26% | 41% |
| | The loan requested was too large | 26% | 28% | 20% | 16% | 21% |
| | Inadequate documentation provided | 7% | 15% | 9% | 6% | 9% |
| | Others | 8% | 15% | 4% | 6% | 7% |
| **Did not apply for credit when needed for fear of denial** | | | | | | |
| | | 15% | 18% | 19% | 18% | 16% |
| **Total Number of Firms** | | 2907 | 2599 | 2399 | 2124 | 2000 |

Data source: Kauffmann Firm Survey Data (Public Use Data), 2007-2011, own tabulation, multiple answers are possible. Notes: The sample includes only newly founded businesses in 2004 who survived until the respective year.

# B Details on the Time-varying Parameter VAR

This section describes the priors and estimation algorithm used for the time-varying parameter estimations.[64]

[64] This Section heavily draws on the "Appendix B: Bayesian Estimation of a VAR with Time-Varying Parameters and Stochastic Volatility" in Baumeister and Peersman (2013).

### B.1 Priors

To initiate the Kalman filter, I follow Primiceri (2005) and Baumeister and Peersman (2013) and use informed priors for the time-varying parameters $\theta^t, \alpha_t$ and $\ln h_t$ from the point estimates of a constant coefficient VAR on a training sample ranging from 1973Q2 to 1979Q4. As is common in the literature (see Primiceri, 2005 for a detailed discussion), I assume normal priors for $\theta_t, \alpha_t$ and $\ln h_t$. More precisely,

$$\theta_0 \sim N(\hat{\theta}^{OLS}, 4 \cdot Var(\theta^{OLS})$$

where $\hat{\theta}^{OLS}$ denotes the OLS point estimate of the training sample based on a linear VAR. Regarding the prior for $\alpha_0$ and $h_0$, I follow Benati and Mumtaz (2007). Let $AD^{\frac{1}{2}}$ denote the Choleski-factor of the time-invariant variance-covariance matrix $\hat{\Sigma}_{OLS}$ of the reduced-form innovations of the linear VAR, with **A** denoting the lower-triangular matrix and $D^{\frac{1}{2}}$ is a diagonal matrix containing the standard deviations of residuals. The prior for log-volatilities is set to

$$ln\ h_0 \sim N(ln\ \mu_0, 10 \times I_n)$$

where $\mu_0$ is a vector with the diagonal elements of $D^{\frac{1}{2}}$ and $I_n$ denotes the identity matrix which is multiplied by 10 to make the prior only weakly informative. I further set the priors for the contemporaneous correlations as follows

$$\alpha_0 \sim N(\tilde{\alpha}_0, 10 \times \tilde{\alpha}_0)$$

where $\tilde{\alpha}_0$ is a stacked vector containing the diagonal elements of the inverse of the matrix **A**. Regarding the priors for the hyperparameters, I follow Baumeister and Peersman (2013) and Benati and Mumtaz (2007) and assume that **Q** follows an inverse Wishart distribution.

$$Q \sim IW(\bar{Q}^{-1}, T_0),$$

with $T_0$ denote the prior degrees of freedom, which equal the length of the training sample. The scale matrix is set to $\bar{Q} = (0.01)^2 T_0$, which is a conservative choice and only weakly informative. The block-diagonal matrix **S** also follows an inverse Wishart distribution with

$$S_i \sim IW(\bar{S}_i^{-1}, i+1),$$

where $i = 1,2,3$ denote the blocks of S. As in Benati and Mumtaz (2007) $\bar{S}_i$ is a diagonal matrix with the elements of $\tilde{\alpha}_0 \times 0.001$. The variances to the innovations of the stochastic volatilities follow an inverse-Gamma distribution (as in Cogley and Sargent, 2005)

$$\sigma_i^2 \sim IG(\frac{0.0001}{2}, \frac{1}{2}),$$

### B.2 Estimation Algorithm

The Markov Chain Monte Carlo (MCMC) Algorithm used to generate a sample of the joint posterior of four blocks of parameters: $\theta^T, A^T, H^T$ and the hyperparamters denoted $V$. The set of hyperparameters consists of $Q, S$, and $\sigma_i^2$ for $i = 1, \ldots, 4$. (with the superscript $T$ denoting the entire sample) is based on Gibbs sampling. The number of iterations of the Gibbs Sampler is $n = 100.000$, where the first 50.000 draws are discarded as burn-in. The posterior distribution of each step are conditional on the observations $Y^T$ and the parameters drawn in the previous step. The estimation algorithm follows Baumeister and Peersman (2013). After initializing $A^T$, $H^T$, $Y^T$ and $V$, the steps are the following:

1. **Draw coefficient states $\theta^T$.**
   The measurement equation is linear and has Gaussian innovations with known variance. Hence, the conditional posterior is a product of Gaussian densities and $\theta$ can be drawn from a standard simulation smoother (see Carter and Kohn, 1994). The density $p(\theta^T | Y^T, A^T, H^T, V)$ can be factored as

$$p(\theta^T | Y^T, A^T, H^T, V) = p(\theta_T | Y^T, A^T, H^T, V) \Pi_{t=1}^{T-1} p(\theta_t | \theta_{t+1}, Y^t, A^t, H^t, V),$$

   where

$$\theta_t | \theta_{t+1}, Y^t, A^T, H^T, V \sim N(\theta_{t|t+1}, P_{t|t+1}) \tag{B.1}$$
$$\theta_{t|t+1} = E(\theta_t | \theta_{t+1}, Y^t, A^T, H^T, V), \tag{B.2}$$
$$P_{t|t+1} = Var(\theta_t | \theta_{t+1}, Y^t, A^T, H^T, V). \tag{B.3}$$

   Starting with the terminal state of a forward Kalman filter, we obtain the conditional mean and variance of the posterior distribution. The backward recursion uses draws from this distribution and produces smoothed draws that take into account the information of the entire sample.

