Financial Constraints, Firm Age, and the Labor Market[†]

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Abstract

I document the heterogeneous effects of credit crunches on the labor market by firm age and over time. 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' collateralizable housing assets, which restricted their borrowing capacity. To disentangle the relative contribution of the credit supply and net worth channels, 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 shift 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.

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

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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 within the last five years are significant drivers of employment dynamics in the United States, accounting for nearly 14% of total employment and 85% of total net job creation in 2006. The share of young firms in the overall decline in employment and net job creation during and after the Great Financial Crisis (GFC) 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 lower net worth compared to older businesses.[1] At the same time, young firms have high growth potential and require external finance to expand (see Sterk, Sedláček, and Pugsley, 2021, Sedláček and Sterk, 2017, Haltiwanger, Jarmin, and Miranda, 2013). In this context, the paper assesses the extent to which young firms are impeded from creating jobs due to financial constraints, and the resulting implications for aggregate outcomes.

To this end, I use a structural time-varying framework and develop a heterogeneous firm model with financial frictions to analyze how young and old firms respond to credit crunches over time. My empirical work documents that 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 to obtain a business loan, 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.

My paper makes two contributions to the understanding of the effects of credit crunches on firms' employment decisions: First, I demonstrate that employment effects caused by credit crunches vary over time and differ depending on firm age. Second, I present a theoretical model that disentangles the contribution of credit supply and net worth channels. The interaction of both can explain the stronger employment response of young firms after the Great Financial Crisis. Without the decline in young business owners' housing net worth, the U.S. unemployment rate would have been almost two percentage points lower during the GFC. These findings highlight the significant role of young firms in amplifying and propagating macroeconomic shocks.

I use a structural time-varying parameter vector autoregression (TVP-VAR) model with stochastic volatility to estimate the age-specific employment responses to shocks to credit supply. This approach complements existing empirical work by capturing both time-varying and age-specific effects, which are often ignored by studies that focus on either the microeconomic perspective[2] or on time-invariant effects of credit crunches.[3] Additionally, this methodology is particularly useful

[1] See survey evidence based on the *"Kauffman Firm Survey"* in Table 6 of Appendix C.

[2] See Chodorow-Reich, 2014, Chodorow-Reich and Falato, 2022, Gilchrist, Siemer, and Zakrajsek, 2018, and Siemer, 2019.

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

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	13.5%	31.7%	18.6%	84.9%
Δ_{06-11}, **Overall**	-6.1%	-21.9%	-13.7%	-55.3%
Δ_{06-11}, **at Young Firms**	-23.8%	-32.4%	-20.6%	-42.9%
Δ_{06-11}, **Ratio Young Firms/Overall**	3.89	1.48	1.49	0.78
Δ_{06-11}, **Share of Young Firms in Overall Decline**	52.4%	46.8%	27.8%	66.0%

Notes: Δ_{06-11} denotes the change in the corresponding labor market variable between 2006 and 2011. A young firm is defined as a business established up to five years previously. 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).

for addressing the diverging views in the literature on whether *young or old firms* respond more strongly to aggregate shocks. While Fort, Haltiwanger, Jarmin, and Miranda (2013) find that young and small firms showed the strongest employment response during the GFC, Moscarini and Postel-Vinay (2012) report that net job destruction is proportionally higher in larger firms when unemployment is above trend. According to Fort et al. (2013), the disagreement stems from differences in sample periods and underlying cyclical indicators. The TVP-VAR methodology can shed light on this disagreement as it does not rely on any imposed business cycle indicator.

My analysis reveals two key findings. First, labor market reactions to credit crunches are time-varying and diverge by firm age. Second, credit supply shocks have been important drivers of unemployment dynamics in the U.S. since the late 1990s, with young firms showing significantly stronger reactions to credit crunches since the Great Financial Crisis. A variance decomposition shows that credit supply disturbances accounted for 60% of the variance in the U.S. unemployment rate during the GFC. These results are consistent with previous studies that argue age is a relevant proxy for financially constrained firms (see Cloyne, Ferreira, and Surico, 2019 and Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova, 2018), and highlight the important role of credit supply shocks in shaping the employment responses of young firms.

The divergence in employment responses by firm age coincided with the decline in U.S. house prices that began in 2006. As house prices began to recover, the employment responses of young firms became less pronounced. Additionally, evidence from the "Survey of Business Owners" highlights the increased significance of private real estate collateral for newly established firms.[4] By examining regional variation at the metropolitan statistical area level, I find that areas with larger declines in house prices experienced significantly greater sensitivity of young firms' job creation to local credit conditions. This finding underscores the role of business owners' private home equity in the hiring decisions of young firms, which is consistent with recent research emphasizing 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. The model incorporates a financial friction that arises due to the asymmetry of information between lenders and borrowers. It extends the financial accelerator model of Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1999) by adding endogenous firm entry, firm

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

age structure, and the ability of firms to raise equity from households and pay out dividends. In the model, households provide initial net worth to business entrants, and as firms grow older, they accumulate net worth. Newer businesses have lower net worth and higher agency costs, reflecting the empirical fact that new firms face difficulties in accessing credit markets. Survey evidence based on the *"Kauffman Firm Survey"* shows that insufficient collateral and not being in business long enough were the main reasons for loan rejections for a significant proportion of firms in 2007.[5]
After parametrizing 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 during the GFC. Using the quantitative model, I present three key findings. First, the isolated impact of the credit supply shock is inadequate in explaining the time variation and heterogeneity in the effect by firm age. The credit crunch led to a higher increase in borrowing costs for young firms, resulting in a decline in their demand for capital and labor. However, the decline in young firms' employment was not persistent enough to account for the divergent employment responses observed in the empirical analysis following the GFC based on firm age.

Second, by taking into account the additional decline in the value of young firms' collateralizable assets, the model reconciles well with the empirical findings. The deteriorating balance sheets of young firms lead to higher compensation demands from lenders due to the increased likelihood of default and associated agency costs. As borrowing costs rise, the already restricted access to credit of young firms further reduces their economic activity and depresses their net worth. The financial accelerator mechanism worsens the contractionary effect on young firms through the endogenous link between external finance premiums and borrowers' net worth. Consequently, the demand for labor exerted by young firms declines significantly for a long period. In contrast, old firms experience only temporary effects as they have higher net worth, lower agency costs, and reshuffle their portfolio towards more equity in response to the credit crunch, which dampens the impact of the shock on them.

Finally, examining an alternative scenario for the U.S. unemployment rate, where I shut off the drop in collateralizable assets for young firms, highlights the critical role of young firms in shaping aggregate labor market effects. As young firms would have resumed job creation more rapidly, this would have translated to an average of 1.8 percentage points lower unemployment rate between 2009 and 2012. Moreover, the U.S. unemployment rate would have returned to its pre-crisis level two years sooner, highlighting the significance of supporting young firms during economic downturns.

Relation to the literature: My work contributes to four strands of the literature. First, I add to the empirical literature on the effects of credit supply shocks on labor market outcomes, building on previous research by Chodorow-Reich (2014), Duygan-Bump, Levkov, and Montoriol-Garriga (2015), and Siemer (2019). These studies demonstrate the significant influence of credit supply shocks on employment during the Great Financial Crisis, with young or small firms being particularly affected. However, while previous research has taken a microeconomic perspective, my study seeks to estimate the potentially time-varying effects of credit supply shocks on employment by firm age, taking a complementary macroeconomic view. In doing so, I build on the work of scholars such as Gilchrist and Zakrajšek (2012), Bassett et al. (2014), Barnichon et al. (2022), and Gambetti and Musso (2017), who have used linear vector autoregressions (VARs) to study the consequences

[5] For details see Table 6 in Appendix C.

of credit tightening, but have not considered labor market outcomes. Moreover, this macroeconometric approach enables me to measure the impact of financial market shocks on U.S. unemployment dynamics over an extended period of time.

Second, I contribute to the literature on the heterogenous impact of aggregate shocks on firms, which has been explored by Gertler and Gilchrist (1994), Ottonello and Winberry (2020), and Buera and Moll (2015), among others. Ottonello and Winberry (2020) 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. According to Khan and Thomas (2013), a credit crunch can trigger a prolonged economic recession as firms' capital allocation deviates from the one suggested by their productivity levels, leading to persistent declines in aggregate 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.

Third, my work complements the literature on the role of housing net worth for newly established businesses, which has been explored by Davis and Haltiwanger (2021), Adelino et al. (2015), Schmalz, Sraer, and Thesmar (2017), Schott (2015), Kaas et al. (2016).[6] 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. While previous research has investigated the impact of housing net worth on young firms' activity, my study complements theirs by investigating time-varying divergent responses by firm age and focusing on financial frictions as opposed to labor market frictions (as in Schott, 2015, for example.)

Finally, I contribute to the literature on factors that help explain the slow recovery of the U.S. labor market after the Great Financial Crisis. Existing work has identified several factors, including the countercyclical extension of unemployment benefits (Mitman and Rabinovich, 2019), a decline in firm entry (Sedláček, 2020), and a shift in job opportunities away from routine work (Jaimovich and Siu, 2020). My research adds to this body of work by examining the role of credit supply shocks and net worth declines for young firms in explaining the sluggish labor market recovery.

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

In this section, I describe the empirical methodology used to estimate employment responses to a credit supply shock. I apply a time-varying parameter vector autoregression (TVP-VAR) model with stochastic volatility, which is based on the works of Primiceri (2005) and Cogley and Sargent (2005).

[6] Mian and Sufi (2014) demonstrate that the decline in employment during the GFC was driven significantly by demand-side effects that mainly impacted non-tradable employment, with housing net worth playing a crucial role. 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).

The main benefit of this methodology is its flexibility, as it permits the use of distinct sets of coefficients and variance-covariance matrices at each time period. This allows to differentiate between changing shock sizes and variations in the contemporaneous relationship between variables over time. It is essential to incorporate stochastic volatility as coefficients would be biased otherwise (Nakajima, 2011). This methodology captures both possible structural changes and state-dependent effects, which is important for two reasons. First, the effects of financial shocks may vary over time due to structural or cyclical reasons, or changes in the transmission mechanism. Second, compared to other classes of nonlinear time series models, such as threshold or smooth-transition VARs, 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. Furthermore, a TVP-VAR model enables the computation of generalized impulse response functions (GIRFs) for every point in time, which allows for the comparison of reactions across specific time periods.

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 (see Kilian and Lütkepohl, 2017 for details). The matrix Ω_t can be decomposed into $A_t^{-1} H_t (A_t^{-1})'$, where A_t is a lower triangular matrix that contains the time-varying contemporaneous relationships among endogenous variables, and 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

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

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

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

Here, θ_t and α_t follow driftless random walks, and the stochastic volatilities h_t are geometric random walks. Q and S are positive definite matrices. The model assumes that the innovations of the model equation and the three state equations are jointly normally distributed and independent of each other. Following Primiceri (2005) and Baumeister and Peersman (2013), the shocks to the coefficients of the contemporaneous relations are assumed to be correlated within equations but uncorrelated across equations, which 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. I estimate the model with Bayesian methods using a Markov Chain Monte Carlo (MCMC) algorithm with Gibbs Sampling.[7] 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). Online Appendix A provides details on the estimation algorithm and the choice of priors.

2.2 Data and Empirical Specification

The empirical analysis for my baseline study uses data on employment by firm age from the Quarterly Workforce Indicators (QWI) and Longitudinal Employer-Household Dynamics (LEHD) data set. To account for the monetary policy stance, I use the effective federal funds rate (FFR). For the period after 2008, I rely on the shadow federal funds rate of Wu and Xia (2016), which is unconstrained at zero and constructed from the observed Treasury yield curve.

To measure credit supply conditions, I use the Excess Bond Premium (EBP) introduced by Gilchrist and Zakrajšek (2012). They create a corporate bond spread called the "GZ spread," which represents both maturity and credit quality in the corporate cash market for a specific month. Using a micro-level data set of secondary market prices of outstanding senior unsecured bonds issued by non-financial U.S. corporations, they decompose the GZ spread into a component of firm-specific default risk and firm-specific bond characteristics, and a residual component called the excess bond premium (EBP). The EBP is the portion of the corporate bond credit spread cleared of firms' individual default risk. According to Gilchrist and Zakrajšek (2012), the EBP represents the "effective risk-bearing capacity of the financial sector" and, as a result, credit supply conditions. Figure 23 in Appendix C shows a high correlation between the EBP and bank tightening standards for small businesses, which supports the choice of the EBP as a proxy for bank lending standards.

The frequency of my data is quarterly. The estimation period of my baseline specification ranges from 1994Q1 to 2017Q4. I use the first five years as a training sample to obtain priors. The baseline empirical specification is

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

where EMP_t^j denotes employment by age category $j \in$ (young, old), which enters the model sequentially, and INT_t refers to the interest rate (i.e. the shadow rate for the period of the zero lower bound). I set the lag length p to 2 and demean all variables prior to estimation because I estimate the model without an intercept.

