Financial Constraints, Firm Age, and the Labor Market†

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Abstract

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

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1 Introduction

How do credit crunches affect firms' employment decisions over time and over the business cycle? The answer depends on the age of the business. Young firms established up to five years previously are quantitatively important drivers for aggregate employment dynamics in the United States. In 2006, young firms accounted for nearly 14% of total employment, but 85% of total net job creation. The share of young firms in the overall decline in employment and net job creation during and after the Great Financial Crisis (GFC) between 2006 and 2011 was disproportionate: They accounted for more than half of the decline in employment and two-thirds of the decrease in total net job creation (see Table 1). Young firms are more likely to be financially constrained as they have high idiosyncratic risk, a short business history, and tend to have low net worth compared to older businesses (Gertler and Gilchrist, 1994). At the same time, they have high growth potential and require external finance in their process of growing (see Sterk, Sedláček, and Pugsley, 2021, Sedláček and Sterk, 2017, Haltiwanger, Jarmin, and Miranda, 2013). In this paper, I assess to which extent young firms are hindered from creating jobs due to financial constraints and the implications for aggregate outcomes.

To this end, I apply a structural time-varying framework and develop a heterogeneous firm model with financial frictions. My empirical work documents that the relative employment reaction of young vs. old firms in response to credit crunches varies considerably over time. Especially since the onset of the GFC, young firms react considerably stronger to credit crunches compared to old firms. I identify fluctuations in young business owners' private housing net worth, which is used as collateral, as an important driver for the heterogeneous impact of financial shocks by firm age. Motivated by this empirical evidence, my quantitative model reconciles the empirical evidence on the more marked employment response of young firms after the GFC by considering the interaction of credit crunches and the decline in young business owners' housing net worth. In my calibrated model, old firms restructure their capital portfolio towards less debt and more equity in response to credit crunches. Young firms depend more on debt and face a steeper marginal cost curve in response to the shocks. This dampens their demand for capital and labor strongly and persistently.

The main contribution of my paper is twofold: First, I document that credit crunches cause employment effects that vary over time and are heterogeneous by firm age. Second, I propose a theoretical model that disentangles the relative contribution of the credit supply and the net worth channel. The interaction of both can explain the more marked employment response of young firms in the aftermath of the Great Financial Crisis. Absent the decline in young business owners' housing net worth, the U.S. unemployment rate would have been 1.5 percentage points lower during the GFC. My findings stress the important role of young firms in the amplification and propagation of aggregate macroeconomic shocks.

My baseline empirical specification estimates the age-specific employment responses to shocks to credit supply, measured by the excess bond premiums (EBP, see Gilchrist and Zakrajšek, 2012), in 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 mi-

Table 1: The Role of Young Firms for U.S. Employment Dynamics, 2006-2011

	Employment	**Job Creation**	**Job Destruction**	**Net Job Creation**
Share of Young Firms ($\leq$ 5 years)	13.5%	31.7%	18.6%	84.9%
Overall Δ_{06-11}	-6.1%	-21.9%	-13.7%	-55.3%
Young Firms, Δ_{06-11}	-23.8%	-32.4%	-20.6%	-42.9%
Ratio Young Firms/Overall Δ_{06-11}	3.89	1.48	1.49	0.78
Share of Young Firms in Overall Δ_{06-11}	52.4%	46.8%	27.8%	66.0%

Notes: Shares of young firms in overall employment, (net) job creation and job destruction are based on the year 2006. Data source: Business Dynamics Statistics (BDS).

croeconomic perspective[1] or on time-invariant effects of credit crunches.[2]. I obtain two key findings: In response to credit crunches, labor market reactions (i) are time-varying and (ii) diverge by firm age. In performing a historical shock decomposition, I find that 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 old 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, and Surico, 2019 and Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova, 2018).[3]

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"*[4] illustrates the increased importance of business owners' private real estate collateral for newly established companies. Using cross-regional variation at the 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 business owners' private home equity 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, Davis and Haltiwanger, 2021, and Bahaj, Foulis, Pinter, and Surico, 2022).

Motivated by these empirical facts, I propose a quantitative general equilibrium model with firm dynamics. 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 a financial friction. I extend the financial accel-

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

[2] See Gilchrist and Zakrajšek, 2012, Bassett, Chosak, Driscoll, and Zakrajšek, 2014, Barnichon, Matthes, and Ziegenbein, 2022

[3] I discuss the difference between firm age and firm size in detail in Subsection 3.2.

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

erator 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: (i) I add endogenous firm entry and a detailed firm age structure, (ii) firms can 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, households provide business entrants with initial net worth. As firms grow older, they accumulate net worth. Thus, the more recently a business was established, the lower 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.[5]

After parameterizing the model to match the relative distribution of firm age, I target the magnitudes of the decline in aggregate loans and the drop in young firms' collateralizable assets experienced during the GFC. Using the quantified model, I show three main results. First, the isolated impact of the credit supply shock is not sufficient to explain either time variation or the heterogeneity in the impact by firm age. The credit crunch increases borrowing costs for young firms by more, causing a decline in their demand for capital and labor. However, the drop in young firms' employment is not persistent enough to explain the divergent employment responses by firm age found in the empirical analysis in the aftermath of the GFC.

Second, considering an additional drop in the value of young firms' collateralizable assets finally reconciles the model with my empirical findings. As young firms' balance sheets deteriorate, lenders demand higher compensation for the increased probability of default and the associated agency costs, making borrowing even more costly. Due to their restricted access to credit, young firms' economic activity drops sharply, further depressing their net worth. A financial accelerator mechanism exacerbates the contractionary effect on young firms via the endogenous link between the external finance premium and borrowers' net worth. 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 lower agency costs, and, in response to the credit crunch, reshuffle their portfolio towards more equity. This dampens the impact of the shock for them.

Finally, an alternative scenario for the U.S. unemployment rate, for which I shut off the drop in collateralizable assets for young firms, highlights the importance of young firms for aggregate labor market effects. As young firms would have resumed job creation quicker, this would have translated, on average, to a 1.5 percentage points lower unemployment rate between 2009 and 2012. In addition, the U.S. unemployment rate would have returned to its pre-crisis level two years sooner.

Relation to the literature: First, my work adds to the empirical literature on the effects of credit supply shocks on labor market outcomes. Chodorow-Reich (2014), Duygan-Bump, Levkov, 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 employ-

[5] I provide survey evidence based on the *"Kauffman Firm Survey"* which covers firms that were established in 2004. 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.

ment during the Great Financial Crisis. They find that young or small firms in particular reduce employment in response to credit contractions.[6] These papers study the effects of credit supply shocks from a microeconomic perspective. In taking a complementary, macroeconomic view, my study seeks to estimate the potentially time-varying effects of credit supply shocks on employment by firm age. 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. (2022) focus on the asymmetric effects. My inclusion of time-variation and firm heterogeneity adds to this existing work.[7]

Second, I contribute to the literature on the heterogenous impact of aggregate shocks on firms. As such, my work relates to Gertler and Gilchrist (1994) who proxy capital market access with firm size and show that small manufacturing firms react disproportionately stronger to monetary policy tightening. This is related to Ottonello and Winberry (2020) who study the role of financial heterogeneity in terms of high and low debt burden in firms' investment reaction to monetary policy shocks and show that firms with low default risk are more responsive as they face a flatter marginal cost curve for investment. Specific to credit shocks, Khan and Thomas (2013) show that a credit crunch can induce a long-lasting recession via the change in the distribution of capital causing persistent declines in total factor productivity. Buera and Moll (2015) show that credit crunches show up as different wedges depending on how the underlying heterogeneity is modelled. They stress the importance of modelling the heterogeneity that gives rise to financial transactions due to interactions of financial frictions with the underlying heterogeneity. In this paper, I argue that firm age is an adequate proxy for financially constrained firms.[8]

I further complement the literature on the role of housing net worth for newly established businesses. Davis and Haltiwanger (2021) 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.[9] Adelino et al. (2015), Schmalz, Sraer, and Thesmar (2017), Kaas et al. (2016) find that the value of real estate collateral is an important driver for entrepreneurship and job creation. Related to that, Cloyne et al. (2019) and Bahaj et al. (2022) stress the importance of the household balance sheet channel (especially housing net worth and mortgages) in the transmission of monetary policy. My paper further relates to Schott (2015), who also connects the decline in house prices to persistently high unemployment rates and low job creation among new businesses. Complementary to his work, I provide detailed empirical TVP-VAR evidence and focus on financial frictions as opposed to labor market frictions.

Finally, I add to the literature on the sluggish recovery of the U.S. labor market after the Great

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

[7] 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.

[8] My paper is further related to the literature on heterogeneous firms under financial frictions, see Bernanke and Gertler (1989) and Cooley and Quadrini (2001).

[9] 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).

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 lost generation of firms due to a decline in firm entry causing long-lasting labor market effects.

Structure of the paper: Section 2 introduces the structural empirical approach and Section 3 presents the empirical findings. I discuss the role of housing net worth in Section 4. Section 5 sets out the theoretical model, Section 6 details its calibration, and Section 7 presents the simulation results. Section 8 concludes.

2 Structural Empirical Analysis

This section explains the empirical methodology. I apply a time-varying parameter vector autoregression (TVP-VAR) model with stochastic volatility to the end of estimating employment responses to a credit supply shock.[10]

Advantage of this Approach: The advantage of this methodology is its flexibility. A TVP-VAR with stochastic volatility allows for a different set of coefficients and a different variance-covariance matrix at each point in time. Further, it is crucial to allow for stochastic volatility (changing variance of the exogenous shocks hitting the economy) if our aim is to distinguish between changing shock sizes and variations in the contemporaneous relationship between variables over time.[11] As such, this methodology captures both possible structural changes and state-dependent effects. This is important for two reasons. First, the effects of financial shocks may vary over time. Potential reasons for time variation can be structural (e.g. deregulation) or cyclical (stronger effects in recessions compared to booms) and can arise due to different shock sizes or from changes in the transmission mechanism. Second, compared to other classes of nonlinear time series models, this methodology does not hinge on any imposed threshold or a specific switching variable that dictates changes in parameters, as the model parameters evolve smoothly over time.[12] Furthermore, a TVP-VAR model allows to compute generalized impulse response functions (GIRFs) for every point in time, which enables the comparison of reactions for specific time periods.

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, Haltiwanger, Jarmin, and Miranda (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. This disagreement underlines the advantage of my approach, which is not dependent on any imposed business cycle indicator.

[10] See Primiceri (2005) and Cogley and Sargent (2005) for seminal work on TVP-VAR models.
[11] Ignoring stochastic volatility if the variance of the shocks is time-varying leads to biased coefficients.
[12] This is the case for threshold or smooth-transition VARs.