2. **Draw covariance states $A^T$.**
   The posterior of $A^T$ is conditional on $Y^t, \theta^T, H^T, V$ and is also a product of normal densities that can be calculated as in step (2). Note that the procedure of applying the backward recursion of the Kalman filter can be applied, because I assume that $S$ is block diagonal (for more details see Appendix B in Baumeister and Peersman, 2013).

3. **Draw volatility states $H^T$.**
   The orthogonalized observations $\epsilon_t = A_t(y_t - X_t'\theta_t)$ have variance $\text{var}(\epsilon_t) = H_t$ and are observable conditional on $\theta^T, A^T$ and $Y^T$. Since the state space representation of $\ln h_{i,t}$ is not Gaussian, I follow Baumeister and Peersman (2013), Benati and Mumtaz (2007), Cogley and Sargent (2005) and apply the procedure proposed in Jacquier, Polson, and Rossi (1994) and draw the volatility states one at a time.

4. **Draw hyperparameters $V$.**
   The error terms of the transition equations 3.2 - 3.4 are observable given $\theta^T, A^t, H^T, Y^T$.

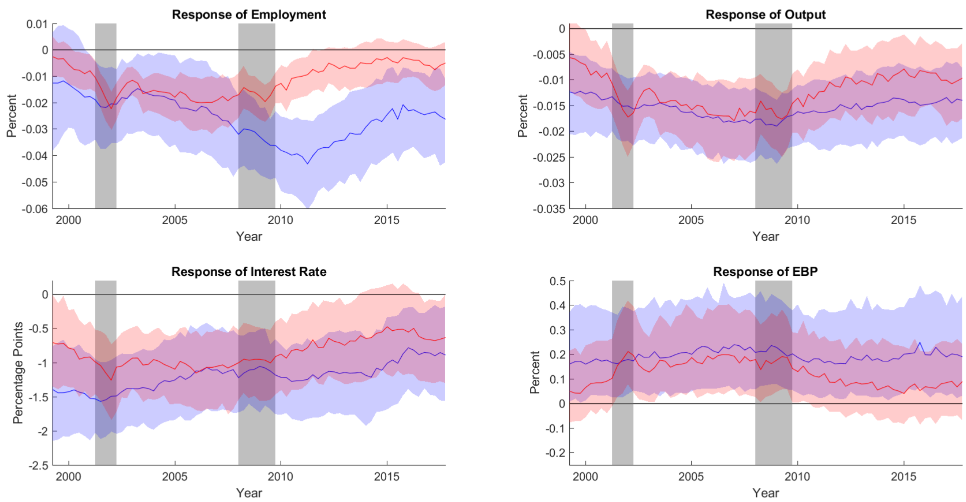
Thus, the hyperparameters $Q$,$S$ and $\sigma_i^2$ can be directly drawn from their respective posterior distributions $p(Q,S,\sigma_i^2|\theta^T,A^T,H^T,Y^T)$.

# C Further Empirical Evidence

**Figure 20:** Generalized impulse response functions (GIRFs) in Response to a Credit Supply Shock: 1 Period after the Shock

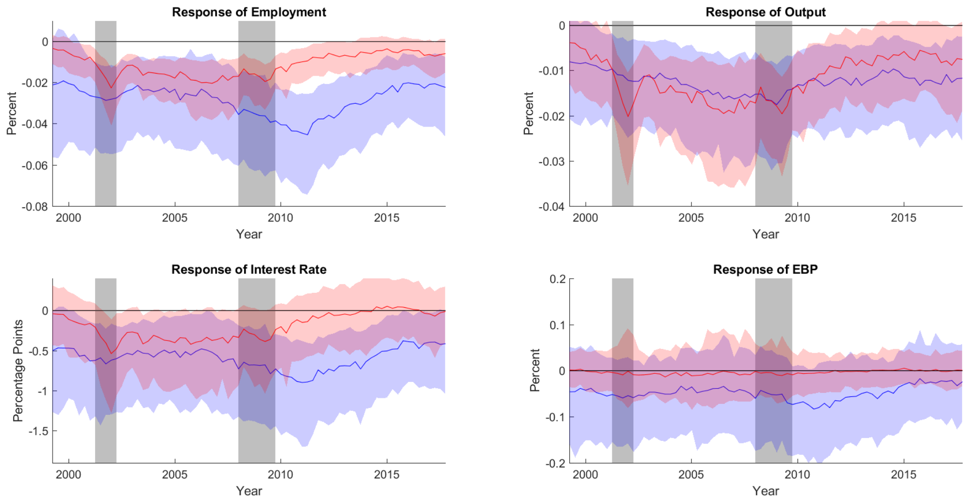

Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 1 quarter to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior distribution for young (old) firms. Grey shaded areas denote NBER recession periods.

