Financial Constraints, Firm Age, and the Labor Market†

JOB MARKET PAPER

Brigitte Hochmuth[1,2]

[1]Friedrich-Alexander University of Erlangen-Nürnberg (FAU)
[2]Institute for Advanced Studies, Vienna (IHS)

January 2021

Click for latest version

Abstract

This paper shows that credit crunches cause labor market effects that are nonlinear over time and diverge by firm age. During the 2007-2008 Great Financial Crisis, a credit supply shock caused young firms to reduce employment significantly more than older ones, because the housing bust of 2006 had led to a decline in young firms' housing collateral and restricted their ability to borrow. To understand the underlying mechanism, I propose a model of financial frictions that explicitly considers firm age. A simultaneous credit crunch and a decline in young firms' net worth can reconcile the model with my empirical results. While older firms are able to switch to equity financing, younger ones depend on debt financing and cut labor demand. As young firms disproportionately drive aggregate job growth, my findings can 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 sooner.

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

† I am indebted to my advisors Christian Merkl and Kurt Mitman for their guidance and Christian Haefke and Michael Reiter for their repeated advice. My thanks are likewise due to Katharina Bergant for her insightful discussion of my paper. Arpad Abraham, Guido Ascari, Christian Bredemeier, Carlos Carrillo-Tudela, Kieran Larkin, Per Krusell, Jochen Güntner, Philipp Hochmuth, Matthias Rottner, Claire Thurwächter, and Felix Schröter all provided extremely helpful comments. I have obtained very useful feedback at the EEA, the SNDE, and the Verein für Socialpolitik 2020 and at seminars at NYU Abu Dhabi, the IIES, and ifo Institut Munich. I am further grateful for feedback from the NOeG Winter Workshop 2019.
e-mail: brigitte.hochmuth@fau.de.

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, with net job creation dropping by 30 percent between 2006 and 2009[1], and the unemployment rate doubled and remained persistently high. Young firms founded up to five years previously accounted for 60 percent of the decline in employment and 66 percent in the decline in job creation between 2006 and 2011. Against this background, I study how financial constraints affect firms' employment decisions over time and by firm age. 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. This approach is complementary to existing empirical work focusing either on the microeconomic perspective[2] or on time-invariant effects of credit crunches.[3] I provide evidence that the effects of credit supply shocks vary over time and by firm age. Second, using cross-regional variation, I identify the private housing net worth of the owners of young businesses as an important driver of differences by firm age. Third, I set up a model of firm dynamics with financial frictions to understand the underlying mechanism. The model allows investigating the interaction between the credit supply channel, the (housing) net worth channel, and firms' labor demand.

This structural empirical analysis generates two key findings: In response to credit crunches, labor market reactions (i) are nonlinear over time and (ii) diverge by firm age. In performing a historical shock decomposition, I detect a structural break: Credit supply shocks have been important drivers of unemployment and output dynamics in the U.S. since the late 1990s, but were statistically and economically insignificant prior to this period. During the GFC, credit supply disturbances accounted for 60% of the variance in the U.S. unemployment rate. I further estimate the employment responses of young and older firms to an exogenous tightening of credit supply. With the onset of the Great Financial Crisis, young firms showed significantly stronger reactions to credit supply shocks, with no systematic difference apparent in relation to firm size. This finding is in line with the body of literature arguing that age is the relevant proxy for financially constrained firms (c.f., for example, Cloyne, Ferreira, Froemel, and Surico, 2019 and Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova, 2018).[4]

In the first step of my analysis, I apply a time-varying parameter vector autoregression (TVP-VAR) model with stochastic volatility to estimate the net job creation rate (NJCR) and employment reactions in response to a credit supply shock.[5] The advantage of this methodology is its flexibility. A TVP-VAR with stochastic volatility allows for a different set of coefficients and a different

[1] Data source: Business Dynamics Statistics.

[2] See Chodorow-Reich, 2014, Chodorow-Reich and Falato, 2018, Gilchrist, Siemer, and Zakrajsek, 2018, and Siemer, 2019.

[3] See Gilchrist and Zakrajšek, 2012, Bassett, Chosak, Driscoll, and Zakrajek, 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.

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

[5] See Primiceri (2005) and Cogley and Sargent (2005) for seminal work on TVP-VAR models.

variance-covariance matrix at every point in time.[6] 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 transmission mechanism. Second, compared to other classes of nonlinear time series models, this methodology does not hinge on any imposed threshold or a specific switching variable that dictates changes in parameters.[7]

Descriptively, the divergence of employment responses in accordance with firm age coincides with the bust in U.S. house prices starting in 2006. As house price growth picked up again, young firms' employment responses became less pronounced. In addition, evidence based on the 'Survey of Business Owners'[8] illustrates the increased importance of business owners' private real estate collateral for newly founded companies.

In the second step of my analysis, I investigate whether changes in house prices explain the stronger employment reaction of young firms. Using cross-regional variation at metropolitan statistical area (MSA) level, I find that in areas with a larger decline in house prices, young businesses' job creation is significantly more sensitive to local credit conditions. This finding suggests an important role for housing net worth in the hiring decisions of young firms, in line with recent literature stressing the importance of the housing collateral channel for newly and recently established businesses (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 also offers a potential explanation for the gain in significance of financial market shocks 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, for example, Favara and Imbs, 2015). In combination with a relaxation of credit standards and a shift in beliefs regarding future demand for housing (see Keys, Seru, and Vig, 2012 and Kaplan, Mitman, and Violante, 2020), the level of household debt increased substantially. Given the importance of real estate collateral for owners of young businesses, these developments strengthened the link between financial market conditions and labor market dynamics.

In a third step, I uncover the mechanism underlying these observations and construct 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. An asymmetry of information between the financial intermediary and firms who require loans to fund their risky operations gives rise to 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 dimensions. First, I add endogenous firm entry and a detailed firm age structure. Second, I allow firms to raise equity from households and pay out dividends. I follow Bernanke and Gertler (1989) in defining net worth as collateralizable assets (such as buildings, land etc.) which reflect a capacity to self-finance. In the model,

[6] As such, it captures both possible structural changes and state-dependent effects, such as effects that differ in recessions and in expansions).

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

[8] For details on the 'Survey of Business Owners', see `https://www.census.gov/programs-surveys/sbo/about.html`.

households provide business entrants with an initial net worth. As firms grow older, they accumulate net worth. Thus, the more newly established a business, the lower is its net worth and the higher the agency costs (in terms of informational asymmetry). This is consistent with empirical evidence that new firms face more difficulties in accessing credit markets.[9]

After parameterizing the model to match the relative distribution of firm age, I simulate a credit crunch and a decline in young firms' net worth. A credit supply shock leads to an initial, short-lived drop in labor demand for all firms. As young firms face higher financing costs, their borrowing declines and they reduce economic activity. The effect on young firms' demand for labor is more pronounced than in the case of old firms, but not large enough to explain the divergent employment responses by firm age found in the empirical analysis. Adding a decline in the value of young firms' collateralizable net worth reconciles the model with my empirical findings. As young firms' balance sheets deteriorate, lenders demand 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 sharply, which further depresses net worth. A financial accelerator mechanism thus exacerbates the contractionary effect on young firms: the endogenous link between the external finance premium and borrowers' net worth amplifies the impact of the shock. The result is a long-lasting decline in the demand for labor exerted by young firms. By contrast, the effect on old firms is only temporary. They have higher net worth, experience low agency costs, and, in response to the credit crunch, households are willing to provide them with equity. Their ability to switch from debt to equity financing dampens the impact of the shock.

Overall, I find that the persistence in the impact on young firms' employment stems from the decline in their net worth and the resulting higher cost of borrowing. A counterfactual exercise shows that absent the housing net worth channel, young firms would have resumed job creation more quickly and the U.S. would have returned to its pre-crisis unemployment rate two years earlier. This would have translated, on average, to a two percentage points lower unemployment rate between 2012 and 2016.

The contribution of my paper is threefold. First, I document the divergence in employment responses to credit supply shocks between young and old firms since the onset of the Great Financial Crisis. I identify housing net worth of young business owners and the bust in house prices as key factors for this divergence. Second, I show that since the late 1990s, credit supply shocks have been an important driver of unemployment dynamics but were not important before. Third, I propose a theoretical model that sheds light on the economic mechanism underlying these findings. The model disentangles the relative contribution of the credit supply and net worth channels, which jointly lead to divergent employment responses by firm age. My findings point to the significant role of firm age in the amplification and propagation of aggregate macroeconomic shocks.

Relation to the literature: First, my work adds to the empirical literature analyzing the effects of credit supply shocks on employment outcomes. Chodorow-Reich (2014), Duygan-Bump, Lev-

[9] I provide survey evidence based on the Kauffman Firm Survey. In the year 2007, a large proportion of firms that had had a loan application rejected reported that the main reason for the rejection was insufficient collateral (44%) or 'not being in business long enough'(35%); multiple responses were possible. For details see Table 5 in Appendix A.

kov, and Montoriol-Garriga (2015), Gilchrist et al. (2018) and Siemer (2019) use either employee- or firm-level data to document the significant influence of credit supply shocks in the decline in employment during the Great Financial Crisis. They find that young or small firms in particular reduce employment in response to credit contractions.[10] These papers study the effects of credit supply shocks from a microeconomic perspective. In taking a complementary, macroeconometric view, my study seeks to estimate the potential time-varying effects of credit supply shocks on employment by firm age.

The second contribution of my paper consists in its new empirical insights into 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. My inclusion of time-variation and firm heterogeneity adds to this existing work.[11]

Third, I contribute to the literature on the role of housing for newly and recently established businesses. Davis and Haltiwanger (2019) show that young firms' activity depends on local credit supply and house price changes in the surrounding geographical area. While their analysis focuses on the relative distribution of employment between young and mature firms, my work complements theirs in investigating time-varying divergent responses by firm age.[12] My paper further relates to Adelino et al. (2015), Schmalz, Sraer, and Thesmar (2017), Kaas et al. (2016), and Bahaj et al. (2020) who find that the value of real estate collateral is an important driver for entrepreneurship and job creation. Complementing Schott (2015), who also connects the decline in house prices to persistently high unemployment rates and low job creation among new businesses, I provide detailed empirical TVP-VAR evidence for my argumentation and focus on financial frictions as opposed to labor market frictions.

A fourth contribution is to the theoretical literature on financial constraints of heterogeneous firms. Bernanke and Gertler (1989), Cooley and Quadrini (2001) and Khan and Thomas (2013) demonstrate that financial frictions can explain why firms' borrowing structure differs by their size or age.

I also add to the literature on the sluggish recovery of the U.S. labor market after the Great Financial Crisis. Mitman and Rabinovich (2019) show that the countercyclical extension of unemployment benefits contributed to the persistent high unemployment rates after the crisis. Sedláček (2020) shows in a firm dynamics model with search frictions that the crisis led to a lots generation of firms due to a decline in firm entry causing long-lasting labor market effects.

The discussion as to whether the *age or size* of a firm is the most relevant dimension of heterogeneity in relation to financial constraints is ongoing. Focusing on firm size, Covas and Den Haan (2011) and Begenau and Salomao (2018) study debt versus equity issuance over the business cycle. Relatedly, Crouzet and Mehrotra (2020) examine the cyclical character of small and large

[10] Other work pointing to the role of firm age in explaining these employment dynamics is Davis, Haltiwanger, and Schuh (1996), Haltiwanger, Jarmin, and Miranda (2013), and Dinlersoz et al. (2018)

[11] Gambetti and Musso (2017) study the effects of credit supply shocks in a TVP-VAR model with stochastic volatility, but they do not consider labor market outcomes.

[12] 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), and Justiniano, Primiceri, and Tambalotti (2019).

firms. Another strand of work in this area (see Davis et al., 1996, Haltiwanger et al., 2013, and Dinlersoz et al., 2018) emphasizes the importance of firm age in explaining business cycle dynamics. Recent studies argue that firms subject to 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, showing that young, non-dividend-paying companies serve as a good proxy for financially constrained businesses. In this context, I focus my analysis on employment responses to crisis by firm age instead of size for three reasons: First, age is a clear, rank-invariant measure, because it does not vary due to changes in employment levels, as does size.[13] Second, young businesses 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 companies have a short business history that leads to information asymmetries between borrowers and lenders, making external finance more costly for them.

Structure of the paper: Section 2 presents descriptive evidence that motivates my focus on firm's employment responses by their age. Section 3 introduces the structural empirical approach and Section 4 presents the empirical findings. I discuss the role of housing net worth in Section 5. Section 6 sets out the theoretical model, Section 7 details its calibration, and Section 8 presents the simulation results. The concluding section 9 concludes.

2 Stylized Facts

This section presents stylized facts on the correlation between the U.S. credit and labor markets and sets out my rationale for my focus on heterogeneity of firms' crisis responses by firm age.

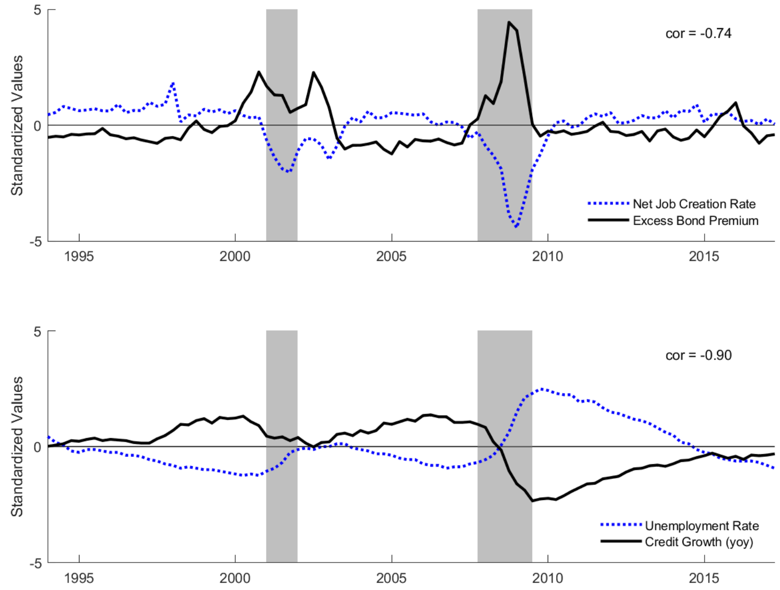
The Credit and Labor Markets: Figure 1 shows a strong negative correlation between the U.S. labor market and financial variables for the timespan 1993Q3 to 2016Q4. For improved visualization, I show standardized values (i.e. the data is demeaned and divided by its standard deviation). The upper panel 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 corporate credit spread which is not due to firms' expected default risk. As such, we can interpret the EBP as a measure of lenders' attitude to risk and thus of credit supply conditions. There are further details of this in Section 3.2. The lower panel of Figure 1 documents the strong negative relationship between credit growth and the unemployment rate in the U.S., which amounts to -0.9.[14]

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, on the basis of the Quarterly Workforce Indicator (QWI). During the two recessions in the sample, the net job creation

[13] See Cloyne et al. (2019) for a similar argument.

