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

Brigitte Hochmuth

University of Vienna & CEPR

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Abstract

I document the heterogeneous effects of credit supply shocks on the labor market over time and by firm age. During the Great Financial Crisis (GFC), a credit crunch caused young firms to reduce employment significantly more than old firms. The housing bust starting in 2006 eroded young firms' collateral, restricting their borrowing capacity. To disentangle the relative contributions of the credit supply and net worth channels, I develop a financial friction model with an explicit firm age structure. The model explains the empirical findings by showing how a simultaneous credit crunch and decline in young firms' net worth disproportionately affect their borrowing capacity and labor demand. While old firms shift toward equity financing in response to the shock, young firms rely heavily on debt financing and are forced to reduce labor demand. Given that young firms disproportionately drive aggregate job growth, these findings explain the sluggish labor market recovery after the GFC and highlight the critical role of firm age in amplifying macroeconomic shocks.

JEL classification: E24, E32, E51, J63.
Keywords: Housing Net Worth, Credit Supply Shock,, Financial Accelerator, TVP-VAR.

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E-mail: brigitte.hochmuth@univie.ac.at.

1 Introduction

How do credit crunches affect firms' employment decisions over time and the business cycle? The answer depends on a firm's age. Young firms are significant drivers of employment dynamics in the United States. Despite representing only 14% of total employment in 2006, they accounted for 85% of net job creation.[1] However, during the Great Financial Crisis (GFC), young firms bore the brunt of the decline in employment and job creation, contributing to more than half of the total employment contraction and two-thirds of the reduction in net job creation (see Table 1). These firms are particularly vulnerable during credit crunches due to their limited business history, lower net worth, and higher reliance on external finance.[2] Despite their high growth potential, young firms' reliance on external finance makes them especially sensitive to changes in credit conditions (see Sterk, Sedláček, and Pugsley, 2021, Sedláček and Sterk, 2017, Haltiwanger, Jarmin, and Miranda, 2013). This paper investigates how credit supply shocks and the resulting financial constraints on young firms shaped labor market dynamics during and after the GFC, highlighting their critical role in amplifying macroeconomic shocks.

To analyze the role of young firms in shaping employment dynamics during credit crunches, this paper combines empirical evidence with a quantitative model of heterogeneous firms. Using a structural time-varying empirical framework, I document the disproportionate employment responses of young firms to credit supply shocks, emphasizing the role of housing net worth. Building on these findings, I develop a quantitative model that examines how firm age and financial frictions shape the macroeconomic effects of credit crunches.

This paper makes two key contributions to understanding how credit supply shocks affect labor market dynamics. First, it demonstrates that the employment effects of credit crunches vary significantly by firm age and evolve over time, highlighting the vulnerabilities of young firms. Second, it develops a theoretical model that disentangles the effects of credit supply shocks from changes in firm owners' net worth. By incorporating firm age and endogenous entry into a framework with financial frictions, the model offers new insights into why young firms face sharper and more persistent declines in employment during financial crises. By capturing these dynamics, the model provides a mechanism that explains the prolonged recovery of the U.S. labor market following the Great Financial Crisis. Unlike previous studies focusing on monetary policy shocks (see e.g. Cloyne, Ferreira, Froemel, and Surico, 2023, Gnewuch and Zhang, 2025), I show that the heightened sensitivity of young firms also extends to credit supply shocks, which operate through a distinct transmission mechanism: whereas monetary policy primarily affects the cost of borrowing via changes in the risk-free rate, credit supply shocks reflect a tightening in the availability of loans due to lenders' reduced willingness to bear risk. In my model, this tightening raises agency costs, which become particularly binding for young firms that have limited net worth and short credit histories.

I use a structural time-varying parameter vector autoregression (TVP-VAR) model with stochastic volatility to estimate age-specific employment responses to credit supply shocks. This approach offers two key advantages. First, it captures both time-varying and age-specific effects, which are often overlooked in studies that focus exclusively on the microeconomic perspective[3] or on time-

[1] These numbers refer to firms established within the last five years.

[2] See survey evidence based on the *Kauffman Firm Survey* in Table 6 of Appendix D.

[3] See Chodorow-Reich, 2014, Chodorow-Reich and Falato, 2022, Gilchrist, Siemer, and Zakrajsek, 2018, and Siemer,

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).

invariant effects of credit crunches.[4] Second, the TVP-VAR methodology addresses ongoing debates in the literature about whether young or old firms respond more strongly to aggregate shocks. Unlike local projections, the TVP-VAR framework provides a detailed understanding of how the effects of credit supply shocks evolve over time, without requiring prior assumptions about the timing of these changes. While Fort, Haltiwanger, Jarmin, and Miranda (2013) find that young and small firms exhibited the strongest employment responses during the Great Financial Crisis (GFC), Moscarini and Postel-Vinay (2012) argue that net job destruction was proportionally higher in larger firms when unemployment was above trend. According to Fort et al. (2013), these conflicting results stem from differences in sample periods and cyclical indicators. By avoiding reliance on any imposed business cycle indicator, the TVP-VAR framework clarifies these disagreements and provides a more robust picture of firm-age-specific dynamics.

My empirical analysis shows that labor market reactions to credit crunches are both time-varying and heterogeneous by firm age. Crucially, I find no significant differences between small and large firms when controlling for firm size, reinforcing the importance of age as a key proxy for financial constraints.[5] These results highlight the significant role that credit supply shocks play in shaping the employment responses of young firms.

The divergence in employment responses by firm age began as U.S. house prices declined in 2006, and it became less pronounced as house prices recovered in 2011. Evidence from the "Survey of Business Owners" highlights the increased significance of private real estate collateral for newly established firms. By using regional variation at the metropolitan statistical area (MSA) level, I find that areas with larger house price declines exhibit significantly greater sensitivity of young firms' job creation to local credit conditions. This finding highlights 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, 2024, and Bahaj, Foulis, Pinter, and Surico, 2022).

I propose a quantitative general equilibrium model with firm dynamics to analyze how credit supply shocks affect firms differently based on age. The model incorporates financial frictions stemming from information asymmetry between lenders and borrowers, extending the financial accelerator framework of Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1999). I in-

2019.

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

[5] See Cloyne, Ferreira, and Surico, 2019 and Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova, 2018.

troduce endogenous firm entry, a firm age structure, and the capacity for firms to raise equity from households and distribute dividends. Households provide initial net worth to new firms, which gradually accumulate net worth as they age. Younger firms, however, face higher agency costs due to their limited credit history and insufficient collateral, consistent with survey evidence from the *Kauffman Firm Survey*. For example, in 2007, many firms were denied loans primarily because of insufficient collateral or their short operating history, making them appear too risky to lenders.[6]
The model yields two key insights. First, the isolated impact of a credit supply shock is insufficient to fully explain the observed time variation and heterogeneity in employment responses by firm age. While the credit crunch led to higher borrowing costs for young firms, resulting in reduced demand for capital and labor, these effects alone do not account for the more persistent employment declines observed empirically. Second, the model aligns closely with the empirical findings when incorporating the additional decline in the value of young firms' collateralizable assets. The deterioration of young firms' balance sheets forces lenders to demand higher risk premiums, reflecting the increased likelihood of default and the associated agency costs. This tightening of credit conditions further depresses young firms' economic activity and net worth, magnifying the contractionary effects through the financial accelerator mechanism. In contrast, older firms with higher net worth and lower agency costs can mitigate the impact of the credit crunch by shifting their financing toward equity. This endogenous adjustment dampens the effects on older firms' labor demand, while young firms face prolonged declines in employment due to their inability to access affordable credit.