[7] As proposed by Geweke (1992), I check the convergence of the Markov chain by computing the inefficiency factors of the draws.

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

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

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.
In order to obtain the restrictions, I apply a Cholesky decomposition as a baseline, which imposes that $A_t, t = 1, \ldots, T$ is lower triangular. While maintaining the same recursive identification strategy for all $t = 1, \ldots, T$, the contemporaneous reaction varies over time. The lower triangular structure is crucial as the ordering of variables can affect the results. In this study, the corresponding labor market variable is ordered first, and the measure for credit supply (the excess bond premium, EBP) last. This imposes 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 responds immediately to a shock in credit supply. This ordering of variables is based on the "slow-moving" to "fast-moving" principle that is well-established in existing literature (e.g., Bernanke et al., 1999). Other studies, including Lown and Morgan, 2006, Gilchrist and Zakrajšek, 2012, Bassett et al., 2014, and Barnichon et al., 2022, also impose recursive ordering between macroeconomic and financial variables. To address the sensitivity of the recursive identification strategy to the ordering of variables, a robustness analysis is performed in Section A.2. In addition, I apply an alternative identification based on sign restrictions derived from the theoretical model in Section 5 to check the sensitivity of the results to the chosen identification strategy. Its details and results are presented in Appendix A.2.

3 Empirical Results

This section presents the main findings of the structural empirical analysis. First, I present the results of the impulse response analysis of a credit supply shock on young and old firms' employment. Then, I contrast these results with the employment reactions by firm size. In Subsection 3.3, I analyze the significance of credit supply shocks since the 1980s. Appendix A.2 provides additional extensions and robustness checks related to the role of firm dynamics, the measure of credit supply, the definition of young firms, the role of uncertainty, and the identification strategy.

3.1 Results by Firm Age

Figure 1 presents the generalized impulse response functions (GIRFs) that show the response of the variables to a credit supply shock across all periods and the entire impulse response horizon in a three-dimensional manner. Panel (a) displays the evolution of the effects over time, while panel (b) provides a rotated view of the same figure, enabling a closer inspection of the effects over the impulse response horizon. To ensure comparability over time, the shock size is normalized to one in every period. The color scale illustrates the effects in response to a credit supply shock in percent, with darker colors indicating stronger effects. The results show that during the 2001 recession, young and old firms displayed similar employment responses to a credit supply contraction. However, this similarity diminishes over time. Starting in the mid-2000s, young firms show a considerably stronger employment response when credit supply tightens. Moreover, their responses are more persistent compared to those of old firms. While old firms' responses recovered quickly after the GFC, around 2009. Young firms experienced their strongest employment impact in response to the post-crisis credit supply shock in 2012.

In order to better understand the time-variation of employment effects in response to a credit supply shock by firm age, I examine the corresponding employment reactions by firm age six quarters after the shock in the cross-section over the entire estimation period (1999Q1 to 2017Q4). The sixth quarter after the shock is chosen as it allows for a clear and comprehensive understanding of the materialization of the shock. Results remain consistent for slightly different periods, as shown in Appendix A.1. Figure 2 illustrates the impact on employment of a credit supply shock by firm age over time. The remaining endogenous variables' responses over time can be found in Figure 13 in Appendix A.1. Note that the responses of young firms come with higher estimation uncertainty. Prior to 2006, the median employment responses of young and old firms are almost identical. However, with the onset of the 2007-2008 Great Financial Crisis, young firms started to respond more markedly, whereas old firms' responses remained constant or even weakened. 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

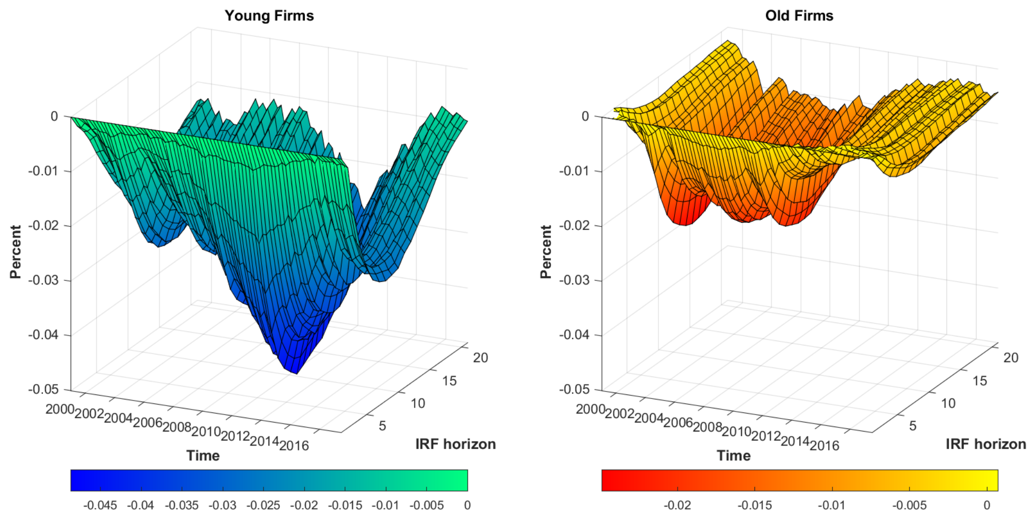
Ideally, I would like to distinguish between financially constrained and unconstrained firms. However, as there is no reliable measure of financial constraints in the data, I have to rely on a proxy. I focus on the role of age, and not size, of firms as proxy for three reasons. First, age is a clear and rank-invariant measure. Given my focus on effects over time and the business cycle, this is of particular relevance here. 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.[8]

Second, younger firms show the highest growth potential and are likely to face financial constraints when they want to expand. Young firms tend to be small, but not all small firms are young.[9] As the QWI does not provide data on young *and* small firms, I focus on young firms (i.e. firms that were established up to five years previously) in general. Table 2 shows the share of absolute job creation in an age/size matrix in percent of overall job creation. The share of small, young firms in overall job creation is 2.5 times higher than their share in overall employment. Similarly, the share of young, larger firms in overall job creation is twice that of their share in overall employment. This is consistent with the recent literature documenting that young firms have the highest growth

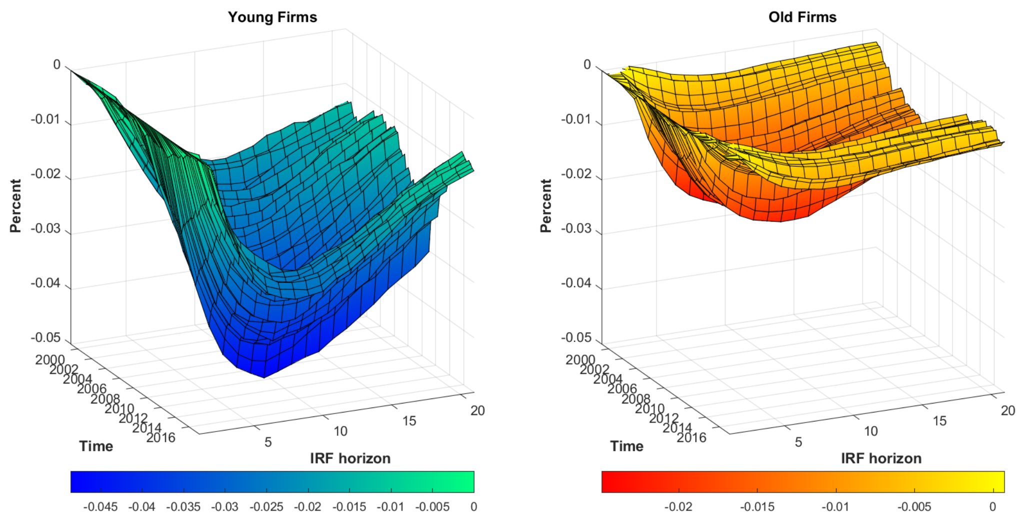
[8] There is a large body of corporate finance literature on identifying proxies for financial constraints; however, the debate on their validity is ongoing; see, among others, Farre-Mensa and Ljungqvist (2016) and Crouzet and Mehrotra (2020).

[9] According to the BDS, on average, around 50 percent of young firms have fewer than 20 employees, and only around 10 percent of young firms are relatively large (i.e., have more than 500 employees) for the years 2000 to 2014.

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



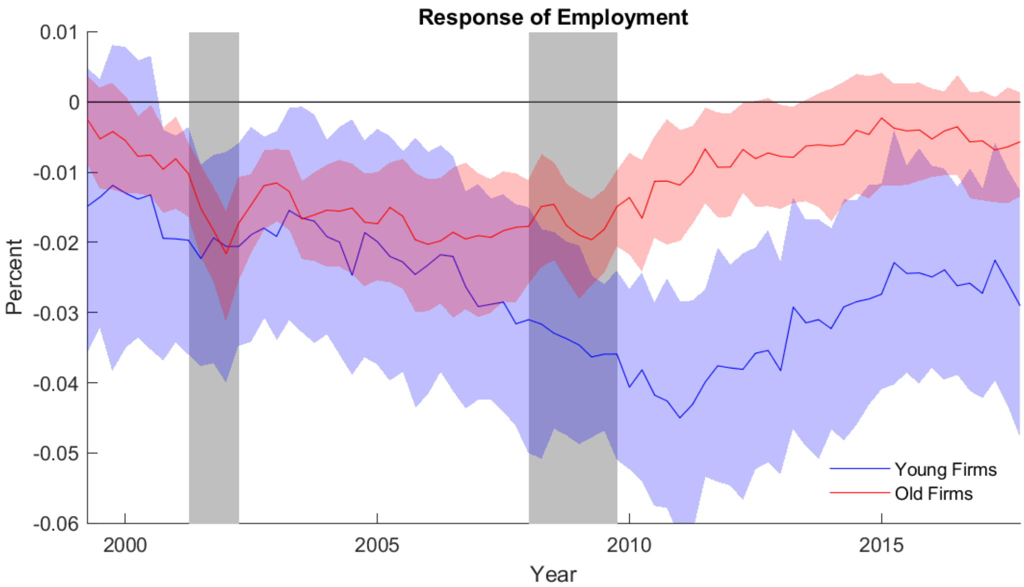
(a) Employment Response over Time and IRF Horizon



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

Notes: The figure shows median responses of young (blue) and old (red) firms to a one-standard deviation shock in external finance premium (EBP), normalized to one. The x-axis displays the time period of the response, while the y-axis represents the impulse response horizon. The strength of effects is indicated by the color scale on the z-axis. The lower panel provides a rotated view of the same figure for a closer examination of the effects over the impulse response horizon.

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.

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.

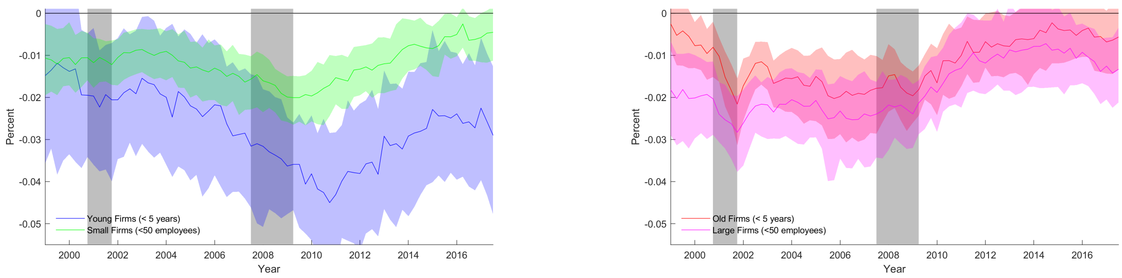
potential (see Haltiwanger, Jarmin, Kulick, and Miranda, 2016, Sedláček and Sterk, 2017, and Sterk et al., 2021). However, the number of young, larger firms is small, making them quantitatively less important.

Third, young firms face particular challenges in accessing credit markets due to their short credit history and the informational asymmetry between lenders and borrowers. Micro-level evidence from the Kauffman Firm Survey shows that in 2007, 35% of firms that had a loan application rejected were rejected because they were not in business long enough. This confirms that younger firms are more susceptible to encountering financial constraints.[10]

TVP-VAR Evidence: TVP-VAR evidence supports the argument that firm age, rather than size, matters for the effect of a credit tightening shock on firms' employment. The left panel of Figure 3 shows

[10] This was the third most important reason for credit refusal after "personal credit history" (45%) and "insufficient collateral" (44%); see Table 6 in Appendix A for details. The Kauffman Firm Survey tracks a sample of firms founded in 2004 over time.