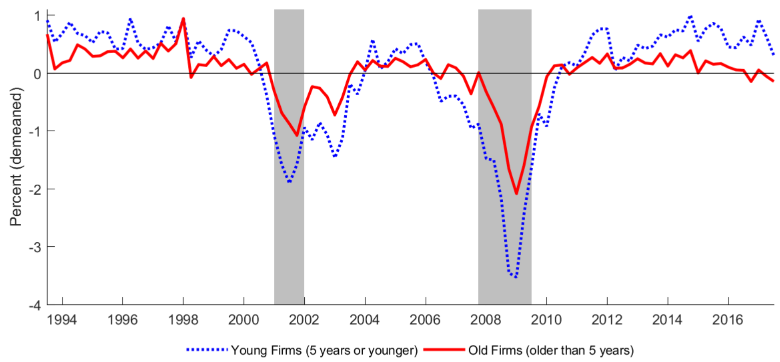
[14] I use data on net job creation from the Quarterly Workforce Indicator (QWI), which limits the sample period to the timespan illustrated. For increased comparability, I choose the same timespan for credit growth and unemployment. Note, however, that the negative correlation between credit growth 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 (NJCR) is defined as (job creation - job destruction)/employment. The Excess Bond Premium (EBP) is a measure of credit supply (see main text for details). Gray-shaded areas denote NBER recession periods. Lower panel: Credit growth refers to total credit supplied to the non-financial private sector. All data series are demeaned and divided by their standard deviation. The sample period is 1993Q3 to 2016Q4. Appendix F provides details on data sources.

Figure 2: Net Job Creation Rates by Firm Age



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

rate dropped markedly. Unsurprisingly, the fall in net job creation rates was strongest during the Great Financial Crisis. The net job creation rate of newer businesses (i.e. those established up to five years ago) dropped to a considerably greater extent as compared to older firms.

Quantitative Importance: It is well-known that young firms and especially start-ups, are an important engine of job growth in the U.S . As Fort, Haltiwanger, Jarmin, and Miranda (2013) have emphasized, younger businesses account disproportionately for the decline in employment growth between 2006 and 2009. Table 1 shows that firms aged up to five years supply 13.5%

of overall employment, but were responsible for around one-quarter of the aggregate fall in net job creation. If we extend the definition of young firms up to age 10 (as do Haltiwanger et al., 2013 and Foster, Haltiwanger, and Syverson, 2016), this group of companies accounts for 23.3% of total employment but 35.7% of the fall in net job creation. Considering the contribution of young firms to the drop in net job creation between 2006 and 2011, young firms' account for two thirds of the decline. This finding indicates that this disproportionate contribution of young firms to the decline in employment in this period persists, and points to the quantitative significance of young firms as a factor in aggregate employment dynamics.

Table 1: Contribution of Young Firms

	0-5 years	0-10 years
Share in Overall Employment	13.5%	23.3%
Contribution to drop in NJC 06-09	24.9%	35.7%
Contribution to drop in NJC 06-11	66.0%	74.7%

Notes: NJC denotes absolute net job creation; the drop is calculated between the years 2006 and 2009 (2011 respectively); shares in overall employment 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). I chose this empirical model on the basis of its flexibility. Unlike a threshold VAR or a smooth transition VAR, it does not require the specification of a switching variable or the imposition of a certain threshold. This is of particular benefit in light of diverging views in the existing literature on whether *young or old firms* respond more markedly to aggregate shocks. Fort et al. (2013) find that young and small firms showed the strongest employment response during the Great Financial Crisis. This stands in contrast to the finding of Moscarini and Postel-Vinay (2012) that net job destruction is proportionally higher in larger as opposed to smaller firms if unemployment is above trend . According to Chari, Christiano, and Kehoe (2013) and Fort et al. (2013), the disagreement stems from differences in sample periods and underlying cyclical indicators. The divergence here underlines the advantage of my TVP-VAR approach, which is not dependent on any imposed business cycle indicator. A further advantage is that it enables us to look at the effects at a specific point in time, as it is permissible to change the coefficients for every quarter. In this way, the coefficients capture possible changes in the lag structure of the model due to nonlinearities or state dependency. Further, it is crucial to allow for stochastic volatility if our aim is to capture changing sizes of shock and variation in the contemporaneous relationship between variables over time.
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 θ_t and X_t contains the lags of all endogenous variables y_t. The error term ϵ_t is normally distributed with mean zero and a covariance matrix Ω_t that varies over time.[15] Ω_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 non-zero 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, θ_t and α_t follow random walks and the stochastic volatilities h_t are geometric random walks. Q denotes the covariance of θ_t, S is the covariance of α_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 a Markov Chain Monte Carlo (MCMC) algorithm with Gibbs Sampling.[16] 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 θ_t, contemporaneous relations α_t, variances H_t and the hyperparameters of the variance-covariance matrices (Q, S and σ_i^2).[17]

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), on the basis of data from the Longitudinal Employer-Household Dynamics (LEHD) data set. I use the effective federal funds rate

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

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

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

(FFR) to control for monetary policy stance. For the post-2008 period, I use the shadow federal funds rate of Wu and Xia (2016).[18] 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 non-financial U.S. 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). The EBP is thus 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. Further, Figure 19 in Appendix A shows that the EBP and bank tightening standards for small businesses 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; the estimation period ranges from 1994Q1 to 2017Q4, with the first five years used as a training sample to obtain priors. The sample therefore begins in 1999Q1. In the second specification, the sample ranges from 1973Q1 to 2019Q2. I use the first seven years as a training sample, therefore commencing the estimation in 1980Q3.[19]

3.3 The Empirical Model

The baseline empirical specification is

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

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

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

where NJCR_t^j refers to the net job creation rate and EMP_t^j denotes the total employment stock by firm age category.[20] I set the lag length p to 2 and demean all variables prior to estimation.[21]

[18] On the basis of the observed Treasury yield curve, Wu and Xia (2016) construct a federal funds rate that is not constrained at zero.

[19] I selected the sample periods on the basis of 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 further periods.

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

[21] 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, θ_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. 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 $A_t, t = 1,\ldots,T$ is lower triangular. While I maintain the same recursive identification strategy for all $t = 1,\ldots,T$, 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 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 (see, for example, 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 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).

In addition, I apply an alternative identification scheme and identify credit supply shocks based on sign restrictions to further check the sensitivity of my results on the imposed timing assumptions.[22] This approach builds on Faust (1998), Canova and Nicolo (2002), and Uhlig (2005), among others. I derive the sign restrictions on output, the interest rate, and the excess bond premium based on my theoretical model laid out in detail in section 6 and leave the response of my main variable of interest, the labor market variable, unrestricted. Based on these theoretical foundations, I impose that a credit supply shock leads to an increase in the Excess Bond Premium, a fall in the interest rate and a contraction of output. As I am solely interested in the credit supply shock, I follow Uhlig (2005) and do not identify the remaining $n-1$ fundamental innovations. I discuss the results of the alternative identification scheme in Section 4.3.

4 Empirical Results

This section presents the findings of the structural empirical analysis. First, I present the impulse response analysis of a credit supply shock on younger and older firms' labor market variables.

[22] See also Gambetti and Musso (2017) for an application of sign restrictions in the context of a TVP-VAR with credit supply shocks.

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 significance of credit supply shocks since the early 1980s.

4.1 Results by Firm Age

One advantage of a TVP-VAR is that it allows us to compute generalized impulse response functions (GIRFs) for every point in time. Figure 3 depicts the GIRFs in response to a credit supply shock across 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 enables us to inspect the effects over time, while 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 each figure illustrate median responses regarding businesses' net job creation rates (NJCR), with young firms on the left (in green/blue) and older firms on the right (in yellow/orange).[23] 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. Further, the contraction of young firms' NJCR lasted until the year 2012, which was a longer period compared to that of 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 NJCR, whereas the effect on younger ones is highly persistent.

The lower two panels in Figures 3 and 4 depict employment response by firm age. Regarding employment, differences over time and the impulse response horizon by firm age are even more marked in comparison to net job creation rate. During the 2001 recession, young and older firms showed similar employment responses to a credit supply contraction. However, this similarity vanishes over time; commencing in the mid-2000s, young firms show a considerably stronger employment response when credit supply tightens.[24] Young firms' responses were not only more pronounced, but also much more persistent compared to those of older firms (see the lower panel of Figure 4 for a rotated view). Older firms' responses relaxed soon after the Great Financial Crisis, that is, around 2009, whereas the post-crisis impact on employment at younger firms was strongest around the year 2012.

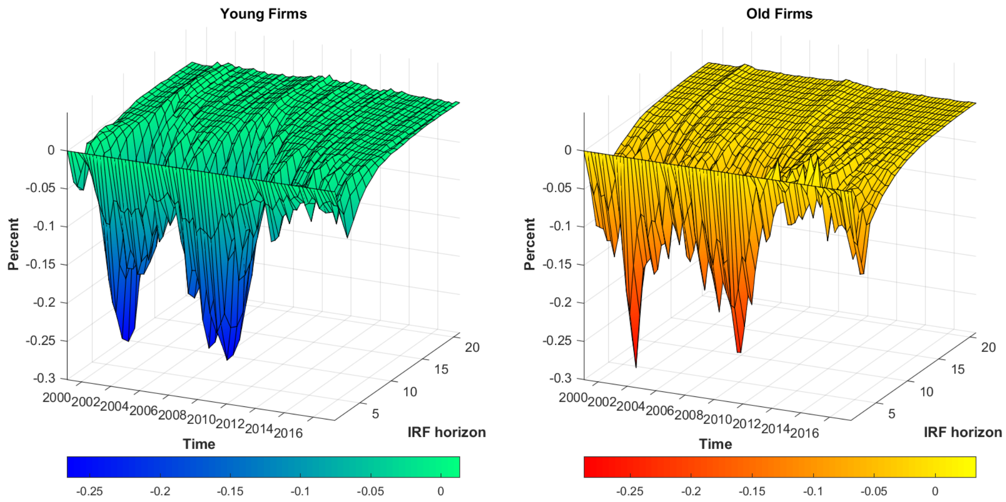
Next, I analyze the time-variation of the labor market effects in response to a credit supply shock. For this purpose, I consider the reaction six quarters after the shock over the entire estimation period (from 1999Q1 to 2017Q4). I choose the sixth quarter after the shock because it takes several quarters for the shock to materialize to its full extent and for a clear picture to emerge. However, results are similar for slightly different periods.[25] Figure 5 illustrates the impact on the net job creation rate in young (blue line) and older firms (red line) over time in response to a credit supply shock. The findings can be summarized as follows: The NJCR of young firms responds more markedly in recessions (as defined by the NBER and illustrated as gray-shaded areas), whereas

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

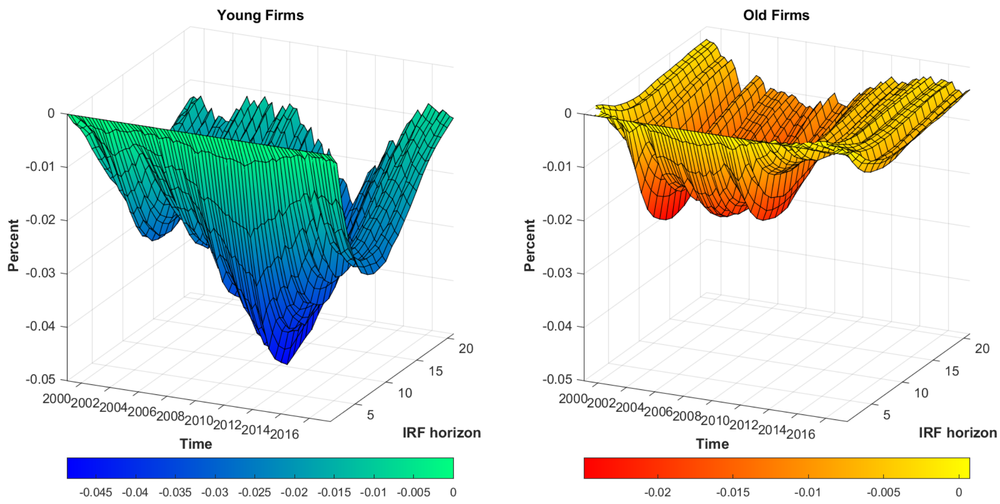
[24] Figure 23 in Appendix C compares the IRFs in recessionary periods and the Great Financial Crisis only.

[25] 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 as endogenous labor market variable.

Figure 3: Median Generalized Impulse Response Functions (GIRFs) by Firm Age over Time and IRF Horizon.



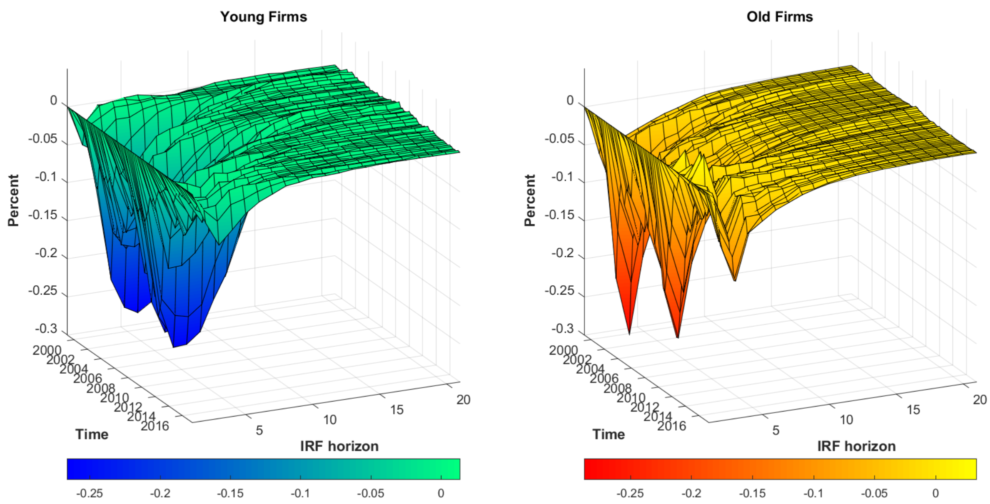
(a) Net Job Creation Rate Response over Time and IRF Horizon



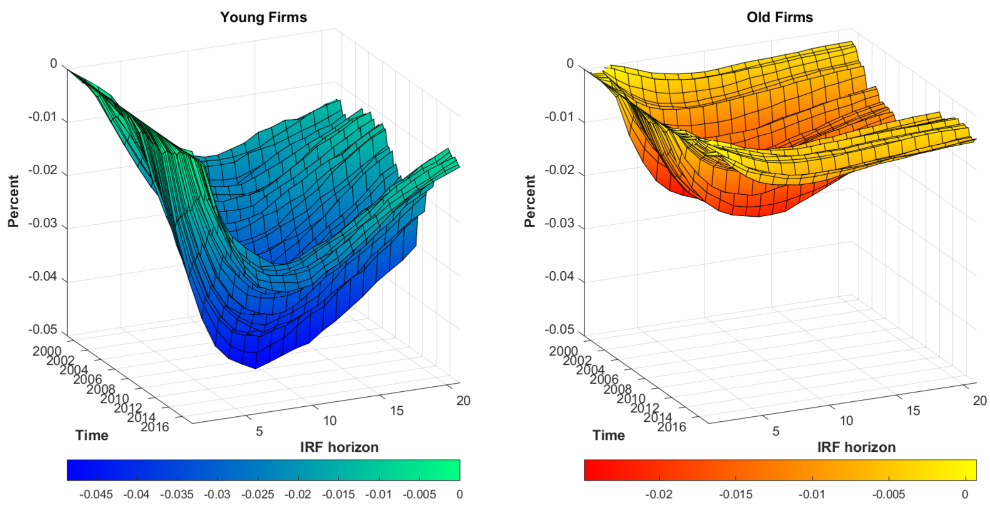
(b) Employment Response over Time and IRF Horizon

Notes: Median responses to a 1 std. EBP shock (normalized to one); young firms are depicted in blue, older ones 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).