Finally, I examine an alternative scenario for the U.S. unemployment rate in which the drop in collateralizable assets for young firms is eliminated. This counterfactual highlights the critical role young firms play in shaping aggregate labor market outcomes. Without the decline in collateral values, young firms would have resumed job creation more quickly, resulting in an average reduction in the unemployment rate of 1.8 percentage points between 2009 and 2012. Furthermore, the U.S. unemployment rate would have returned to its pre-crisis level two years earlier.

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 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 heterogeneous impact of aggregate shocks on firms, which has been explored by Gertler and Gilchrist (1994), Ottonello and Winberry (2020), and Buera

[6] For details, see Table 6 in Appendix D.

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 are different wedges depending on how the underlying heterogeneity is modeled. They stress the importance of modeling 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 (2024), Adelino et al. (2015), Schmalz, Sraer, and Thesmar (2017), Schott (2015), Kaas et al. (2016).[7] 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.). In addition, Cloyne et al. (2023) show that young non-dividend paying firms react significantly stronger to monetary policy shocks than old firms who pay out dividends. Complementary to their work, my paper shows that the stronger response of young firms also holds in the case of credit supply shocks and is not limited to changes in interest rates. This distinction is important, as credit supply shocks reflect shifts in lenders' risk tolerance and directly tighten borrowing conditions for financially fragile firms, providing a broader perspective on how financial market disruptions affect firm dynamics.

Finally, this paper contributes to the literature on collateral constraints. While Kiyotaki and Moore (1997) develop a framework linking collateral values to economic fluctuations, their model does not account for firm heterogeneity by age. Complementing Iacoviello (2005) and Liu, Wang, and Zha (2013), who emphasize the amplification role of collateral tied to housing or land prices, I show that young firms' dependence on housing equity makes them particularly vulnerable to credit crunches. My work also complements Cooley and Quadrini (2001), who emphasize the role of financial frictions in shaping firm dynamics, particularly for younger firms with lower net worth. My findings also build on Jermann and Quadrini (2012) by showing that young firms, unlike older firms, cannot shift toward equity financing during credit tightening, exacerbating employment declines. Extending Lian and Ma (2021), who focus on cash flow- versus asset-based lending, I emphasize firm age as a critical factor in borrowing constraints. By disentangling credit supply and net worth channels in a general equilibrium model, I explain why young firms amplify labor market contractions in crises and are central to 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

[7] 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).

out the theoretical model, Section 6 discusses 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 work of Primiceri (2005) and Cogley and Sargent (2005). I opt for a TVP-VAR model over local projections or threshold VARs due to its flexibility in capturing smooth, time-varying changes in economic relationships without requiring exogenous state thresholds. Unlike state-dependent local projections, a TVP-VAR allows coefficients and variance-covariance matrices to evolve continuously, accommodating both structural shifts and state-dependent effects.[8] This is particularly valuable, as the effects of financial shocks can vary over time due to structural or cyclical factors and changes in transmission mechanisms. Additionally, the TVP-VAR framework incorporates stochastic volatility—essential to avoid biased coefficient estimates (Nakajima, 2011)—and enables the computation of generalized impulse response functions (GIRFs) at each point in time, facilitating direct comparisons of responses across different 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

[8] Furthermore, a TVP-VAR models the entire system of variables simultaneously, capturing essential feedback effects and interactions that may be overlooked in single-equation local projections.

and h_t a vector containing non-zero elements of H_t; the state equations are given by

$$\begin{aligned} \theta_t &= \theta_{t-1} + \nu_t, & \nu_t &\sim N(0,Q) & (2.2) \\ \alpha_t &= \alpha_{t-1} + \zeta_t, & \zeta_t &\sim N(0,S) & (2.3) \\ \ln h_{i,t} &= \ln h_{i,t-1}, + \sigma_i \eta_{i,t} & \eta_t &\sim N(0,1). & (2.4) \end{aligned}$$

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.[9] 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). Appendix A provides details on the estimation algorithm and the choice of priors.

2.2 Data and Empirical Specification

I use data on total U.S. employment by firm age from the Quarterly Workforce Indicators (QWI) and Longitudinal Employer-Household Dynamics (LEHD) data set. *Young firms* are defined as those established within the past five years, while *old firms* are those established more than five years ago. (In an extension, I apply a ten-year age cut-off to distinguish between young and old firms.)[10]
I use the effective federal funds rate (FFR) to account for the monetary policy stance. 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). The EBP is derived from the "GZ spread," a corporate bond spread that Gilchrist and Zakrajšek decompose into firm-specific default risk and bond characteristics, leaving the EBP as a residual free from individual firm risk. This residual directly captures shifts in the financial sector's capacity to bear risk, reflecting changes in credit supply. Ferreira, Ostry, and Rogers (2023) confirm that fluctuations in the EBP indicate shifts in credit supply, especially during financial downturns when financial intermediaries' risk-bearing capacity is reduced. Specifically, they show that increases in the EBP correspond to constrained credit access across firms due to supply-side limitations rather than demand factors.

Figure 23 in Appendix D demonstrates a strong correlation between the EBP and bank tightening standards for small businesses, highlighting the EBP's relevance beyond large, bond-financed firms.

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

[10] Note that due to data availability at a quarterly frequency, I have to use the total number of employed individuals in the U.S. (instead of employment per firm) at either young or old firms.

This close alignment suggests that shifts in the EBP, which capture credit supply constraints in the corporate bond market, mirror broader lending standards applied across firms of different ages, including small businesses that rely on bank financing. Thus, the EBP serves as a robust proxy for overall lending standards in the financial sector, effectively reflecting credit supply conditions across the spectrum of firm ages.

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 demean all variables prior to estimation, as the model is estimated without an intercept. I also set the lag length p to 2 to balance model fit with computational tractability.[11]

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 identification strategy to the results, I apply an alternative identification based on *sign restrictions* derived from the theoretical model in Section 5. Its details and results are presented in Appendix 3.3.

[11] In TVP-VAR models with stochastic volatility, additional lags increase the dimensionality of the state space, raising computational complexity for estimating time-varying coefficients and volatilities. A lag length of 2 balances capturing relevant dynamics with computational tractability, especially under Bayesian estimation using MCMC methods.