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: Solid lines illustrate median responses after 6 quarters to a 1 std. EBP shock (normalized to one); Left Panel: blue (green) shaded areas denote 16th and 84th percentiles of the posterior distribution for young (small) firms. Right Panel: red (magenta) shaded areas denote 16th and 84th percentiles of the posterior distribution for old (large) firms. Gray-shaded areas denote NBER recession periods.

that the employment effects of credit crunches of young firms are significantly stronger compared to those of small firms during and after the GFC, while the right panel contrasts the effects of large firms to those of old firms. These findings suggest that financial frictions arising from asymmetric information affect young firms more severely than small firms, and that there is a higher degree of informational asymmetry between financial intermediaries and young firms (see Gertler and Gilchrist, 1994 for a discussion). The results depicted in Figure 3 also hold for different thresholds of "small" and "large" firms, as shown in Figure 21 in Appendix A.

3.3 Taking a Historical View

How much did credit supply shocks contribute to U.S. unemployment dynamics in the past 40 years? To answer this question, I estimate the following specification of the TVP-VAR model with stochastic volatility:

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

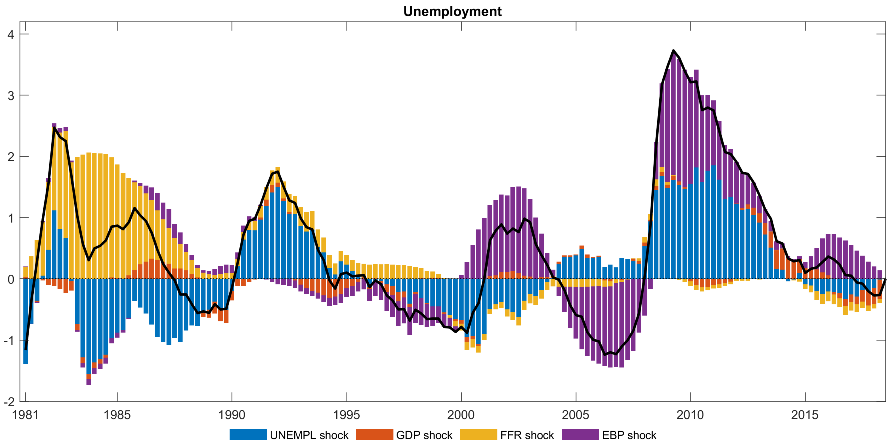
where $unemp_t$ is the unemployment rate (in percent) and ΔGDP_t denotes GDP growth. The data span from 1973Q1 to 2019Q2, with the first seven years serving as a training sample.

Historical Decomposition: Figure 4 displays the historical contribution of credit supply shocks to unemployment. The corresponding impulse responses over time are illustrated in Figure 22 of Appendix A.3. Credit supply shocks have become increasingly important in explaining unemployment dynamics since 2000. These shocks account for almost all of the rise in unemployment during the 2001 recession and about 40% of the increase during the Great Financial Crisis. In contrast, monetary policy shocks and labor market shocks were the dominant drivers of unemployment fluctuations in the early 1980s. These findings reveal how macroeconomic fluctuations have changed in the U.S. over the past four decades, and highlight the importance of credit market frictions in understanding these fluctuations.[11]

Forecast Error Variance Decomposition: In Figure 5, I present the contribution of credit sup-

[11] Due to data limitations, the analysis does not distinguish between the effects of credit supply shocks on young and old firms as the Quarterly Workforce Indicator is limited to the period from 1993 onwards, while the data from the Business Dynamics Statistics is only available on an annual basis.

Figure 4: Historical Decomposition of Unemployment



Notes: The figure shows the historical shock decomposition of unemployment. Blue bars represent the contributions of shocks to the unemployment rate, red bars denote contributions to GDP growth, yellow bars show contributions to the federal funds rate, and purple bars indicate contributions to the external finance premium (EBP). The solid black line represents the actual data, the baseline forecast is based on the demeaned unemployment.

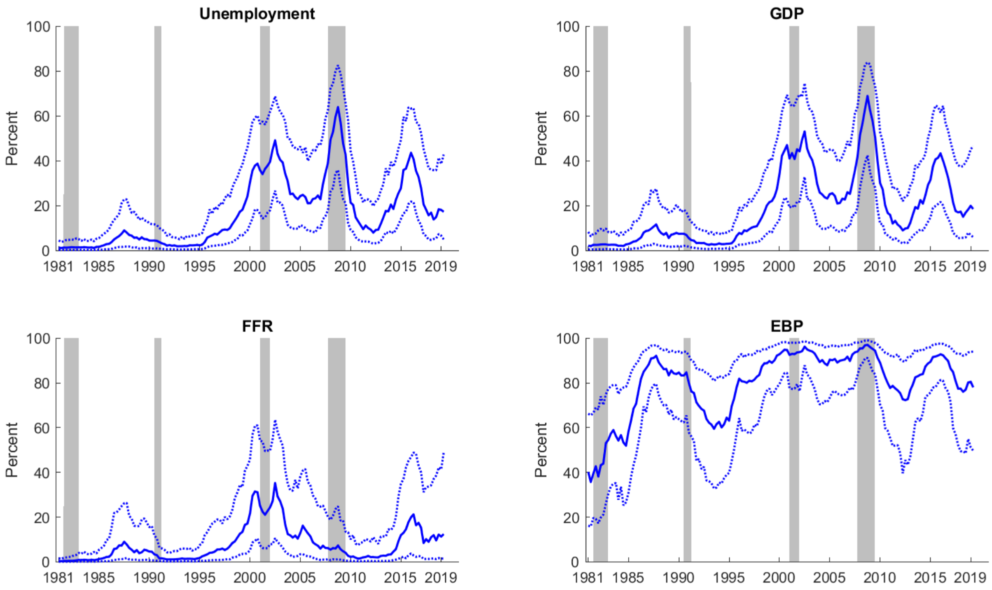
ply shocks to the forecast error variance of all four endogenous variables six quarters after the shock (solid line) along with the sixteenth and eighty-fourth percentiles of the posterior distribution (dashed lines). The proportion of unemployment and GDP growth volatility due to credit supply shocks has varied significantly over time. Before the late 1990s, credit supply shocks had little impact on the volatility of unemployment or GDP. However, since then, changes in credit supply conditions have played a more significant role in the volatility of macroeconomic variables. During the early 2000s recession, financial conditions accounted for around 40 percent of unemployment volatility, and this increased to around 60 percent during the GFC.

Potential Drivers: What drove the shift in the contribution of economic shocks to unemployment? Financial conditions have been a key driver of unemployment since the late 1990s, coinciding with marked deregulation in U.S. financial markets.[12] The subsequent rise in securitization fundamentally changed the nature of housing finance. Lenders in the mortgage market lowered their standards on down payments and screening practices, leading to an increase in mortgage-backed securities issuance from 2000 to 2006 by a factor of ten. Favara and Imbs (2015) establish a causal link between financial deregulation and the supply of mortgage credit in the 1990s and the U.S. housing price boom, which was further boosted by optimism about future housing demand (see Kaplan, Mitman, and Violante, 2020).

How does financial deregulation relate to firms' employment responses during crises? One potential mechanism is the role of housing net worth as collateral and startup capital for young firms. The surge in house prices led to an appreciation of households' housing net worth, which, combined with a relaxation of credit standards, enabled owners of young businesses to borrow significant amounts, expanding their activities (see Adelino et al., 2015). The next section provides a detailed discussion of the role of house prices in the firm age-related difference in employment dynamics.

[12] The Financial Services Modernization Act of 1999, among other developments, is commonly believed to have promoted risk-taking behavior among financial firms and led to the rise of new financial products, hedge funds, and 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.

4 The Role of House Prices

The empirical analysis presented in Section 3 highlights a divergence in employment reactions by firm age 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 older firms (right axis). The timing of the divergence in employment responses coincides with the collapse of house prices in the United States. In the second quarter of 2006, growth in U.S. house prices fell by 20% compared to the previous year. At the same time, in response to a credit supply shock, young firms began to adapt much more significantly along the employment margin, whereas the response of older firms remained stable. Only in 2011, when house prices started picking up again, did young firms' employment response weaken.

House Prices in the TVP-VAR: Next, I investigate the role of house prices in my structural empirical setting. For this purpose, I compute the employment responses by firm age in the TVP-VAR setting where house price growth enters as a fifth endogenous variable.[13] I analyze the role of house prices in two dimensions. First, I examine the employment responses of young and old firms to *house price shocks* (see the corresponding GIRFs presented in Figure 15a of Appendix A). The results show no significant direct effect on employment, and there is no meaningful difference between young and old firms.

Second, I explore the potential role of house prices as a *transmission mechanism* by examining the

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

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 represents median employment responses after 6 quarters to a 1 standard deviation EBP shock (normalized to one).

employment responses of young and old firms in an extended specification that includes house price growth as the fifth variable. The corresponding GIRFs are presented in Figure 15b of Appendix A. Compared to the baseline specification, the difference in responses by age is less pronounced, suggesting that the endogenous interaction between employment and house prices in response to a credit crunch explains a significant proportion of the divergence in responses. These findings highlight the importance of real estate value in the transmission of credit supply shocks.

Collateral for New Businesses: The transmission mechanism may operate via the value of collateral for new businesses.[14] A considerable proportion of newly established and young businesses use the homes of their owners as startup capital and collateral for business loans. The use of housing collateral allowed high ability individuals with a less-established track record to overcome credit constraints and become entrepreneurs (see e.g. Jensen, Leth-Petersen, and Nanda, 2022). Evidence based on the *"Survey of Business Owners"* illustrated in Table 7 in Appendix A shows that the importance of home equity as a source of startup capital has increased in recent years. Thus, if housing serves as an important source of collateral for newly established and young businesses (see Bahaj et al., 2022), a decline in the value of housing makes borrowing more costly or even impossible.[15] Given that young businesses are more dependent on external finance than old ones (see Begenau and Salomao, 2018 for descriptive evidence), a contraction in credit supply hits them harder, with the contractionary response further amplified if the owners' housing net worth loses value.

Cross-Regional Evidence: To further analyze the role of house prices in the employment responses shown by young firms to credit supply shocks, I perform cross-regional estimations at the

[14] 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.

[15] Meisenzahl (2014) uses the Federal Reserve Board's Survey of Small Business Finances for the years 1998 and 2003 and documents that 50 percent of firms required collateral to obtain a loan, 54 percent of loans granted were secured by personal guarantees made by the owner, and 30 percent of businesses provided both.

metropolitan statistical area (MSA) level. Using long-difference estimations, 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 B provides a detailed description of the approach, and the results are presented in Table 5 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. This points towards 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 allow for drawing conclusions on causality, they provide supporting evidence for my key empirical findings. Favara and Imbs (2015) provide causal evidence that the financial deregulation that took place in the late 1990s led to an increase in home ownership rates and a surge in house prices. Young businesses were able to take on high levels of debt using their housing net worth as collateral, leading to a closer connection between credit conditions, house prices, and labor market dynamics (see also Mian and Sufi, 2014). This 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 young businesses' net worth and provides an in-depth discussion of the transmission channel.

5 The Quantitative Model

The model economy consists of households, financial intermediaries, and a business sector comprising risky firms in different age cohorts (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 convert capital into effective capital. I will refer to them simply as "firms". Households, capital goods producers, and output goods producers are described in detail in Online Appendix B.

Firms enter the market endogenously and start in the entrants' cohort. They move to the next age cohort if they do not default or exit exogenously. Each age cohort $j \in (E, 1, \cdots, K, O)$ consists of a continuum of firms i. Every period, each age cohort pools their earnings to enable aggregation within each cohort. Moreover, they operate under constant returns to scale, facilitating straightforward aggregation. Except for entrants, every age cohort has access to two financing channels: debt and equity financing. Equity financing involves paying out dividends to households or raising new equity if dividends are negative. I assume that entrants are initially equipped with some net worth from households and cannot pay out dividends yet.