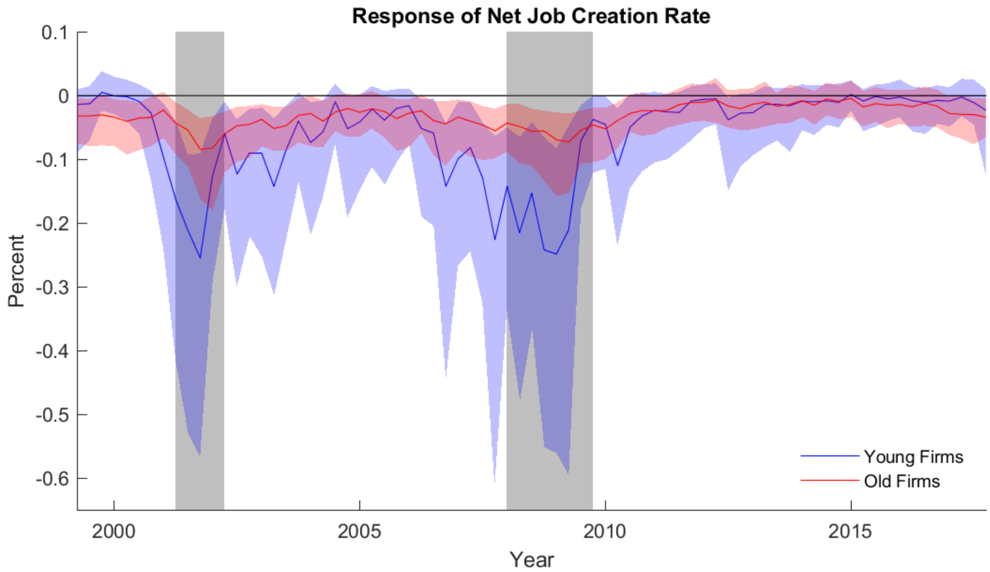
(a) Net Job Creation Rate Response over Time and IRF Horizon



(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, older ones in red. The response over time is depicted on the x-axis, the IRF horizon is on the y-axis.

Figure 5: Impact on 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 16th and 84th percentiles of the posterior distribution for young (older) firms. Gray-shaded areas denote NBER recession periods.

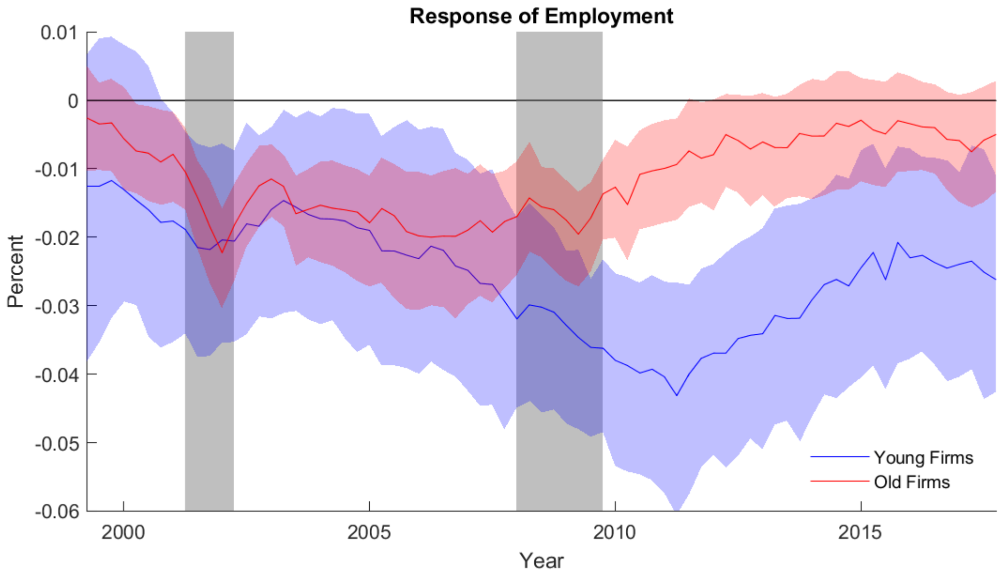
in expansions the effects are similar and small. The response of younger firms is associated with higher estimation uncertainty. Regarding the timing of effects, young firms' median NJCR responds earlier than does that of older ones. From around 2006, the median responses of young and old firms start to diverge and, young firms' response becomes much stronger. Similarly, Figure 6 illustrates the impact on employment of a credit supply shock by firm age over time. Again, the response of young firms comes with higher estimation uncertainty. Until the year 2006, the median employment responses of younger and older firms are almost identical. This picture changes in a statistically significant way with the 2007-2008 Great Financial Crisis. Young firms begin to respond significantly more markedly to a decrease in credit supply, whereas old firms' responses remain relatively constant. Although the employment response of young firms returns to an upward-trend commencing in 2011, there is still a (weakly significant) difference in level between their median responses.

4.2 Age vs Size

I focus on the role of age, and not size, of firms for three reasons. First, age is a clear measure (compared to size) and a good proxy for businesses under financial constraints. Second, younger 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 asymmetry of information makes borrowing more costly for young firms. In this subsection, I discuss these reasons in more detail and present empirical TVP-VAR results relating to the distinction by size.

Measurement: Ideally, I would make a clear distinction between financially constrained and

Figure 6: Impact on 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 16th and 84th percentiles of the posterior distribution for young (older) firms. Gray-shaded areas denote NBER recession periods.

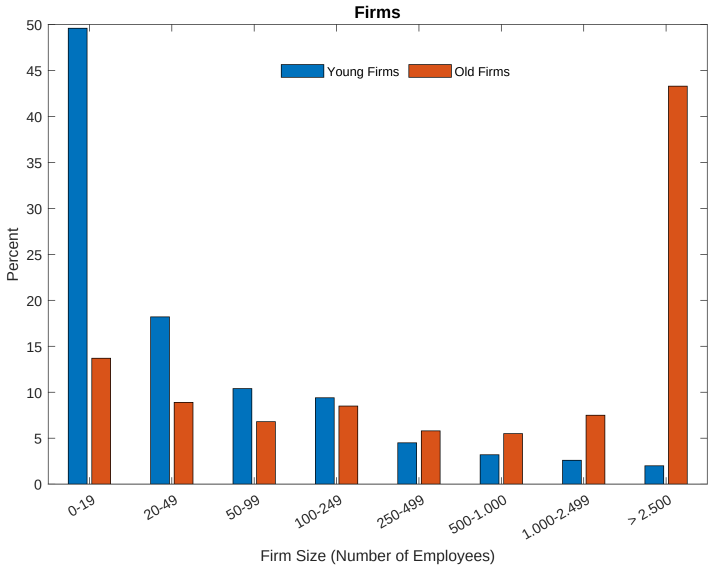
unconstrained firms. However, as there is no reliable measure of financial constraints in the data, I am compelled to use a proxy. As discussed in Cloyne et al. (2019), one important advantage of firm age as a proxy is rank invariance. This is of particular relevance here given my focus on effects over 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, for example, as they reduce their number of employees.[26]

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 older firms for the years 2000 to 2014. Around 50 percent of young firms have fewer than 20 employees, and only a few young firms are relatively large (around ten percent have more than 500 employees). Older firms tend to be large, but there is also a considerable proportion (around 23 %) that are small. Firms that are both older and small are less likely to show high growth rates and are less dependent on debt financing. My principal interest here is in younger, smaller firms. Unfortunately, the QWI does not provide detail on this distinction. I therefore focus on young firms (i.e. firms that were established up to five years previously) in general. Table 2 shows the share of absolute job creation in an age/size matrix in percent of overall job creation. The share of small, young firms in overall job creation is 2.5 times higher than their share in overall employment. Similarly, the share of young, larger firms in overall job creation is twice that of their share in overall employment. This is consistent with the recent literature which documents that young firms have the highest growth potential (see Haltiwanger et al., 2016, Sedláček and Sterk, 2017, and Pugsley and

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

Şahin, 2018). However, the number of young, larger firms is small, making them quantitatively unimportant.

Figure 7: Size Distribution by Firm Age



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

Table 2: Share in overall Job Creation by Age and Size

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

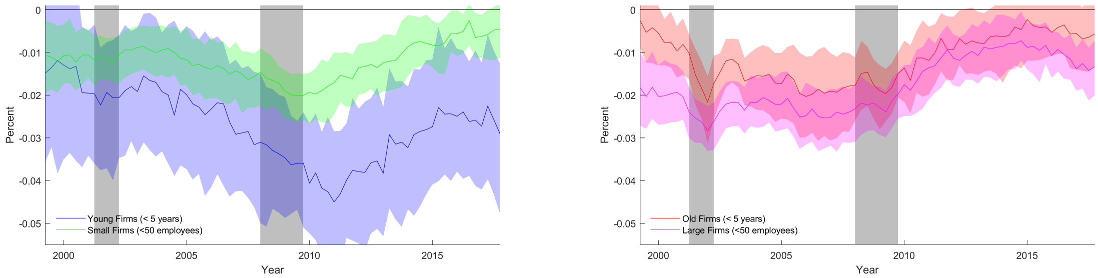
Notes: Young firms are defined as being up to five years old and small firms are defined as having fewer than 50 employees. Data source: BDS, averages over the timespan 2000-2014.

Asymmetry of Information: For lenders, a firms' short credit history is a noisy signal. Newly established firms show a high idiosyncratic risk of defaulting. The asymmetry of information between borrowers and lenders, specifically the inability of lenders to observe the firms' productivity at such an early stage in its life, makes younger firms particularly susceptible to encountering financial constraints. Micro-level evidence on the basis of the Kauffman Firm Survey confirms this: In 2007, 35% of firms which had had a loan application rejected reported that the reason given for the rejection was that their firm was too new.[27]

TVP-VAR Evidence: To understand differences in responses to a credit supply shock by firm age versus size, I estimate the empirical model with small and large firms and compare the corre-

[27] This was the third most important reason for credit refusal after personal credit history (45%) and insufficient collateral (44%) (see Table 5 in Appendix C for details). The Kauffman Firm Survey tracks a sample of firms founded in 2004 over time.

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



(a) Young vs Small

(b) Old vs Large

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

sponding employment responses. I define a small firms as having up to 50 employees and a large firm as employing 50 people or more. Figure 8 compares the results of my baseline estimation using firm age with the results by firm size. The right-hand panel illustrates the effects over time 6 quarters subsequent to the shock for young (blue-shaded area) and small (green-shaded area) firms. The left-hand panel of Figure 8 compares the corresponding results for older (red-shaded area) to larger firms (pink-shaded area). During the GFC, the employment response of younger firms is significantly more pronounced than that of small firms overall. By contrast, older and larger firms show identical employment responses. This finding is independent of different definitions of small and large.[28] We can therefore note that credit tightening shocks have a more intense impact on young firms than on small ones. The effect observed here was particularly strong during and after the GFC. This confirms my choice of firm age as the relevant proxy for a firm subject to financial constraints. I interpret this result as evidence for greater needs for external financing among younger firms and the existence of a higher degree of informational asymmetry between financial intermediaries and young firms than would be the case if the firm were longer established. Financial frictions arising due to asymmetric information affect young firms more severely than small firms (see Gertler 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, it may be that firm entry and exit are the drivers of younger and older firms' divergent responses to a credit supply shock.[29] To check for this, I perform the following two robustness checks: First, I add to the estimation the number of jobs destroyed by business exits as a fifth endogenous variable.[30] Figure 24a in Appendix A illustrates median employment responses six quarters after the shock across the estimation sample. The estimation

[28] I estimate the TVP-VAR for different thresholds of small and large firms (up to 20 and up to 250 employees respectively), with unaltered findings.

[29] Pugsley and Şahin (2018) document a decline in the establishment of new businesses and identify a link to the jobless recovery in the U.S.

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

uncertainty for young firms increases, but the key finding here, the significantly more marked employment response of young firms, still holds. Second, to test whether it is very new businesses that are driving these findings, I re-estimate the baseline specification (see Equation 3.5) without the youngest age group, businesses founded fewer than two years previously. Figure 24b in the Appendix depicts the resulting median employment responses over time. The result remains robust to the exclusion of very young firms.

Measure of Credit Supply: The EBP is based on a credit spread of corporate bonds issued by a representative sample of non-financial U.S. firms. Whereas corporate bonds are an important financing instrument, they may not be the financing option most frequently accessed by newly launched and young firms. Figure 19 in Appendix A depicts the EBP and banks' tightening standards for loans to small firms, two highly correlated measures of credit supply, with the EBP serving 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 banks' tightening standards for commercial and industrial loans to small businesses, whereas for older firms I use banks' tightening standards for larger businesses. Figure 26a in Appendix C illustrates the results. The use of banks' tightening standards leads to an even more pronounced difference between young and older firms, with a significantly more marked response among younger firms since the early 2000s.

Definition of Young Firms: If I consider a firm established up to ten years previously to be a young firm (see panel b of Figure 26b), the divergence in employment responses is less pronounced. Employment levels at young firms up to the age of ten years responds more markedly in recessionary phases, but the difference by age is much less notable than that seen with a definition of young as encompassing firms up to five years post-establishment. Immediately after the Great Financial Crisis, median employment responses overlap, indicating that the difference by age is mostly relevant up to a threshold of around five years. This finding is consistent with the up-or-out dynamics observed among young businesses (see Haltiwanger et al., 2013 or Haltiwanger et al., 2016). Firms that survive their first five years 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 those aged between 6 and 10 years.[31] 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; business owners are additionally less dependent on their private homes as sources of collateral. Second, asymmetry of information between borrowers and lenders is smaller.

Identification Strategy I: Ordering of Variables To analyze the sensitivity of the results to the identification strategy I have chosen, I change the ordering of the variables in the baseline estimation. First, I interchange the ordering of the last two variables, placing the excess bond premium third and the federal funds rate fourth.[32] This addresses the imposed restriction that a financial shock does not affect the federal funds rate contemporaneously. The findings on em-

[31] Source: my own calculations on the basis of average establishment exit rates by firm age taken from the BDS between 1999 and 2014. The exit rate for young firms is weighted by their corresponding shares in the overall number of firms.

[32] 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.

ployment response 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 relating to 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 as compared to older businesses under various assumptions as regards timing of the endogenous variables appear in Figure 27 in the Appendix. Again, they remain robust, albeit the difference between young and old firms is less pronounced in the specification with the EBP ordered first.

Identification Strategy II: Sign Restrictions As an alternative identification scheme for credit supply shocks, I apply sign restrictions and impose, based on theoretical insights, a contractionary effect on output, a decline in the interest rate and an increase in the EBP for at least two periods (see Section 3.4 for details).[33] Figures 28 and 29 depict the results. Under sign restrictions, the response of young firms is slightly stronger prior to the GFC, however, the significant divergence by firm age during and after the crisis remains. Further the employment responses illustrated in Figure 29 confirm the choice of using the recursive identification strategy as baseline identification approach: The impact response of employment is concentrated around zero even though it is kept unrestricted.

4.4 Taking a Historical View

What has been the significance of credit supply shocks for U.S. unemployment and output dynamics in the past 40 years? To answer this question, I estimate a different empirical model. Due to data limitations, I cannot perform the analysis for young and older businesses separately.[34] For this reason, I estimate the following empirical model

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

where unemp_t is the unemployment rate and ΔGDP_t denotes GDP growth.[35] The estimation period stretches from 1980Q3 to 2019Q2.[36] As a robustness check, I estimate the same model with employment instead of unemployment. The corresponding results are illustrated in Appendix C (Figure 32).