3 Empirical Results

This section presents the main findings of the structural empirical analysis. First, I discuss the impulse response results of a credit supply shock on the employment of young and old firms, where the shock size is normalized to one over time to ensure that time variation is not driven by changes in the shock itself. I then compare these results with the employment responses based on firm size. Finally, I provide additional analysis and robustness checks, addressing factors such as firm dynamics, the measurement of credit supply, the definition of young firms, the role of uncertainty, and the identification strategy.

3.1 Results by Firm Age

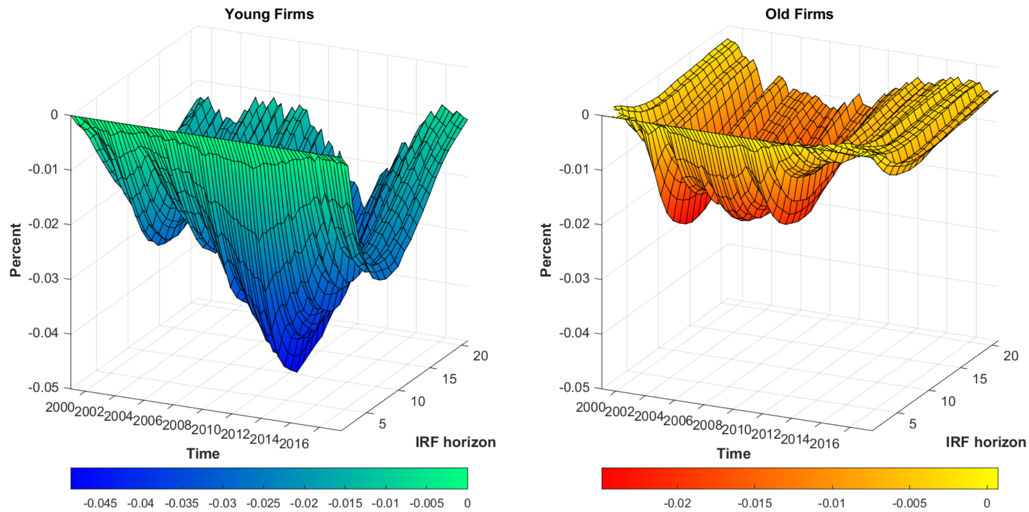
Figure 1 presents the generalized impulse response functions (GIRFs) that show the response of the variables to a credit supply shock across all periods and the entire impulse response horizon in a three-dimensional manner. Panel (a) displays the evolution of the effects over time, while panel (b) provides a rotated view of the same figure, enabling a closer inspection of the effects over the impulse response horizon. 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.

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 B.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 16 in Appendix B.1. Note that the responses of young firms come with higher estimation uncertainty. Before 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.

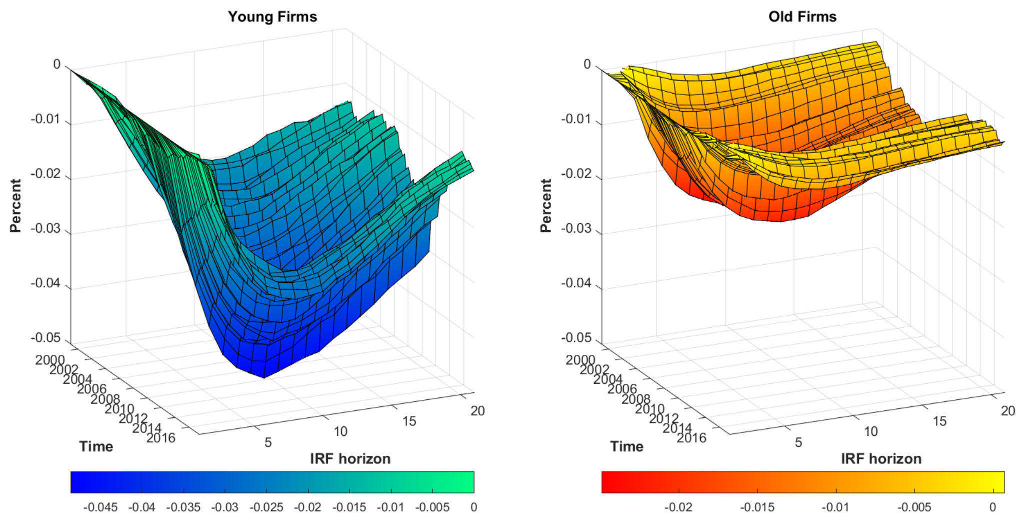
3.2 Age vs. Size

Ideally, I would like to distinguish between financially constrained and unconstrained firms. However, since there is no reliable measure of financial constraints in the data, I must rely on a proxy. I focus on the role of age, and not size, of firms as a proxy for three reasons. First, age is a clear and

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



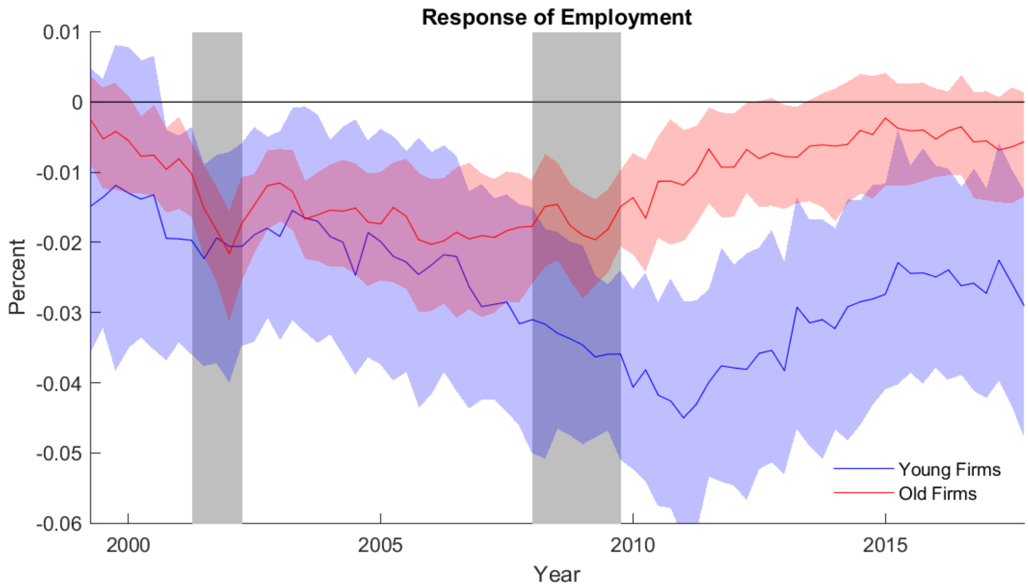
(a) Employment Response over Time and IRF Horizon



(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 the 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.

rank-invariant measure. Given my focus on effects over time and the business cycle, this is particularly relevant 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.[12]

Second, younger firms exhibit the highest growth potential and are more likely to face financial constraints when they seek to expand. Young firms tend to be small, but not all small firms are young.[13] 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, expressed as a percentage 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 finding is consistent with recent literature that documents young firms have the highest growth potential (see Haltiwanger, Jarmin, Kulick, and Miranda, 2016, Sedláček and Sterk, 2017, and Sterk et al., 2021). However, the number of young, larger firms is small, making them quantitatively less important.