All firms require loans from a financial intermediary to fund their risky operations. They face idiosyncratic productivity shocks $\omega^{i,j}$, which follow a log-normal distribution and determine

whether they remain in business or declare bankruptcy.[16] Bankruptcy is endogenous and determines the end-of-period net worth of each age cohort (Bernanke et al., 1999).
In each period, there is a probability of $1-\gamma^j$ that an exogenous proportion of each age cohort will exit the market, where $j \in (E, 1, \cdots, K, O)$ denotes the age cohorts. The final goods producer rents capital from firms and hires labor. To prevent all labor from being supplied to the highest paying firm, the wage is uniform across all age cohorts, and wage adjustment costs are incurred.
Asymmetric information creates a friction between financial intermediaries and the business sector. Banks incur monitoring costs to observe the realization of the productivity shock $\omega^{i,j}$ for the firms, which corresponds to the costly state verification (CSV) contract analyzed in Townsend (1979), Gale and Hellwig (1985), and Bernanke et al. (1999).
Timing of Events: Each period proceeds as follows: households decide how much to consume, how much to save in the form of riskless deposits with banks, and how many equity shares to buy from firms. Potential entrants decide upon entry, and those who enter the market receive an exogenous amount of starting net worth from households. Firms of each cohort j decide on the optimal loan contract given the range of contracts on offer from the financial intermediary, which involves making decisions on the amount of capital to purchase for use in the next period and the optimal expected default threshold $\bar{\omega}^j$. The cohort-specific capital goods producer makes an investment decision subject to adjustment costs and sells capital to the firm. The cohort-specific final goods producer rents capital from firms and hires labor. 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 exit the market exogenously, and their net worth is destroyed and enters the resource constraint. Age cohorts differ in their exogenous survival rate γ^j, which increases with age. Finally, all cohorts except the entrants decide how much dividends they want to pay out to households (if 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 collects deposits from households and supplies loans to firms, holding an exogenous fraction r_t of deposits D_t as reserves, which means that 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 r_t reduces the amount of credit in the economy,

[16] Note that $\omega^{i,j}$ is i.i.d. 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 $E(\omega) = 1$.

thus serving as a credit supply shock.
Firms require net worth $N_t^{i,j}$ and loans $B^{i,j}$ borrowed from the financial intermediary to finance capital purchases $K_t^{i,j}$ at price Q_t^j. Moreover, firms are subject to idiosyncratic productivity shocks $\omega_t^{i,j}$, which determine whether they remain in business or declare bankruptcy. A firm's total return on capital in period $t+1$ is $E_t\left\{\bar{\omega}_{t+1}^{i,j}R_{t+1}^{k,j}\right\}Q_t^{i,j}K_t^{i,j}$, where 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 gain from selling non-depreciated capital $(1-\delta)Q_t^j$ back to the capital goods producer.
To enter into a contract with a firm in age cohort j, the financial intermediary requires its expected return on a loan to be greater than or equal to the riskless return that the bank has promised households on their deposits. The bankruptcy rate $F(\bar{\omega}_t^{i,j})$ is given by the cumulative distribution function (CDF) at the cutoff point $\omega_t^{i,j}$ (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 $1-F(\bar{\omega}_t^{i,j})$.
Further, the lender's expected share of profits and expected monitoring costs are

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

where $\mu^j \in (0,1]$ denotes relative monitoring costs as the fixed proportion of the firms' total return on capital in period $t+1$, $E_t\left\{\bar{\omega}_{t+1}^{i,j}R_{t+1}^{k,j}\right\}Q_t^{i,j}K_t^{i,j}$. The share of a cohort's earnings that goes to lenders net of monitoring costs can thus be expressed as $\Gamma(\bar{\omega}_t^{i,j}) - \mu^j G(\bar{\omega}_t^{i,j})$, and $1-\Gamma(\bar{\omega}_t^{i,j})$ 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 $E_t\left\{R_{t+1}^{k,j}\right\}Q_t^{i,j}K_t^{i,j}$ at the cutoff $E_t\left\{\bar{\omega}_{t+1}^{i,j}\right\}$.
The ex-post cutoff is given by

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

The firm repays the lender the amount $E_t\left\{\bar{\omega}_{t+1}^{i,j}R_{t+1}^{k,j}\right\}Q_t^{i,j}K_t^{i,j}$.
In the case that $E_t\left\{\omega_{t+1}^{i,j}\right\} > E_t\left\{\bar{\omega}_{t+1}^{i,j}\right\}$, the firm keeps the remaining profit $E_t\left\{(\omega_{t+1}^{i,j} - \bar{\omega}_{t+1}^{i,j})R_{t+1}^{k,j}\right\}Q_t^{i,j}K_t^{i,j}$. If $E_t\left\{\omega_{t+1}^{i,j}\right\} < E_t\left\{\bar{\omega}_{t+1}^{i,j}\right\}$, the financial intermediary pays monitoring costs and seizes the remainder of the firms' net worth $E_t\left\{(1-\mu^j)\omega_{t+1}^{i,j}R_{t+1}^{k,j}\right\}Q_t^{i,j}K_t^{i,j}$. In this case, the firm declares bankruptcy and receives nothing. After dropping the superscript i

for notational convenience, the lender's participation constraint can be written as

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

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.[17] 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

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

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.[18] 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. The entry decision is described in more detail in Subsection 5.3. 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:

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

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

$$\max_{\{K^E_t, \bar{\omega}^E_{t+1}\}} E_t\left\{(1-\Gamma(\bar{\omega}^E_{t+1}))R^{k,E}_{t+1}\right\}Q^E_t K^E_t$$

[17] Following Bernanke et al. (1999), I assume that the participation constraint of lenders has to be fulfilled ex post.
[18] 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.

subject to the participation constraint of lenders (equation 5.5) and the balance sheet constraint (equation 5.7).[19] 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 $j \geq 1$ 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:

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

where N^j, with $j \in (E, \cdots, O)$ is defined below.

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, that the adjustment is sluggish, 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 inflows for $k \in (1, \cdots, K)$:

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

[19] See Online Appendix B.1 for the corresponding first-order conditions.

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

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

For the flow-of-funds constraint, all intra-period flows are required. 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.[20]

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.

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

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

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

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):

$$N_t^O = \gamma^o (1-\Gamma(\bar{\omega}_t^O)) R_t^{k,O} Q_{t-1}^O K_{t-1}^O + N_t^K - \varphi(d_t^O). \tag{5.13}$$

In the baseline simulation, the shock process nw_t is only present in the net worth of young cohorts.[21] 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 idiosyncratic productivity cutoff of the entry cohort ($\bar{V}_t^E$) is at least as high as the entry costs.[22] The entry firm value is given by the share of earnings remaining in the entrant cohort (after payment of

[20] See Online Appendix B.1 for the corresponding first-order conditions.

[21] In a robustness check, I also include a shock to the net worth of old firms.

[22] As the realization of the idiosyncratic productivity cutoff is private information to the firms, the entry costs include costs to observe the productivity realization.

monitoring costs to the bank) at the idiosyncratic productivity cutoff:

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

This results in the free entry condition $E_t \left\{ \tilde{V}_t^E \right\} = \bar{\epsilon}_t^e$, 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.

$$\theta_t^E = \int_{-\infty}^{\bar{\epsilon}_t^E} f(\epsilon^E)\, d\epsilon^E \;\forall d. \tag{5.15}$$

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

$$\theta_t^1 = \gamma^E \theta_{t-1}^E \tag{5.16}$$

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

$$\theta_t^O = \gamma^O \theta_{t-1}^O + \gamma^K \theta_{t-1}^K \tag{5.18}$$

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

5.4 Aggregates and Closing the Model

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

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

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:

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

The aggregate economy-wide resource constraint holds:

$$Y_t = C_t + I_t + \mathrm{m}_t + C_t^e. \tag{5.19}$$

6 Calibration and Steady State

To keep the model tractable and reflect the deterministic aging structure of firms, I calibrate it to semi-annual frequency and include $K = 9$ young firm cohorts, in addition to the entrants. Firms older than five years are classified as "old firms" in my model, consistent with the definition used in my empirical analysis. Therefore, a firm is considered "young" for the first five years before becoming "old".

Table 3 presents an overview of the parameter choices for calibration. Unless otherwise stated, parameter values are identical among age cohorts. I target an annualized riskless interest rate of 3%, resulting in a semi-annual household discount factor of 0.985. The capital depreciation rate is set to 5% (semi-annual frequency), while the weight of capital in the production function is 0.33, as commonly assumed in the literature. Productivity is normalized to 1 in steady state, and the Frisch elasticity of labor supply is set to 1. 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.

To establish the parameters for the optimal debt contract between banks and entrepreneurs, I follow the approach of Ottonello and Winberry (2020) and Bernanke et al. (1999), targeting an annual average default rate of 3% across all age cohorts. The default rate is almost 5% for the youngest firms, decreasing by age to 2.4% for old firms. The default rates depends on three parameters: the monitoring costs, the variance of the idiosyncratic productivity distribution, and the idiosyncratic productivity cutoff. Based on Afanasyeva and Güntner (2020), I set the relative monitoring costs in case of default to $\mu^j = 0.2$, which falls within the range of estimates reported in Carlstrom and Fuerst (1997) and Levin, Natalucci, and Zakrajsek (2004). I assume that the idiosyncratic productivity draws follow a log-normal distribution with a unit mean and a variance of 0.18. These two age-invariant parameters, along with the cohort-specific idiosyncratic productivity cutoffs, ranging from 0.35 (old cohort) to 0.4 (young cohort), pin down the cohort-specific default rates. The amount of reserves held by financial intermediaries is $r = 0.2$.

The functional form of Λ for the capital goods producer is given by

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

where η^i is 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. Consistent with panel data estimates, I set $\eta^i = 0.25$. I calibrate a^K and b^K to hit the target of a ratio of semi-annual investment to the capital stock, as proposed by Gertler, Kiyotaki, and Prestipino (2020). I also set the parameter of dividend adjustment costs to $\kappa^d = 0.15$, close to the value used in Jermann and Quadrini (2012), and the parameter of wage adjustment costs to $\kappa^W = 20$ (see the household sector in Online Appendix B).

I assume that idiosyncratic entry cost shocks follow a lognormal distribution. To target a unit measure of firms in the economy with a 5.5% share of entrants in steady state, which is consistent with BDS data, I set the scale parameter of the distribution. The location parameter of the distribution is fixed at 0. I also target the average pre-crisis share of young and old firms in the total number of firms as given in the BDS for the period 1990 to 2006. These data indicate that around 63% of firms

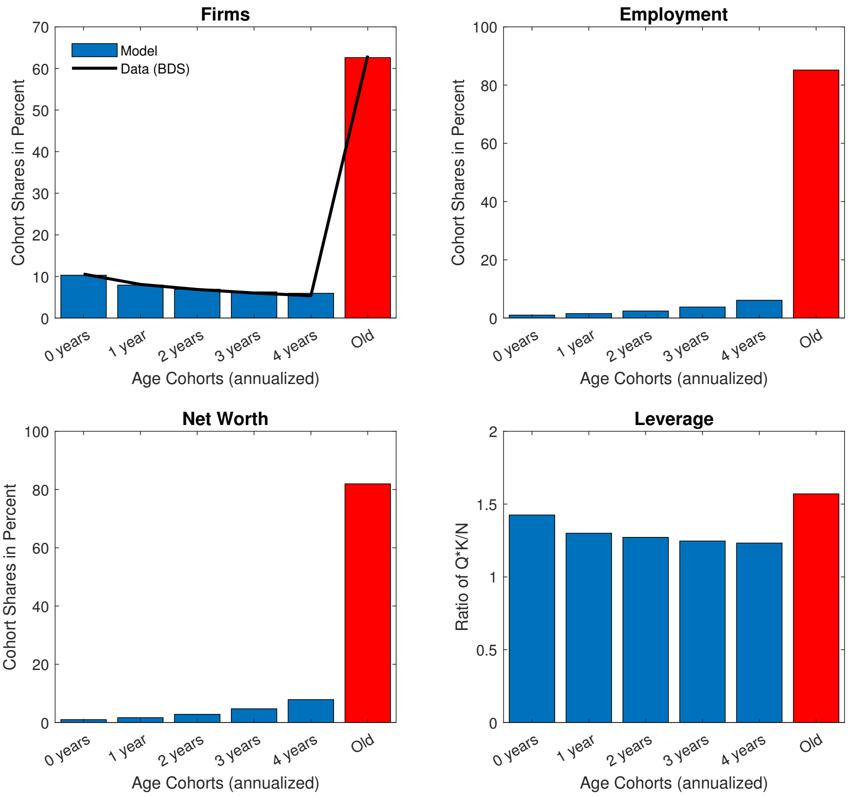
Table 3: Calibration

	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	1
Financial Frictions and Policy			
	Monitoring costs in case of default	μ^j	0.20
	Standard deviation of idiosyncratic realizations	σ^j	0.42
	Range of idiosyncratic productivity cutoffs (old-young)	$\bar{\omega}^O - \bar{\omega}^E$	0.35-0.4
	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	20.00
	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

are old. To achieve 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. Therefore, the total exit rate of firms by cohort is given by the sum of the endogenous default rate and the exogenous rate of death.

Solution and Shock Processes: The economy is initially in steady state and unexpectedly receives two innovations. First, I study the effects of an unexpected shock to the financial intermediary's reserve requirements ϵ_t^r. In the second step of the analysis, I study the effects of an unexpected innovation to young firms' net worth ϵ_t^{nw} in combination with the shock to ϵ_t^r, followed by a perfect foresight transition back to the model's steady state. To solve the model under perfect foresight, I apply a Levenberg-Marquardt mixed complementarity problem solver (Kanzow and Petra, 2005). To determine the size of the credit supply shock (ϵ_t^r), I choose the aggregate loan amount to decline by 8%, which corresponds to the drop in the loan amount during the GFC. To determine the size of the housing net worth shock ϵ_t^{nw} of young firms, 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%. Both shock processes are mutually uncorrelated, and I set the autocorrelation of both to 0.9.