Response over Time: The left-hand panel of Figure 9 depicts the GIRFs of a credit supply contraction on unemployment in the GFC (red lines) and all other NBER recession periods (dashed, blue lines). The reaction during the Great Financial Crisis was markedly stronger compared to previous NBER recessions. If we consider the cross-section of all unemployment responses since 1980, six quarters after the shock for each period (right-hand panel of Figure 9), we observe that

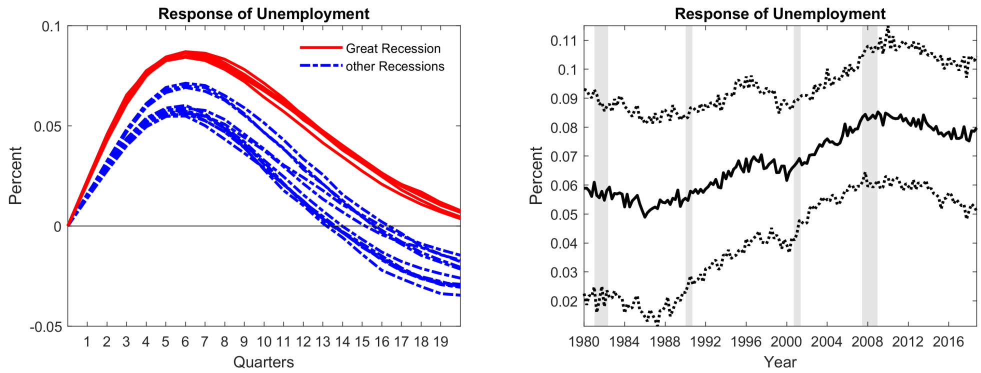
[33] Under this identification approach, a contemporaneous response of employment, the federal funds rate, and output is permitted.

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

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

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

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



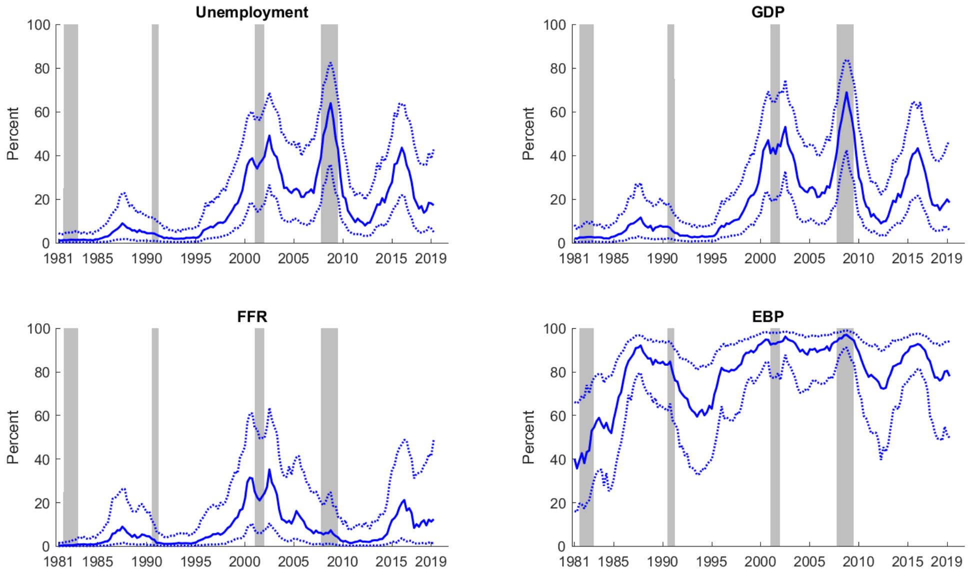
Notes: Left-hand panel: GIRFs of unemployment in response to a 1 std. EBP shock (normalized to one) in NBER recession periods excepting the Great Financial Crisis (blue) and the Great Financial Crisis separately(red). Right-hand panel: Cross-section of unemployment responses over time. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one); dashed lines denote 16th and 84th percentiles of the posterior distribution. Gray-shaded areas denote NBER recession periods.

the unemployment response intensified over time, peaking after the Great Financial Crisis. The difference over time therefore stems not from stronger reactions in recessions compared to expansions, but from an overall trend of a stronger and more persistent unemployment reaction over time. In the specification using employment (see Figure 32 in Appendix C), a similar picture (with opposite sign) emerges.

Forecast Error Variance Decomposition: Figure 10 depicts the forecast error variance of all four endogenous variables six quarters after the shock (solid line) with the sixteenth and eighty-fourth percentiles of the posterior distribution (dashed lines). The proportion of unemployment and GDP growth volatility that is due to a credit supply shock varies strongly over time. Prior to the late 1990s, a credit supply shock made almost no contribution to the volatility of unemployment or GDP. Since then, changes in credit supply conditions have begun to exert a more significant role in the volatility of macroeconomic variables. During the recession of the early 2000s, financial conditions accounted for around 40 percent of unemployment volatility; this rose to around 60 percent during the GFC.

Historical Decomposition: Figure 11 displays the historical contribution of credit supply shocks 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 (shocks to the unemployment rate) were of no significance in explaining unemployment dynamics. However, from 2000 onward, credit supply shocks have come to account for a large proportion of developments in unemployment. In my empirical model, exogenous increases in EBP are almost entirely responsible for the rise in unemployment during the recession of 2001. Around 40 percent of the rise in unemployment during the Great Financial Crisis is attributable to credit supply shocks. The remaining part originated from the labor market itself. Regarding GDP, credit supply shocks began to exert a significant influence in the late 1990s, but explain an even larger proportion of variations during the GFC.

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.

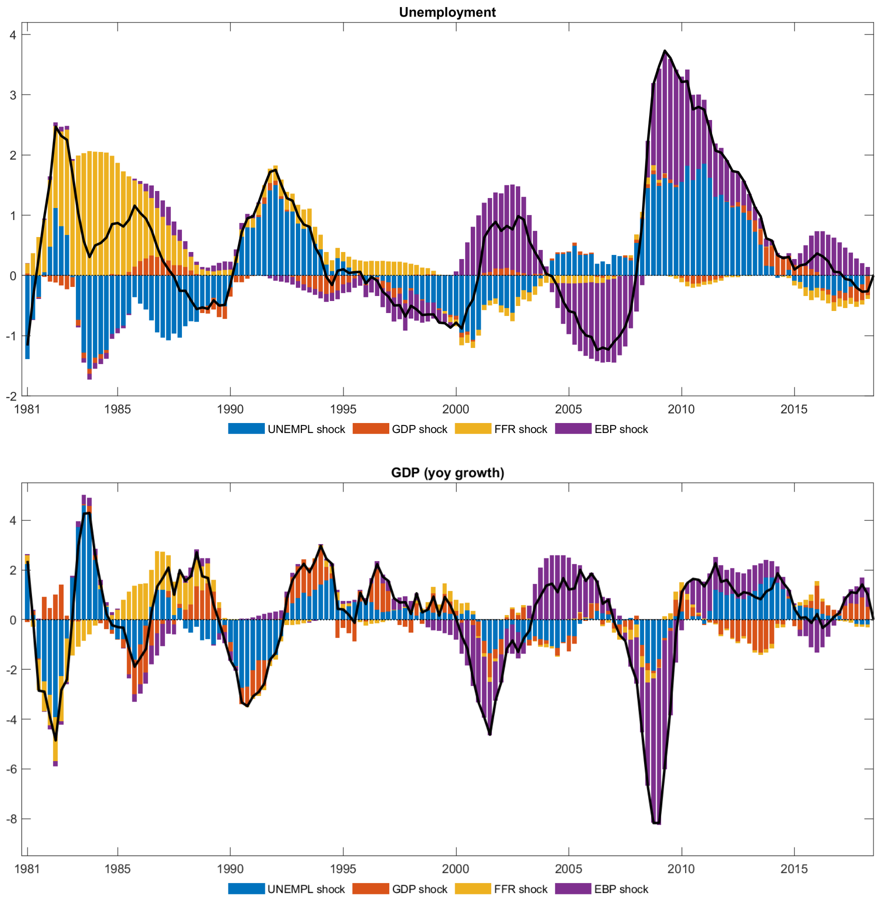
The Role of Financial Deregulation: What caused the shift in the contribution of economic shocks to unemployment and GDP growth dynamics? The declining importance of monetary policy shocks (i.e. shocks to the FFR) in the early 1980s stemmed from the Great Moderation and the change in monetary policy during Volcker's chairmanship of the Fed.[37] Financial conditions have been an important driving force of unemployment and output dynamics since the late 1990s. At the same time, U.S. financial markets have undergone marked deregulation.[38] 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 et al., 2012). Between the years 2000 and 2006, the issuance of private mortgage-backed securities in the U.S. increased tenfold. Favara and Imbs (2015) establish a causal link between financial deregulation in relation to the supply of mortgage credit in the 1990s and the U.S. house price boom. Optimism about future housing demand boosted house prices further (see Kaplan et al., 2020).

How is financial deregulation and securitization related to firms' employment responses to crises? The mechanism works via the role of housing net worth as collateral and startup capital for young firms. The surge in house prices led to an appreciation of household net worth. This, in combination with a relaxation of credit standards, meant that owners of young businesses could borrow high amounts, allowing them to expand their activities. However, as house prices collapsed, they found themselves highly leveraged due to the depreciation of their hous-

[37] An exemplary discussion is in Clarida, Galí, and Gertler (2000).

[38] It is a common belief that the Financial Services Modernization Act of 1999, among other developments, promoted risk-taking behavior among financial firms which led to the rise of new financial products and hedge funds and of the securitization of loan obligations.

Figure 11: Historical Decomposition of Unemployment and GDP Growth.



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

ing net worth. The section that follows provides a detailed discussion of the role of house prices in the firm age-related difference in employment dynamics.

5 The Role of House Prices

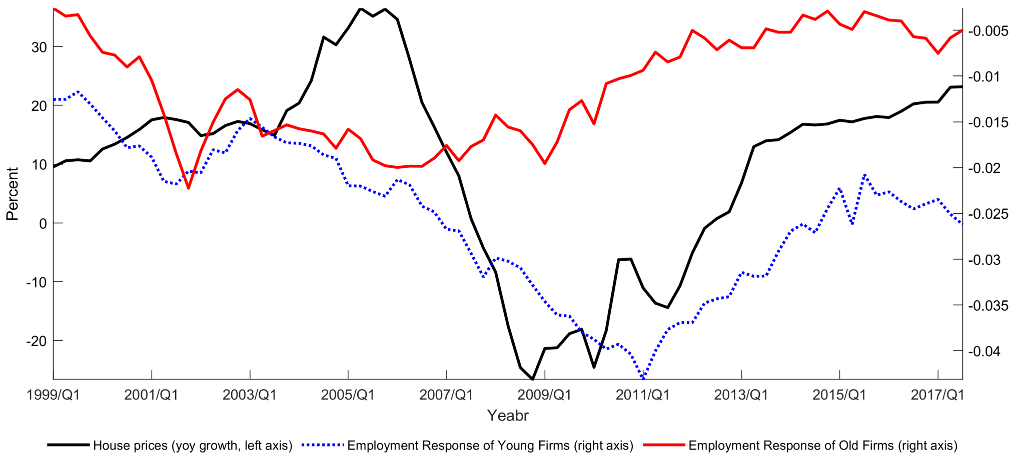
The empirical analysis in Section 4 highlights the divergence in employment by firm age at the onset of the GFC and in response to a credit supply shock. This section investigates the role of house prices in these developments.

Descriptive Evidence: Figure 12 displays year-on-year growth rates for U.S. house prices (left axis) and median employment responses to credit supply shocks for younger and older firms (right axis).[39]. It reveals that the timing of the divergence in employment responses coincides with the collapse of house prices in the U.S. In the second quarter of 2006, growth in 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 began to adapt much more significantly along the employment margin, whereas the response of older businesses remained stable. Only in 2011, when house prices

[39] The displayed median employment responses correspond to those depicted in Figure 6

started to pick up again, did 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 in the All-Transactions House Price Index for the United States (Data source: U.S. Federal Housing Finance Agency). The dashed blue (dotted red) line represent median employment responses after 6 quarters to a 1 std. EBP shock (normalized to one).

House Prices as an Endogenous Variable: As a next step, I investigate employment responses by firm age in the TVP-VAR setting while controlling for house price growth as a fifth endogenous variable in the estimation.[40] The corresponding employment responses, illustrated in Figure 30 of Appendix C, show that the difference by age is considerably less pronounced compared to the baseline specification. Controlling for the endogenous interaction between employment and house prices in response to a credit crunch therefore explains a significant proportion of the divergence in responses by firm age. However, the employment response of young firms is still significantly more pronounced than that of old firms.

Collateral for New Businesses: Why is the value of business owners' personal homes relevant to job creation among those businesses?[41] A considerable proportion of newly established and young businesses use the homes of their owners as startup capital and collateral for business loans. Evidence based on the *Survey of Business Owners* illustrated in Table 3 shows that the proportion of business owners who have taken out a personal home equity loan has increased from 6.2 percent (in the 1990s) to more than 9 percent in 2006. For businesses established in the year 2006, the importance of home equity as a source of startup capital has increased by more than 36% compared to the situation in the 1990s. In the year 2007 (as house prices collapsed), the proportion of business owners using personal home equity loans decreased considerably.

A recent paper by Bahaj et al. (2020) emphasizes the role of housing collateral for newly estab-

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

[41] Several papers attribute (a large proportion of) the drop in employment during and after the Great Financial Crisis to the deterioration in households' balance sheets caused by a housing channel (see, for example, 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 Startup 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: Proportion of business owners who used the corresponding source(s) of startup or acquisition capital by year the business was established. The first column refers to the change observed between businesses established 1990 - 1999 and those established in 2006. Data source: 2007 Survey of Business Owners (SBO) Public Use Microdata Sample (PUMS). Totals may come to more than 100 as multiple responses were permissible.

lished and young businesses. The authors use U.K. firm-level data to show that 70% of loans to small and medium-sized enterprises use real estate as collateral. The U.S. 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 loans granted were secured by personal guarantees made by the owner, and 30 percent of businesses provided both.[42]

Thus, if housing serves as an important source of collateral for newly established and young businesses, a decline in the value of housing makes borrowing more costly. Given that young businesses are more dependent on external finance than are older ones (see Begenau and Salomao, 2018 for descriptive evidence), a contraction in credit supply hits younger businesses harder, with the contractionary response further amplified if the owners' housing net worth loses value.[43]

Cross-Regional Evidence: In the next step, I perform cross-regional estimations at metropolitan statistical area (MSA) level to the end of analyzing the role of house prices in the employment responses shown by young firms to credit supply shocks. My empirical long-difference approach builds on Giroud and Mueller (2017). I regress the change in job creation among young firms on an interaction term of the change in the amount of small business loans granted, and the change in MSA-level house prices. Appendix D describes the approach in detail; the results appear in Table 6 in the Appendix. The cross-regional regression results indicate that areas with a more substantial decline in house prices exhibit a larger elasticity in job creation among young businesses with respect to small business loans.[44] This points toward an important role for the housing net worth (i.e. collateral) channel in young businesses' access to credit and their hiring decisions. Although these results do not permit us to draw conclusions on causality, they provide

[42] A personal guarantee means that business owners pledge their own (personal) assets to repay debt should it be required.

[43] This finding is also in line with Chaney, Sraer, and Thesmar (2012), who point to 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.

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

a supporting interpretation for my key empirical findings. The financial deregulation that took place in the late 1990s led to an increase in home ownership rates and a surge in house prices. Young businesses were able to take on high levels of debt using their housing net worth as collateral. This occasioned a closer connection between credit conditions, house prices, and labor market dynamics (see also Mian and Sufi, 2014) and explains the structural break that appears in my empirical findings (see Figure 11). However, the collapse in house prices led to the depreciation of business owners' housing net worth (and as such their collateral). This, alongside the more restrictive credit conditions then imposed by lenders, caused younger businesses to respond significantly more markedly to financial market shocks compared to older businesses. The theoretical model outlined in Section 6 permits the combination of a credit supply shock and a decline in businesses' 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 a business sector consisting of risky firms in various cohorts of firm age (entrants, young cohorts of age one to J and older firms) and age-cohort specific producers of capital goods and output goods. Risky firms are subject to idiosyncratic productivity shocks and transform capital into effective capital. Henceforth, I refer to them as solely "firms". Households, capital goods producers and output goods producers are described in detail in Appendix E.