2.1 A Time-Varying Parameter VAR with Stochastic Volatility

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

$$y_t = B_{1,t} y_{t-1} + \cdots + B_{p,t} y_{t-p} + \epsilon_t = X_t' \theta_t + \epsilon_t, \tag{2.1}$$

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.[13] 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

$$\theta_t = \theta_{t-1} + \nu_t, \qquad \nu_t \sim N(0, Q) \tag{2.2}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t, \qquad \zeta_t \sim N(0, S) \tag{2.3}$$

$$ln\ h_{i,t} = ln\ h_{i,t-1}, + \sigma_i \eta_{i,t} \qquad \eta_t \sim N(0, 1). \tag{2.4}$$

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.[14] 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).[15]

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

[14] 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).

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

2.2 Data & Empirical Specification

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 (FFR) to control for monetary policy stance. For the post-2008 period, I use the shadow federal funds rate of Wu and Xia (2016).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' individual 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 12 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.[16]

The baseline empirical specification is

$$y_t = [log(\mathrm{EMP}_t^j) \quad log(\mathrm{GDP}_t) \quad \mathrm{INT}_t \quad \mathrm{EBP}_t] \tag{2.5}$$

where INT_t refers to the interest rate (i.e. the shadow rate for the period of the zero lower bound) and EMP_t^j denotes employment by age category $j \in$ (young, old), which enters the model sequentially. I set the lag length p to 2 and demean all variables prior to estimation.[17]

2.3 Identification

After estimating the reduced-form Equation 2.1, I am interested in the structural interpretation of shocks. Given the structural representation of the TVP-VAR

$$y_t = X_t' \theta_t + A_t^{-1} u_t, \tag{2.6}$$

[16] 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.

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

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., 2022 impose recursive ordering between macroeconomic and financial variables.

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.I discuss the results of the alternative identification scheme in Appendix C.1.

3 Empirical Results

This section presents the main findings of the structural empirical analysis. First, I present the impulse response analysis of a credit supply shock on young and old firms' employment. Then, I show results on the time variation of employment responses by firm size compared to firm age. In Subsection 3.3, I analyze the significance of credit supply shocks since the early 1980s. Appendix C.1 provides several extensions and robustness checks regarding firm dynamics, the measure of credit supply, the definition of young firms, and the identification strategy.

3.1 Results by Firm Age

Figure 1 depicts the GIRFs in response to a credit supply shock across all periods and the entire impulse response horizon in a three-dimensional manner with panel (b) illustrating the results from a rotated view. Thus, panel (a) in Figure 1 enables to inspect the effects over time, while the rotated view in panel (b) visualizes the effects over the impulse response horizon. To ensure comparability over time, I normalize the shock size to one in every period. 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. During the 2001 recession, young and old 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. Young firms' responses were not only more pronounced, but also much more persistent compared to those of old firms. Old firms' responses recovered soon after the Great Financial Crisis, that is, around 2009, whereas the post-crisis impact on employment for young firms was strongest around the year 2012.

To obtain a clearer picture on the time-variation of employment effects in response to a credit supply shock by firm age, I consider the reaction six quarters after the shock in the cross-section 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.[18] Figure 2 illustrates the impact on employment of a credit supply shock by firm age over time. The response of young firms comes with higher estimation uncertainty. Until the year 2006, the median employment responses of young and old 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.

3.2 Age vs Size

Ideally, I would like to single-out financially constrained firms, i.e. make a clear distinction between financially constrained and unconstrained firms. However, as there is no reliable measure of financial constraints in the data, I am compelled to use a proxy. I focus on the role of age, and not size, of firms as proxy 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: 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.[19]

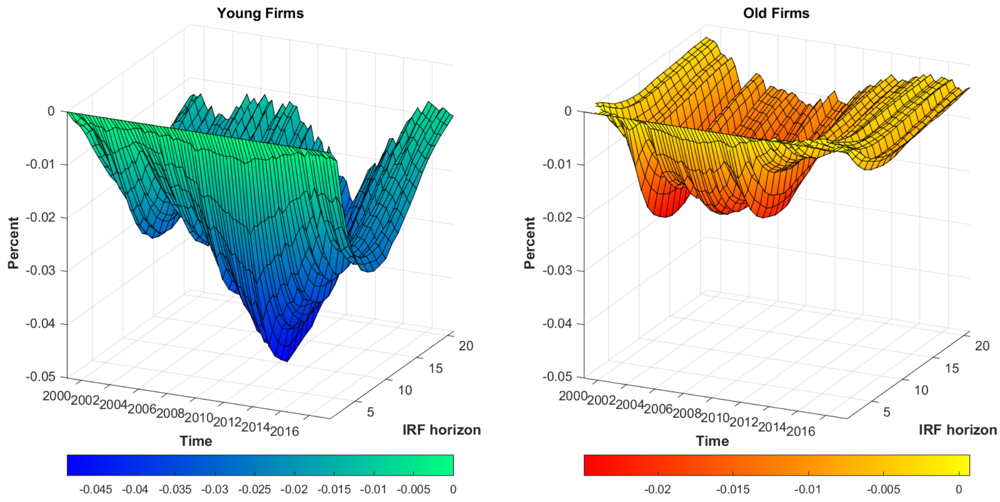
Growth Potential: Young firms tend to be small, but not all small firms are young. [20] My principal interest lies in younger, smaller firms. Unfortunately, the QWI does not provide data on this distinction. I therefore focus on young firms (i.e. firms that were established up to five years

[18] See Figures 14 to 16 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.

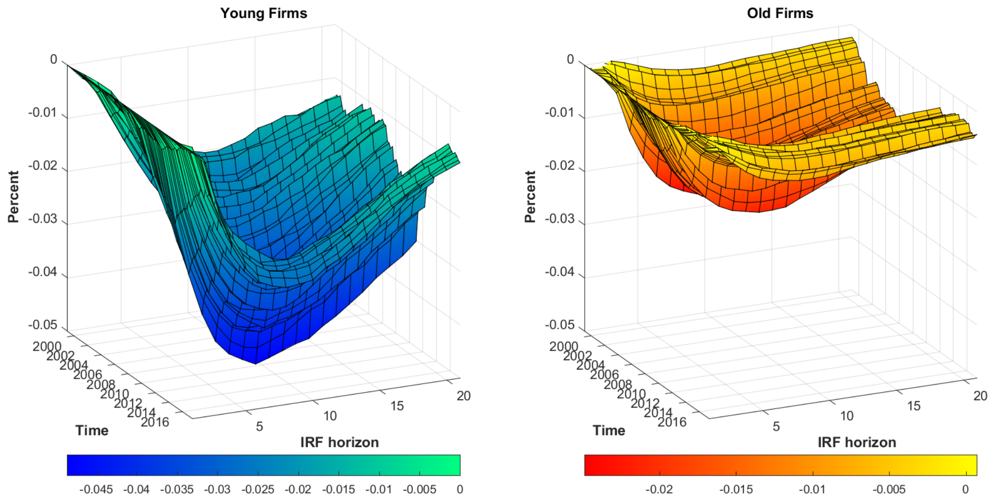
[19] There is a large body of corporate finance literature on identifying proxies for financial constraints; however, the debate on their validity is ongoing; see, among others, Farre-Mensa and Ljungqvist (2016) and Crouzet and Mehrotra (2020).

[20] Figure 13 in Appendix A depicts the average size distribution of young and old 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).

Figure 1: Median Generalized Impulse Response Functions (GIRFs) in Response to a Credit Supply Shock by Firm Age over Time and IRF Horizon.



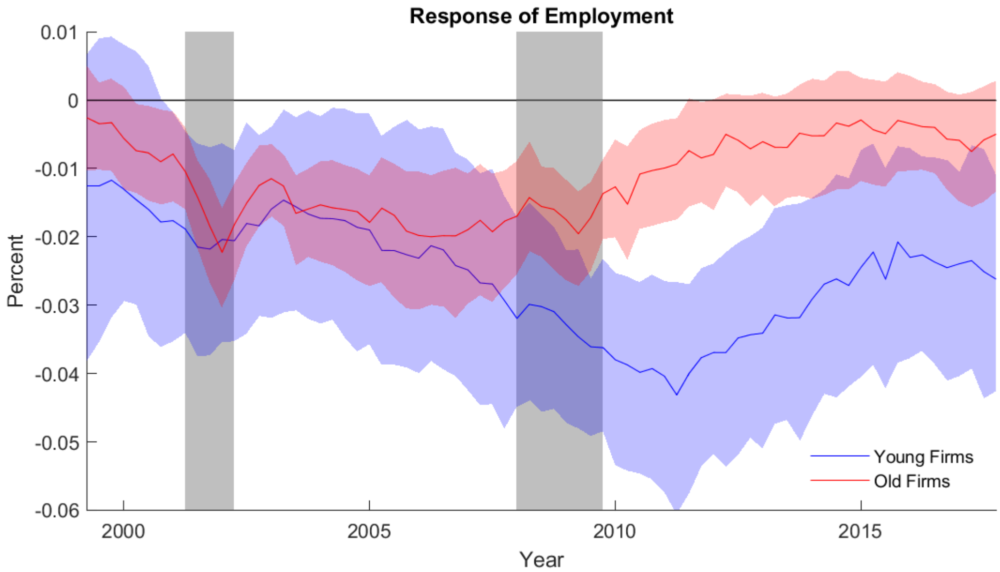
(a) Employment Response over Time and IRF Horizon



(b) Employment Response over Time and IRF Horizon (rotated)

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

Figure 2: Impact of a Credit Supply Shock 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 (old) firms. Gray-shaded areas denote NBER recession periods.

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 documenting that young firms have the highest growth potential (see Haltiwanger, Jarmin, Kulick, and Miranda, 2016, Sedláček and Sterk, 2017, and Sterk et al., 2021). However, the number of young, larger firms is small, making them quantitatively less important.

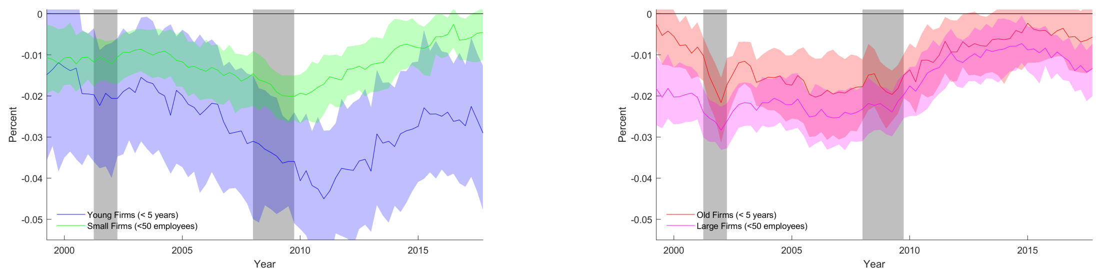
Table 2: Share in Overall Job Creation by Age and Size

	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
Old 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 young firms' short credit history is a noisy signal. 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

Figure 3: Impact of a Credit Supply Shock on Employment by Firm Size vs. Age over Time



(a) Young vs. Small

(b) Large vs. Old

Notes: Cross-section of GIRFs 6 quarters after the shock. The solid(dashed) line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), dotted lines are 16-th and 84-th percentiles. Grey shaded areas denote NBER recession periods.

rejected reported that the reason given for the rejection was that their firm was too young.[21]

TVP-VAR Evidence: Figure 3 compares the employment effects of credit crunches of young firms to those of small firms (left panel) and the effects of large firms to those of old firms (right panel).[22] The employment response of young firms turns significantly stronger compared to small firms during and after the GFC. This result further confirms that firm age rather than its size (measured in number of employees) matters for the effect of a credit tightening shock on firms' employment. 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).