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 target the relative proportion of young (established up to five years ago) to old firms in steady state. Figure 7 shows that the model's age distribution of firms in the cross-section (upper left-hand panel) is in line with the distribution observed in the Business Dynamics Statistics (BDS) data (solid line). The model endogenously captures the up-or-out dynamics, as young firms have a high probability of exit, leading to a decreasing proportion of young firms over time, as documented in Haltiwanger et al. (2013).

Figure 7 also displays the distribution of several variables of interest by age cohort in equilibrium. The left-hand panel shows that old firms account for around 85.5% of total employment, which is close to the 85.2% proportion observed in the BDS data between 1990 and 2006. The middle panel illustrates that net worth increases with firm age and is concentrated in the old cohort, which holds around 80% of the total.

The lower right-hand panel of Figure 7 reports that leverage in my model, defined as the capital-to-net worth ratio, decreases as firms grow older and accumulate net worth. However, the old firm cohort has the highest leverage ratio, which is consistent with the participation constraint of lenders (see Equation 5.5). As firms age, they select the highest possible leverage for a given idiosyncratic productivity cutoff and net worth, which the bank is willing to offer. This result is broadly in line with the findings of Dinlersoz et al. (2018), who observe that publicly listed firms are highly leveraged as they grow older.

7 Simulation Results

This section presents the main theoretical results of the paper. First, I examine the impact of an unexpected credit crunch and investigate whether the employment response of young firms compared to old firms is consistent with the empirical evidence presented in Section 3. Second, I demonstrate that the model can only be reconciled quantitatively with my empirical findings when a shock equivalent in size to the drop in U.S. house prices for young firms' collateralizable assets (i.e., housing net worth) is introduced. Finally, I use my quantitative model to analyze the relative importance of both shocks in explaining U.S. unemployment dynamics after the GFC. Note that as I consider the perfect foresight transition path back to steady state in response to unexpected innovation(s), there is no distinction between the ex-ante expected real interest rate and the ex-post realized interest rate (see Ottonello and Winberry, 2020).

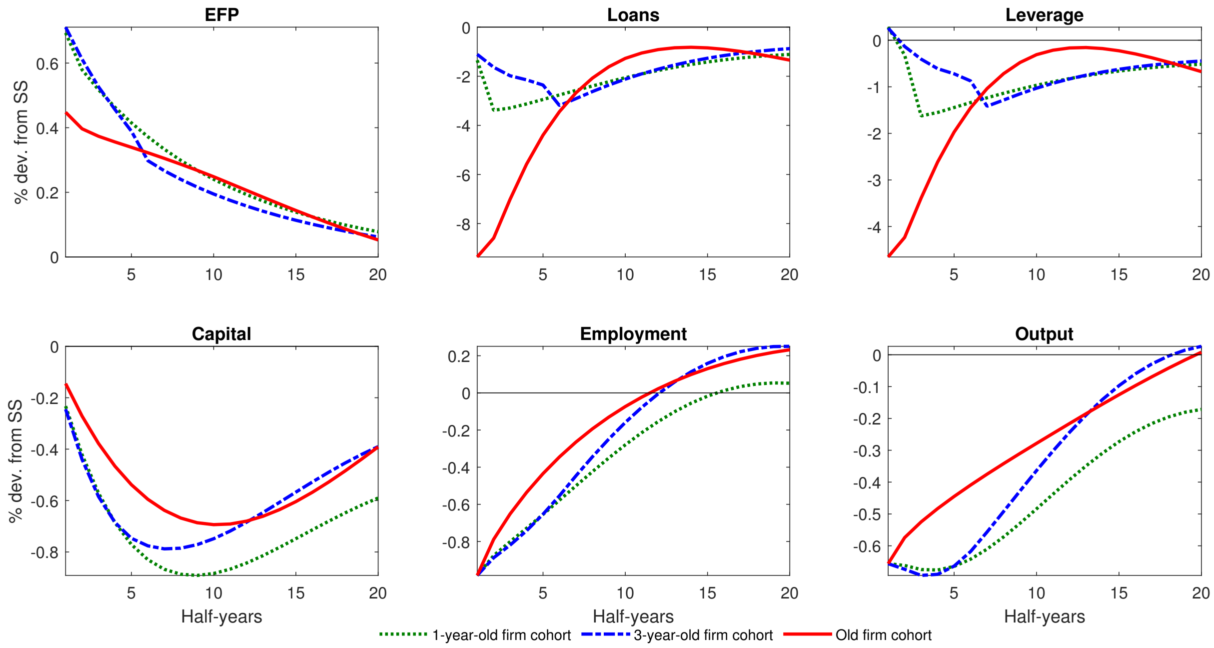
7.1 Effects of a Credit Crunch

Figure 8 presents the responses of three different age cohorts to a contractionary credit supply shock, a one-year-old firm (Y_1), a three-year-old firm (Y_5), and the old firm (Y_O). The results indicate that young firms face a stronger increase in their external finance premium compared to old firms, leading to a higher cost of borrowing and reduction in the loan amount. In contrast, old firms substitute between debt and equity financing and reduce the amount borrowed more compared to young firms. This is consistent with the findings of Begenau and Salomao (2018), who show that in recessions, large firms tend to restructure their capital portfolio towards more equity and less debt, whereas small firms adapt their capital structure pro-cyclically. Old firms have relatively less costly equity financing, which allows them to raise equity from households and decrease their leverage. In contrast, young firms are more financially constrained, leading to a stronger decline in capital, employment, and output. The aggregate results of a credit supply shock are illustrated in Figure 24 in Appendix D.

Although old firms have a higher debt-to-net worth ratio in steady state, it is the younger ones that reduce economic activity more strongly because old firms reshuffle their capital structure towards less debt and more equity. The credit supply shock in the quantitative model can partially explain the more marked employment response of young vs. old firms documented in Section 3. Table 4 compares the relative employment responses by firm age 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' of my quantitative theoretical model (second row) for the same time period (1.5 years after the shock).[23] However, it is unable to account for the stronger employment response of young firms during and after the GFC. In the next subsection, I investigate if a decline in the value of collateralizable assets could help reconcile the empirical employment responses with the theoretical ones.

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

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



Notes: Responses to an unexpected 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 $K = 5$). Impulse responses are computed as the perfect foresight transition path as the economy converges back to steady state.

7.2 The Role of Collateralizable Assets for Young Firms

Figure 9 depicts the results of an unexpected credit crunch and a simultaneous unexpected decline in the collateralizable assets of young firms, 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).[24]

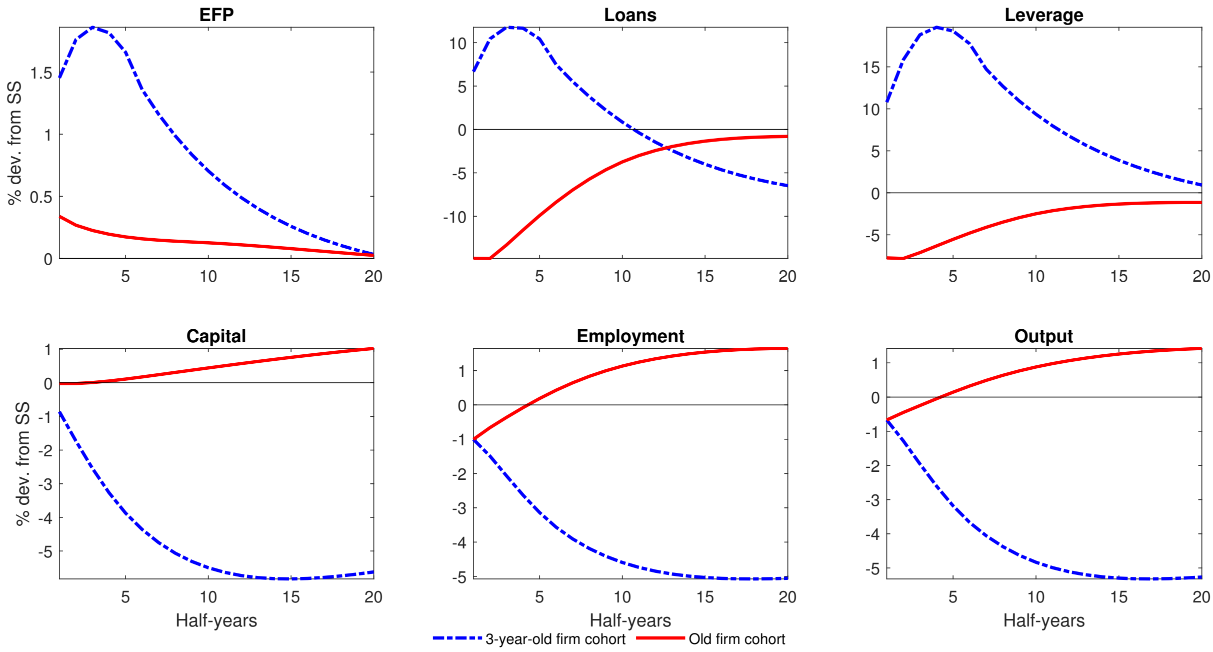
The occurrence of both shocks leads to a considerable decline in young firms' demand for capital, which is even more pronounced than for old firms due to their heavier reliance on debt financing and higher leverage. The decline in net worth also increases the risk perceived by lenders, leading to a rise in the age-specific idiosyncratic productivity cut-off and a further increase in the loan rate charged by the financial intermediary. As a result, young firms face a more significant increase in the external finance premium but require more loans to finance their operations as they depend stronger on debt financing.

However, with tighter credit supply and a higher external finance premium, the amount of loans available to young firms is reduced, intensifying the friction between borrowers and lenders. This creates a financial accelerator mechanism that further amplifies the negative effects, especially on young firms, as borrowing becomes more expensive, decreasing their demand for capital and labor even more.

The second column of Table 4 provides a comparison of the theoretical and empirical models and shows that the decline in collateralizable assets is a crucial factor in matching the relative employment responses of young and old firms after the GFC. Once the decline in collateralizable assets is

[24] As this interpretation holds only for young firms, old firms are only indirectly affected by the net worth shock in the baseline scenario (via the net worth that aging, formerly young firms bring to the "old" cohort when they join it).

Figure 9: Responses to a Credit Supply and Net Worth Shock: Young vs Old Firms



Notes: Responses to an unexpected contractionary credit supply shock and net worth shock. The solid red line depicts the response of an old firm. The dashed blue line illustrates the response of a three-year-old firm (cohort $K = 5$). Impulse responses are computed as the perfect foresight transition path as the economy converges back to steady state.

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).

Figure 25 in Appendix D depicts the corresponding results if the shock to net worth hits young *and* old firms.[25] It becomes clear that the divergence in employment responses does not hinge on assuming that only young firms are affected by the credit crunch. Old firms' responses become more marked but as they shift from debt to equity financing, they are less leveraged and do not face long-lasting declines in employment.

In summary, a decline in young firms' collateralizable assets makes it even more difficult for them to access external finance. These challenges are intensified by the the higher risk perceived by lenders and the resulting financial accelerator effect. The next subsection inspects the key economic mechanism causing differences by firm age.

7.3 Drivers of Heterogeneous Responses by Firm Age

Figure 10 illustrates the key mechanism driving different responses to shocks between young and old firms. The left panel depicts a young firm, while the right panel shows an old firm. The panels show the firms' marginal cost and marginal benefit schedules as a function of capital accumulation k'.[26] The marginal benefit of capital (MB) is horizontal for both firms, reflecting constant returns to scale within their respective age cohorts. When the demand for capital can be met entirely by net worth, the marginal cost of capital (MC) is also horizontal and equals the risk-free rate R^n. However, if capital demand exceeds net worth, the marginal cost curve becomes upward-sloping, reflecting

[25] For this exercise, I keep the shock sizes unchanged.

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

Table 4: Empirical IRFs vs. Theoretical IRFs: Employment effects, Young/Old Firms

	Employment Response of Young/Old Firm	
TVP-VAR Model	**2006/Q2**	**2014/Q1**
	1.30	4.73
Theoretical Model	**Credit Crunch**	**+ Net Worth Shock**
	1.23	4.76

Notes: The upper part of the table shows the relative employment reactions of a young vs. an old firm 6 quarters after the impact of the credit supply shock from the TVP-VAR model in the periods 2006/Q2 and 2014/Q1. The lower part of the table depicts the corresponding relative employment reactions of a three-year-old firm vs. an old firm three model-periods (equivalent to 6 quarters) after the shock in the theoretical model (left column: only the credit crunch; right column: credit crunch and net worth shock).

the financial intermediary's need for compensation for the increased default risk. The firm's optimal choice of capital occurs where the marginal benefit and marginal cost curves intersect.

There are two reasons why young and old firms differ in their responses. First, young firms have lower net worth, so they require a higher loan amount to achieve the same capital accumulation level as old firms. Thus, for a young firm, the marginal cost curve becomes upward-sloping at lower levels of k'. Second, the loan rate Z_t^Y reacts more strongly to shocks for young firms.