**Figure 21:** Generalized impulse response functions (GIRFs) in Response to a Credit Supply Shock: 6 Periods after the Shock



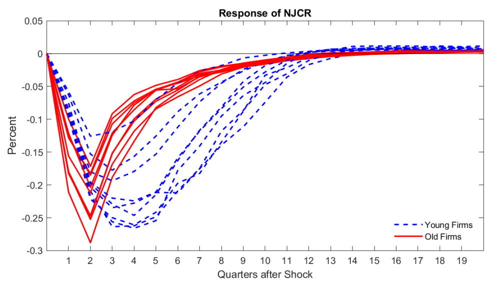

Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior distribution for young (old) firms. Grey shaded areas denote NBER recession periods.

**Figure 22:** Generalized impulse response functions (GIRFs) in Response to a Credit Supply Shock: 12 Periods after the Shock

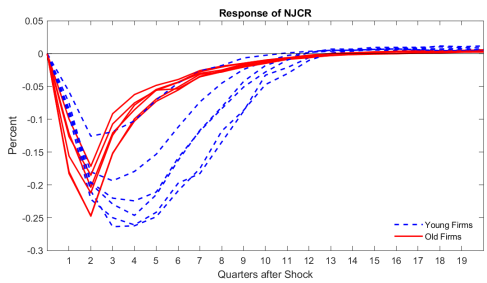



Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 12 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior distribution for young (old) firms. Grey shaded areas denote NBER recession periods.

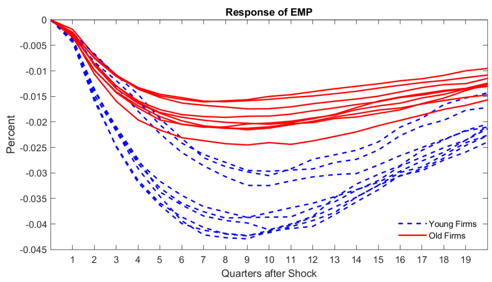
**Figure 23:** Generalized Impulse Response Functions in Response to a Credit Supply Shock in Recessions for Young and Old Firms



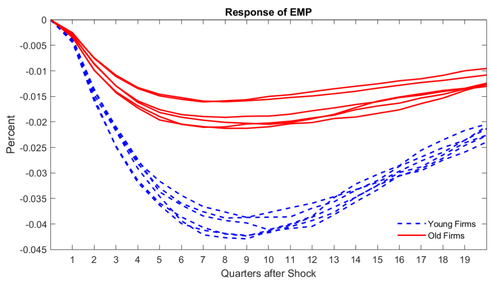

**(a)** Net Job Creation Rate, all recessionary periods




**(b)** Net Job Creation Rate, Great Recession



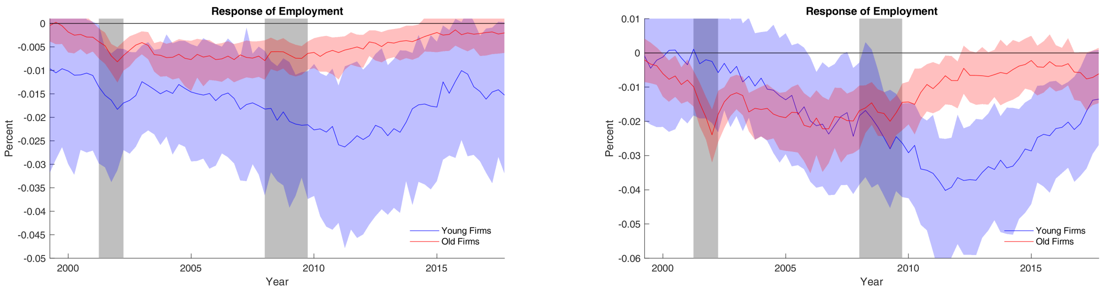

**(c)** Employment, all recessionary periods




**(d)** Employment, Great Recession

Notes: Generalized impulse response functions (GIRFs) in NBER recession periods and the Great Recession for young (dashed, blue lines) and old (solid red lines) firms to a one standard deviation increase in the EBP on the Net Job Creation Rate and Employment. The shock size is normalized to one in each period.

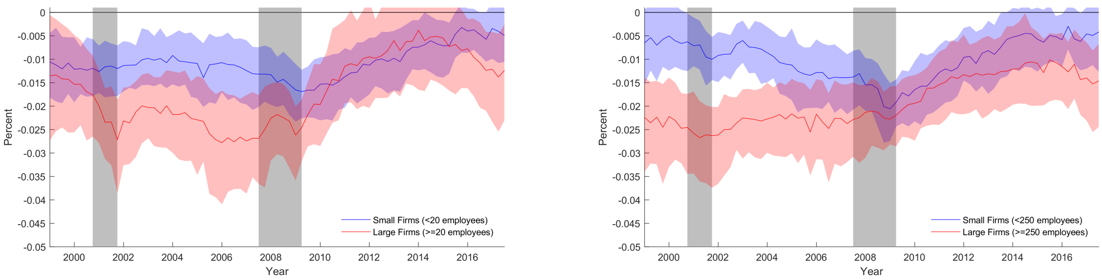
**Figure 24:** Controlling for Firm Dynamics: GIRFs in Response to a Positive Credit Supply Shock