Firms enter the market endogenously. Upon entry, they operate in the cohort of entrants and, if they do not default or exit exogenously, they eventually move to the next age cohort. Besides the entrants, there exist $K-1$ more cohorts of younger and older firms. Let us assume that each age cohort $j \in (E, 1, \cdots, K, O)$ consists of a continuum of risk-neutral firms i. Each period, every age cohort pools their earnings, which enables aggregation for each cohort.[45] Except for the entrants (newly established businesses), every age cohort has two financing channels, debt and equity financing. Equity financing refers to the firm's decision of retaining earnings or paying out dividends to households. If dividends are negative, firm raise equity from households. I assume that newly established firms are equipped with some initial net worth from households and cannot pay out dividends yet.

All firms require loans from a financial intermediary to fund 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.[46] As in the model described in Bernanke et al. (1999), bankruptcy is endogenous and determines the end-of-period net worth of each age cohort. Further, in each period there is a probability of $1-\gamma^j$ that an exogenous proportion of each age cohort will die, where $j \in (E, 1, \cdots, K, O)$ denote the age cohorts.[47] The

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

[46] Note that $\omega^{i,j}$ is iid across firms 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 $E(\omega) = 1$.

[47] This implies that the total number of exiting firms by cohort is the sum of those exogenously dying and those going bankrupt (i.e. those with idiosyncratic productivity shocks below some cutoff).

final goods producer rents capital from entrepreneurs and hires labor. Figure 33 in Appendix E gives an overview of the model's basic framework. Financial intermediaries collect deposits from households. They keep some exogenous fraction r as reserves and use the remaining fraction of deposits to issue 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 business sector due to asymmetric information. Banks have to pay monitoring costs to observe the realization of the shock to the firms' productivity $\omega^{i,j}$. 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 to consume and how much to save in the form of riskless deposits with banks, and how many equity shares they buy from firms. 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 optimum loan contract given the range of contracts on offer from the financial intermediary (i.e. they make decisions on the amount of capital to purchase for use in the next period and the optimum 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 as to which cohort-specific final goods producer they work for. At the beginning of the next period, firms observe the realization of their idiosyncratic productivity. Final goods producers pay the rental rate for capital $R^{k,j}$ to firms and make wage payments to households. Firms 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 firms across age cohorts. In each cohort, a proportion $(1-\gamma^j)$ of entrepreneurs die exogenously.[48] Note that age cohorts differ in their survival rate γ^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 to the next age cohort.

6.1 The Financial Intermediary

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

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

where r_t is an AR(1)-shock process

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

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

with ρ^r denoting the autocorrelation of the shock process, r_{SS} the steady-state value of r_t, and ϵ_t^r an exogenous innovation. An exogenous increase in the proportion of deposits that the bank must hold reduces 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 a 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 than or equal to the riskless 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 proportion of firms of age $j \in (E, 1, \cdots, K, O)$ who become bankrupt, as

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

The proportion of firms that are above the cutoff is given by $1 - F(\bar{\omega})$. Further, the expected proportion of business 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 a cohort's earnings going to lenders 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 proportion of earnings kept by the firm.

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 a firm's risky operation $E_t\left\{R_{t+1}^{k,j}\right\} Q_t^{i,j} K_t^{i,j}$ at the cutoff $E_t\left\{\bar{\omega}_{t+1}^{i,j}\right\}$.[49] Firms' expected gross return for 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

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

The firm repays the lender the amount $E_t\left\{\bar{\omega}_{t+1}^{i,j} R_{t+1}^{k,j}\right\} Q_t^{i,j} K_t^{i,j}$. In the case that $E_t\left\{\omega_{t+1}^{i,j}\right\} > E_t\left\{\bar{\omega}_{t+1}^{i,j}\right\}$, the firm keeps the remaining profit $E_t\left\{(\omega_{t+1}^{i,j} - \bar{\omega}_{t+1}^{i,j}) R_{t+1}^{k,j}\right\} Q_t^{i,j} K_t^{i,j}$. If $E_t\left\{\omega_{t+1}^{i,j}\right\} < E_t\left\{\bar{\omega}_{t+1}^{i,j}\right\}$, the financial intermediary pays monitoring costs and seizes the remainder of the

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

profit $E_t\left\{(1-\mu)\omega^{i,j}_{t+1}R^{k,j}_{t+1}\right\}Q^{i,j}_t K^{i,j}_t$. In this case, the firm declares bankruptcy and receives nothing.

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

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

The financial intermediary has a different participation constraint for each age cohort, which states that the loan repayment expected from every cohort has to equal the riskless return on the amount of household deposits used to issue the loan B^j_t.[50] The economy-wide loan amount B_t equals the sum across 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 cohort of firms 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 Business Sector

The business sector consists of firms, output goods producers, and capital goods producers that are in different age cohorts $j \in (E, 1, \cdots, K, O)$. The model features an endogenous entry decision. Upon entry, firms are denoted as 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 pre-determined net worth and the amount of capital purchased jointly pin down the loan amount required.

The individual firm i, in cohort j, transforms the capital purchased into effective capital and rents it to output goods producers.[51] The return per unit of capital is given by the realization of idiosyncratic productivity multiplied by aggregate return on capital, $\omega^{i,j}_{t+1}R^{k,j}_{t+1}$.

Age cohort E (Start-ups):

A firm will decide to enter the market if the expected average profit for a non-defaulting firm is higher than the fixed entry costs F^e.[52] Households equip entrants with exogenous starting net worth N^{ST}. Within the entrant cohorts, firms purchase capital K^E_t at the price Q^E_t for use in $t+1$. They fund these purchases with their starting net worth and the loan received from the financial intermediary B^E_t. This results in an aggregate balance sheet constraint of the entrant cohort as

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

[51] 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.

[52] Note that the entrant's case is closest to the standard costly-state-verification 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.

follows:

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

Aggregating over the entire entrant 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).[53] The end-of-period net worth of age cohort E amounts to the profit of those firms that do not go bankrupt and those who do not exit the market exogenously.

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

At the end of the period, firms in 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 $j = 1$.

Firms in Age Cohort $j \geq 1$

Among age cohorts j, we can differentiate between three types of sub-cohorts . First, cohort 1, that is last period's entrant cohort; second, the remaining young cohorts 2 to K; and third, the old cohort O. A firm in cohort j takes her net worth as given and requires the loan amount B_t^j to finance her 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 firms in age cohort $j = 1$ onward have the option of paying out dividends and, should these dividends be negative, raising equity from households.

However, raising equity is costly (see Jermann and Quadrini, 2012). As a result, the actual cost for the firm age cohort $j \in (1, \cdots, K, O)$ equals 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 denote 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 motives for dividend smoothing exist.

In contrast to firms entering the market, firms in age cohort j maximize the stream of 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

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

(equation 6.9), and the flow-of-funds constraint, which equates this period's 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 entrant cohort.[54] Note that for the flow-of-funds constraint, we require all intra-period flows. As the return on capital and therefore firms' earnings materialize only in the next period, the last period's 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 firms that have not been paid out as dividends.

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

where nw_t^k denotes a shock to the net worth of age cohort k. The shock process is defined as

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

with ρ^{nw} denoting the autocorrelation of the process, nw_{ss} the steady state value and ϵ_t^{nw} is an exogenous innovation with $\epsilon_t^{nw} \sim N(0, \sigma^{NW})$. The older firms' beginning-of-period net worth consists of the net worth of previously older, surviving and non-bankrupt firms and the net worth of firms from age cohort Y_K who did not go bankrupt before turning old (i.e. entered the business sector more than K periods ago) :

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

Note that the shock process nw_t is only present in the net worth of young cohorts. The shock represents a decline in the value of housing belonging to firms, which is only a significant part of overall net worth in the case of younger firms (see Section 5).

6.3 Endogenous Entry and Age Dynamics

As in 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 a firm after entry is at least as high as the entry costs.

The average value of a firm after entry is given by the proportion of earnings remaining in the age cohort of the entering firms (after payment of monitoring costs to the bank) divided by the

[54] See Appendix E.1 for the corresponding first-order conditions.

number of firms 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 θ_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 newly established firms, age cohort $k=2$ by the number of surviving entrepreneurs of age cohort $k=1$, and so on. Firms in age cohort $k=K$ attain the status of an old firm in the subsequent period. As a result, the number of old firms θ_t^O is given by the number of already old firms surviving with their businesses in the last period, $\gamma^O\theta_{t-1}^O$, and the number of firms surviving from cohort K, thus who attain the status of old ($\gamma^K\theta_{t-1}^K$).
Aggregating across 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 amounts, 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 firms are 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. My choice is driven by the deterministic aging structure of firms, as this allows me to keep the model (and the number of young firm 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 more than five years old are old firms. This age cutoff is consistent with the corresponding definition in my empirical analysis. Hence, including the entering cohort, firms are young for five years before they attain the status of old.

Table 4 gives an overview of all parameter choices in the calibration. Parameter values are identical among age cohorts if not stated otherwise. I target an annualized riskless interest rate of 3 percent, which results in a semi-annual household discount factor β of 0.985. As is standard in the literature, I set the capital depreciation rate δ to 5 percent and the weight of capital in the production function α^j to 0.33. Productivity is normalized to 1 in steady state. Further, 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 across all firms, the disutility of labor parameter χ^j is pinned down endogenously.

In setting the parameters for the optimum 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). Further, 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 a unit mean and variance of 0.18. The amount of reserves held by financial intermediaries is 20% of household deposits.

Regarding the capital goods producer, Λ 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 η^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 investment technology. Following Gertler, Kiyotaki, and Prestipino (2020), I 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 from my baseline TVP-VAR estimation by firm age and calculate the resulting standard deviation of the empirical structural EBP shock. Figure 31 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. I therefore target a maximum decline of 23% in young firms' net worth.[55] I

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

set the autocorrelation of both shock processes to 0.8.

Further, I target the average pre-crisis proportion of young and older firms in the total number of firms as given in the BDS (for the period 1990 to 2006). These data give the proportion of old firms as around 63%. For this target, I set the survival rates of two cohorts of entrepreneurs, the entering cohort ($\gamma^E = 0.855$) and the older cohort ($\gamma^O = 0.954$). The remaining survival rates arise endogenously in steady state. The endogenously resulting survival rates are increasing with firm age. In addition to exogenous exits, firms whose idiosyncratic productivity realization is below the cutoff value $\bar{\omega}^j$ exit endogenously. The total exit rate of firms by cohort is therefore given by the sum of the endogenous default rate and the exogenous rate of death.[56]

Table 4: Calibration and Targets

	Parameter name	Symbol	Value
Preferences and Production			
	Discount factor	β	0.985
	Risk aversion	σ_c	2.00
	Capital depreciation	δ	0.025
	Weight on capital in production	α	0.33
	Productivity (SS)	a_t^j	1.00
	Frisch elasticity of labor supply	η	2
Financial Frictions and Policy			
	Monitoring costs in case of default	μ^j	0.20
	Standard deviation of idiosyncratic realizations	σ^j	0.42
	Idiosyncratic productivity cutoff	$\bar{\omega}^j$	0.35
	Reserves (SS)	r	0.20
	Capital adjustment cost	η^i	0.25
	Wage adjustment cost	κ^W	61.36
	Dividend adjustment cost	κ^d	0.15
Survival Rates			
	Entrants	γ^E	0.855
	Older cohort	γ^O	0.954
Shocks			
	Autocorrelation of credit supply shock process	ρ^r	0.80
	Standard deviation of credit supply shock process	σ^r	0.84
	Autocorrelation of net worth shock process	ρ^{nw}	0.80
	Standard deviation of net worth shock process	σ^{nw}	1.45

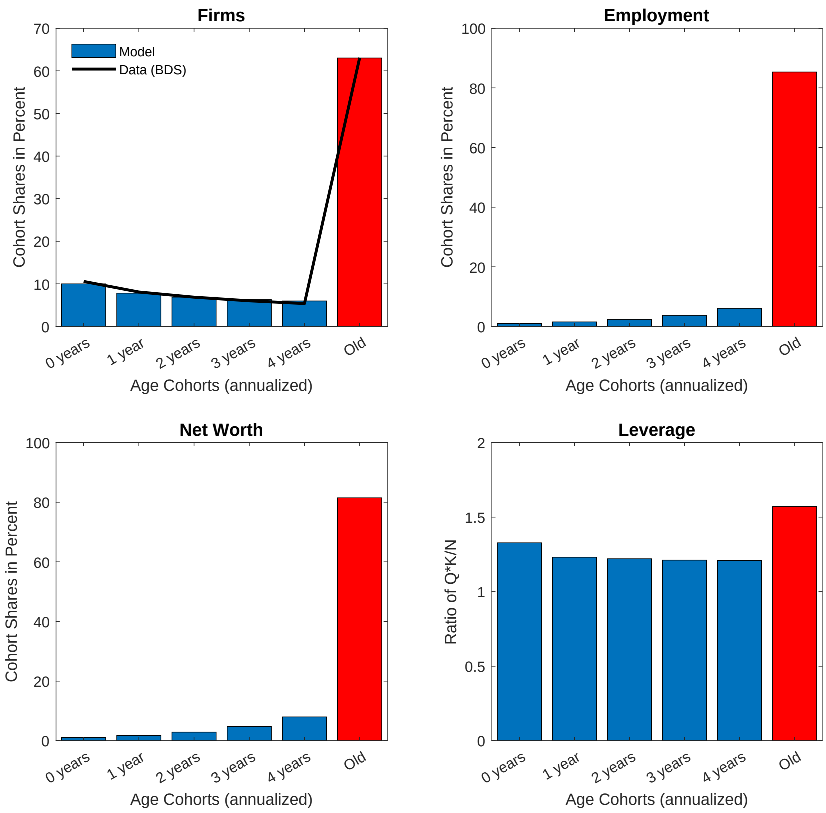
7.1 The Model in Steady State

I parameterize the model to match the relative proportion of young (established up to five years ago) to old firms in steady state. The bars in the upper left-hand panel of Figure 13 depict the model' age distribution of firms in the cross-section as compared to the BDS data (solid line). The model endogenously captures a realistic distribution within young firms (i.e. a high proportion of entrants and a decreasing proportion of young firms).[57] This is consistent with a higher prob-

[56] Note that the age-invariant calibration regarding the parameters of the debt contract implies that the endogenous default rate is identical in steady state for all firms. However, in response to a shock, bankruptcies evolve differently by cohort.

[57] Note that only the relative proportions of young and older firms are a calibration target.

Figure 13: Firm Age Distribution in Steady State



Notes: Selected variables by age cohorts in steady state. The upper left-hand 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.

ability of exit for young firms and mimics 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-hand panel depicts proportions of total employment by firm age cohort. Without this being an explicit target, the steady-state proportion of total employment attributable to older firms, as given by the model, amounts to 85.5%, which is close to the 85.2% proportion accounted for by older firms in the BDS (again, this is the average proportion for the years 1990 to 2006). The middle panel further depicts the proportion of total net worth by age cohort. Net worth increases with firm age and is concentrated in the old cohort, which accounts for around 80 percent of the total.

The lower right-hand panel of Figure 13 depicts leverage (capital-to-net worth ratio) by firm age cohort. As firms grow older and accumulate net worth, they are less leveraged. The old firm cohort, however, has the highest leverage ratio. The reason for this is that these firms will select the highest possible leverage for a given $\bar{\omega}^j$ that the bank is willing to offer.[58] 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 con-

[58] 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.

sistent with Dinlersoz et al. (2018), who document that publicly listed firms are highly leveraged as they grow older.