In response to a credit supply shock, both the marginal benefit curve and the marginal cost curve shift. The marginal benefit curve shifts down for both young and old firms as the return on capital $R^{k,j}$ decreases. However, the decline is more pronounced for young firms. The risk-free rate also declines, and the spread Z^j/R^n increases due to higher default probability, which shifts the marginal cost curve down and makes it steeper (denoted by MC_{rr}). Again, the effect is more pronounced for young firms. Consequently, the demand for capital declines for both young and old firms from $k_0^{j'}$ to $k_{rr}^{j'}$, but young firms experience a larger decline due to the steeper slope of their marginal cost curve. The decline in young firms' collateralizable assets further steepens their marginal cost curve to MC_{rr+nw}, leading to even lower capital demand ($k_{rr+nw}^{j'}$).

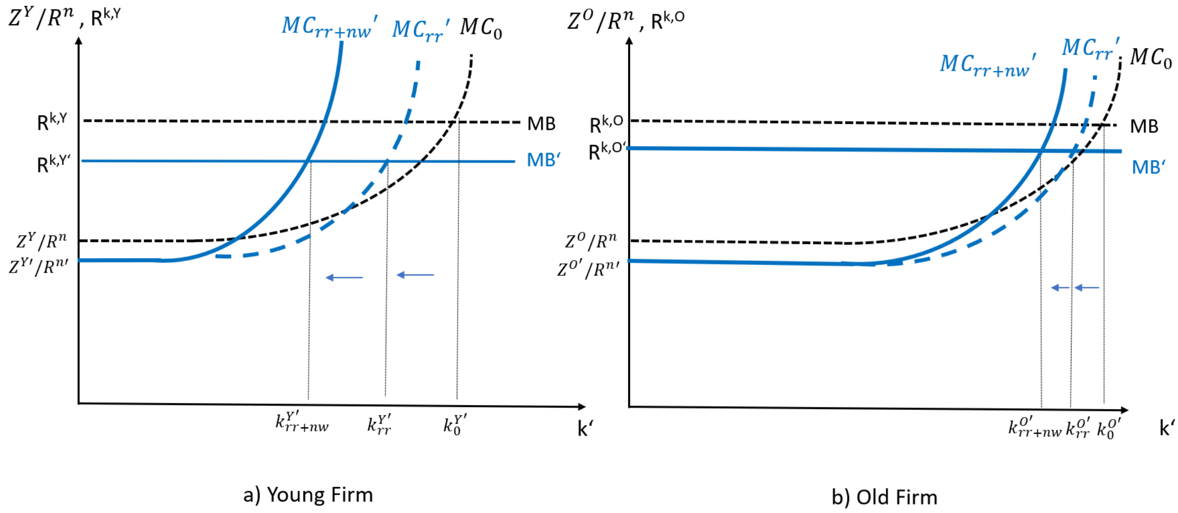
7.4 The Relative Contribution of Shocks and Alternative Scenarios

To determine the extent to which the net worth shock contributed to the decline in employment, I take two steps. First, I use the historical decomposition depicted in Figure 4 to gauge the contribution of financial shocks to U.S. unemployment dynamics. Second, 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 based on my quantitative model.[27] According to my model, the net worth shock accounted for approximately 50% of the decline in employment after two years (4 model periods) and over 90% after ten years (20 model periods).

Based on the contributions of financial shocks and the relative importance of the net worth shock, I decompose the U.S. unemployment rate to quantify the increases caused by the credit crunch and those driven by the decline in the value of collateralizable assets. To do this, I calculate the absolute annual change in employment among young firms caused by the net worth shock during

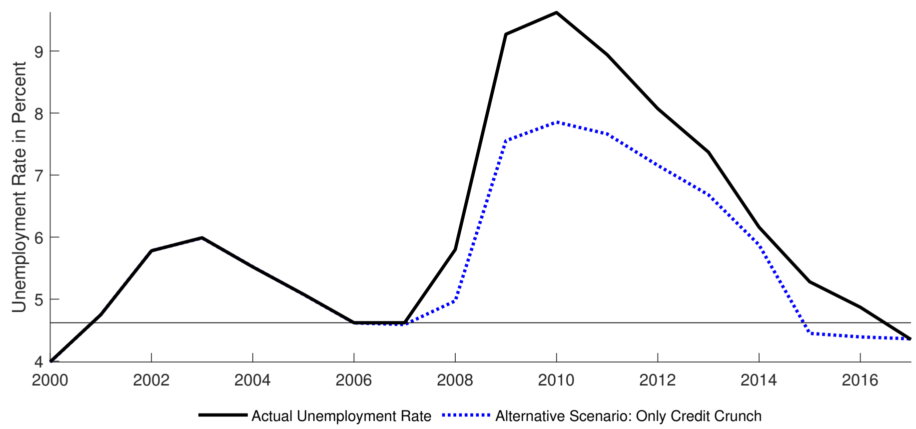
[27] For this purpose, I compute the difference in employment responses with and without the net worth shock.

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



Notes: Responses to a contractionary credit supply 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.

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.

and after the GFC, compared to the pre-crisis year of 2006.[28] As shown in Figure 11, the actual U.S. unemployment rate (solid black line) is contrasted with an alternative scenario in which only the credit crunch hit the U.S. economy (dashed blue line). This scenario assumes no declines in real estate values and thus eliminates the net worth channel as an additional transmission mechanism of financial shocks.[29] The results show that in the absence of the net worth shock, the U.S. unemployment rate would have returned to its pre-crisis level two years earlier. Furthermore, at the peak of the GFC, the unemployment rate would have been 1.8 percentage points lower.

[28] I use BDS data by firm age; see `https://www.census.gov/data/tables/time-series/econ/bds/bds-tables.html`.

[29] Clearly, this scenario abstracts from the fact that the GFC was triggered by a collapse in house prices.

8 Conclusion

Young firms play a significant role in overall job growth, therefore, it is crucial for economists and policymakers to understand the obstacles they face in creating jobs after economic downturns. A key factor is young firms' access to credit, as they pose a higher risk of bankruptcy, typically have lower net worth and shorter business histories, which makes borrowing for them more expensive and loan denials more likely. While previous research has focused on the microeconomic effects of credit crunches or has assumed linear effects over time, my paper contributes to the literature by studying the non-linear labor market impact of financial market shocks by firm age and over time from a macroeconomic perspective. Specifically, I disentangle the relative importance of the credit supply and net worth channel.

Since the Great Financial Crisis (GFC), credit supply shocks have resulted in more significant employment reactions among younger firms. Local house prices and fluctuations in the value of young business owners' private home equity are important explanatory factors for these differences by age. To rationalize these empirical findings, I develop a general equilibrium model that features cohorts of young and old firms and frictions in the financial market.

My model shows that 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. During the GFC, young firms faced not only tighter credit conditions but also a decline in their value of (private real estate) collateral. The interaction of these two disturbances forced them to reduce economic activity and cut labor demand persistently, while old firms were much less affected by the bust in house prices and switched from debt to equity financing as credit supply tightened. I find that the drop in young firms' (housing) net worth, and therefore their possibility to self-finance, caused their stronger employment reaction. Through a decomposition of the credit supply and net worth channel, I find that without the bust in house prices, the U.S. unemployment rate would have been almost two percentage points lower during the GFC.

These findings suggest that the government could potentially play a role to provide support to young firms facing financial constraints. Loan guarantee programs could be an effective policy tool to mitigate the impact of financial market shocks on young firms. These programs alleviate credit constraints faced by young firms and encourage them to invest and create jobs. However, it is essential to ensure that loan guarantee programs are well-targeted to reach those firms with the highest growth potential. One way to achieve this could be by pooling funds at the bank level and letting the bank select the beneficiaries, which could promote that the loan guarantees are allocated to firms that are most likely to benefit from the program.

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Figure 12: Generalized Impulse Response Functions (GIRFs) in Response to a Credit Supply Shock: 1 Period after the Shock

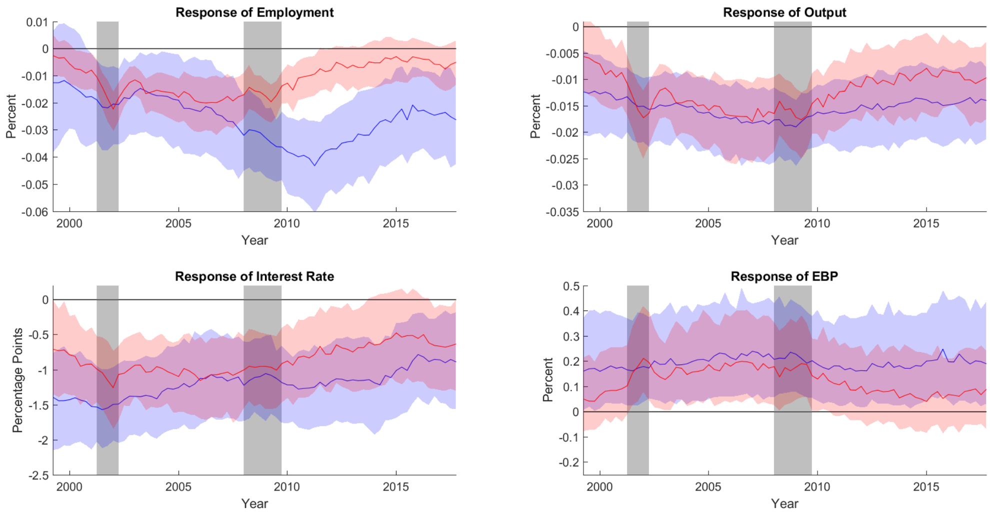
Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 1 quarter to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior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

A Further Empirical Evidence, Robustness, and Extensions

A.1 Different GIRF-horizons

This subsection displays generalized impulse responses to a credit supply shock i) 1 period after the shock (Figure 12), ii) 6 periods after the shock (Figure 13), and iii) 12 periods after the shock (Figure 14) for all endogenous variables, i.e. employment, output, the interest rate, and the EBP.

Figure 13: Generalized Impulse Response Functions (GIRFs) in Response to a Credit Supply Shock: 6 Periods after the Shock

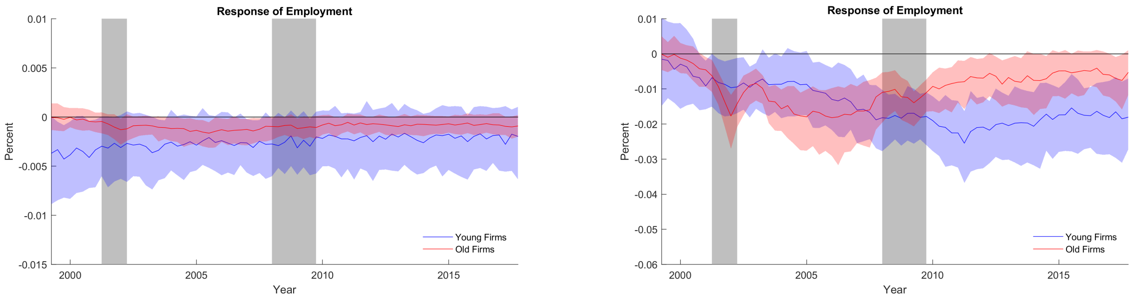


Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote 16-th and 84-th percentiles of the posterior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

Figure 14: 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 15: A Shock to House Prices and House Prices as Transmission Mechanism



(a) A House Price Shock **(b)** Controlling for House Price Growth

Notes: Left Panel: GIRFs of Employment in response to a contractionary house price shock shock for young (blue) and old (red) firms with house price growth in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t \quad \Delta HP_t]$. ΔHP_t denotes the year-on-year growth rate of the 'All-transactions House Prices Index' for the United States. Right Panel: 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 in the same specification. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

A.2 Robustness and Extensions

This subsection describes 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, 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 16). I assume that firm birth/death rates react more quickly than GDP and order them third. Second, I estimate the baseline specification without the youngest age group (i.e., businesses founded fewer than two years previously) to check if young firms are driving the findings. Figure 17a 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 17b). 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. The significantly more marked employment response of young firms holds when performing all these robustness checks.

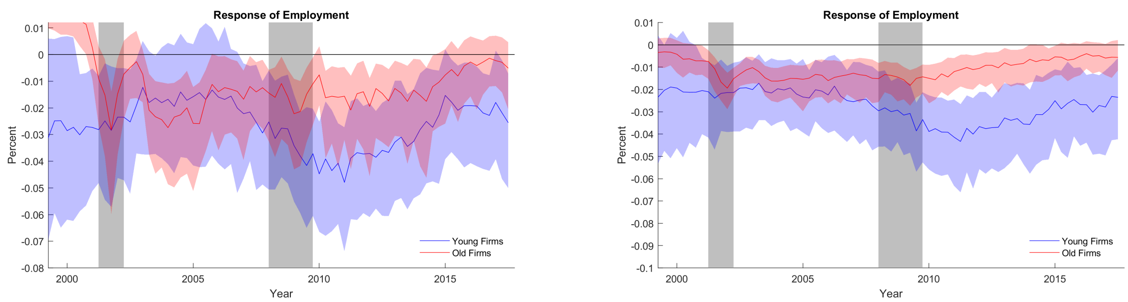
Measure of Credit Supply: The EBP is based on a credit spread of corporate bonds issued by a representative sample of non-financial U.S. firms. Whereas corporate bonds are an important financing instrument, they may not be the financing option commonly available to newly established and young firms. To address this issue, I use banks' tightening standards instead of the EBP in the TVP-VAR estimation. For young firms, I use banks' tightening standards for commercial and industrial loans to small businesses, while for old firms, I use banks' tightening standards for larger businesses. The results indicate an even more pronounced difference between young and old firms, with a significantly stronger response among young firms since the early 2000s. Figure 23 in Appendix C 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.