**(a)** Controlling for Job Destruction of Exiting Firms **(b)** Excluding Firms Younger than Two Years

Notes: Right Panel: GIRFs based on two five-variable TVP-VAR estimation of $Y_t = [log(EMP_t^j)\ log(JD\_exit_t)\ log(GDP_t)\ FFR_t\ EBP_t]$ where $JD\_exit_t$ denotes the number of destroyed jobs of exiting firms and $EMP_t^j$ denotes employment at young (≤ 5 years) and old firms respectively. Left Panel: GIRFs based on two four-variable TVP-VAR estimation excluding employment at firms younger than two years. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

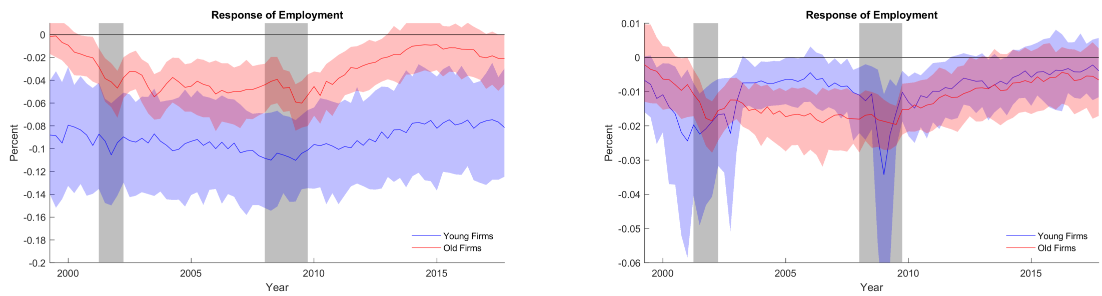
**Figure 25:** Firm Size: GIRFs of Employment in Response to a Credit Supply Shock




**(a)** Cutoff at 20 employees **(b)** Cutoff at 250 employees

Notes: GIRFs of Employment in response to a positive credit supply shock for small and large firms with the size cutoff at 20 and 250 employees respectively. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

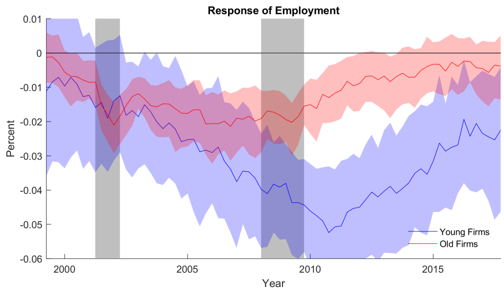
**Figure 26:** Robustness: Banks Tightening Standards (LHS) and for a Broader Definition of Young Firms (≤ 10 years, RHS).



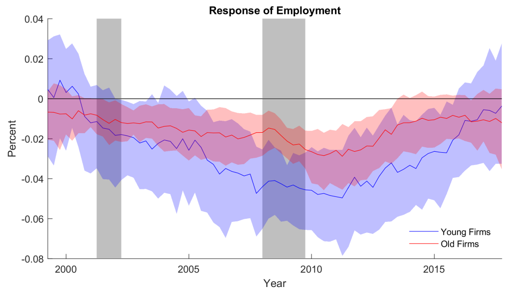

**(a)** Banks Tightening Standards **(b)** Definition Young Firm: up to 10 Years

Notes: LHS: GIRFs based on two four-variable TVP-VAR estimation of $Y_t = [log(EMP_t^j)\ log(GDP_t)\ FFR_t\ BL_t^i]$ where $EMP_t^j$ denotes employment at young (between two and five years old) and old firms respectively and $BL_t^i$ denotes banks tightening standards for commercial and industrial loans to small firms (for young firms) or medium sized and large firms (for old firms). RHS: The age cutoff in the definition between young and old firms is at the age of 10 years (young ≤ 10). Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