3.3 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 old firms separately.[23] For this reason, I estimate the following empirical model

$$Y_t = [log(\text{unemp}_t)\ \ \Delta\text{GDP}_t\ \ \text{INT}_t\ \ \text{EBP}_t].$$

where $unemp_t$ is the unemployment rate (in percent) and ΔGDP_t denotes GDP growth.[24] The estimation period stretches from 1980Q3 to 2019Q2.[25]

[21] 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.

[22] I define a large firm as employing 50 people or more. However, the results depicted in Figure 3 also holds for different thresholds of "small" and "large" firms (up to 20 and up to 250 employees respectively).

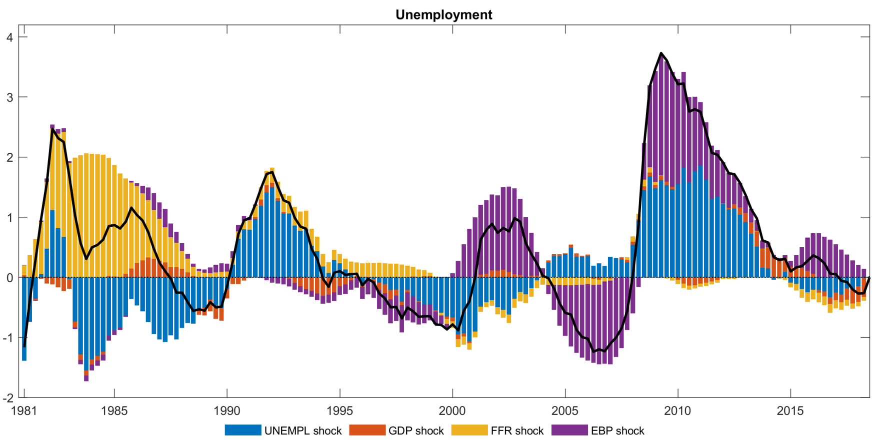
[23] The Quarterly Workforce Indicator is available from 1993 onward only and data from the Business Dynamics Statistics is in annual frequency.

[24] 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.

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

Historical Decomposition: Figure 4 displays the historical contribution of credit supply shocks on unemployment (upper panel) and year-on-year GDP growth (lower panel).[26] 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.

Figure 4: Historical Decomposition of Unemployment and GDP Growth.



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

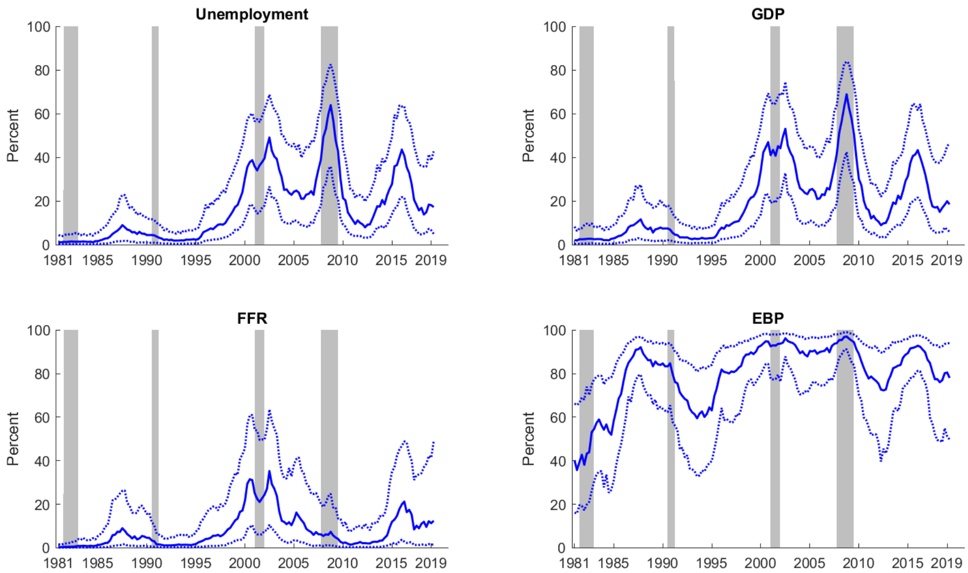
Forecast Error Variance Decomposition: Figure 5 depicts the contribution of credit supply shocks to the forecast error variance of all four endogenous variables six quarters after the shock (solid line) with the sixteenth and eighty-fourth percentiles of the posterior distribution (dashed lines). The 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.

Potential Drivers: What caused the shift in the contribution of economic shocks to unemployment and GDP growth dynamics? 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.[27] The subsequent rise in securitization changed the nature of housing finance. Securitization caused lenders in the mortgage market to lower their bar on down payments and screening practices (Keys, Seru, and Vig, 2012). Between the years

[26] The corresponding impulse responses over time are illustrated in Appendix C.2.

[27] 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 5: 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.

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, Mitman, and Violante, 2020). The next section provides a detailed discussion on the role of house prices in the firm age-related difference in employment dynamics.

4 The Role of House Prices

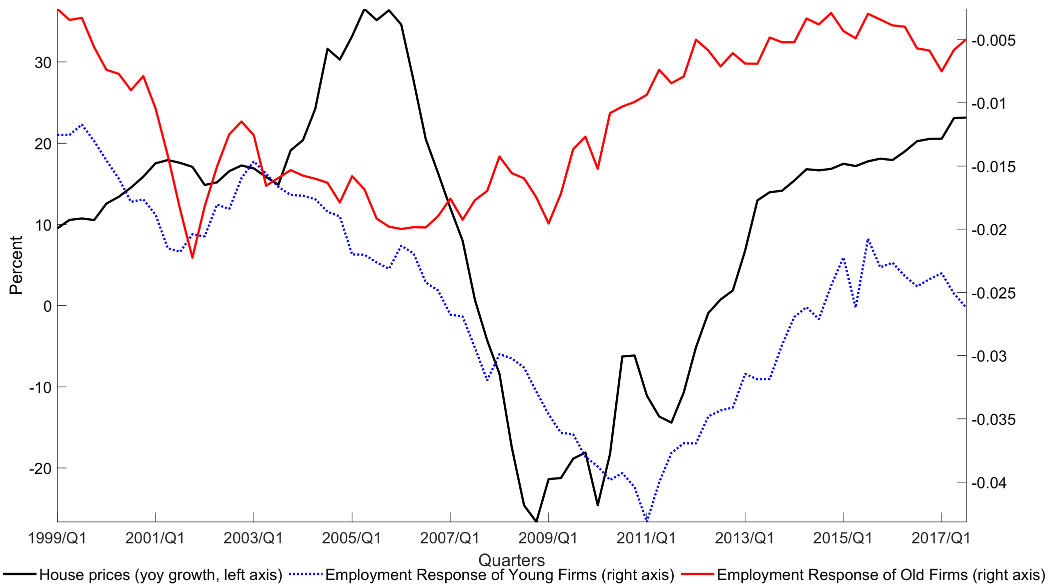
The empirical analysis in Section 3 highlights the divergence in employment by firm age at the onset of the GFC and in response to a credit supply shock. This section investigates the role of house prices in these developments.

Descriptive Evidence: Figure 6 displays year-on-year growth rates for U.S. house prices (left axis) and median employment responses to credit supply shocks for younger and old firms (right axis).[28] 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 old firms remained stable. Only in 2011, when house prices started picking up again, did young firms' employment response get weaker.

House Prices as an Endogenous Variable: As a next step, I investigate employment responses by

[28] The displayed median employment responses correspond to those depicted in Figure 2.

Figure 6: 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).

firm age in the TVP-VAR setting while controlling for house price growth as a fifth endogenous variable in the estimation.[29] The corresponding employment responses, illustrated in Figure 17 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?[30] A considerable proportion of newly established and young businesses use the homes of their owners as startup capital and collateral for business loans. Using matched employer-employee data for Denmark, Jensen, Leth-Petersen, and Nanda (2022) find that the use of housing collateral allowed high ability individuals with a less-well-established track record to overcome credit constraints and become entrepreneurs. Evidence based on the *"Survey of Business Owners"* illustrated in Table 6 in Appendix C shows that 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

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

[30] 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.

decreased considerably.

Bahaj et al. (2022) emphasizes the role of housing collateral for newly established 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.[31]

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 or even impossible. Given that young businesses are more dependent on external finance than are old 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.[32]

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 7 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.[33] 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 to draw conclusions on causality, they provide 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 (see Favara and Imbs, 2015 for causal evidence). 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 increased importance of financial market shocks in my historical decomposition (see Figure 4). 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 young businesses to respond significantly more markedly to financial market shocks compared to old ones. The theoretical model outlined in Section 5 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.

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

[32] 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.

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

5 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 old 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 young and old firms. Let us assume that each age cohort $j \in (E, 1, \cdots, K, O)$ consists of a continuum of firms i. Each period, every age cohort pools their earnings, which enables aggregation for each cohort.[34] Except for the entrants (newly established businesses), every age cohort has two financing channels, debt and equity financing. Equity financing refers to paying out dividends to households, or, if dividends are negative, raising equity. 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.[35] 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.[36] The final goods producer rents capital from firms and hires labor. 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 firms. 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, firms 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

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

[35] 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 $E(\omega) = 1$.

[36] 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).

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 firm. The cohort-specific final goods producer rents capital from firms 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. Output 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 firms die exogenously.[37] 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.