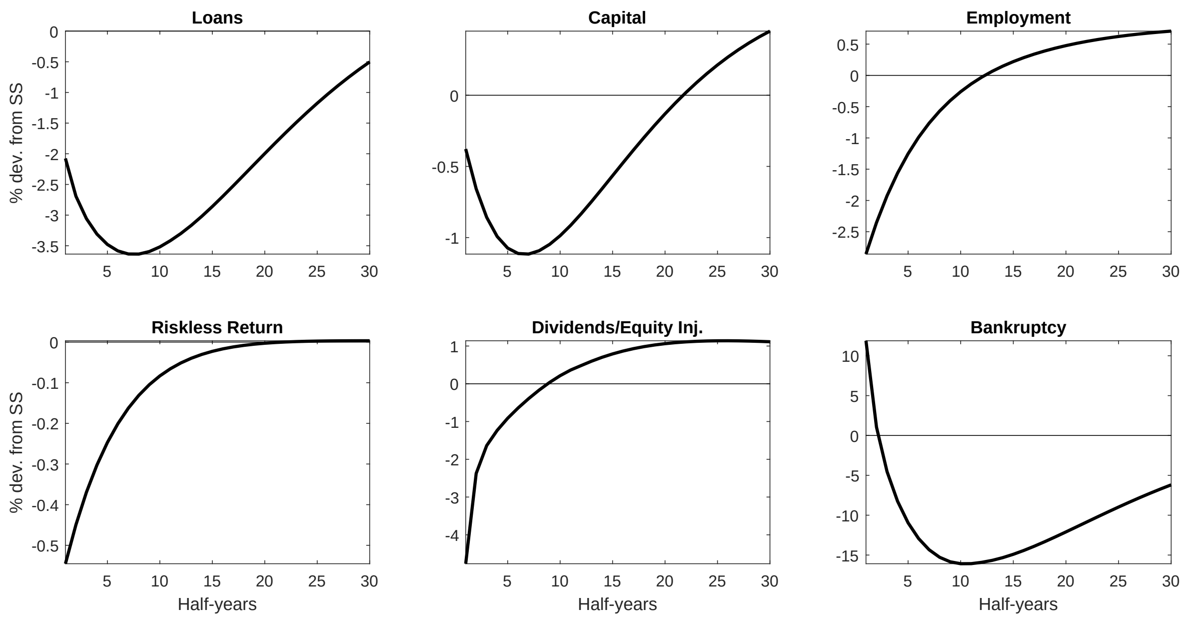
8 Effects of Credit Crunches and Declines in Net Worth

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

8.1 Aggregate Effects

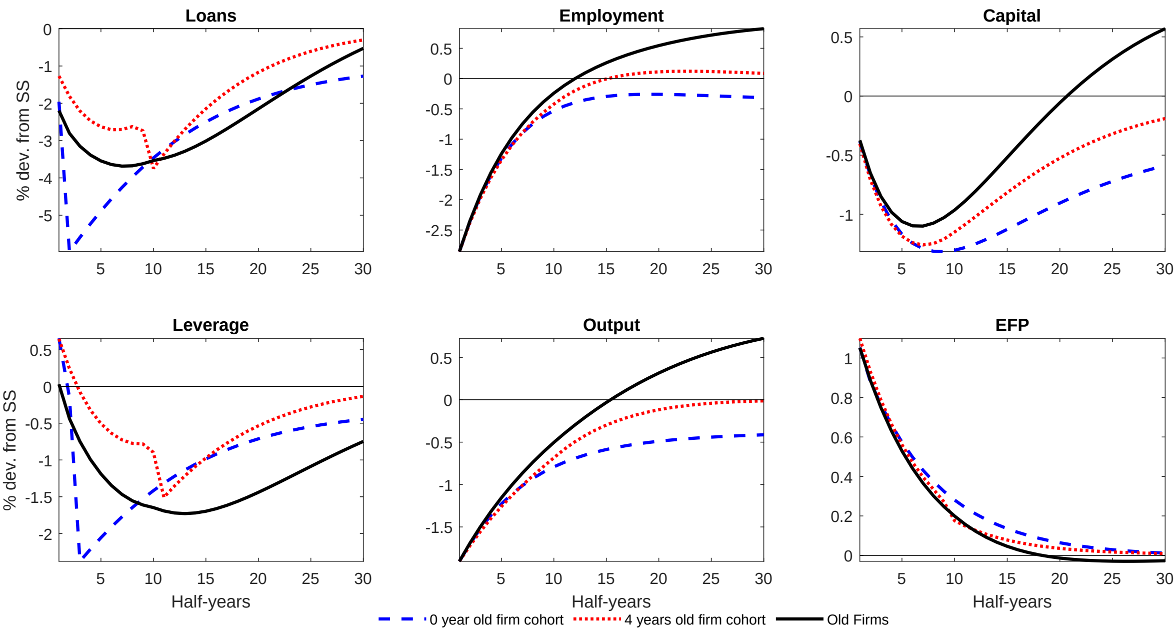
Figure 14 depicts the model's responses to an increase of one standard deviation in the reserves financial intermediaries must hold. This leads to a sharp decline in the aggregate amount of loans in the economy, and, as such, acts as a credit supply shock. Given the balance sheet identity of a firm $Q_t^j K_t^j = N_t^j + B_t^j$, a fall in loan amount reduces demand for capital 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 markedly on impact. As both capital and employment fall, so too does economy-wide output decline. Further, the riskless return on household deposits drops. As a result, households prefer to equip entrepreneurs with equity instead of savings in the form of riskless deposits at banks (the drop in dividends corresponds to an equity injection). 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 firms to be less leveraged. Overall, we observe a strong and persistent contraction in 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 substantial heterogeneity among responses according to firm age. For expositional clarity, I illustrate the responses among three different age cohorts: the recently established firm cohort (depicted by the dashed blue line), the four-year-old firm cohort (depicted by the dotted red line), and the old firm cohort (depicted by the solid black line).

All age cohorts face a steep decline in their loan amount. The immediate reaction is strongest for the youngest age cohort, due to its highly leveraged status, and less severe for the four-year-old firm. Although younger firms have access to equity from households, they can raise only a small amount due to the costs incurred. For older firms, the response regarding loans becomes more muted. Older firms also show a marked contraction in amounts borrowed in response to the credit supply shock. They substitute between debt and equity financing and reduce loan amounts as they receive equity injections from households. This is consistent with recent empirical evidence from Begenau and Salomao (2018). Old firms can raise equity more easily compared to younger ones because in steady state, old firms pay out a higher level of dividends d^O than do younger firms, with d^k for $k = 1, \dots, K$ at approximately zero. This arises endogenously in steady state, as younger firms aim to accumulate net worth. Due to the underlying cost function, which is identical for young and old firms, the cost of raising the same amount of equity is some multiples higher for young than for old firms.

Although old firms have a higher debt-to-net worth ratio in steady state, it is the younger ones that are more financially constrained, because old firms can switch to equity finance more easily. In this sense, despite their highly leveraged status, they suffer less impact from a decline in credit supply. In addition, instead of depositing savings with the financial intermediary, the household prefers to buy shares from old firms due to the now lower riskless rate offered by banks on deposits.

Although all age cohorts decrease their demand for capital and labor in response to the shock, the effect is heterogeneous across cohorts. Regarding capital, the initial drop is similar among cohorts, but the effect's persistence differs by firm age. After the shock, they face a substantial reduction in loans, but, unlike old firms, cannot easily raise equity from households. As a result, the youngest age cohort sees the most severe and persistent decline in capital. Demand for capital among old firms, by contrast, 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 for employment compared to capital. Employment within the cohort of old firms recovers more quickly than does that at younger ones. Lower employment and capital at young firms translates to a decline in output.

A core mechanism of this type of financial friction model is the financial accelerator. Its most important effect is its amplification of the impact for those firms with low net worth (i.e. young firms). The credit supply shock leads to a rise in the external finance premium (EFP), which slowly returns to its initial steady state.[59] 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. A further reduction in net worth complicates young firms' access to external finance further as banks charge a higher loan rate, reducing the amount borrowed again. The financial accelerator mechanism therefore amplifies the effects of the credit supply shock heterogeneously among age cohorts. On employment, the model's response 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 to the simultaneous occurrence of a tightening of credit supply and a decline in firms' net worth. Bernanke and Gertler (1989) define net worth as collateralizable assets. Given that it is mainly tangible assets (such as buildings and land) that can be collateralized, I interpret the shock to young firms' net worth as a house price shock. This interpretation only holds for newly established and young firms. Therefore, old firms are not directly affected by the net worth shock.[60]

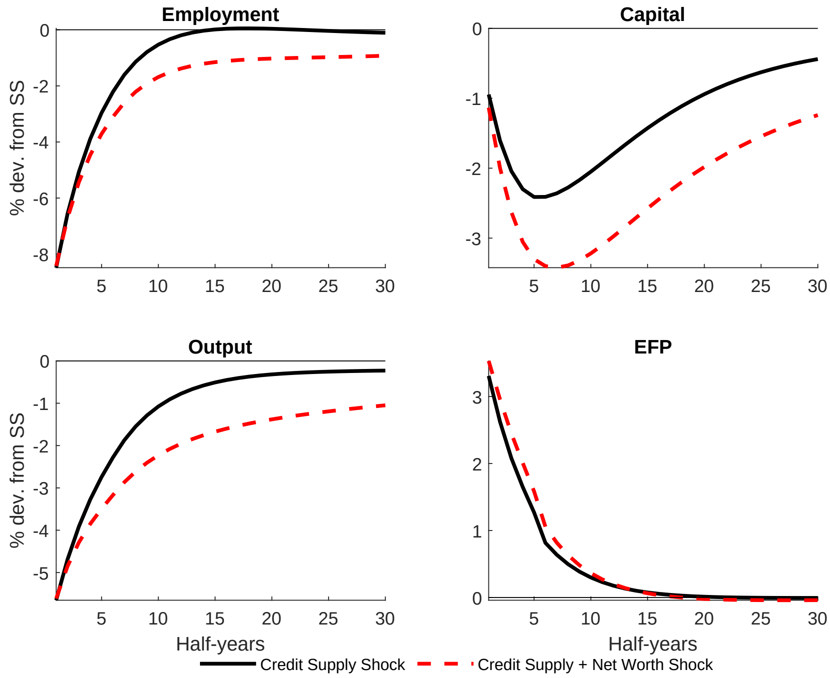
Shock Sizes: The relative magnitude of shock sizes is of significant relevance to the analysis of two simultaneous shocks. Focusing on the period of the 2007-2008 Great Financial Crisis, I use the structural shocks of my empirical TVP-VAR to pin down the shock size for the credit contraction. Figure 31 in Appendix C illustrates the series of structural shocks drawing on my baseline (long horizon) specification. I choose the structural credit supply shock from the period 2008Q4, which is the largest shock and amounts to a value of 2.55.[61] For the size of the net worth shock, I target the overall decline in young firms' net worth so it corresponds to the peak-to-trough de-

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

[60] Old firms are indirectly affected via the net worth that aging, formerly young firms bring to the older cohort when they join it.

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

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



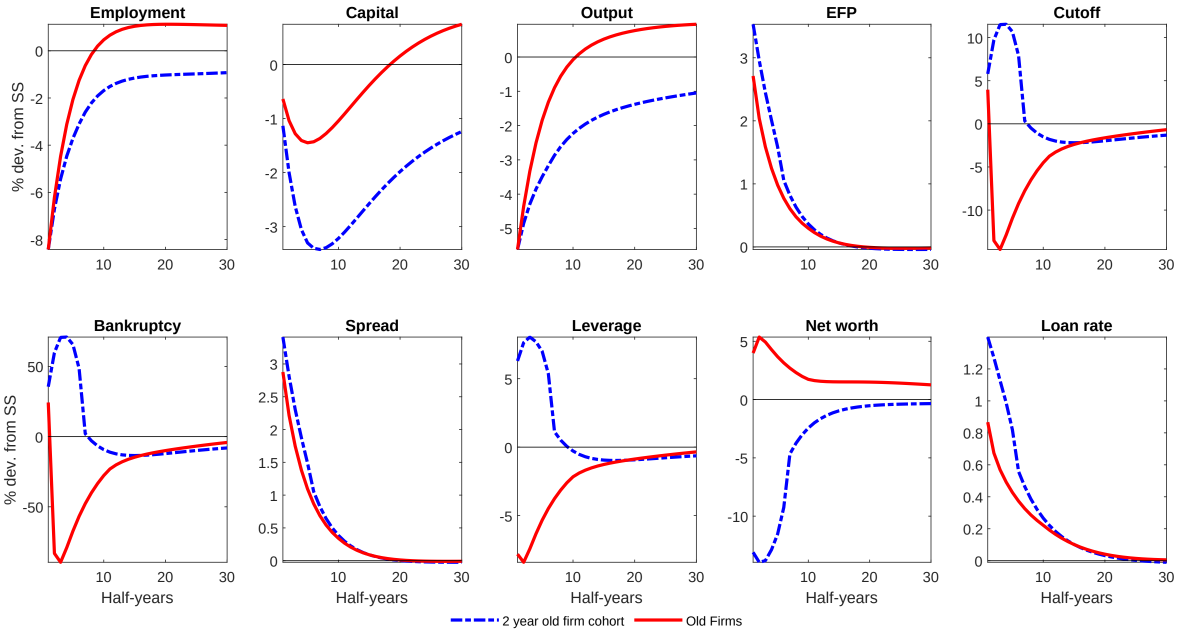
Notes: Responses to a contractionary credit supply shock and net worth shock for a two-year-old firm (age cohort $K = 5$). The solid black line depicts the credit supply shock only; the dashed red line illustrates the model's response if both shocks hit the model economy simultaneously. The size of the 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.

cline in U.S. house 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's responses change if, on top of the credit supply shock, young firms experience a simultaneous decrease in their net worth. The responses depicted are 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 dotted red line shows the responses to both shocks . 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-hand panel). As a result, the demand for capital drops much more sharply and more persistently compared to the scenario in which only credit supply tightens. The decline in capital transmits to labor input. The initial response as regards employment is almost identical to that in the scenario in which only the credit supply shock affects the economy, but employment is subsequently depressed for a long time and recovers only slowly. The contractionary effect on output is more persistent compared to only the credit supply shock as well. We therefore note that it takes a combination of lower net worth and tighter credit supply to cause a large and persistent negative effect on demand for labor among young firms.

The Effect by Firm Age: Figure 17 shows the difference in the responses of young and old firms if both shocks hit the model economy at the same time. 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. In a manner consistent with the empirical evidence detailed in Section 4, employment responses

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



Notes: Responses to a contractionary credit supply shock and net worth shock. The solid red line depicts the response of an old firm. The dashed blue 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.

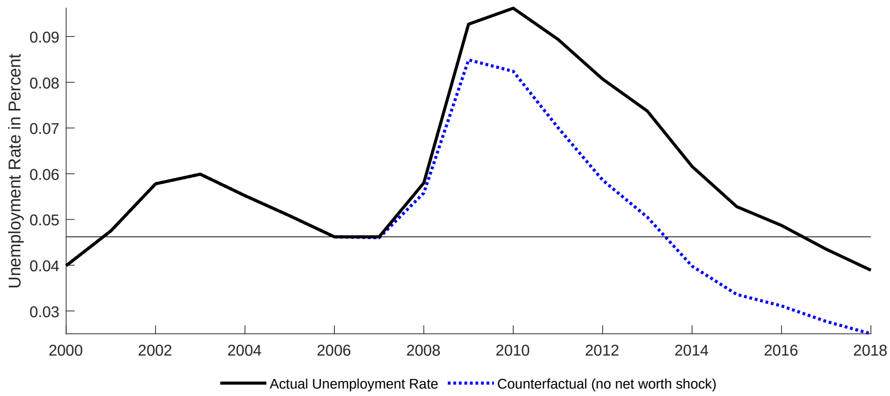
diverge between young and old firms after a similar initial drop in employment. This divergence is even more marked for capital. The exogenous decrease in net worth makes young firms more leveraged, which increases the cost to them of additional borrowing and causes their idiosyncratic productivity cutoff to rise. The financial intermediary demands a higher loan rate and the spread for young firms is much higher compared to that for old firms. The effect of the net worth shock on old firms is limited to an impact via the (lower) net worth of young firms that join the older group. Old firms can raise equity from households, which gives them higher net worth and they are less leveraged. 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 recovers quickly from the shock.