**Figure 27:** Robustness: Identification Strategy



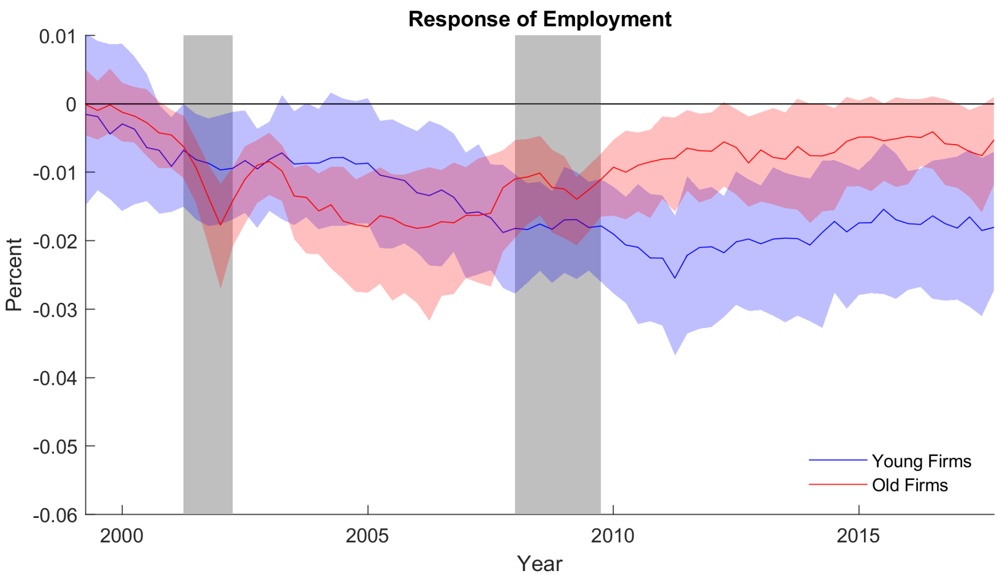

**(a)** Employment reaction, EBP ordered third




**(b)** Employment reaction, EBP ordered first

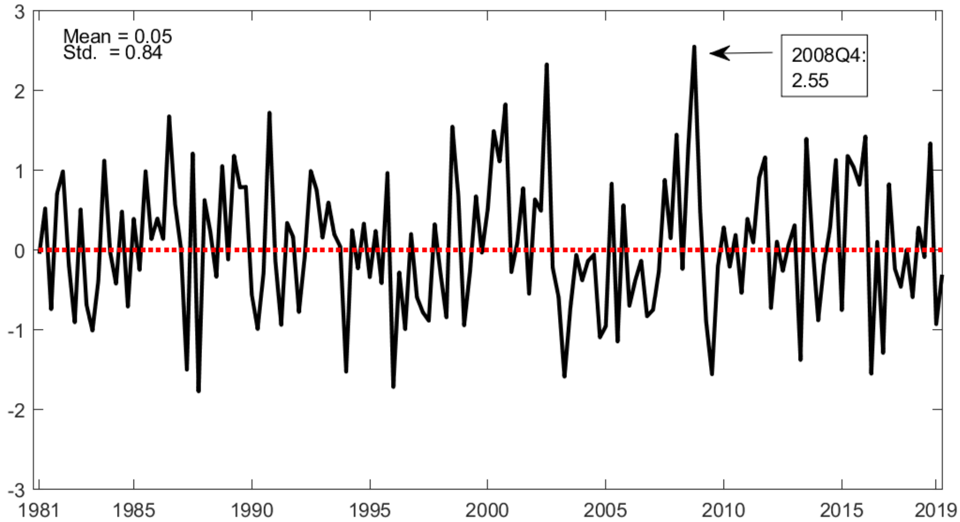
Notes: GIRFs of Employment based on two four-variable TVP-VAR estimation of different ordering of variables with young and old firms respectively. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

**Figure 28:** House Price Growth as Endogenous Variable



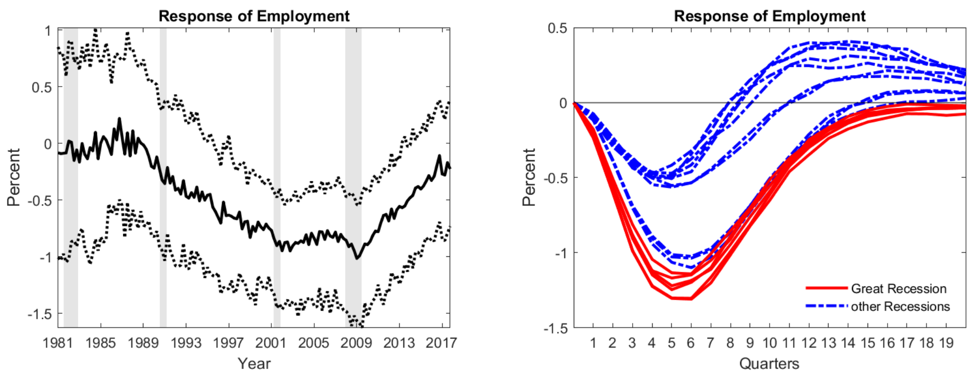

Notes: GIRFs of Employment in response to a positive credit supply shock for young (blue) and old (red) firms with house price growth as fifth endogenous variable. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

**Figure 29:** Structural Credit Supply Shocks (Long Horizon)




Notes: Structural Credit Supply Shocks based on the TVP-VAR estimation for the baseline long-horizon specification for the sample period 1981Q1-2019Q2.

**Figure 30:** GIRFs of Employment in Response to a Credit Supply Shock (Long Horizon). Recessionary Periods and over Time.




Notes: Left Panel: GIRFs of Employment in Response to a Negative Credit Supply Shock in NBER recession periods except the Great Recession (blue) and the Great Recession (red). Right Panel: Cross-section of unemployment responses over time. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), dashed lines denote 16-th and 84-th percentiles of the posterior distribution. Grey shaded areas denote NBER recession periods.

# D Cross-regional Estimation on MSA-level

To perform cross-regional estimations, I build a MSA-level dataset including job creation of young firms from the BDS, data on small business loans from the Community Reinvestment Act (CRA), and the US house price index.[65]

I estimate the following long-difference equation

$$\begin{aligned}\Delta JC_{m,07-09} =& \beta \Delta Log(HP)_{m,06-09} + \alpha \Delta SBL_{m,06-09} \\ &+ \gamma \Delta Log(HP)_{m,06-09} \times \Delta SBL_{m,06-09} + X_{m,06} + \epsilon_m.\end{aligned} \tag{D.1}$$

The dependent variable $\Delta JC_{m,07-09}$ is the percentage change in young firms' MSA-level job creation from 2007 to 2009. $\Delta Log(HP)_{m,06-09}$ denotes MSA-level house price changes between the years 2006 and 2009 and $\Delta$Loan amount$_{m,06-09}$ is the change in the *total loan amount* of loans to small businesses, $X_{m,06}$ denotes MSA-level controls of the year 2006.[66] The coefficient of interest is the interaction term $\gamma$. It captures whether the elasticity of young firms' job creation with respect to the total amount of small business loans depends on house price changes at the MSA-level. To account for the MSA-level firm composition, I control for the share of young firms, the share of young firms' MSA-level employment and the MSA-specific employment shares of two-digit NAICS industries in the year 2006. All regressions are weighted by the population density in the year 2000.