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

[12] 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).

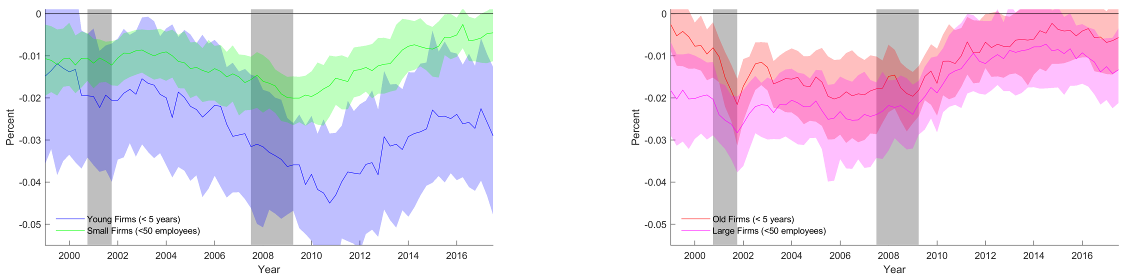
[13] According to the BDS, on average, around 50 percent of young firms have fewer than 20 employees, and only around 10 percent of young firms are relatively large (i.e., have more than 500 employees) for the years 2000 to 2014.

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.

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.

more susceptible to encountering financial constraints.[14]

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 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 19 in Appendix B.

3.3 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 a fifth endogenous variable to the estimation (see Figure 4). I

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

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 drive the findings. Figure 5a depicts the median employment responses over time. Third, I add the number of jobs destroyed by business exits as a fifth endogenous variable (see Figure 5b). Maintaining the assumption that macro variables respond with a lag of one quarter to movements in 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 D 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.

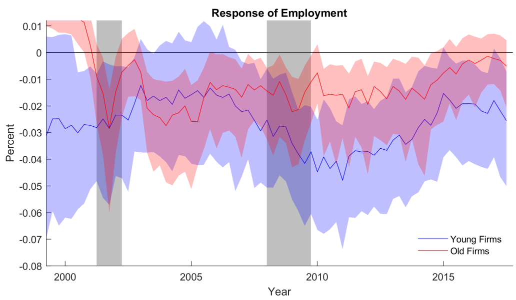
Uncertainty: A potential alternative explanation for the stronger reaction of young firms in response to financial market shocks is economic uncertainty, as, in times of high uncertainty, lenders may be less willing to provide recently established businesses with loans. To check whether economic uncertainty drives my results, I augment my baseline specification with the economic uncertainty index of Baker, Bloom, and Davis (2016). Figure 6b displays the corresponding employment reactions and shows that young firms' reactions are still significantly more pronounced compared to the responses of old firms.

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 7b 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 18 confirm the choice of using the recursive identification strategy as a baseline identification approach: The impact response of employment is concentrated around zero even though it is kept unrestricted.

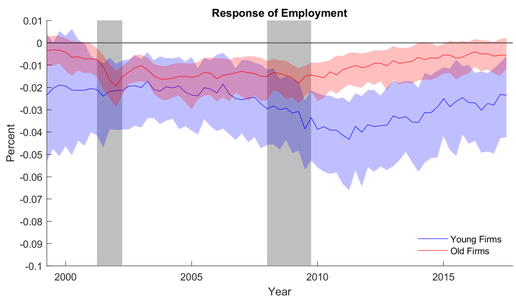
Definition of Young Firms: I find that defining a firm established up to ten years previously to be a "young" firm leads to a less pronounced divergence in employment responses (see Figure 7a). The difference by age is less notable than with a definition of "young" encompassing firms up to five years 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.

The time-varying effects of credit crunches since 1980 In addition, I modify my empirical model slightly to analyze the potential time-varying effects of credit crunches over time starting in the 1980s. In this specification, I focus only on aggregate unemployment as opposed to employment by firm age due to data availability (data by firm age is only available from 1993 onward). The results are depicted in Appendix C. Figure 21 depicts the historical decomposition of credit supply shocks to unemployment and shows that these shocks have been the main driver of U.S. unemployment dynamics since 2000 but have been unimportant before that period. The timing of the increased importance of financial market shocks coincides with financial market deregulation in the United States (e.g. the Financial Services Modernization Act in 1999) that gave rise to securitization and led to an increase in mortgage-backed securities.

Figure 4: Controlling for Firm Births/Deaths: GIRFs in Response to a Positive Credit Supply Shock



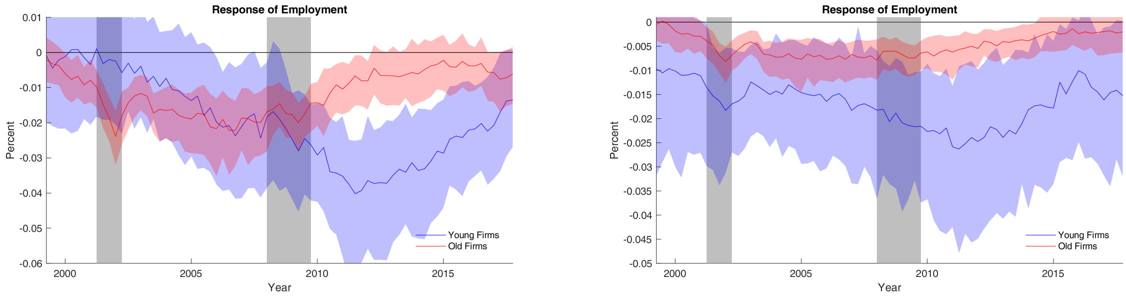
(a) Controlling for Firm Births



(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.

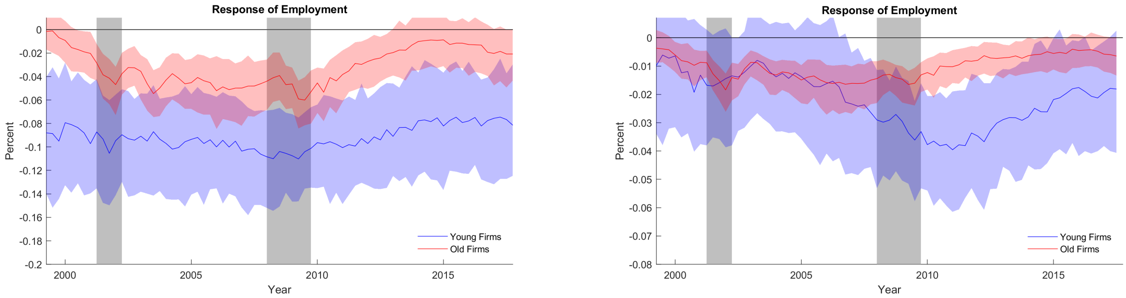
Figure 5: Controlling for Firm Dynamics II: GIRFs in Response to a Positive Credit Supply Shock



(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.