Uncertainty: A potential alternative explanation for the stronger reaction of young firms in response to financial market shocks is economic uncertainty as in times of high uncertainty, lenders may be less willing to provide recently established businesses with loans. To check whether economic uncertainty drives my results, I augment my baseline specification with the economic uncertainty index of Baker, Bloom, and Davis (2016). Figure 18b displays the corresponding employment reactions and shows that young firms' reaction is still significantly more pronounced compared to the response of old firms.

Definition of Young Firms: I find that defining a firm established up to ten years previously to be a "young" firm leads to a less pronounced divergence in employment responses (see Figure 19a). The difference by age is less notable than with a definition of "young" encompassing firms up to five years post-establishment, 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.

Identification Strategy - Sign Restrictions: To check the validity and robustness of my identification strategy for credit supply shocks, I apply sign restrictions (see Faust, 1998, Canova and Nicolo, 2002, and Uhlig, 2005, among others). I derive restrictions on the signs of the impact responses for output, the interest rate, and the excess bond premium based on my theoretical model laid out in section 5 and leave the response of my main variable of interest, employment, unrestricted. 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 the theoretical insights from my model (as discussed in Sections 5 and 7), a contractionary effect on output, a decline in the interest rate and an increase in the EBP for at least two periods. Under this identification approach, a contemporaneous response of employment, the federal funds rate, and output is permitted. Figure 19b 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. This makes me confident that the main empirical results by firm age are robust to the chosen identification strategy. Further, the employment responses illustrated in Figure 20 confirm the choice of using the recursive identification strategy as baseline identification approach: The impact response of employment is concentrated around zero even though it is kept unrestricted.

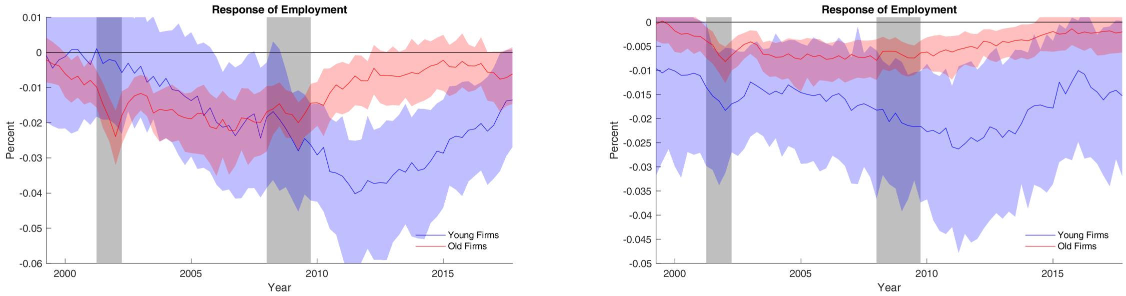
Figure 16: Controlling for Firm Births/Deaths: GIRFs in Response to a Positive Credit Supply Shock



(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.

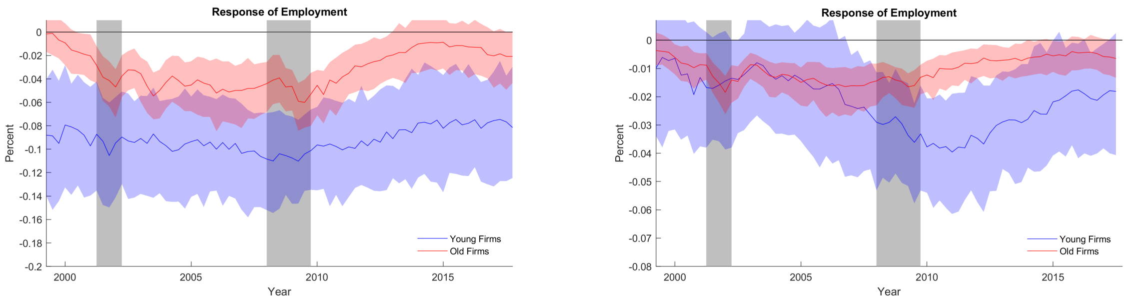
Figure 17: Controlling for Firm Dynamics II: GIRFs in Response to a Positive Credit Supply Shock



(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 ($\leq$ 5 years) and old firms respectively. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

Figure 18: Robustness: Banks Tightening Standards (LHS) and Economic Uncertainty (RHS).



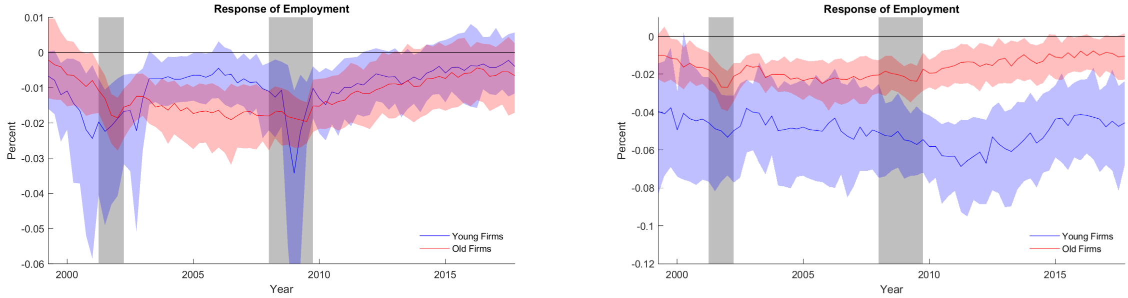
(a) Banks Tightening Standards **(b)** Controlling for Economic Uncertainty

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 et al. (2016): $Y_t = [log(EMP_t^j) \;\; log(GDP_t) \;\; UC_t \;\; FFR_t \;\; EBP_t^i]$ 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.

A.3 Historical View: Impulse Responses over Time

Figure 22 shows the generalized impulse response functions (GIRFs) of a credit supply contraction on unemployment during the Great Financial Crisis (GFC) and other NBER recession periods. The left-hand panel depicts the GIRFs with red lines representing the GFC and dashed blue lines representing all other recession periods. The unemployment response during the GFC was significantly stronger compared to previous NBER recessions. In the right-hand panel, which presents the cross-section of all unemployment responses since 1980 six quarters after the shock for each period, it is observed that the unemployment response has intensified over time, peaking after the GFC. This difference over time is not due to state-dependent effects such as stronger reactions during recessions compared to expansions, but instead reflects an overall trend of a stronger and more persistent unemployment reaction over time.

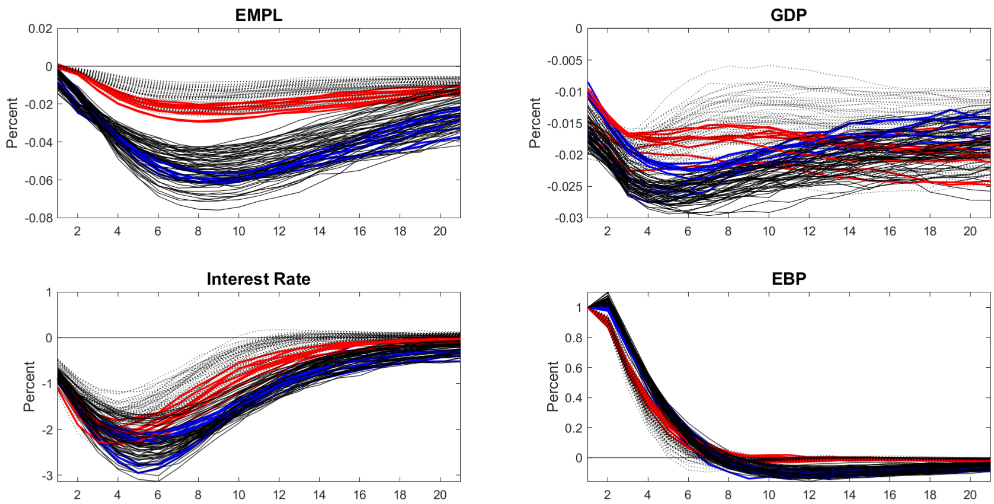
Figure 19: Robustness: A Broader Definition of Young Firms ($\leq$ 10 years) and Sign Restrictions.



(a) Definition Young Firm: up to 10 Years **(b)** Identification: Sign Restrictions

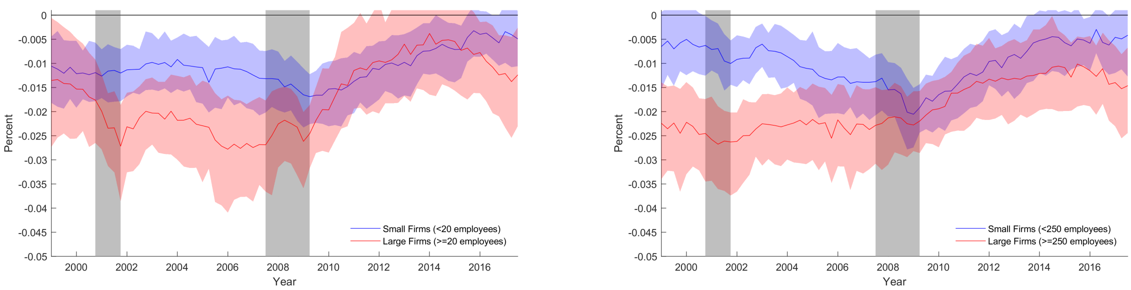
Notes: GIRFs of Employment in response to a positive credit supply shock after 6 quarters. LHS: The age cutoff in the definition between young and old firms is at the age of 10 years (young $\leq$ 10). RHS: GIRFs of Employment in response to a positive credit supply shock using sign restrictions instead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

Figure 20: Robustness: Identification Strategy, Impact on All Endogenous Variables



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

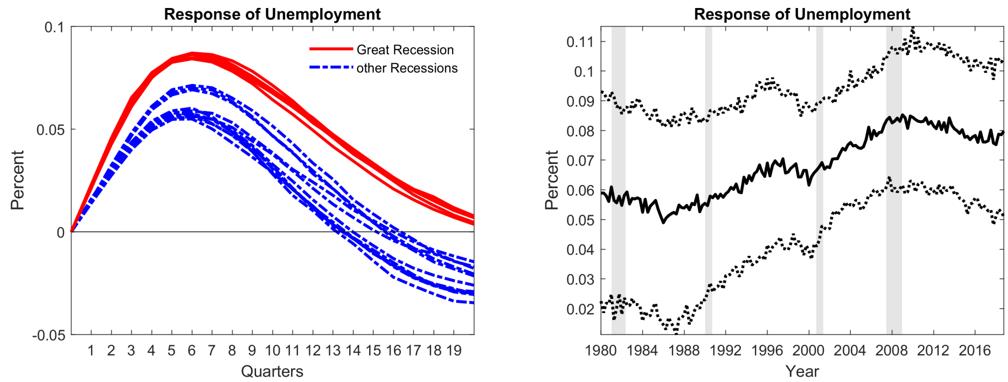
Figure 21: Firm Size: GIRFs of Employment in Response to a Credit Supply Shock



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

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

Figure 22: GIRFs of Unemployment in Response to a Credit Supply Shock (Long Horizon). Recessionary Periods and over Time.



Notes: Left Panel: GIRFs of Unemployment in Response to a Negative Credit Supply Shock in NBER recession periods except the Great Recession (blue) and the Great Recession (red). Right Panel: Cross-section of 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.

B Cross-regional Estimation on MSA-level

In this section, I investigate the role of house prices in driving the employment responses of young firms to credit supply shocks at the metropolitan statistical area (MSA) level. To do so, I construct a dataset at the MSA level that includes job creation of young firms from the Business Dynamics Statistics (BDS), data on small business loans from the Community Reinvestment Act (CRA), and the U.S. house price index. Table 9 in Appendix B provides an overview of the data sources.
I estimate the following long-difference equation

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

where the dependent variable, $\Delta JC_{m,07\text{–}09}$, 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 $\Delta SBLm, 06-09$ is the change in the total loan amount of loans to small businesses. $X_{m,06}$ denotes MSA-level controls for the year 2006.[30] I use population density in the year 2000 to weight all regressions. The coefficient of interest is the interaction term γ, which 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. My results, shown in Table 5, indicate a highly statistically significant elasticity of the change in job creation to the change in MSA-level house prices. Furthermore, the interaction term for the change in the total loan amount and the change in house prices is statistically significant in all specifications. In areas with a larger decline in house prices, job creation of young firms shows

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

a higher elasticity with respect to the amount of small business loans. This suggests that if the amount of loans declines, young firms reduce hiring significantly more in areas that experienced a more pronounced drop in house prices.