The results are illustrated in Table 6. Besides the highly statistically significant elasticity of the change in job creation to the change in MSA-level house prices, the interaction term for the change in the total loan amount and the change in house prices is statistically significant for all specifications. In areas with a larger decline in house prices, job creation of young firms shows a higher elasticity with respect to the amount of small business loans. This can be interpreted as follows: In response to a reduction of the number of loans, young firms reduced hiring significantly stronger in areas that experienced a more pronounced drop in house prices.

Overall, these results point towards a link between credit conditions for young businesses and local house prices. This relation further impacts job creation of young firms. Although this approach does not allow for causal statements, it points towards the important role of real estate as collateral for young business owners. Fluctuations in young firms' real estate collateral affect their lending capacities as borrowing costs increase and the probability that a loan is denied increases. As a result, young firms reduce job creation. This finding is in line with recent causal evidence of Bahaj et al. (2020) who find that employment of young, highly levered firms is more sensitive to monetary policy.

[65] Table 8 in Appendix D gives an overview of the data sources.

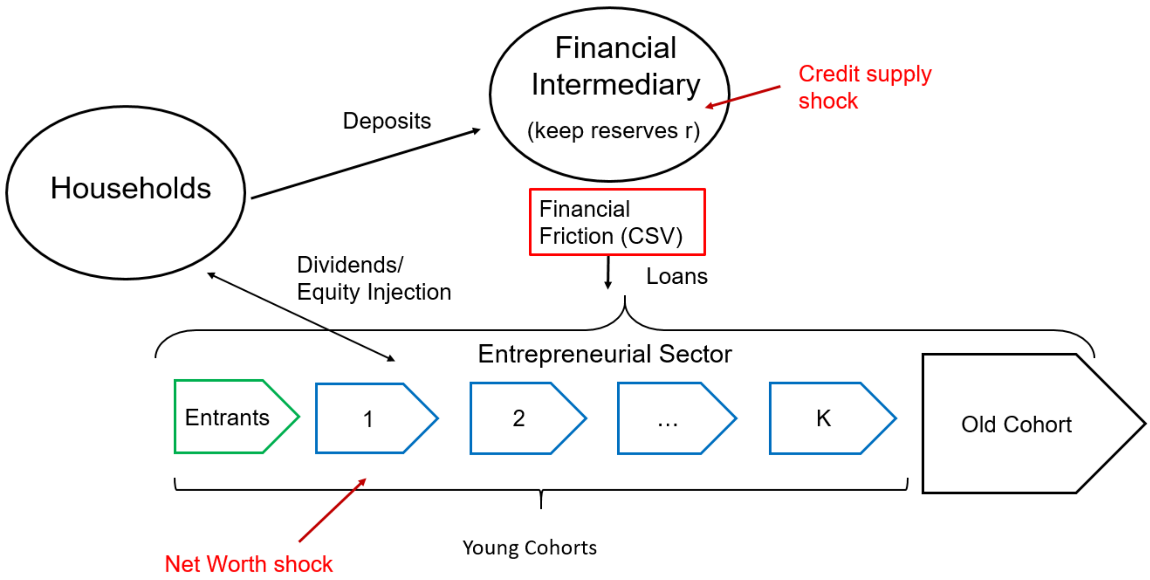
[66] Small businesses are businesses with gross annual revenues < \$ USD 1 million in the relevant time span.

**Table 6:** Cross-Regional Estimation Results

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | $\Delta$ Job_creation$_{07-09}$ | | | |
| | (1) | (2) | (3) | (4) |
| $\Delta$ Loan amount$_{06-09}$ | −0.110 | −0.104 | −0.103 | −0.127 |
| | (0.088) | (0.087) | (0.088) | (0.098) |
| $\Delta$ HPI$_{06-09}$ | 0.674*** | 0.729*** | 0.726*** | 0.778*** |
| | (0.220) | (0.220) | (0.220) | (0.250) |
| $\Delta$ Loan amount$_{06-09}$:$\Delta$ HPI$_{06-09}$ | 0.827** | 1.007** | 1.001** | 1.246*** |
| | (0.371) | (0.392) | (0.392) | (0.465) |
| Constant | −0.341*** | −0.225** | −0.226** | 0.131 |
| | (0.039) | (0.088) | (0.089) | (0.475) |
| Share of Young Firms | No | Yes | Yes | Yes |
| Young Firms' Employment Share | No | No | Yes | Yes |
| MSA × Industry controls | No | No | No | Yes |
| Observations | 254 | 254 | 254 | 252 |
| $R^2$ | 0.068 | 0.076 | 0.076 | 0.163 |
| Adjusted $R^2$ | 0.056 | 0.061 | 0.058 | 0.095 |