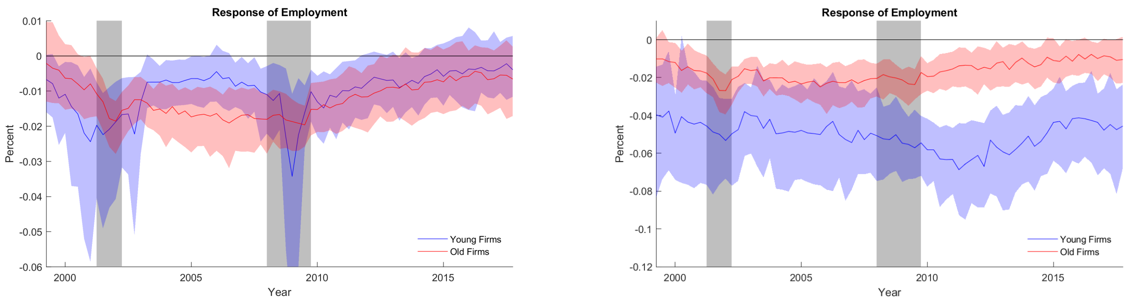
Figure 6: Robustness: Banks Tightening Standards (LHS) and Economic Uncertainty (RHS).



(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.

Figure 7: 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 8: 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).

4 The Role of House Prices

The empirical analysis presented in Section 3 highlights 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 8 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 increasing again, did young firms' employment response weaken.

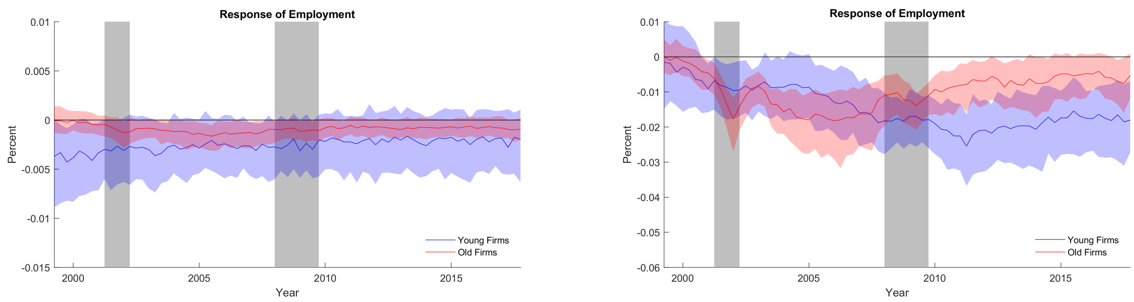
House Prices in the TVP-VAR: Next, I investigate the role of house prices in my structural empirical setting. For this purpose, I compute the employment responses by firm age in the TVP-VAR setting where house price growth enters as a fifth endogenous variable.[15] I analyze the role of house prices 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 9a of Appendix B). 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 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 9b of Appendix

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

B. 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 transmitting credit supply shocks.

Figure 9: 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 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 a fifth endogenous variable in the same specification. Red (Blue) shaded areas indicate 68 percent posterior credible sets. Grey-shaded areas denote NBER recession periods.

Collateral for New Businesses: The transmission mechanism may operate via the value of collateral for new businesses.[16] 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 B 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, Foulis, and Pinter, 2020 and Bahaj et al., 2022), a decline in the value of housing makes borrowing more costly or even impossible.[17] 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: I investigate the impact of house prices on young firms' employment responses to credit supply shocks, using a dataset at the metropolitan statistical area (MSA) level. This dataset includes young firms' job creation from the Business Dynamics Statistics (BDS), small business loan data from the Community Reinvestment Act (CRA), and the U.S. house price index.[18]

[16] 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, Mitman, and Violante (2020) find that house prices affect credit conditions via changes in household leverage.

[17] 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.

[18] For an overview of data sources, see Appendix C.

I estimate the following long-difference model:

$$\Delta JC_{m,07-09} = \beta \Delta Log(HP)_{m,06-09} + \alpha \Delta SBL_{m,06-09} + \gamma \Delta Log(HP)_{m,06-09} \times \Delta SBL_{m,06-09} + X_{m,06} + \epsilon_m, \tag{4.1}$$

The dependent variable, $\Delta JC_{m,07-09}$, represents the percentage change in MSA-level job creation by young firms from 2007 to 2009. $\Delta \log(HP)m, 06-09$ and $\Delta SBLm, 06-09$ denote MSA-level house price changes and the change in small business loan amounts, respectively, between 2006 and 2009. $X_{m,06}$ includes MSA-level controls for 2006, and I weight all regressions by population density of the year 2000.

Table 3 depicts the results, showing a significant elasticity of the change in job creation to the change in MSA-level house prices. The interaction term indicates that in areas with larger house price declines, job creation by young firms is more elastic to small business loan amounts. These findings suggest a link between credit conditions for young businesses and local house prices, which affects young firms' job creation. Specifically, fluctuations in real estate collateral for young firms influence their borrowing capacities, as lower house prices increase borrowing costs and the likelihood of loan denial, ultimately reducing job creation.

While these results don't establish causality, they align with findings by Favara and Imbs (2015) and Mian and Sufi, 2014, suggesting a connection between financial deregulation, home-ownership rates, house prices, and labor market dynamics. The house price collapse led to decreased business owners' collateral, impacting young businesses' responses to financial market shocks more than older businesses.

Table 3: 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

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 three building blocks: 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, a financial intermediary (i.e. bank), and a representative household. Risky firms are subject to idiosyncratic productivity shocks and convert capital into effective capital. I will refer to them simply as "firms".

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).

The novelty of the model lies in the expansion of the conventional debt contract framework as expounded by Bernanke et al. (1999), enriched along two dimensions. Primarily, the model introduces a detailed firm age structure with endogenous entry. Second, besides debt, firms have also

access to equity.
Firms enter the market endogenously and start in the entrants' cohort. Those who do not go bankrupt or die exogenously at the end of the period move to the next age cohort ($j = 1$). Each age cohort $j \in (E, 1, \cdots, K, O)$ consists of a continuum of firms i.[19] 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. Entrants are equipped with some initial (housing) net worth (i.e. collateralizable assets) from households and cannot pay out dividends yet.
Each risky firm i in age cohort j is subject to idiosyncratic productivity shocks $\omega^{i,j}$, which are private information and crucial in determining their capacity to convert raw capital into effective capital and thereby, whether they remain in business or declare bankruptcy.[20]. Specifically, firms use their net worth and loans to purchase raw capital $K_t^{i,j}$ at a price $Q_t^{i,j}$. They then transform this capital into effective capital $E_t\left\{\omega_{t+1}^{i,j}\right\}Q_t^{i,j}K_t^{i,j}$, which they rent out to cohort-specific capital producers to earn a return $E_t\left\{R_{t+1}^{k,j}\omega_{t+1}^{i,j}\right\}Q_t^{i,j}K_t^{i,j}$. Bankruptcy is endogenous and determines the end-of-period net worth of each age cohort (Bernanke et al., 1999). Non-bankrupt firms sell their non-depreciated capital back to the capital good producer and settle their debts. The net worth of bankrupt firms is seized by the bank.
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 cohort-specific final goods producer rents effective capital from firms and hires labor. I assume homogeneous worker skills, thus, all firms pay the same wage.