Overall, my findings suggest a link between credit conditions for young businesses and local house prices, which in turn affects job creation of young firms. This approach 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.

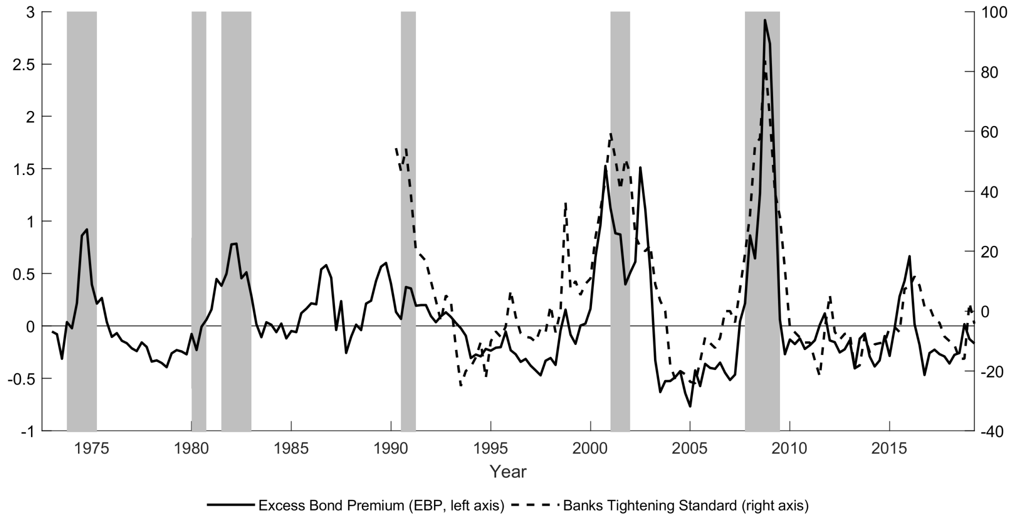
Table 5: Cross-Regional Estimation Results

	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

C More Descriptive Evidence

Figure 23: 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 (U.S.).

Table 6: 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.

Table 7: Sources of Start-up Capital by Year of Business Formation in Percent

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

Notes: Proportion of business owners who used the corresponding source(s) of start-up 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.

D Further Simulation Results

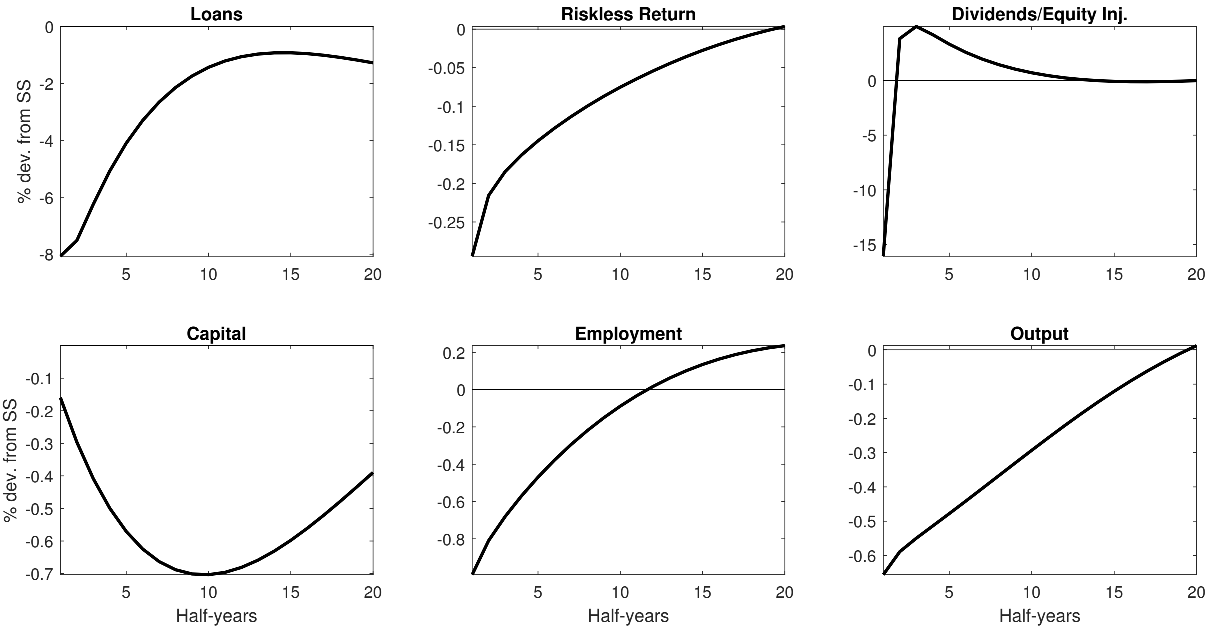
D.1 Aggregate Effects of a Credit Crunch

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 the 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. Declining capital and employment also cause the economy-wide output to fall. Further, the riskless return on household deposits drops. As a result, households prefer to equip firms with equity instead of saving 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.

D.2 A Net Worth Shock Hitting All Firm Age Cohorts

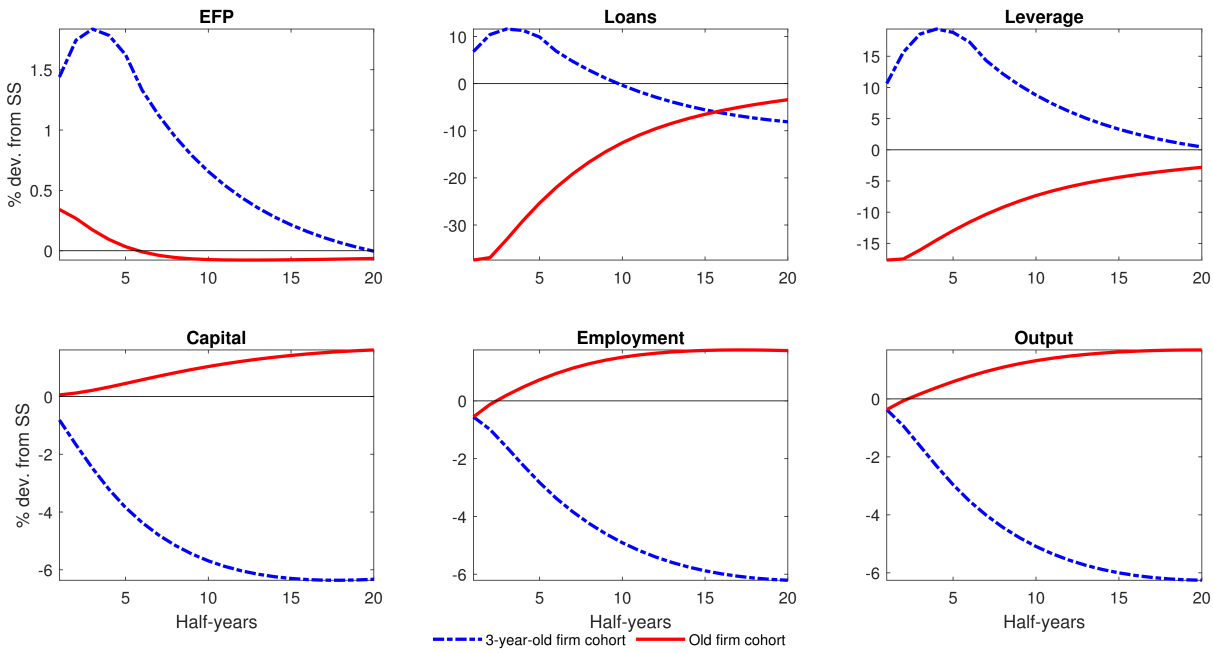
Figure 25 contrasts the model's reaction of a three-year-old firm to an old firm if also old firms are directly hit by the shock to net worth. The reaction of old firms becomes more pronounced, however, as they reduce the amount of loans even stronger and are less leveraged (due to a stronger substitution towards more equity), the difference between young and old firms becomes even more pronounced.

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



Notes: Responses to an unexpected contractionary credit supply shock on aggregate variables. Impulse responses are computed as the perfect foresight transition path as the economy converges back to steady state.

Figure 25: Responses to a Credit Crunch and Net Worth Shock to All Cohorts: Effects by Firm Age



Notes: Responses to an unexpected contractionary credit supply shock and net worth shock to all firms. The solid red line depicts the response of an old firm. The dashed blue line illustrates the response of a three-year-old firm (cohort $K = 5$). Impulse responses are computed as the perfect foresight transition path as the economy converges back to steady state.

Online Appendix (not for publication)

A Details on the Time-varying Parameter VAR

This section describes the priors and estimation algorithm used for the time-varying parameter estimations.[31]

A.1 Priors

To initiate the Kalman filter, I adopt the approach of Primiceri (2005) and Baumeister and Peersman (2013), and use informed priors for the time-varying parameters θ_t, α_t, and $\ln h_t$ based on the point estimates of a constant coefficient VAR on a training sample from 1973Q2 to 1979Q4. Specifically, I assume normal priors for θ_t, α_t, and $\ln h_t$, while Q is assumed to follow an inverse Wishart distribution. 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 $\mathbf{A}$ denoting the lower-triangular matrix and $D^{\frac{1}{2}}$ is a diagonal matrix containing the standard deviations of residuals. The prior for log-volatilities is set to

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

where μ_0 is a vector with the diagonal elements of $D^{\frac{1}{2}}$ and I_n denotes the identity matrix which is multiplied by 10 to make the prior only weakly informative. I further set the priors for the contemporaneous correlations as follows

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

where $\tilde{\alpha_0}$ is a stacked vector containing the diagonal elements of the inverse of the matrix $\mathbf{A}$.
Regarding the priors for the hyperparameters, I assume that $\mathbf{Q}$ follows an inverse Wishart distribution as suggested in Baumeister and Peersman (2013) and Benati and Mumtaz (2007):

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

with T_0 denote the prior degrees of freedom. The scale matrix is set to $\bar{Q} = (0.01)^2 T_0$, which is a conservative choice and only weakly informative (Baumeister and Peersman, 2013).
The block-diagonal matrix $\mathbf{S}$ also follows an inverse Wishart distribution with

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

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

where $i = 1,2,3$ denote the blocks of S. $\bar{S}_i$ 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):

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

A.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

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

   Starting with the terminal state of a forward Kalman filter, I 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). The procedure of applying the backward recursion of the Kalman filter can be applied, because I assume that S is block diagonal (for more details see Appendix B in Baumeister and Peersman, 2013).

3. **Draw volatility states H^T.**
   The orthogonalized observations $\epsilon_t = A_t(y_t - X_t'\theta_t)$ have variance $\text{var}(\epsilon_t) = H_t$ and are observable conditional on θ^T, A^T and Y^T. Since the state space representation of $\ln h_{i,t}$ is not

Gaussian, I 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 $p(Q, S, \sigma_i^2 | \theta^T, A^T, H^T, Y^T)$.

B Model Appendix

B.1 Firms' First Order Conditions

B.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.

B.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.

B.2 Households

The infinitely-lived representative risk-averse household discounts the future with the subjective discount factor $\beta < 1$. She derives utility from consumption and disutility 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 her 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

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

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 ($R^n D_t$), and equity payout from owning shares of firms ($s_{t-1}(d_t + p_t)$). Firms' equity shares denoted by s_t are evaluated at price p_t

This results in the first order optimality conditions:

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

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 that the household chooses the amount of aggregate shares from all firms.

B.3 Capital Good Production

As in Gertler et al. (2020), there is a continuum of measure one of competitive capital goods firms. Firms of each age cohort purchase capital each period from capital good producers for use in the subsequent period. Firm i in cohort j invests $I_t^j(i)$ units of final goods output and produces $\Lambda\left(I_t^j(i)/K_t^j\right)K_t^j$ new capital goods that are sold at price Q_t^j.
Capital evolves according to

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

where δ denotes the depreciation rate. The quantity of newly produced capital depends on 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.[32] The maximization problem for the capital goods producer j is

$$\max_{\{I_t^j(i)\}} Q_t^j \Lambda_t \left(\frac{I_t^j}{K_t^j}\right) K_t^j - I_t^j(i).$$

Due to symmetry, $I_t^j(i) = I_t^j$. This results in the following first order condition:

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

B.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

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

firm cohort j is hence given by

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

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

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

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

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

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

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

C 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 (year-on-year)	Total Credit to Private Non-Financial Sector	Bank for International Settlements
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)
House Price Index	All-Transactions House Price Index for the U.S.	U.S. Federal Housing Finance Agency

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