Notes: This table presents MSA-level regressions results. The share of young firms and young firms' employment shares correspond to the year 2006. MSA × industry controls are the MSA-specific employment shares of all available two-digit NAICS industries in 2006. Robust standard errors in parenthesis. All regressions are population weighted (weighting year 2000). *p<0.1; **p<0.05; ***p<0.01

**Figure 31:** Overview of Basic Model Framework




# E Model Appendix

## E.1 Entrepreneurs' First Order Conditions

### E.1.1 The Entrant

The first-order optimal conditions for entrepreneurs of cohort $E$ are given by

$$\bar{\omega}^E_{t+1} : E_t\left\{\Gamma'(\bar{\omega}^{i,E}_{t+1})\right\} = E_t\left\{\lambda^{PC,E}_t\left[\Gamma'(\bar{\omega}^E_{t+1}) - \mu^E G'(\bar{\omega}^E_{t+1})\right]\right\}$$

$$K^E_t : E_t\left\{\left[1-\Gamma'(\bar{\omega}^E_{t+1})\right]R^{k,E}_{t+1} + \lambda^{PC,E}_t\left[\Gamma(\bar{\omega}^{i,E}_{t+1}) - \mu^E G(\bar{\omega}^E_{t+1})\right]R^{k,E}_{t+1}\right\} = \lambda^{PC,E}_t \frac{R^n_t}{(1-r_t)},$$

where $\lambda^{PC,E}_t$ denotes the Lagrange multiplier on the participation constraint.

### E.1.2 Age Cohort $j$

The first-order optimal conditions for entrepreneurs of cohort $j$ are given by

$$d^j_t : \lambda^{FC,j}_t = \frac{1}{\left(1+2\kappa^d(d^j_t - d^j_{SS})\right)}$$

$$\bar{\omega}^j_{t+1} : E_t\left\{-\lambda^{FC,j}_{t+1}\Gamma'\left(\bar{\omega}^j_{t+1}\right)\right\} = \lambda^{PC,j}_t E_t\left\{\left[\Gamma'(\bar{\omega}^j_{t+1}) - \mu^j G'^j(\bar{\omega}^j_{t+1})\right]\right\}$$

$$K^j_t : \lambda^{PC,j}_t E_t\left\{\left[\Gamma(\bar{\omega}^j_{t+1}) - \mu^j G(\bar{\omega}^j_{t+1})\right]\right\} = \lambda^{PC,j}_t \frac{R^n_t}{(1-r_t)} + E_t\left\{\lambda^{FC,j}_{t+1}\gamma^j\left[1-\Gamma'(\bar{\omega}^j_{t+1})\right]\right\},$$

where $\lambda^{PC,K}$ denotes the Lagrange multiplier on the participation constraint and $\lambda^{FC,K}$ the Lagrange multiplier on the flow-of-funds constraint.

## E.2 Households

The infinitely-lived representative risk-averse household discounts the future with the subjective discount factor $\beta < 1$. He derives utility from consumption and dis-utility from providing labor to output goods producers.

The household chooses consumption $C_t$, the amount of labor $L_t$ (denoted in hours), savings $D_t$ and number of equity shares $s_t$ to maximize its utility

$$\max_{\{C_t, L_t, D_t, s_t\}} U(C_t, L_t) = E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{C_t^{(1-\sigma^c)}}{(1-\sigma^c)} - \chi \frac{L_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}} \right\}.$$

subject to the budget constraint

$$C_t + D_t + s_t p_t + N^{ST} = w_t L_t + R_{t-1}^n D_{t-1} + s_{t-1}(d_t + p_t) + C_t^e. \tag{E.1}$$

The household finances consumption, savings in form of risk-free deposits, buying equity shares $s_t$ and equipping start-ups with an exogenous amount of net worth $N^{ST}$ with wage payments $(W_t L_t)$, risk-free interest payments on last period's deposits $(R^n D_t)$, equity payout from owning shares of entrepreneurs $(s_{t-1}(d_t + p_t))$, and the remaining equity from exiting entrepreneurs $C_t^e$ that is transferred back to the household. Entrepreneurs' equity shares denoted by $s_t$ are evaluated at price $p_t$

This results in the first order optimality conditions:

$$\begin{aligned}
C_t &: \lambda_t = C_t^{-\sigma^C} \\
L_t &: \lambda_t W_t = \chi L_t^{\frac{1}{\eta}} \\
D_t &: \lambda_t = \beta E_t \{\lambda_{t+1}\} R_t^n \\
s_t &: p_t = E_t \left\{ \frac{\beta \lambda_{t+1}(d_{t+1} + p_{t+1})}{\lambda_t} \right\}.
\end{aligned}$$

Note that the last condition for the equity shares can we rewritten (by forward substitution)

$$p_t = E_t \left\{ \sum_{j=1}^{\infty} \left( \frac{\beta^j \lambda_{t+j}}{\lambda_t} \right) d_{t+j} \right\},$$

where $\beta^j \lambda_{t+1}/\lambda_t$ is the household's stochastic discount factor. Note the household chooses the amount of aggregate shares from the entire entrepreneurial sector.

## E.3 Capital Good Production

As in Bernanke et al. (1999) and Gertler et al. (2020), there is a continuum of measure unity of competitive capital goods firms. Entrepreneurs of each age cohort purchase capital each period from capital good producers for use in the subsequent period. Note that there are $j$ capital good producers, one for each cohort. Each capital goods firm produces investment goods that are sold at price $Q_t^j$.