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 with $r_t = \rho^r r_{t-1} + (1-\rho^r)r_{SS} + \epsilon_t^r$, 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, 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 $E_t\left\{\bar{\omega}_{t+1}^{i,j}R_{t+1}^{k,j}\right\}Q_t^{i,j}K_t^{i,j}$.
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

[19] As they operate under constant returns to scale, aggregation within cohorts is straightforward.
[20] 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 $E(\omega) = 1$.

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

$$E_t\left\{\bar{\omega}_{t+1}^{i,j}\right\} = \frac{Z_t^{i,j} B_t^{i,j}}{E_t\left\{R_{t+1}^{k,j}\right\} Q_t^{i,j} K_t^{i,j}}. \tag{5.2}$$

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

$$\underbrace{E_t\left\{[\Gamma^j(\bar{\omega}_{t+1}^j) - \mu^j G^j(\bar{\omega}_{t+1}^j)] R_{t+1}^{K,j} Q_t^j K_t^j\right\}}_{\substack{\text{Loan repayment by non-defaulting firms \& recovery value} \\ \text{of defaulting firms net of monitoring costs}}} = \underbrace{R_t^n \frac{B_t^j}{(1-r_t)}}_{\text{Riskless return on deposits}} \tag{5.3}$$

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_t^j.[21] The economy-wide loan amount B_t equals the sum across all cohorts $\sum_{j=E}^{O} B_t^j$ for $j \in (E, 1, \cdots, K, O)$ such that Equation 5.1 holds.

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

Total monitoring costs per cohort of firms are given by

$$\mathrm{m}_t^j = \mu^j E_t \left\{ \int_0^{\bar{\omega}_{t+1}^j} \omega dF(\omega) R_{t+1}^{k,j} \right\} Q_t^j K_t^j. \tag{5.4}$$

5.2 The Business Sector

5.2.1 Risky Firms

The individual firm i, in cohort j, transforms the capital purchased into effective capital and rents it to output goods producers.[22] The return per unit of capital is given by the realization of idiosyncratic productivity times the aggregate return on capital, $E_t \left\{ \omega_{t+1}^{i,j} R_{t+1}^{k,j} \right\}$.

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 entry costs. The entry decision is described in more detail in Subsection 5.2.2. Upon entry, households provide potential market entrants with an initial housing net worth, denoted as N^{ST}, which can fluctuate due to changes in house prices, represented by hp_t. These households then leverage this net worth to secure a loan during the initial phase of their business operations. Within the cohort of entrants, firms buy capital K_t^E at price Q_t^E for use in $t+1$. The financing for these capital purchases comes from their initial net worth and the loans they have obtained from financial intermediaries, denoted as B_t^E. Consequently, this establishes an overall balance sheet constraint for the group of new entrants, which can be expressed as:

$$Q_t^E K_t^E = B_t^E + \mathrm{hp}_t N^{ST}, \tag{5.5}$$

Here, hp_t is defined as a first-order autoregressive (AR(1)) shock to the initial net worth of the entrants, reflecting their assets that can be used as collateral.

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

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

subject to the participation constraint of lenders (equation 5.3) and the balance sheet constraint (equation 5.5).[23] 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:

$$N_t^E = Q_t^j \gamma^E (1 - \Gamma(\bar{\omega}_t^E)) R_t^{k,E} Q_{t-1}^E K_{t-1}^E, \tag{5.6}$$

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 iden-

[22] The assumption of constant returns to scale makes the distribution of net worth $N_t^{i,E}$ and capital $K_t^{i,E}$ across firms *within* the cohort irrelevant.

[23] See the Appendix for the corresponding first-order conditions.

tities:

$$B_t^j = \begin{cases} Q_t^j K_t^j - N_t^E & \text{if } j = 1 \\ Q_t^j K_t^j - N_t^{j-1} & \text{if } j \in (2, \cdots, K) \\ Q_t^j K_t^j - N_t^j & \text{if } j = O, \end{cases} \tag{5.7}$$

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:

$$\varphi(d_t^j) = d_t^j + \kappa^d (d_t^j - d_{SS}^j)^2, \tag{5.8}$$

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 expected 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 5.3), the balance sheet constraints (equation 5.7), and the flow-of-funds constraint, which equates this period's outflows to its inflows for $k \in (1, \cdots, K)$:

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

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

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

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.[24]

End-of-Period Net Worth: The end-of-period net worth of age cohorts $k \in (1, \cdots, K)$ is given by the

[24] See the Appendix for the corresponding first-order conditions.

profits of surviving, non-bankrupt firms that have not been paid out as dividends.

$$N_t^k = \gamma^k(1-\Gamma(\bar{\omega}_t^k))R_t^{k,k}Q_{t-1}^k K_{t-1}^k - \varphi(d_t^k), \tag{5.9}$$

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):

$$N_t^O = \gamma^o(1-\Gamma(\bar{\omega}_t^O))R_t^{k,O}Q_{t-1}^O K_{t-1}^O + N_t^K - \varphi(d_t^O). \tag{5.10}$$

Firms may exit the market through two mechanisms: (i) exogenously, based on the cohort-specific survival rate γ^j, and (ii) endogenously, through bankruptcy. Bankruptcy occurs when a firm's idiosyncratic productivity realization falls below the threshold $\bar{\omega}_t^j$, preventing the firm from meeting its debt obligations. Exogenously exiting firms consume their remaining profits before exiting, as described by the following equation:

$$C_t^{e,j} = (1-\gamma^j)(1-\Gamma(\bar{\omega}_t^j))R_t^{k,j}Q_{t-1}^j K_{t-1}^j, \tag{5.11}$$

where $C_t^{e,j}$ enters the resource constraint. In contrast, when a firm goes bankrupt, its remaining net worth is seized by the financial intermediary.