5.1 The Financial Intermediary

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

$$B_t = (1-r_t)D_t, \tag{5.1}$$

where r_t is an AR(1)-shock process

$$r_t = \rho^r r_{t-1} + (1-\rho^r)r_{SS} + \epsilon_t^r, \tag{5.2}$$

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 a firm 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

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

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 that goes to lenders net of monitoring costs can be expressed as

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

thus, $1 - \Gamma(\bar{\omega}_t^{i,j})$ 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 repayment on a loan $Z_t^{i,j} B_t^{i,j}$ must equal the expected revenue of a firm's risky operation $R_{t+1}^{k,j} Q_t^{i,j} K_t^{i,j}$ at the cutoff $\bar{\omega}_{t+1}^{i,j}$.[38] Firms' expected gross return for holding one unit of capital is given by

$$R_t^{k,j} = \frac{r_t^{k,j} + (1-\delta)Q_t^j}{Q_{t-1}^j}, \tag{5.3}$$

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

$$\bar{\omega}_{t+1}^{i,j} = \frac{Z_t^{i,j} B_t^{i,j}}{R_{t+1}^{k,j} Q_t^{i,j} K_t^{i,j}}. \tag{5.4}$$

The firm repays the lender the amount $\bar{\omega}_{t+1}^{i,j} R_{t+1}^{k,j} Q_t^{i,j} K_t^{i,j}$.
In the case that

$$\omega_{t+1}^{i,j} > \bar{\omega}_{t+1}^{i,j},$$

the firm keeps the remaining profit

$$(\omega_{t+1}^{i,j} - \bar{\omega}_{t+1}^{i,j}) R_{t+1}^{k,j} Q_t^{i,j} K_t^{i,j}.$$

If

$$\omega_{t+1}^{i,j} < \bar{\omega}_{t+1}^{i,j},$$

the financial intermediary pays monitoring costs and seizes the remainder of the firms' net worth

$$(1-\mu)\omega_{t+1}^{i,j} R_{t+1}^{k,j} Q_t^{i,j} K_t^{i,j}.$$

In this case, the firm declares bankruptcy and receives nothing.
After dropping the superscript i for notational convenience, the lender's participation constraint

[38] 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.

can be written as

$$\underbrace{[\Gamma^j(\bar{\omega}^j_{t+1}) - \mu^j G^j(\bar{\omega}^j_{t+1})] R^{K,j}_{t+1} Q^j_t K^j_t}_{\substack{\text{Loan repayment by non-defaulting firms \& recovery value} \\ \text{of defaulting firms net of monitoring costs}}} = \underbrace{R^n_t \frac{B^j_t}{(1-r_t)}}_{\text{Riskless return on deposits}} \tag{5.5}$$

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.[39] 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 5.1 holds.
Total monitoring costs per cohort of firms are given by

$$\mathrm{m}^j_t = \mu^j \int_0^{\bar{\omega}^j_{t+1}} \omega dF(\omega) R^{k,j}_{t+1} Q^j_t K^j_t. \tag{5.6}$$

5.2 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.[40] The return per unit of capital is given by the realization of idiosyncratic productivity multiplied by the 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.[41] 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 follows:

$$Q^E_t K^E_t = B^E_t + N^{ST}. \tag{5.7}$$

[39] 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.
[40] 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 firms *within* the cohort irrelevant.
[41] 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 5.3.

Aggregating over the entire entrant cohort, their maximization problem can be rewritten

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

subject to the participation constraint of lenders (equation 5.5) and the balance sheet constraint (equation 5.7).[42] The end-of-period net worth of age cohort E amounts to the profit of those firms that do not go bankrupt or do not exit the market exogenously.

$$N_t^E = \mathrm{nw}_t^E \gamma^E (1-\Gamma(\bar{\omega}_t^E))R_t^{k,E}Q_{t-1}^E K_{t-1}^E, \tag{5.8}$$

where nw^E is an AR(1) shock to net worth defined in equation 5.12. 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 its net worth as given and requires the loan amount B_t^j to finance her capital purchases $Q_t^j K_t^j$. This results in the following balance sheet identities:

$$B_t^j = \begin{cases} Q_t^j K_t^j - N_t^E & \text{if } j=1 \\ Q_t^j K_t^j - N^{j-1} & \text{if } j \in (2,\cdots,K) \\ Q_t^j K_t^j - N_t^j & \text{if } j=O. \end{cases} \tag{5.9}$$

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:

$$\varphi(d_t^j) = d_t^j + \kappa^d (d_t^j - d_{SS}^j)^2, \tag{5.10}$$

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 5.5), the balance sheet constraints (equation 5.9), and the flow-of-funds constraint, which equates this period's outflows to its in-

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

flows for $k \in (1, \cdots, K)$:

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

where for cohort 1, $k-1$ denotes the entrant cohort and for the old cohort $j = O$:

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

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. N_{t-1}^K denotes the net worth of firm cohort K that enters the pool of old firms.[43]

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.

$$N_t^k = \mathrm{nw}_t^k \gamma^k (1-\Gamma(\bar{\omega}_t^k)) R_t^{k,k} Q_{t-1}^k K_{t-1}^k - \varphi(d_t^k), \tag{5.11}$$

where nw_t^k denotes a shock to the net worth of age cohort k (which is identical for all young firms). The shock process is defined as

$$\mathrm{nw}_t^k = \rho^{nw} \mathrm{nw}_t^k + (1-\rho^{nw}) \mathrm{nw}_{ss}^k + \epsilon_t^{nw}, \tag{5.12}$$

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 old firms' beginning-of-period net worth consists of the net worth of previously old, 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):

$$N_{t+1}^O = \gamma^o (1-\Gamma(\bar{\omega}_{t+1}^O)) R_{t+1}^{k,O} Q_t^O K_t^O + N_t^K - \varphi(d_t^O). \tag{5.13}$$

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 4).

5.3 Endogenous Entry and Age Dynamics

Potential entrants are identical and are subject to an idiosyncratic entry cost shock ϵ^E, which is drawn from an entry cost distribution with stable density $f(\epsilon^E)$ and cumulative density $F(\epsilon^E)$. Potential entrants are forward-looking and enter the market if the value of a firm after entry at the

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

idiosyncratic productivity cutoff of the entry cohort ($\bar{V}_t^E$) is at least as high as the entry costs.[44] The entry firm value is given by the share of earnings remaining in the entrant cohort (after payment of monitoring costs to the bank) at the idiosyncratic productivity cutoff:

$$\bar{V}_t^E = \left(1-\Gamma(\bar{\omega}_{t+1}^E)\right) R_{t+1}^{k,E} Q_t^E K_t^E. \tag{5.14}$$

This results in the free entry condition

$$\tilde{V}_t^E = \bar{\epsilon}_t^e, \tag{5.15}$$

where $\bar{\epsilon}_t^e$ denotes the cutoff entry costs (corresponding to the value of an entrant). Potential entrants, who draw idiosyncratic entry costs up to the firm value of the entering cohort will enter the market. This determines the number of entering firms, θ_t^E.

$$\theta_t^E = \int_{-\infty}^{\bar{\epsilon}_t^E} f(\epsilon^E)\, d\epsilon^E \; \forall d. \tag{5.16}$$

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

$$\theta_t^1 = \gamma^E \theta_{t-1}^E \tag{5.17}$$

$$\theta_t^k = \gamma^E \theta_{t-1}^{k-1} \tag{5.18}$$

$$\theta_t^O = \gamma^O \theta_{t-1}^O + \gamma^K \theta_{t-1}^K \tag{5.19}$$

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 firms 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

$$\theta_t = \sum_{j=E}^{O} \theta_t^j. \tag{5.20}$$

5.4 Aggregates and Closing the Model

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

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

[44] Note that as the realization of the idiosyncratic productivity cutoff is private information to the firms, the entry costs include costs to observe the productivity realization

with $j \in (E, 1, \cdots, K, O)$. Monitoring costs and the consumption of exiting firms are weighted by the size of the corresponding age cohort:

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

The aggregate economy-wide resource constraint holds:

$$Y_t = C_t + I_t + \mathrm{m}_t + C_t^e. \tag{5.21}$$

6 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 3 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 (semi-annual frequency) and the weight of capital in the production function α^j to 0.33. Productivity is normalized to 1 in steady state. The Frisch elasticity of labor supply $\eta^{L,j}$ is 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 $r = 0.2$.

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 parame-

Table 3: Calibration and Targets

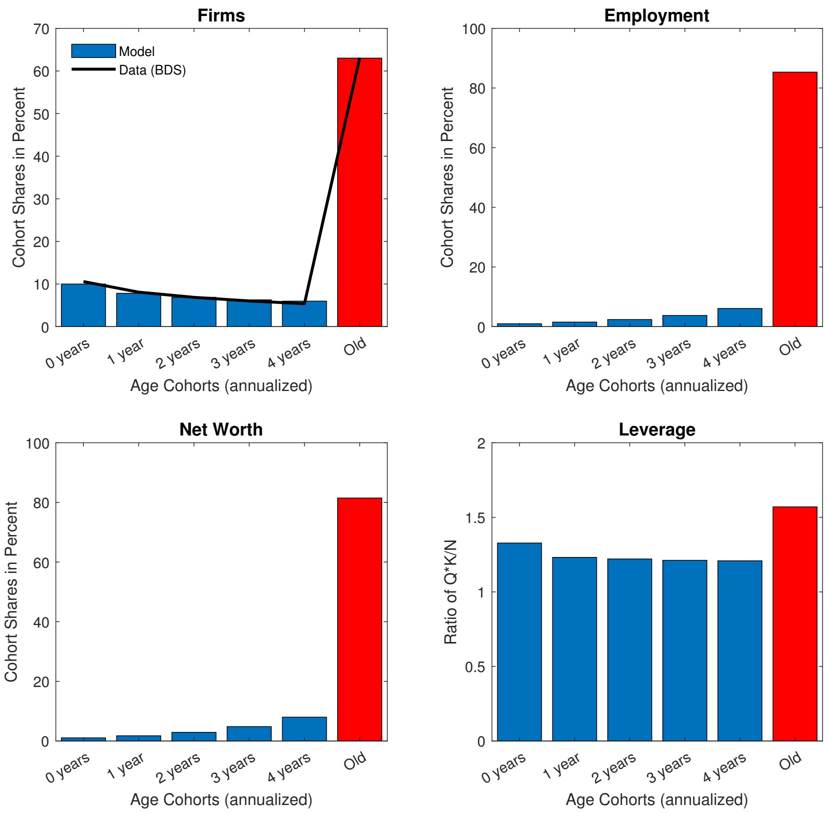
	Parameter name	Symbol	Value
Preferences and Production			
	Discount factor	β	0.985
	Risk aversion	σ_c	2.00
	Capital depreciation	δ	0.05
	Weight on capital in production	α	0.33
	Productivity (SS)	a_t^j	1.00
	Frisch elasticity of labor supply	η	2
Financial Frictions and Policy			
	Monitoring costs in case 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
	Elasticity of price of capital w.r.t investment rate	η^i	0.25
	Wage adjustment cost parameter	κ^W	61.36
	Dividend adjustment cost parameter	κ^d	0.15
Entry & Survival Rates			
	Scale parameter of entry cost distribution	σ^{ent}	3.71
	Location parameter of entry cost distribution	μ^{ent}	0
	Survival rate: Entrants	γ^E	0.855
	Survival rate: "Old" cohort	γ^O	0.954
Shocks			
	Autocorrelation of credit supply shock process	ρ^r	0.90
	Autocorrelation of net worth shock process	ρ^{nw}	0.90

ter 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). I assume that the idiosyncratic entry cost shocks follow a lognormal distribution. I set the scale parameter of the distribution to target a unit measure of firms in the economy with a share of entrants of 5.39% in steady state, which is consistent with BDS data.[45] Further, I target the average pre-crisis proportion of young and old 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 firms, the entering cohort ($\gamma^E = 0.855$) and the "old" cohort ($\gamma^O = 0.954$). The remaining survival rates arise endogenously in steady state and increase 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.[46] Regarding the shocks, I set the autocorrelation of both the credit supply and the net worth shock processes to 0.9. The model is solved under perfect foresight with a non-linear solution algorithm.

[45] I fix the location parameter of the distribution at 0.

[46] 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.