My quantitative model highlights the role of the credit supply and net worth shock in explaining the persistently lower level of young firms' demand for labor 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, while the decline in firms' net worth causes the persistence of the response. Young firms tend to have low net worth and depend heavily on external finance. A drop in the value of their net worth intensifies asymmetries of information between borrowers and lenders. As a result, young firms face an increase in the external finance premium. However, to finance their operations, they now require a greater amount in loans. Given that the financial intermediary has tightened credit supply and young firms have become riskier (due to the increase in their idiosyncratic productivity cutoff), they encounter a considerable increase in loan rate and spread. At this point, the financial accelerator mechanism further amplifies and perpetuates the effects for young firms. Borrowing is even more costly, which depresses these firms' 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 size) across the impulse response horizon.[62] In the first period of the shock, this contribution is slightly negative due to a temporary capital-labor substitution effect in response to a decline in net worth. Subsequently, the contribution increases sharply, amounting to 50 percent after 8 periods (4 years) and more than 80 percent after 12 periods (6 years) have elapsed since the shock. Figure 34 in Appendix E.5 visualizes the relative contribution of the net worth shock to the overall employment response to the shock among young firms. The short-term fall in labor demand can thus be attributed to a tighter credit supply, whereas the effect persists due to the decline in young firms' net worth.

Counterfactual Experiment: Given the relative contribution of the net worth shock to the decline in employment at young firms, I compute the counterfactual development of the U.S. unemployment rate.[63] Figure 18 contrasts the development of the actual U.S. unemployment rate (solid black 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 would have reattained its pre-crisis level two years earlier. The peak of the unemployment rate would have been one percentage point lower and the rate would have been 2 percentage points lower on average between the years 2012 and 2016.

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.

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

[63] I calculate the absolute annual reduction in employment among 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.

9 Conclusion

Given the disproportionate contribution of young firms to job growth, it is crucial for economists and policymakers to understand the reasons and channels that prevent these firms from resuming job creation after a downturn. A key factor is young firms' access to credit, as they are riskier and have typically low net worth and a short business history. Extant literature has either focused on the microeconomic effects of credit crunches or has imposed assumptions on linear effects over time. My paper fills a gap in this context 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 have led to more marked employment reactions among young than among old firms. My analysis at cross-regional MSA level reveals the role of housing net worth for young business owners and the house price collapse of 2006 as explanatory factors in this difference by age. Seen through the lens of my model, the link between firms' net worth and the cost of raising external finance triggers a financial accelerator mechanism that is more powerful for young firms with low net worth. This means that young firms were, during the GFC, exposed to two types of shocks: a decline in their value of collateral and a contraction in credit supply. The interaction of those two disturbances forced them to cut labor demand severely and persistently. By contrast, old firms were not affected by the house price crash and can switch to other financing channels if credit supply tightens.

My work has found that the decline in young firms' net worth and, as such, in their self-financing options caused the decline in their demand for labor and its resistance to speedy recovery. A counterfactual exercise shows that absent the house price crash of 2006, the U.S unemployment rate would have been back at its pre-crisis level two years earlier and that unemployment would have been 2 percentage points lower in the aftermath of the GFC. The decline in young firms' net worth therefore appears to explain the sluggish recovery of the U.S. labor market after the GFC.

Among the policy implications we can draw from these findings is the need for policymakers to break the link between housing net worth and young firms' access to external finance if long-term impacts on the labor market are to be prevented. It is imperative to design macroprudential policy carefully to prevent housing boom-bust cycles. Further, firms that show the highest growth (and job creation) potential should be identified and receive support in accessing external financing.[64]

There are several additional questions on the interaction of credit and labor markets that remain to be investigated. 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 in mortgage delinquencies, considerable losses for banks are the result. In response, the lender's balance sheet deteriorates and they reduce their credit supply. This is of particular relevance if firms borrow predominantly at local banks.[65] Extending the framework to account for the transmission mechanism via the bank's balance sheet channel would give rise to

[64] The identification of these firms could proceed using criteria such as the sector they operate in or whether they had been expanding in terms of new establishments previous to the crisis .

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

further insights on the interaction between the housing net worth channel and young firms' labor market reaction to shocks. Second, adding a frictional labor market would allow a more thorough analysis of the general-equilibrium feedback effects between credit and labor markets.[66] I leave this for future research.

[66] Wasmer and Weil (2004) address a similar question in a model using 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. ZAKRAJEK (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.

CANOVA, F. AND G. D. NICOLO (2002): "Monetary disturbances matter for business fluctuations in the G-7," *Journal of Monetary Economics*, 49, 1131–1159.

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 20089 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," *Amer-*

ican 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.
FAUST, J. (1998): "The robustness of identified VAR conclusions about money," *Carnegie-Rochester Conference Series on Public Policy*, 49, 207–244.
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.
GAMBETTI, L. AND A. MUSSO (2017): "Loan Supply Shocks and the Business Cycle," *Journal of Applied Econometrics*, 32, 764–782.
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.

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.

MITMAN, K. AND S. RABINOVICH (2019): "Do Unemployment Benefit Extensions Explain the Emergence of Jobless Recoveries?" CEPR Discussion Papers 13760, C.E.P.R. Discussion Papers.

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.

SCHMALZ, M. C., D. A. SRAER, AND D. THESMAR (2017): "Housing Collateral and Entrepreneurship," *Journal of Finance*, 72, 99–132.

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

SEDLÁČEK, P. (2020): "Lost generations of firms and aggregate labor market dynamics," *Journal of Monetary Economics*, 111, 16 – 31.

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.

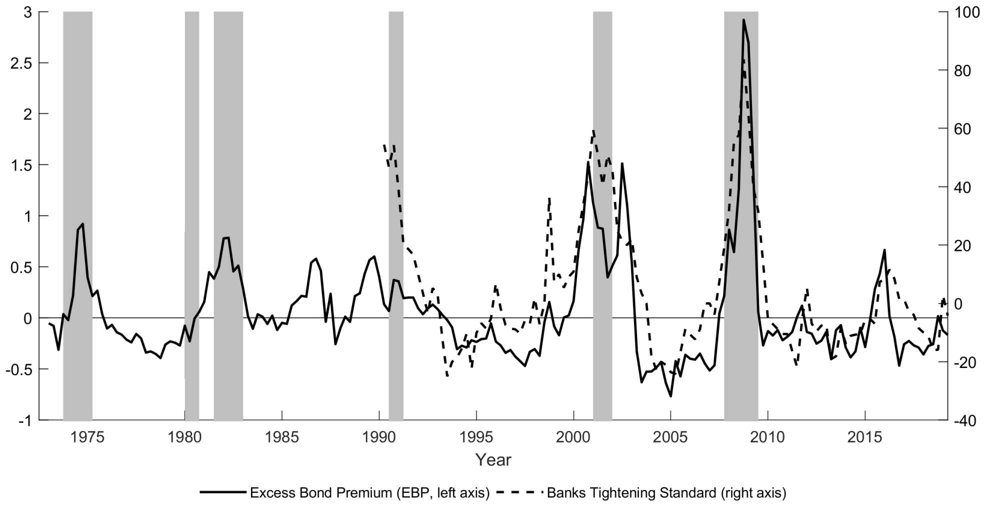
UHLIG, H. (2005): "What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure," *Journal of Monetary Economics*, 52, 381–419.

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.[67]

[67] 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 θ^t, α_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 θ_t, α_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 α_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 μ_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: θ^T, A^T, H^T and the hyperparamters denoted V. The set of hyperparameters consists of Q, S, and σ_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 θ^T.**
   The measurement equation is linear and has Gaussian innovations with known variance. Hence, the conditional posterior is a product of Gaussian densities and θ 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, θ^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 $\mathrm{var}(\epsilon_t) = H_t$ and are observable conditional on θ^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 θ^T, A^t, H^T, Y^T.

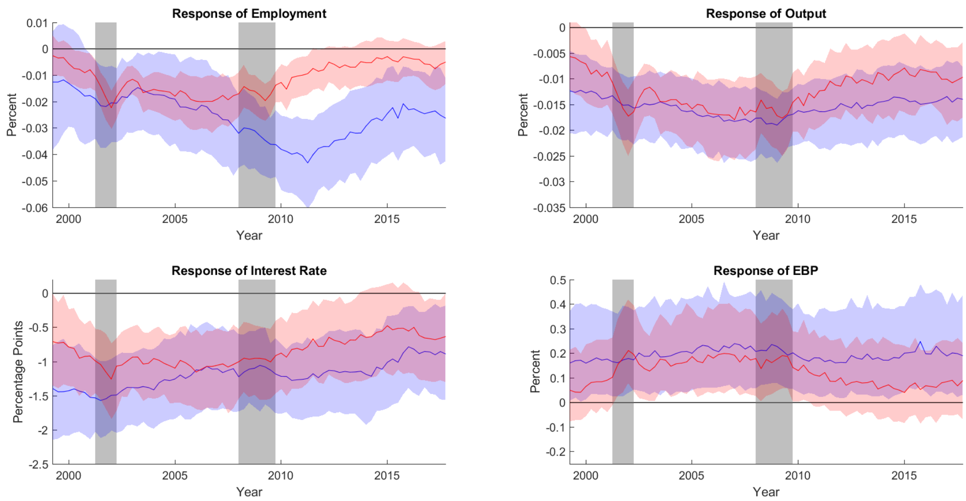
Thus, the hyperparameters Q,S and σ_i^2 can be directly drawn from their respective posterior distributions $p(Q, S, \sigma_i^2 | \theta^T, A^T, H^T, Y^T)$.

C Further Empirical Evidence

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

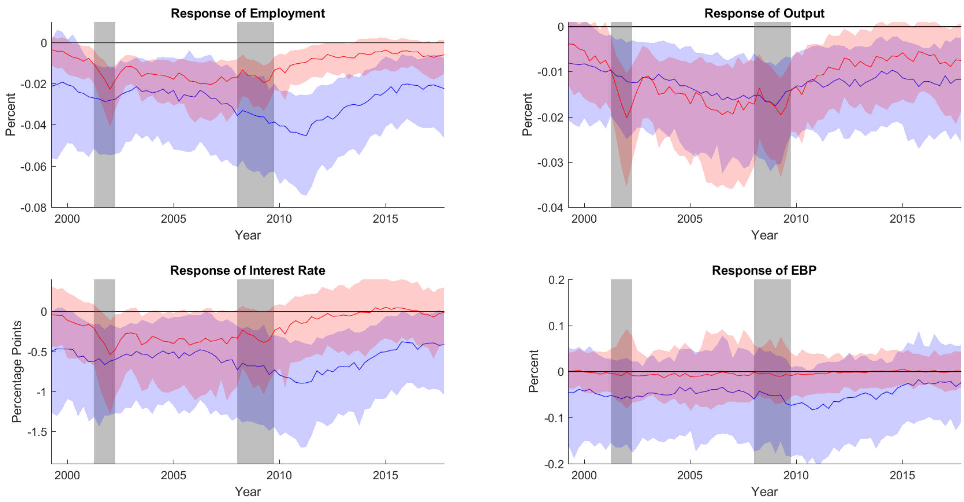
Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 1 quarter to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior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



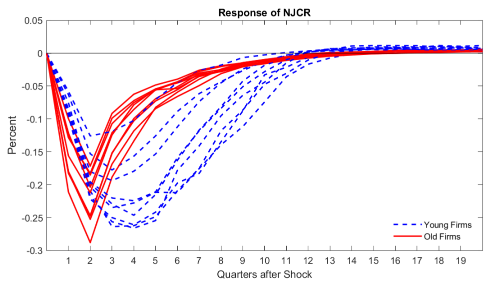
Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior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

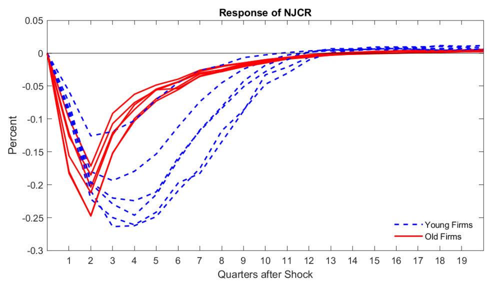


Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 12 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the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

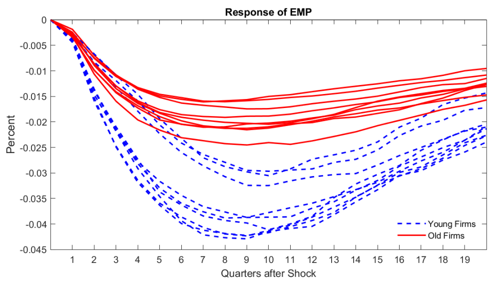
Figure 23: Generalized Impulse Response Functions in Response to a Credit Supply Shock in Recessions for Young and Old Firms



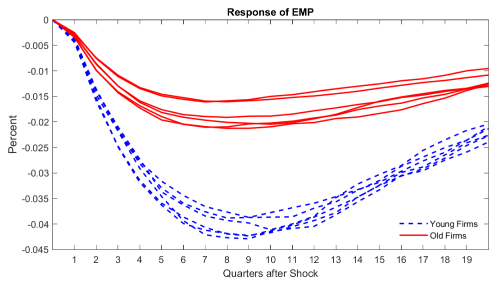
(a) Net Job Creation Rate, all recessionary periods



(b) Net Job Creation Rate, Great Recession



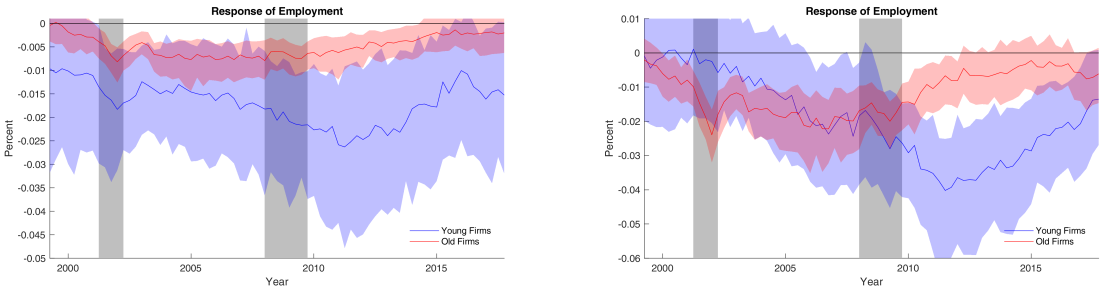
(c) Employment, all recessionary periods



(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.

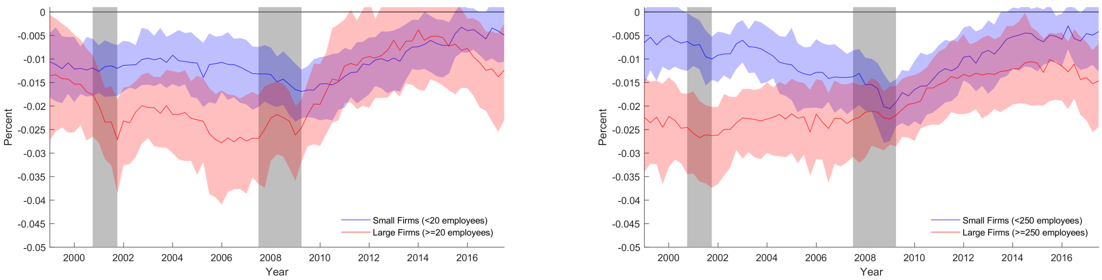
Figure 24: Controlling for Firm Dynamics: GIRFs in Response to a Positive Credit Supply Shock



(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 ($\leq$ 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.