5.2.2 Endogenous Entry and Age Dynamics

The household equips entering firms with an exogenous amount of starting net worth N^{ST}. Potential entrants are identical and face an idiosyncratic entry cost shock, denoted as ϵ^E. This shock is drawn from an entry cost distribution characterized by a stable density $f(\epsilon^E)$ and a 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.[25]

The entry firm value is given by the share of earnings remaining in the entrant cohort after payment of monitoring costs to the bank at the idiosyncratic productivity cutoff:

$$E_t\left\{\tilde{V}_t^E\right\} = E_t\left\{\left(1-\Gamma(\bar{\omega}_{t+1}^E)\right)R_{t+1}^{k,E}\right\}Q_t^E K_t^E. \tag{5.12}$$

Free Entry Condition: The free entry condition equates the expected value of entering the market, $\tilde{V}_t^E$, to the cutoff entry cost, $\bar{\epsilon}_t^e$:

$$E_t\left\{\tilde{V}_t^E\right\} = \bar{\epsilon}_t^e \tag{5.13}$$

where $\bar{\epsilon}_t^e$ is the threshold level of entry costs that firms are willing to incur to enter the market. Potential entrants with idiosyncratic entry costs up to this firm value will enter the market, deter-

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

mining the number of entering firms, denoted by θ_t^E:

$$\theta_t^E = \int_{-\infty}^{\bar{\epsilon}_t^E} f(\epsilon^E)\, d\epsilon^E \ \forall d. \tag{5.14}$$

Evolution of Age Cohorts: The size of each age cohort evolves, with γ^j $(j \in (E, 1, \cdots, K, O))$ representing the survival rates of firms in different cohorts:

$$\theta_t^1 = \gamma^E \theta_{t-1}^E \tag{5.15}$$
$$\theta_t^k = \gamma^{k-1} \theta_{t-1}^{k-1} \tag{5.16}$$
$$\theta_t^O = \gamma^O \theta_{t-1}^O + \gamma^K \theta_{t-1}^K \tag{5.17}$$

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 $(\gamma^K \theta_{t-1}^K)$.

The total number of firms in the economy at any given time, denoted by θ_t, is the sum of firms across all cohorts:

$$\theta_t = \sum_{j=E}^{O} \theta_t^j. \tag{5.18}$$

5.2.3 Capital Good Production

As in Gertler, Kiyotaki, and Prestipino (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

$$K_{t+1}^j = \Lambda\left(\frac{I_t^j(i)}{K_t^j}\right)K_t^j + (1-\delta)K_t^j, \tag{5.19}$$

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.[26] The maximization problem for the capital goods producer j is

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

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

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

$$Q_t^j = \left[\Lambda'\left(\frac{I_t^j}{K_t^j}\right)\right]^{-1}. \tag{5.20}$$

5.2.4 Output Good Production

Capital and labor are combined to produce output goods. For tractability in aggregation within each age cohort, production is assumed to follow constant-returns-to-scale. Each firm cohort j produces output Y_t^j using a production function that combines capital K_t^j and labor L_t^j:

$$Y_t^j = (K_t^j)^{\alpha}(L_t^j)^{1-\alpha}, \tag{5.21}$$

where α is the output elasticity of capital.
Profit maximization of output good producers implies that the wage is set equal to the marginal product of labor

$$W_t = (1-\alpha)\frac{Y_t^j}{L_t^j}. \tag{5.22}$$

The wage is equal for all age cohorts as otherwise all households would supply labor only to the highest-paying firm.
Finally, the real rental rate of capital for each cohort, denoted as $r_t^{k,j}$, is determined by the marginal product of capital:

$$r_t^{k,j} = \alpha\frac{Y_t^j}{K_t^j}. \tag{5.23}$$

Firms' expected gross return for holding one unit of capital is given by

$$R_{t+1}^{k,j} = \frac{r_{t+1}^{k,j} + (1-\delta)Q_{t+1}^j}{Q_t^j}, \tag{5.24}$$

and depends on the capital rental rate $r_t^{k,j}$ and the gain from selling non-depreciated capital $(1-\delta)Q_t^j$ back to the capital goods producer.

5.3 Households

Consider a representative household that lives indefinitely and displays risk aversion, characterized by a subjective discount factor β, where $0 < \beta < 1$. This household gains utility from consumption C_t and incurs disutility from labor L_t, measured in hours worked from providing labor to output goods producers.

The utility maximization for the household is formalized as:

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

where σ^C denotes the coefficient of relative risk aversion for consumption, χ scales the disutility from labor, and η is the elasticity of labor supply relative to the wage rate.
The budget constraint faced by the household in each period is given by:

$$C_t + D_t + s_t p_t + \mathrm{hp}_t N^{ST} = W_t L_t + R_{t-1}^n D_{t-1} + s_{t-1}(d_t + p_t), \tag{5.25}$$

where D_t represents the household's savings in the form of risk-free deposits, s_t is the number of equity shares held with p_t being the price per share, N^{ST} is the exogenous housing net worth dedicated to startups that is subject to house price shocks hp_t, W_t is the wage rate, R_{t-1}^n is the risk-free interest rate on the previous period's deposits, d_t is the dividend from equity.

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:

$$Y_t = C_t + I_t + \mathrm{m}_t + C_t^e. \tag{5.26}$$

6 Calibration and Steady State

To ensure model tractability and align with the deterministic aging structure of firms, I calibrate the model to a semi-annual frequency, incorporating $K = 9$ young firm cohorts, along with new entrants. This setup aligns with my empirical definition of young firms. Firms are classified as "young" for their first five years, after which they are reclassified as "old," consistent with the empirical analysis.
Table 4 presents the calibration parameter choices. Unless stated otherwise, parameters are identical across age cohorts. The annualized riskless interest rate target is 3%, leading to a semi-annual household discount factor (β) of 0.985. The capital depreciation rate (δ) is set at 5% (semi-annual), and the weight of capital in the production function (α) is 0.33, as is typical. In the steady state,

productivity (a_t^j) is normalized to 1, and the coefficient of relative risk aversion (σ_c) is set at 2.00, a standard value in the literature. The Frisch elasticity of labor supply (η) is 1. The disutility of labor parameter (χ) is determined endogenously after solving for steady-state employment across all cohorts.

To establish the parameters for the optimal debt contract between banks and entrepreneurs, I follow 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 are calibrated using three key parameters: monitoring costs, variance of the idiosyncratic productivity distribution, and the idiosyncratic productivity cutoff. Based on Afanasyeva and Güntner (2020), I set the 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 (as in Afanasyeva and Güntner (2020)). These two age-invariant parameters, along with the idiosyncratic productivity cutoffs set to 0.36, 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 adjustment costs. 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 and a price of capital Q equal to unity, as proposed by Gertler et al. (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).

Idiosyncratic entry cost shocks follow a log-normal distribution. To target a unit measure of firms in the economy with a 5.5% share of entrants in steady state, consistent with BDS data, I set the scale parameter of the distribution. The location parameter 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 BDS data from 1990 to 2006. This data shows that around 63% of firms are old. To achieve this target, I set the survival rates for two cohorts: the entering cohort ($\gamma^E = 0.855$) and the "old" cohort ($\gamma^O = 0.954$). The remaining survival rates arise endogenously in the steady state and increase with firm age. In addition to exogenous exits, firms whose idiosyncratic productivity falls below the cutoff value $\bar{\omega}^j$ exit endogenously. Therefore, the total exit rate of firms by cohort is the sum of the endogenous default rate and the exogenous rate of exit.