Figure 7: 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.

6.1 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 7 depict the model's 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).[47] This is consistent with a higher probability of exit for young firms and mimics the "up-or-out dynamics" documented in Haltiwanger et al. (2013).

Figure 7 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 old firms, as given by the model, amounts to 85.5%, which is close to the 85.2% proportion accounted for by old 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.

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

The lower right-hand panel of Figure 7 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.[48] Put differently, by the participation constraint of lenders (see Equation 5.5), the bank is willing to offer a higher amount of debt for a given idiosyncratic productivity cutoff and net worth. This outcome is broadly consistent with Dinlersoz et al. (2018), who document that publicly listed firms are highly leveraged as they grow older.

7 Simulation Results

This section presents the main theoretical results of the paper: the effects of a credit crunch and a shock to collateralizable assets (young firms' net worth) by firm age. First, I discuss the effects of a credit crunch and investigate whether the relative reaction of young vs. old firms' employment response is consistent with empirical evidence presented in Section 3. Second, I investigate whether an additional shock to young firms' collateralizable assets (i.e. housing net worth) can reconcile the quantitative macro model with the relative employment response by firm age. Furthermore, I use my quantitative model to disentangle the relative importance of both shocks in explaining US unemployment dynamics after the GFC. I study the effect of an unexpected innovation to the financial intermediary's reserve requirements ϵ_t^r and in the second step of the analysis, an unexpected innovation to young firms' net worth ϵ_t^{nw}, followed by a perfect foresight transition back to the model's steady state.[49] I choose the size of the credit supply shock (ϵ_t^r) such that the aggregate loan amount declines by 8%, which corresponds to the drop in the loan amount during the GFC. For the size of the housing net worth shock, I target the overall decline in young firms' net worth such that it corresponds to the peak-to-trough decline in U.S. house prices between 2007Q1 and 2012Q4 of 23% (see also Section 6).

7.1 Effects of a Credit Crunch

Figure 8 depicts responses to a contractionary credit supply shock for three age cohorts: a one-year-old firm (Y_1, depicted by the dotted green line), a three-year-old firm cohort (Y_5, depicted by the dashed blue line), and the old firm cohort (Y_O, depicted by the solid red line).

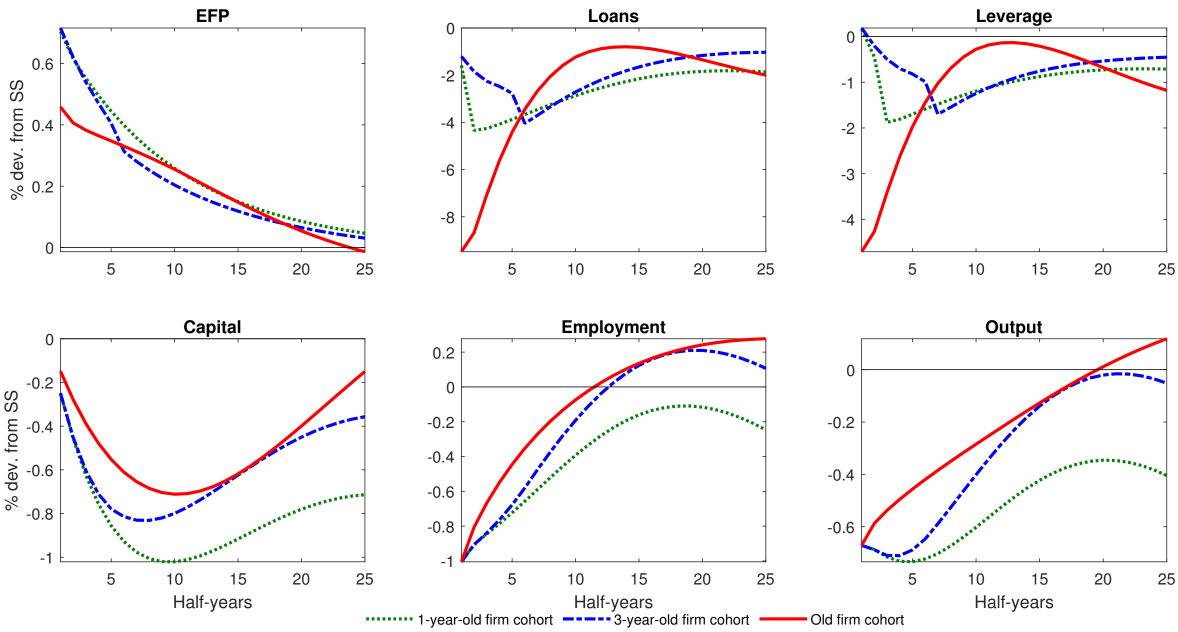
Young firms face a stronger increase in their external finance premium compared to old firms. This makes borrowing for them costlier and they reduce the loan amount. Old firms substitute between debt and equity financing in response to the credit contraction and, thus, reduce the amount borrowed more compared to young firms.[50] For an old firm, raising equity is relatively

[48] 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.

[49] As a result, there is no distinction between the ex-ante expected real interest rate and the ex-post realized interest rate (see Ottonello and Winberry, 2020).

[50] This is consistent with empirical evidence by Begenau and Salomao (2018) who document that in recessions, large firms (which tend to be old) restructure their capital portfolio towards more equity and less debt, whereas small (young) firms adapt their capital structure pro-cyclically.

Figure 8: Responses to a Credit Supply Shock: Young vs Old Firms



Notes: Responses to a contractionary credit supply shock. The solid red line depicts the response of an old firm. The dotted green line denotes the response of a one-year-old firm (cohort $K = 1$), the dashed blue line illustrates the response of a three-year-old firm (cohort $K = 5$).

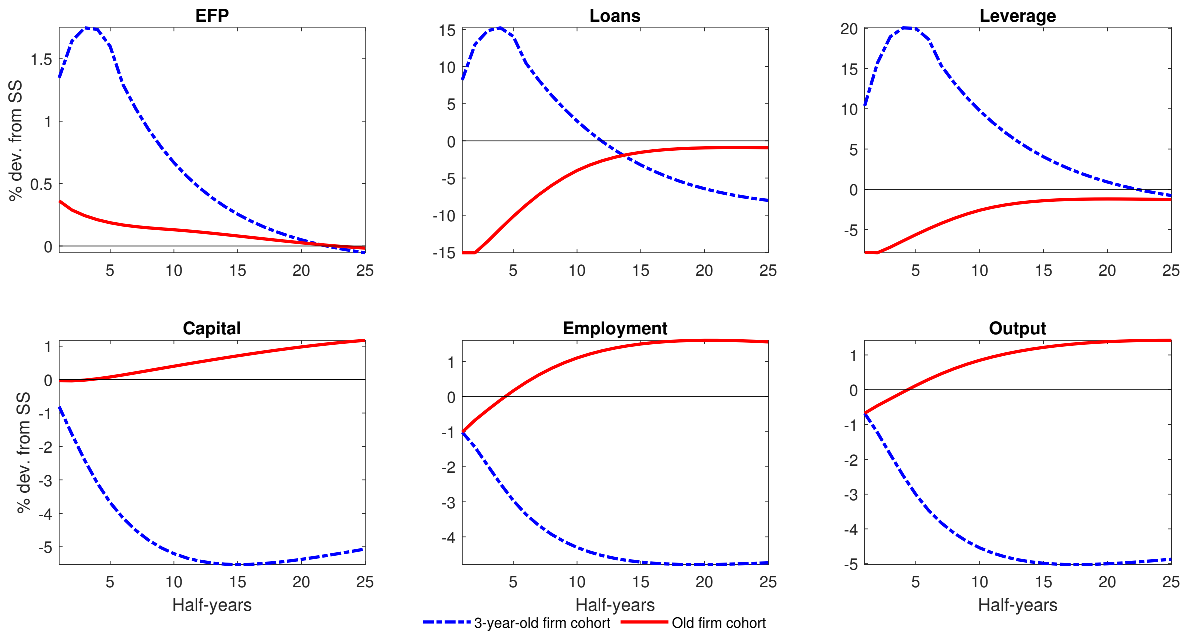
less costly compared to a young firm.[51] Thus, as old firms raise equity from households, their leverage decreases strongly, but they face a less pronounced decrease in the demand for capital. All age cohorts decrease their demand for capital and labor in response to the credit crunch, however, effects are heterogeneous across cohorts: the younger the firm, the stronger is the decline in capital, employment, and output. Although old firms have a higher debt-to-net worth ratio in steady state, it is the younger ones that are more financially constrained and, therefore, reduce economic activity stronger because old firms reshuffle their capital structure towards less debt and more equity.

Can the credit supply shock in the quantitative model explain the more marked employment response of young vs. old firms that I documented empirically in Section 3? Table 4 compares the relative employment responses of a young firm vs. an old firm from my structural TVP-VAR model (first row), which is based on the median impulse responses depicted in Figure 2 to the relative employment reaction of young vs. old firms' based on my quantitative theoretical model (second row).[52] The theoretical model matches the relative employment reaction quite well for the period prior to the GFC (2006/Q2). However, the credit contraction alone is unable to explain the more marked response of young firms during and after the GFC. Thus, the quantitative model is unable to explain the relative employment reactions by firm age solely with a credit crunch. In the next subsection, I investigate whether an additional decline in the value of collateralizable assets helps to reconcile the empirical employment responses with the theoretical ones.

[51] This arises due to the underlying dividend/equity payout-cost function, where in steady state old firms pay out a higher level of dividends d^O than younger firms, where d^k for $k = 1, \ldots, K$ at approximately zero.

[52] I compute the average response of a young firm by weighting all employment responses of young firms by their cohort shares.

Figure 9: 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 dotted magenta line denotes the response of a one-year-old firm (cohort $K = 1$), the dashed blue line illustrates the response of a three-year-old firm (cohort $K = 5$).

7.2 The Role of Collateralizable Assets for Young Firms

Figure 9 depicts the results of a simultaneous credit crunch and a decline in young firms' collateralizable assets, which I model as a shock to their net worth. I follow Bernanke and Gertler (1989) in their interpretation of net worth as collateralizable assets, which are mainly tangible assets (such as buildings and land). As this interpretation holds only for young firms, old firms are not directly affected by the net worth shock.[53]

In a manner consistent with the empirical evidence during and after the GFC detailed in Section 3, employment responses diverge more marked between young and old firms after a similar initial drop in employment. This divergence is even more marked for capital. The reason is that the decline in net worth makes young firms more leveraged (as they rely heavily on debt financing), which increases the cost of additional borrowing and causes the age-specific idiosyncratic productivity cut-off to rise. From the lender's perspective, they become riskier. Thus, the financial intermediary demands a higher loan rate as compensation for the increased default risk. This drives up the spread of young firms and causes a strong decline in their demand for capital. 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 "old" cohort. On the contrary, old firms raise equity from households, which increases their net worth and makes them less leveraged, resulting in a lower idiosyncratic productivity cut-off and bankruptcy rate. As soon as old firms have raised enough equity, their labor demand recovers quickly from the shock.