Capital evolves according to

$$K_{t+1}^j = \Lambda\left(\frac{I_t^j}{K_t^j}\right)K_t^j + (1-\delta)K_t^j, \tag{E.2}$$

where $\delta$ denotes the depreciation rate. The quantity of newly produced capital depends upon investment $I_t^j$ and the beginning of period capital stock $K_t^j$. The investment technology $\Lambda$ is an increasing and concave function of the investment-to-capital ratio $I_t^j/K_t^j$ that captures convex adjustment costs.[67] The capital goods producer's first order condition. The maximization problem for the capital goods producers is $\max_{\{I_t^{j,i}\}} Q_t^j \Lambda_t - I_t^j(i)$. Due to symmetry, $I_t^j(i) = I_t^j$.

$$Q_t^j = \left[\Lambda'\left(\frac{I_t^j}{K_t^j}\right)\right]^{-1}. \tag{E.3}$$

## E.4 Output Good Production

Capital is used with labor to produce the output good. To facilitate aggregation within each age cohort, I assume that production is constant-returns to scale. The production function for each entrepreneurial sector $j$ is hence given by

$$Y_t^j = (K_t^j)^\alpha (L_t^j)^{1-\alpha}, \tag{E.4}$$

where capital $K_t^j$ and labor $L_t^j$ are aggregate input factors (per age cohort). Profit maximization of output good producers implies that the wage is set equal to the marginal product of labor

$$\hat{W}_t = (1-\alpha)\frac{Y_t^j}{L_t^j}. \tag{E.5}$$

where the wage $\hat{W}_t$ is subject to wage adjustment costs of the form

$$\hat{W}_t = W_t\left(1 + \kappa^W\left(\frac{W_t}{W_{t-1}} - 1\right)\frac{1}{W_{t-1}} + \beta\frac{\lambda_{t+1}}{\lambda_t}\kappa^W\left(\frac{W_{t+1}}{W_t} - 1\right)\frac{W_{t+1}}{W_t^2}\right). \tag{E.6}$$

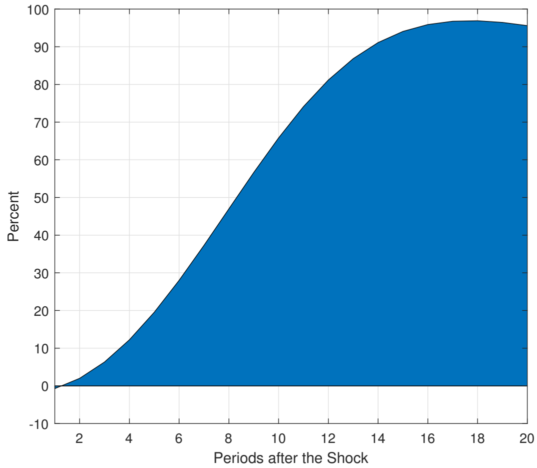
Note that the wage is equal for all age cohorts as otherwise all households would supply labor only to the highest paying firm. The real rental rate of capital is further given by

$$r_t^k = \alpha\frac{Y_t^j}{\tilde{K}_t^j}. \tag{E.7}$$

## E.5 Additional Figures

[67] Note that $\Lambda(0) = 0$.

**Figure 32:** Contribution of Net Worth Shock for the Employment Reaction of Young Firms




Notes: Average contribution of the net worth shock to the decline in employment of young firms weighted by their corresponding firm size. The size of the credit supply shock is based on the structural shock series from the TVP-VAR and amounts to 2.55. The size of the net worth shock targets a decline in young firms' net worth that is equivalent to the observed peak-to-trough decline in U.S. house prices and amounts to 1.45.

# F Data Sources

**Table 7:** Data Sources for the Time-Varying Parameter VAR

| **Name** | **Details** | **Source** |
|---|---|---|
| Excess Bond Premium | Gilchrist and Zakrajšek (2012) | Favara, Gilchrist, Lewis, and Zakrajsek (2016) |
| Unemployment Rate | Civilian Unemployment Rate, Quarterly, S.A. | U.S. Bureau of Labor Statistics |
| Credit Growth (yoy) | Total Credit to Private Non-Financial Sector | Bank for International Settlements |
| Net Job Creation Rate (by Age) | Total (Job Creation - Job Destruction)/Employment, Quarterly, | Quarterly Workforce Indicator |
| Employment (by Age) | Employment | Quarterly Workforce Indicator |
| Real GDP | Billions of Chained 2012 Dollars, Quarterly, S.A. | U.S. Bureau of Economic Analysis |
| Effective Federal Funds Rate | Percent, Quarterly Averages of Monthly Values, | U.S. Board of Governors |
| Shadow Rate | Shadow federal funds rate | Wu and Xia (2016) |

Notes: S.A. denotes seasonally adjusted data.

**Table 8:** Data Sources for Cross-Regional Estimations

| Variable | Source | Frequency | Geographical Level | Sample Length |
|---|---|---|---|---|
| Employment by Firm Age | BDS | annual | MSA | 1977-2014 |
| Small Business Loans (Origin.) | CRA | annual | MSA | 1996-2018 |
| House price index | FHFA | quarterly | MSA | 1975-2019 |