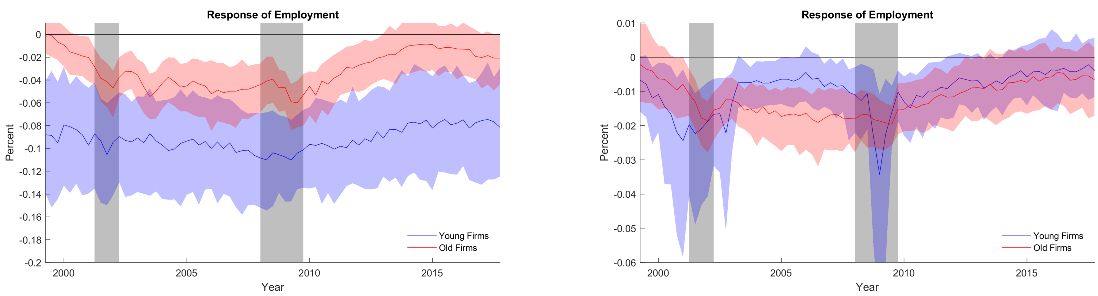
Figure 25: Firm Size: GIRFs of Employment in Response to a Credit Supply Shock



(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.

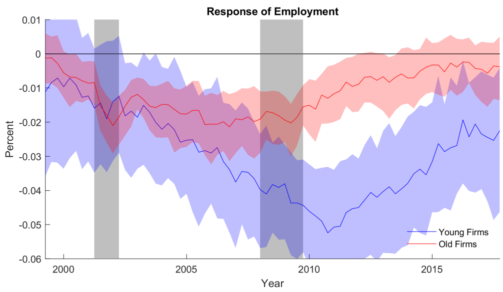
Figure 26: Robustness: Banks Tightening Standards (LHS) and for a Broader Definition of Young Firms ($\leq$ 10 years, RHS).



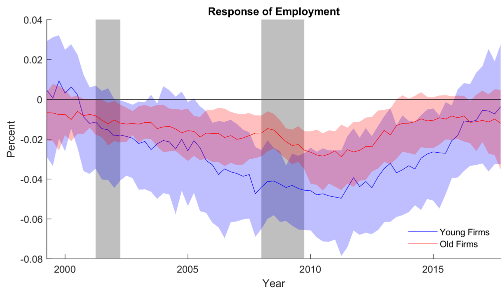
(a) Banks Tightening Standards **(b)** Definition Young Firm: up to 10 Years

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 $\leq$ 10). Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

Figure 27: Robustness: Identification Strategy, Ordering of Variables



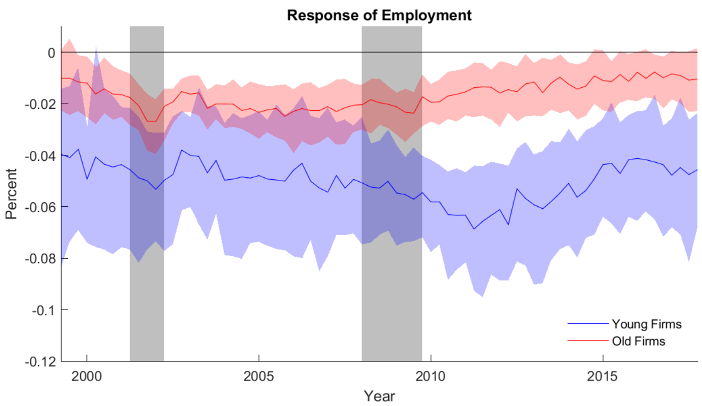
(a) Employment reaction, EBP ordered third



(b) Employment reaction, EBP ordered first

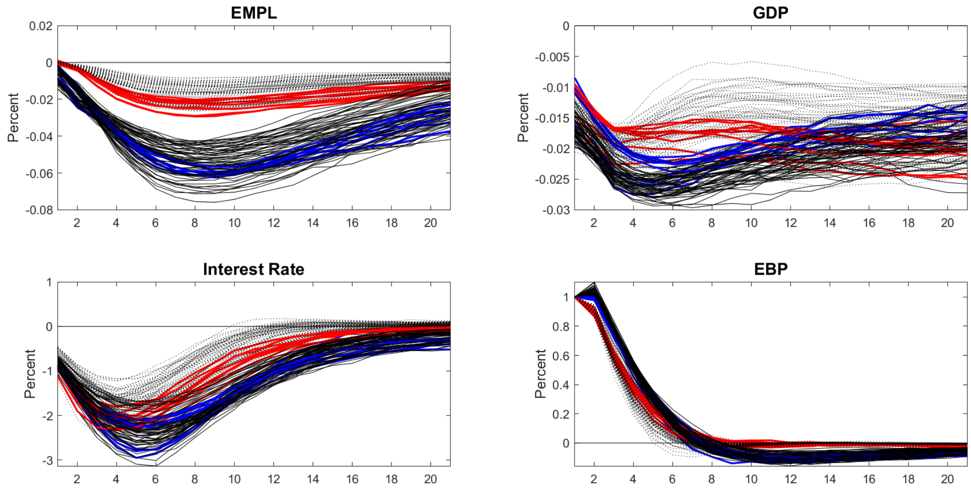
Notes: GIRFs of Employment based on two four-variable TVP-VAR estimation of different ordering of variables with young and old firms respectively. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one) with; blue (red) shaded areas denote 16th and 84th percentiles of the posterior distribution for young (older) firms. Gray-shaded areas denote NBER recession periods.

Figure 28: Robustness: Identification Strategy, Sign Restrictions, Young vs. Old Firms



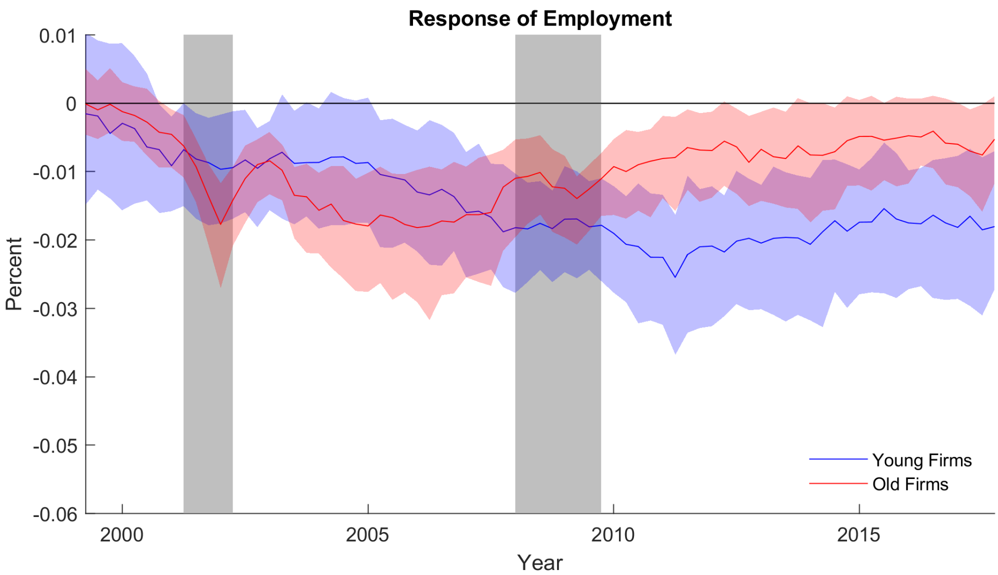
Notes: The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one) with sign restrictions; blue (red) shaded areas denote 16th and 84th percentiles of the posterior distribution for young (older) firms. Gray-shaded areas denote NBER recession periods.

Figure 29: Robustness: Identification Strategy, Impact on All Endogenous Variables



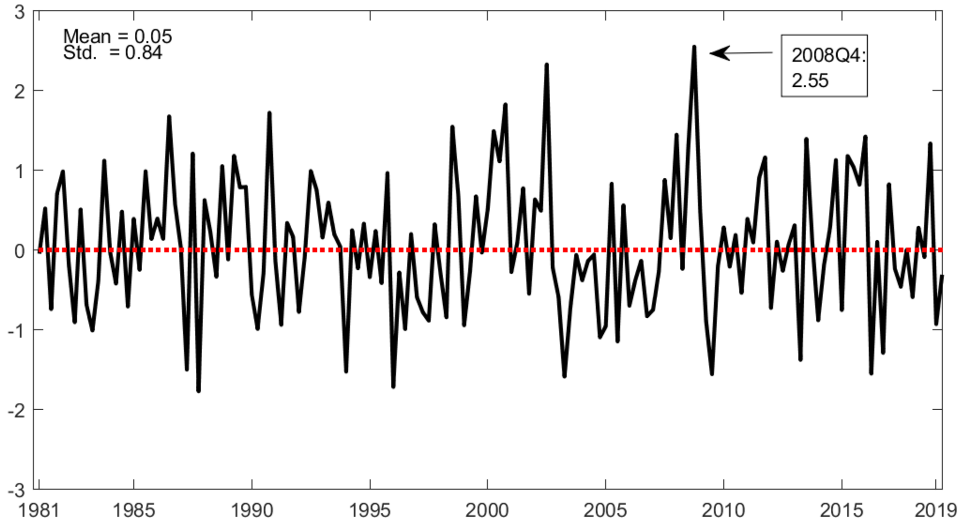
Notes: The solid (dashed) line illustrates median responses over the IRF horizon to a 1 std. EBP shock (normalized to one) with sign restrictions for young (old) firms; blue (red) shaded areas denote median responses for young (old) firms during the Great Financial Crisis.

Figure 30: House Price Growth as Endogenous Variable



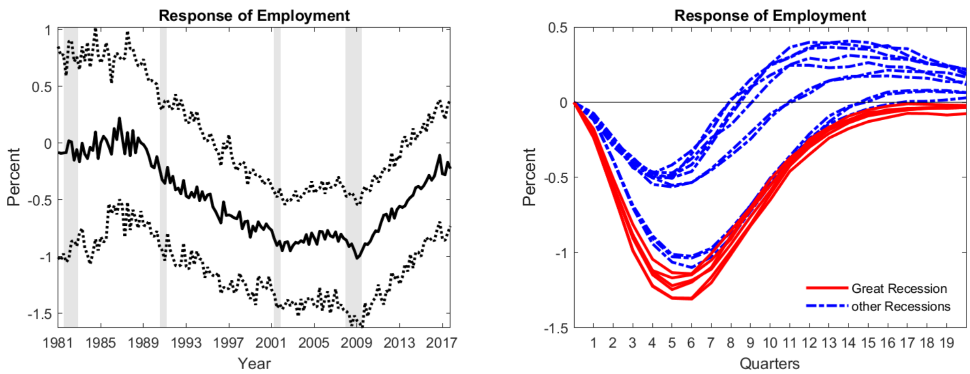
Notes: GIRFs of Employment in response to a positive credit supply shock for young (blue) and old (red) firms with house price growth as fifth endogenous variable. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

Figure 31: 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 32: 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.[68]

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 ΔLoan 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.[69] The coefficient of interest is the interaction term γ. 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.

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

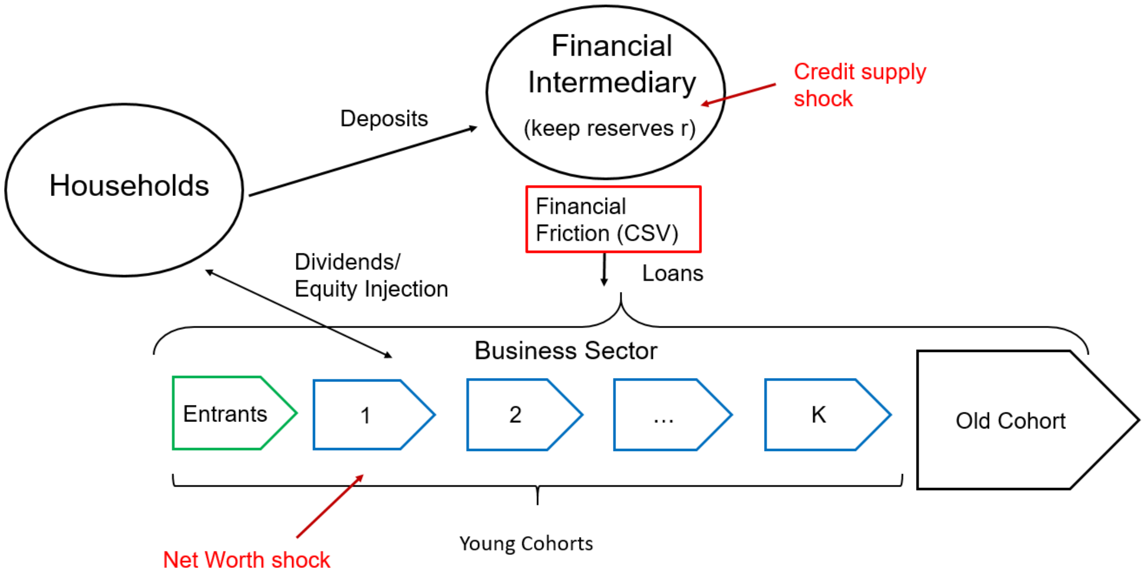
[69] Small businesses are businesses with gross annual revenues < $ USD 1 million in the relevant time span.

Table 6: Cross-Regional Estimation Results

	Dependent variable:			
	Δ Job_creation$_{07-09}$			
	(1)	(2)	(3)	(4)
Δ Loan amount$_{06-09}$	-0.110	-0.104	-0.103	-0.127
	(0.088)	(0.087)	(0.088)	(0.098)
Δ HPI$_{06-09}$	0.674^{***}	0.729^{***}	0.726^{***}	0.778^{***}
	(0.220)	(0.220)	(0.220)	(0.250)
Δ Loan amount$_{06-09}$:Δ 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 33: Overview of Basic Model Framework



E Model Appendix

E.1 Firms' First Order Conditions

E.1.1 The Entrant

The first-order optimal conditions for firms 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 firms 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 firms $(s_{t-1}(d_t + p_t))$, and the remaining equity from exiting firms C_t^e that is transferred back to the household. Firms' 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 all firms.

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. Firms 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 δ 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 Λ is an increasing and concave function of the investment-to-capital ratio I_t^j / K_t^j that captures convex adjustment costs.[70] 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 firm cohort 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

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

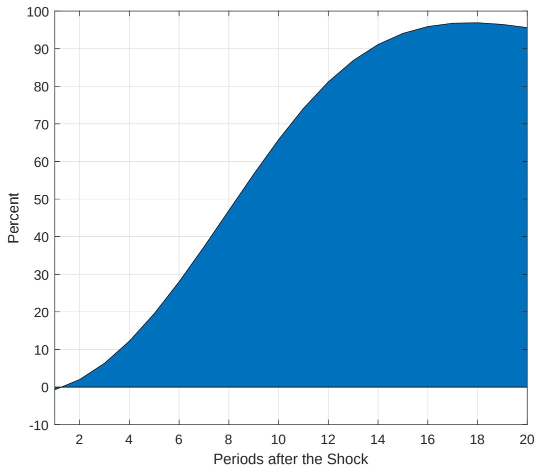
Note that the wage is equal for all age cohorts as otherwise all households would supply labor only to the highest paying firm. The real rental rate of capital is further given by

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

E.5 Additional Figures

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

Figure 34: 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