The second column of Table 4 reports the relative employment reactions by firm age after the

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

Table 4: Empirical IRFs vs. Theoretical IRFs: Long-run employment effects, Young/Old Firms

	Employment Response of Young/Old Firm	
TVP-VAR Model	**2006/Q2**	**2014/Q3**
	1.30	4.34
Theoretical Model	**Credit Crunch**	**Housing Net Worth Shock**
	1.24	4.43

Notes: The upper part of the table illustrate the relative employment reactions of a young vs. an old firm 10 periods after the impact of the credit supply shock from the TVP-VAR model in the periods 2008/Q1 and 2012/Q1. The lower part of the table depicts the corresponding relative employment reactions of a three-year-old firm vs. an old firm 10 periods after the shock in the theoretical model (with a credit crunch, and with a credit crunch and a net worth shock).

GFC in my empirical model compared to the theoretical model with both shocks hitting the model economy. Once the decline in collateralizable assets is accounted for, the more marked relative reactions by age after the GFC can be matched with the relative empirical responses (most closely to those of the year 2014/Q3).

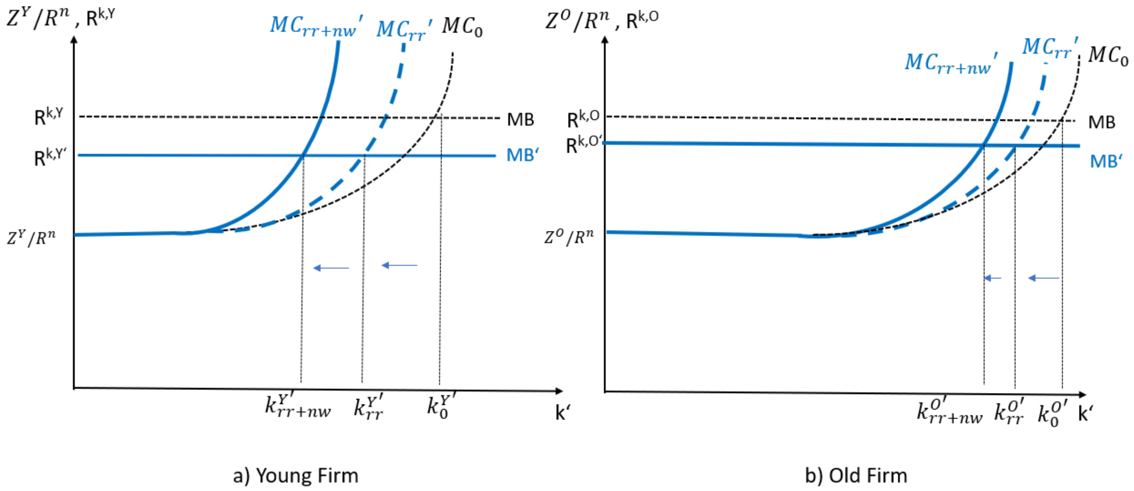
As young firms tend to have low net worth and depend heavily on external finance, a drop in the value of their net worth intensifies asymmetries of information between borrowers and lenders. As a result, young firms face an increase in the external finance premium. However, to finance their operations, they now require a greater amount of loans. Given that the financial intermediary has tightened credit supply and young firms have become riskier (due to the increase in their idiosyncratic productivity cut-off), 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 next subsection inspects the key economic mechanism causing differences by firm age.

7.3 Drivers of Heterogeneous Responses by Firm Age

Figure 10 characterizes the main mechanism driving heterogeneous responses between young and old firms by means of an illustration of firms' marginal cost and marginal benefit schedules as a function of capital accumulation k' for a young firm (left panel) and an old firm (right panel).[54] The marginal benefit of capital (MB) is horizontal (due to constant returns to scale in production within cohorts) at the level of the expected return of capital $R^{k,j}_{t+1}$. As long as the demand for capital can be financed entirely by the firm's net worth, the marginal cost of capital (MC) is horizontal and equal to the risk-free rate R^n. As soon as the demand for capital exceeds the firm's net worth, the marginal cost curve becomes upward-sloping as the financial intermediary demands a compensation for the increase in default risk and, thereby, a higher loan rate Z. The firm's optimal choice of capital is then given by the intersection of the marginal benefit and the marginal cost curve.

[54] A similar illustration can be found in Bernanke et al. (1999) and Ottonello and Winberry (2020).

Figure 10: Inspecting the Mechanism: Young vs. Old Firms



Notes: Responses to a contractionary credit supply shock and net worth shock. Marginal benefit (MB) and marginal cost (MC) curves as a function of next period's capital choice k' for a young firm (left) and an old firm (right). The dashed blue line depicts responses after the credit shock only, the solid blue lines depict the responses after both the credit and the net worth shock.

Differences by firm age arise due to the following reasons: First, the level of net worth: a young firm has lower net worth and requires a higher loan amount to achieve the same level of $k_0^{j,'}$ compared to an old firm. Thus, for a young firm, the marginal cost curve becomes upward-sloping at lower levels of k'. Second, heterogeneous responses of the loan rate Z_t^j in response to shocks: In steady state, all firms are assumed to have the same idiosyncratic productivity cut-off ($\bar{\omega}^j_{t+1}$), which results in an identical spread, and the same slope of the marginal cost curve MC_0. In response to a credit supply shock, both the marginal benefit curve and the marginal cost curve shift.[55] The marginal benefit curve shifts down as the return on capital, $R^{k,j}$, decreases on impact. This decrease is more pronounced for young firms compared to old firms. Furthermore, the default probability and, therefore, the spread (Z^j/R^n) increase on impact making the marginal cost curve steeper (with MC_{rr} denoting the marginal cost curve after the credit crunch shock). Again, the effect is more pronounced for a young firm. The demand for capital declines for each firm cohort j from $k_0^{j,'}$ to $k_{rr}^{j,'}$. Due to the steeper marginal cost curve for young firms, their demand for capital declines by more. The additional decline in the value of young firms' collateralizable assets further increases the steepness of the marginal cost curve to MC_{rr+nw}, which further dampens the demand for capital to $k_{rr+nw}^{j,'}$.

The financial accelerator is at the core of the model's propagation mechanism for the more marked response for young firms. It amplifies the impact for those firms with low net worth (i.e. young firms). Both shocks leads to a rise in the external finance premium (EFP), which slowly returns to its initial steady state.[56] For a young firm, the rise in the EFP is considerably more

[55] For simplicity, I focus here on the immediate reaction, abstracting from dynamic effects caused by general equilibrium forces.

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

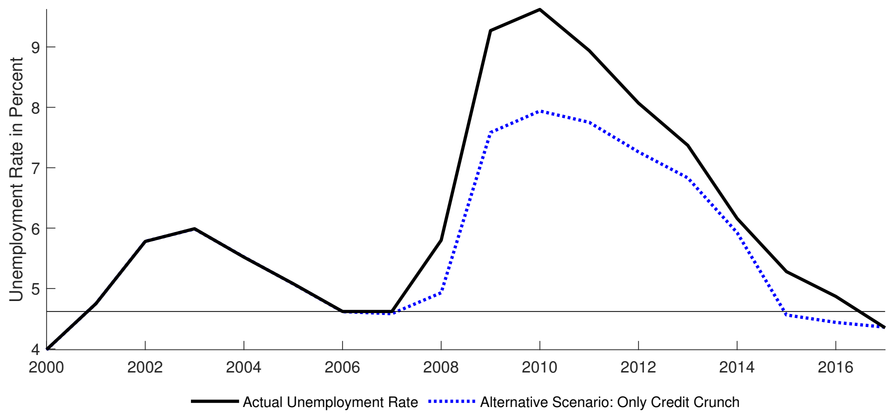
pronounced and more persistent (see Figure 9). A higher EFP further dampens capital demand and depresses net worth. A further reduction in net worth complicates young firms' access to external finance further as banks charge a higher loan rate, reducing the amount borrowed again. The financial accelerator mechanism therefore amplifies the effects of the credit supply and net worth shock heterogeneously among age cohorts.

7.4 The Relative Contribution of Shocks and Alternative Scenarios

How much of the fall in employment can be attributed to the net worth shock? To answer this question, I compute the relative contribution of the net worth shock to the overall decline in young firms' employment (weighted by their size) across the impulse response horizon.[57] After two years (4 model periods), the housing net worth channel amounts to around 50 percent, and more than 90 percent after 10 years (20 model periods).

Given the relative importance of the net worth shock to the decline in employment at young firms, I can decompose the U.S. unemployment rate in increases due to the credit crunch and increases driven by the decline in the value of collateralizable assets.[58] Figure 11 contrasts the development of the actual U.S. unemployment rate (solid black line) with an alternative scenario in which only the credit crunch hit the U.S. 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. At its peak during the GFC, the unemployment rate would have been almost two percentage points lower.

Figure 11: Actual Unemployment Rate and Alternative Scenario (Only Credit Crunch)



Notes: The solid line illustrates the actual U.S. unemployment rate: the dashed blue line depicts the alternative unemployment rate with only the credit supply shock (no shock to young firms' net worth). The horizontal line depicts the pre-crisis unemployment rate.

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

[58] I calculate the absolute annual reduction in employment among young firms caused by 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.

8 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.

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 from local banks.[59] Extending the framework to account for the transmission mechanism via the bank's balance sheet channel would give rise to 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. I leave this for future research.

[59] See Davis and Haltiwanger (2021) for a similar argument.

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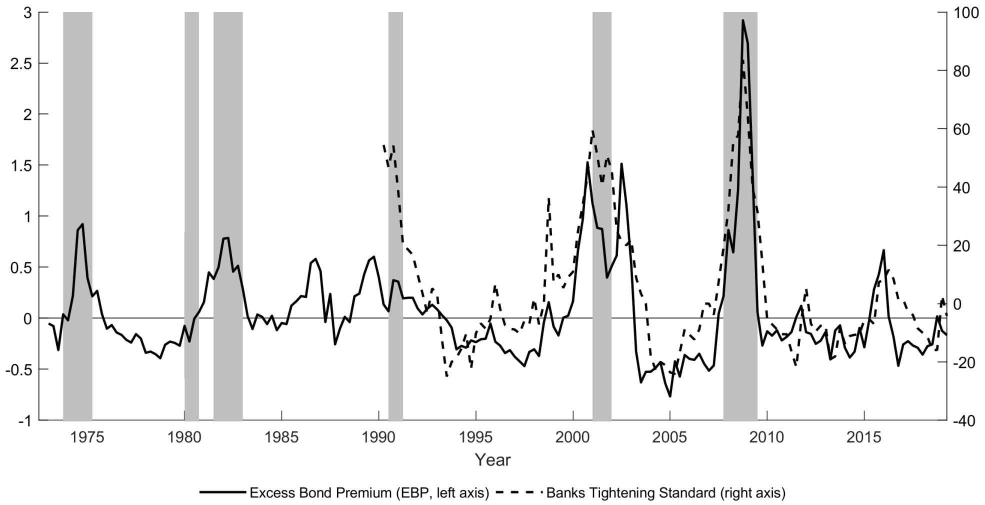
A More Descriptive Evidence

Figure 12: Excess Bond Premium vs. Bank Tightening Standards (Small Firms)



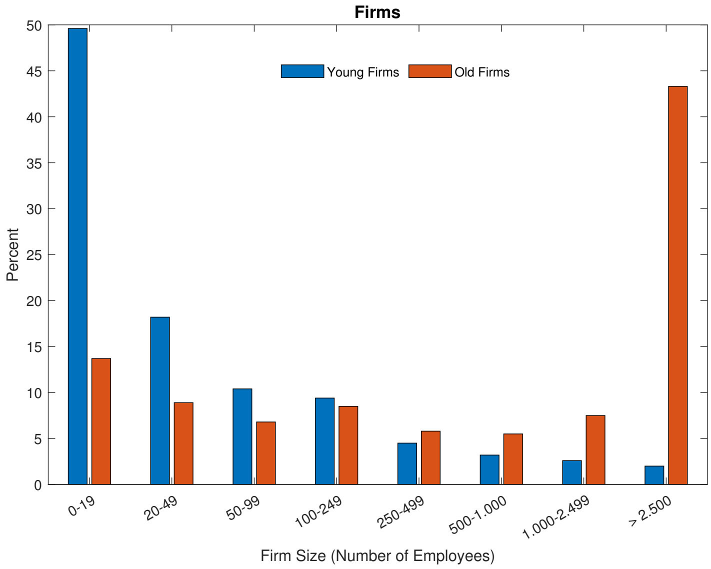
Notes: Excess Bond Premium and Net Percentage of Domestic Banks Tightening Standards for Commercial and Industrial Loans to Small Firms. Data Source: Gilchrist and Zakrajšek (2012) and Board of Governors of the Federal Reserve System (US).

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.

Figure 13: Size Distribution by Firm Age



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

B Details on the Time-varying Parameter VAR

This section describes the priors and estimation algorithm used for the time-varying parameter estimations.[60]

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

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

[60] 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).

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 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.

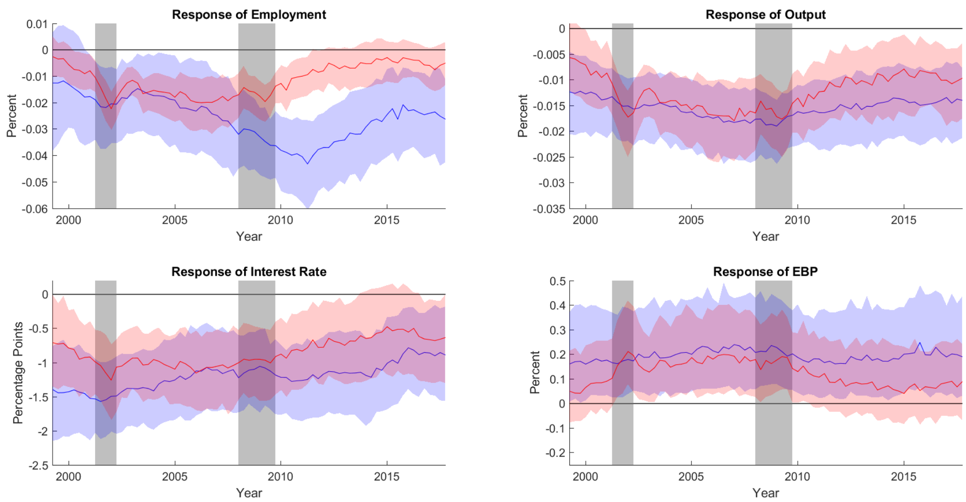
4. **Draw hyperparameters V.**
   The error terms of the transition equations 2.2 - 2.4 are observable given θ^T, A^t, H^T, Y^T. Thus, the hyperparameters Q,S and σ_i^2 can be directly drawn from their respective posterior distributions $p(Q, S, \sigma_i^2|\theta^T, A^T, H^T, Y^T)$.

C Further Empirical Evidence

Figure 14: 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 15: Generalized impulse response functions (GIRFs) in Response to a Credit Supply Shock: 6 Periods after the Shock

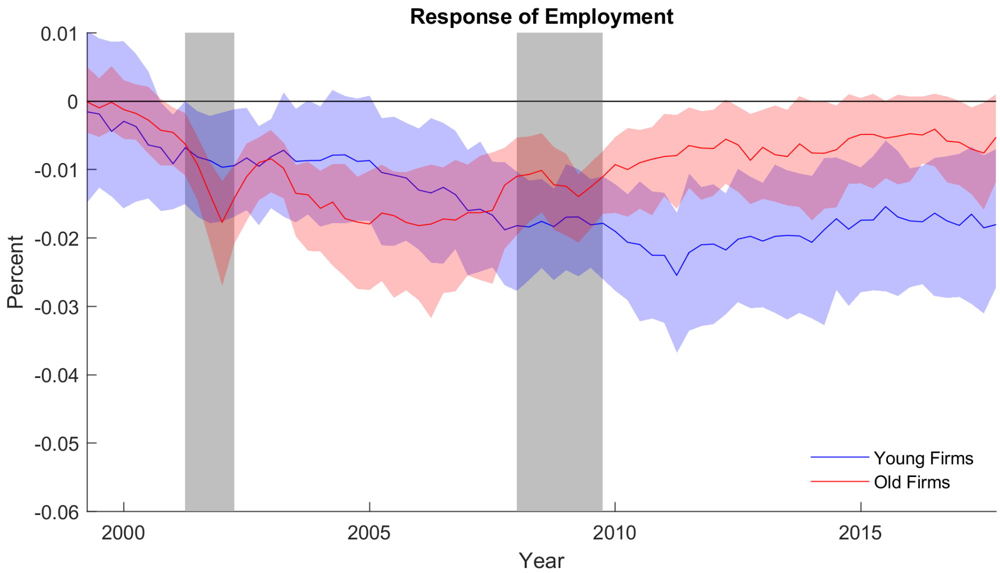


Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior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

Figure 16: 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 17: 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.

Table 6: 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.

C.1 Robustness and Extensions

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

Firm Entry and Exit: To test whether firm dynamics are the drivers of young and old firms' divergent responses to a credit supply shock,[61] I perform the following robustness checks: First, I add the firm birth and firm death rate as fifth endogenous variable to the estimation (see Figure 18 in Appendix A).[62] Second, I check whether it is the youngest age group that are driving these findings, I re-estimate the baseline specification (see Equation 2.5) without the youngest age group (i.e. businesses founded fewer than two years previously). Figure 19a in the Appendix depicts the resulting median employment responses over time. Third, I add the number of jobs destroyed by business exits as a fifth endogenous variable (see Figure 19b).[63] The significantly more marked employment response of young firms holds when performing these robustness checks.

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 commonly available to newly established and young firms. Figure 12 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 old firms I use banks' tightening standards for larger businesses. Figure 20a in Appendix C illustrates the results. The use of banks' tightening standards leads to an even more pronounced difference between young and old firms, with a significantly more marked response among young firms since the early 2000s.

[61] Sterk et al. (2021) document a decline in the establishment of new businesses and identify a link to the jobless recovery in the U.S.

[62] I assume that firm birth/death reacts quicker than GDP, thus, I order the firm birth/death rate third.

[63] 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.

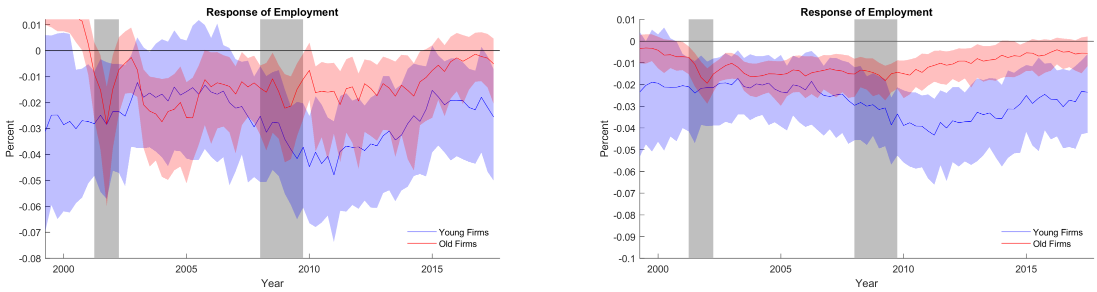
Definition of Young Firms: If I consider a firm established up to ten years previously to be a "young" firm (see panel b of Figure 21a), the divergence in employment responses is less pronounced. Employment levels at young firms up to the age of ten years responds more markedly in recessionary phases, 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.[64] 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 - Sign Restrictions: As an alternative identification scheme for credit supply shocks, I apply sign restrictions. 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 5 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 impose, based on theoretical insights from my model (as discussed in Section 7), a contractionary effect on output, a decline in the interest rate and an increase in the EBP for at least two periods (see Section 2.3 for details).[65] Figure 21 depicts 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.

[64] 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.

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

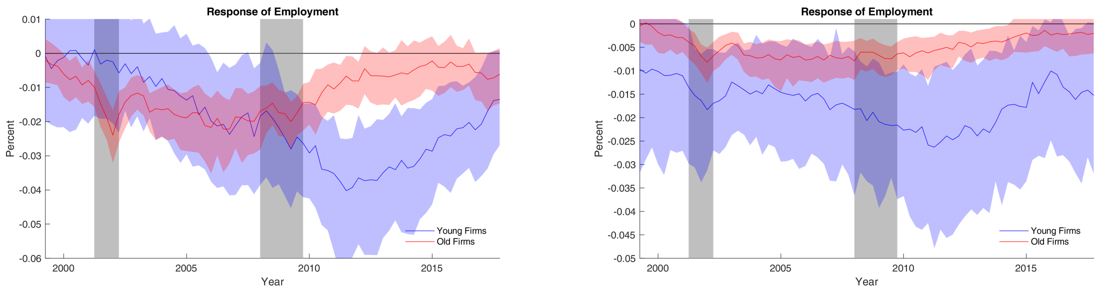
Figure 18: Controlling for Firm Births/Deaths: GIRFs in Response to a Positive Credit Supply Shock



(a) Controlling for Firm Births **(b)** Controlling for Firm Deaths

Notes: Right (Left) Panel: GIRFs based on two five-variable TVP-VAR estimation of $Y_t = [log(EMP_t^j)\ log(GDP_t)\ log(firm\_birth/death\_rate_t)\ FFR_t\ EBP_t]$ where $firm\_birth\_rate_t$ and $firm\_death\_rate_t$ denote the share of newly established (exiting) firms out of all firms respectively. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

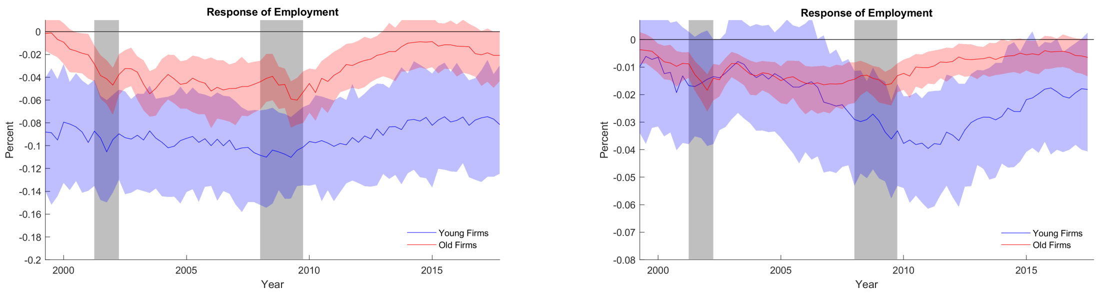
Figure 19: Controlling for Firm Dynamics II: GIRFs in Response to a Positive Credit Supply Shock



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

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

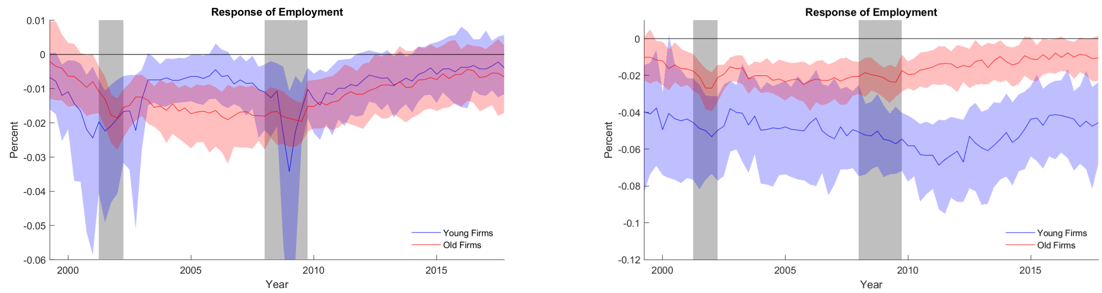
Figure 20: Robustness: Banks Tightening Standards (LHS) and Economic Uncertainty (RHS).



(a) Banks Tightening Standards **(b)** Controlling for Economic Uncertainty

Notes: LHS: GIRFs based on two four-variable TVP-VAR estimations replacing the EBP with banks tightening standards: $Y_t = [log(EMP_t^j)\ log(GDP_t)\ FFR_t\ BL_t^i]$ where 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: GIRFs based on two five-variable TVP-VAR estimations including an equity market-related economic uncertainty index as in Baker, Bloom, and Davis (2016): $Y_t = [log(EMP_t^j)\ log(GDP_t)\ UC_t\ FFR_t\ BL_t^i]$ where UC_t denotes the economic uncertainty index. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

Figure 21: Robustness: A Broader Definition of Young Firms ($\leq$ 10 years) and Sign Restrictions.

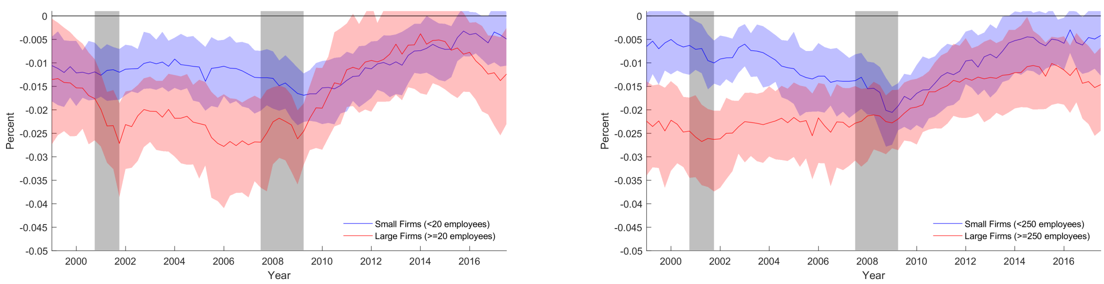


(a) Definition Young Firm: up to 10 Years

(b) Identification: Sign Restrictions

Notes: GIRFs of Employment in response to a positive credit supply shock after 6 quarters. LHS: The age cutoff in the definition between young and old firms is at the age of 10 years (young $\leq$ 10). RHS: GIRFs of Employment in response to a positive credit supply shock using sign restrictions instead of a Cholesky identification. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

Figure 22: 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.

C.2 Historical View: Impulse Responses over Time

The left-hand panel of Figure 23 depicts the GIRFs of a credit supply contraction on employment 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. Considering the cross-section of all unemployment responses since 1980 six quarters after the shock for each period (right-hand panel of Figure 23), we observe that the employment response intensified over time, peaking after the Great Financial Crisis. The difference over time therefore does not stem from stronger reactions in recessions compared to expansions, but from an overall trend of a stronger and more persistent employment reaction over time.

D Cross-regional Estimation on MSA-level

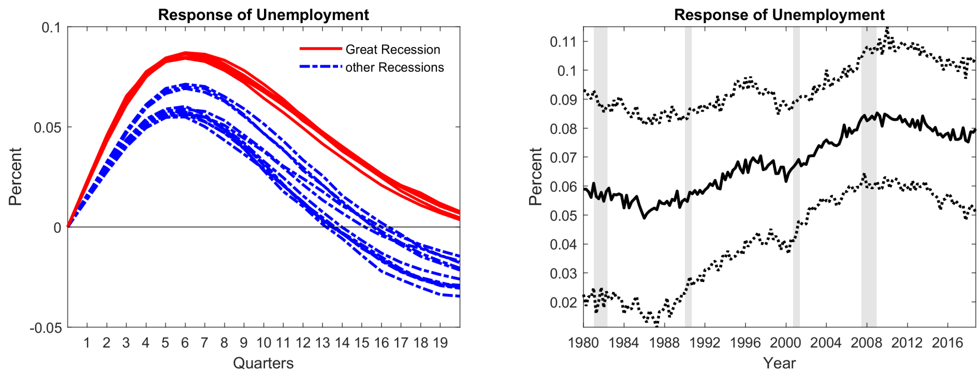
To perform cross-regional estimations, I build a MSA-level dataset including job creation of young firms from the BDS, data on small business loans from the Community Reinvestment Act (CRA), and the US house price index.[66]
I estimate the following long-difference equation

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

The dependent variable $\Delta JC_{m,07-09}$ is the percentage change in young firms' MSA-level job creation from 2007 to 2009. $\Delta Log(HP)_{m,06-09}$ denotes MSA-level house price changes between the years 2006 and 2009 and $\Delta\text{Loan amount}_{m,06-09}$ is the change in the *total loan amount* of loans to small businesses, $X_{m,06}$ denotes MSA-level controls of the year 2006.[67] 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 7. 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 ap-

[66] Table 9 in Appendix D gives an overview of the data sources.
[67] Small businesses are businesses with gross annual revenues < $ USD 1 million in the relevant time span.

Figure 23: 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 employment 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.

proach 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. (2022) who find that employment of young, highly levered firms is more sensitive to monetary policy.

Table 7: 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

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

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

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

$$\begin{aligned}
d^j_t &: \lambda^{FC,j}_t = \frac{1}{\left(1 + 2\kappa^d (d^j_t - d^j_{SS})\right)} \\
\bar{\omega}^j_{t+1} &: -\lambda^{FC,j}_{t+1} \Gamma'\left(\bar{\omega}^j_{t+1}\right) = \lambda^{PC,j}_t \left[\Gamma'(\bar{\omega}^j_{t+1}) - \mu^j G'^j(\bar{\omega}^j_{t+1})\right] \\
K^j_t &: \lambda^{PC,j}_t \left[\Gamma(\bar{\omega}^j_{t+1}) - \mu^j G(\bar{\omega}^j_{t+1})\right] = \lambda^{PC,j}_t \frac{R^n_t}{(1-r_t)} + \lambda^{FC,j}_{t+1} \gamma^j \left[1 - \Gamma'(\bar{\omega}^j_{t+1})\right],
\end{aligned}$$

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

$$C_t + D_t + s_t p_t + N^{ST} = w_t L_t + R^n_{t-1} D_{t-1} + s_{t-1}(d_t + p_t) + C^e_t. \tag{E.1}$$

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:

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

Note that the last condition for the equity shares can be 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.[68] 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

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

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

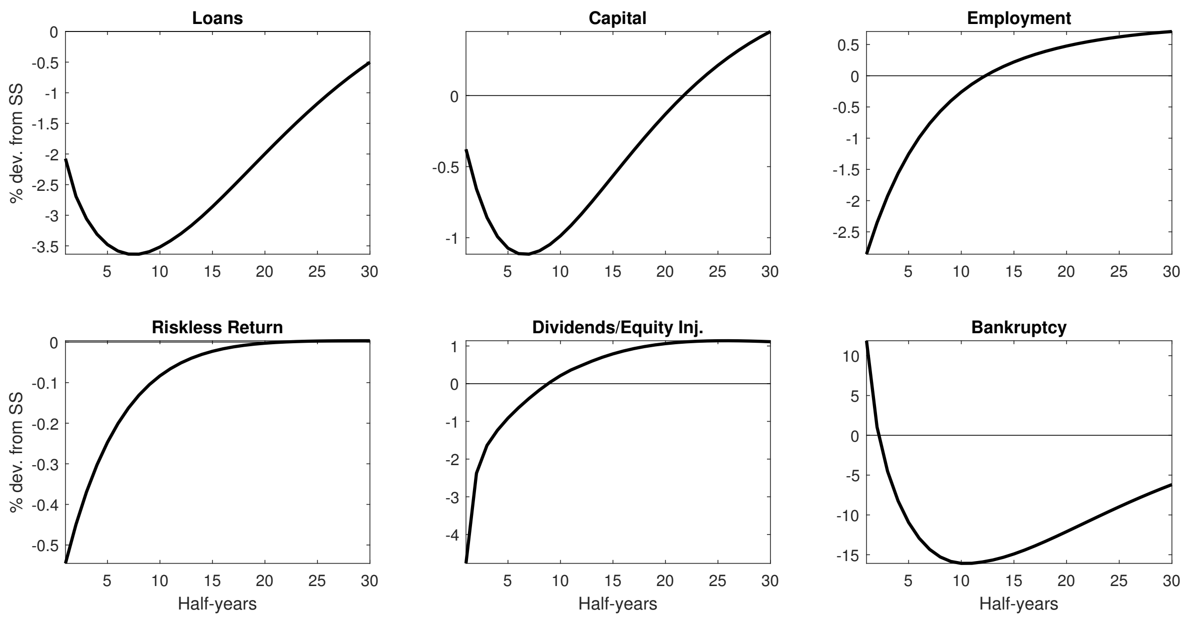
$$r_t^k = \alpha\frac{Y_t^j}{\tilde{K}_t^j}. \tag{E.7}$$

F Further Simulation Results

F.1 Aggregate Effects of a Credit Crunch

Figure 24 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 firms 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 24: Responses to a Credit Supply Shock: Aggregate Effects



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

G Data Sources

Table 8: 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 9: 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