Solution and Shock Processes: The economy starts in a steady state and is subjected to two exogenous shocks: a shock to the financial intermediary's reserve requirements (ϵ_t^r) and an innovation to the housing net worth of entrants (ϵ_t^{hp}). These shocks are assumed to be uncorrelated and follow autoregressive processes with autocorrelation parameters ρ^r and ρ^{hp}. The parameter ρ^{hp} is set to 0.849, reflecting the biannual autocorrelation of the U.S. national Shiller home price index, while ρ^r is calibrated to 0.8. The aggregate loan amount is modeled to decrease by 8%, while the

Table 4: 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 (steady state)	a_t^j	1.00
	Frisch elasticity of labor supply	η	1
	Disutility of labor parameter	χ^j	endog. determined
Financial Frictions and Policy			
	Monitoring costs in case of default	μ^j	0.20
	Variance of idiosyncratic realizations	σ^j	0.18
	Idiosyncratic productivity cutoffs	$\bar{\omega}^j$	0.36
	Reserves (steady state)	r	0.20
	Dividend adjustment costs	κ^d	0.15
	Elasticity of price of capital w.r.t investment rate	η^i	0.25
	Scale parameter of investment adjustment costs	a^K	endog. determined
	Fixed adjustment cost parameter	b^K	endog. determined
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	0.80
	Autocorrelation of house price shock process	ρ^{hp}	0.849
	Size of credit supply shock	ϵ^r	0.0062
	Size of house price shock	ϵ^{hp}	-0.087

decline in young firms' net worth reflects a 23% drop in U.S. house prices from 2007Q1 to 2012Q4, representing the peak-to-trough period.

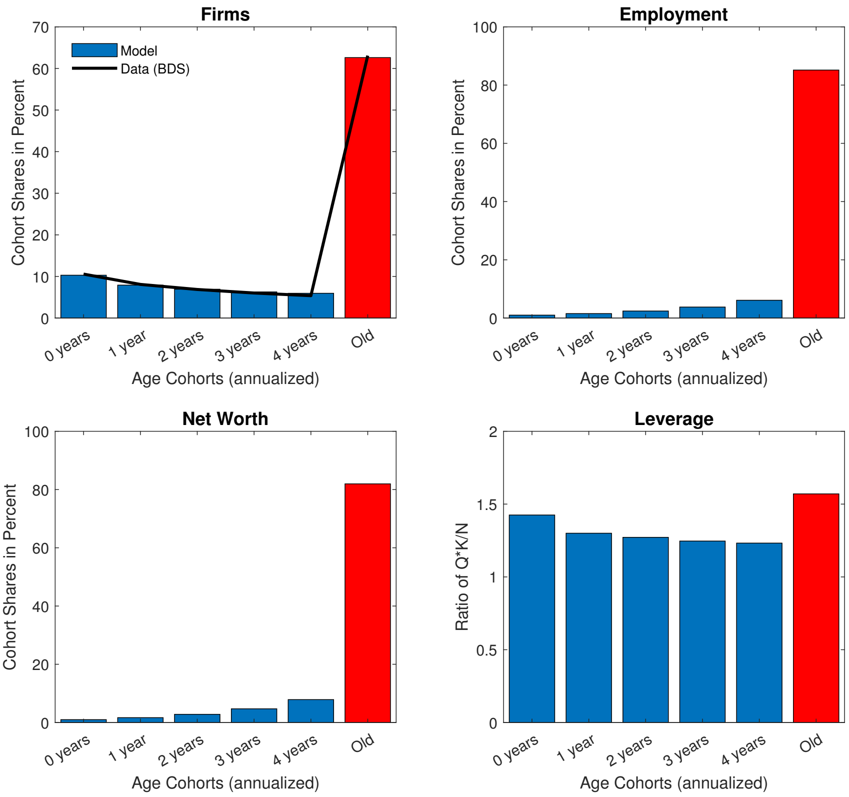
6.1 The Model in Steady State

I target the relative proportion of young (established up to five years ago) to old firms in steady state. Figure 10 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 10 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 10 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 5.3). As firms age, they select the highest possible leverage for a given idiosyncratic

Figure 10: 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.

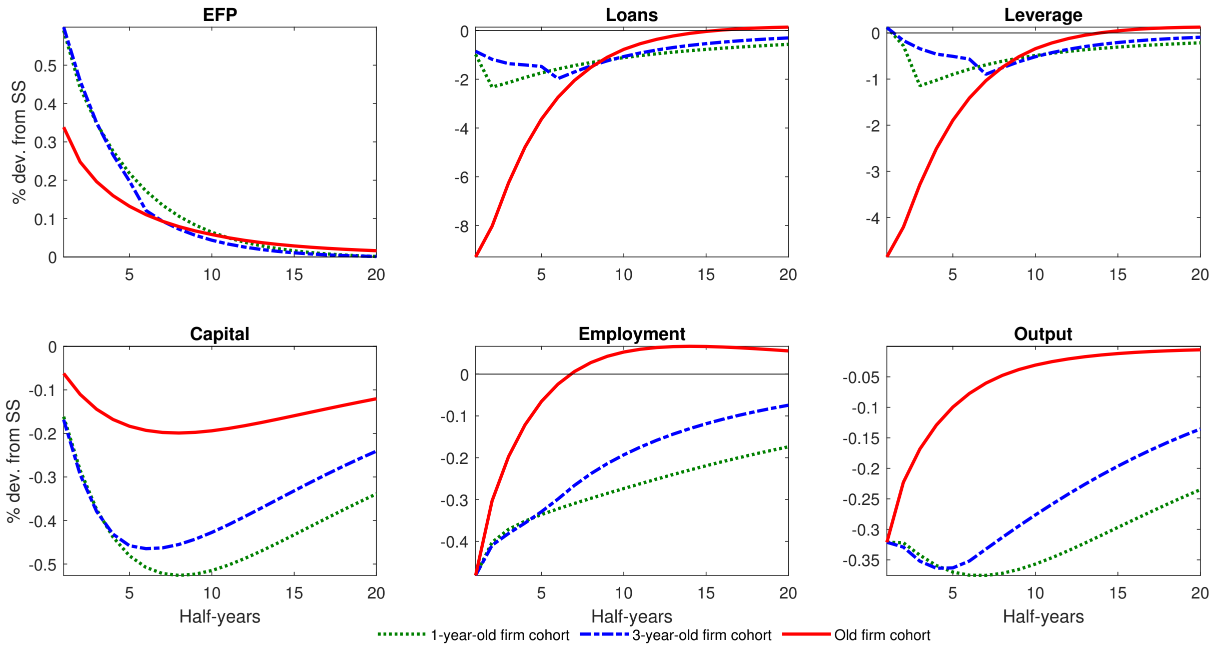
productivity cutoff and net worth, which the bank is willing to offer. This result is broadly in line with the findings of Dinlersoz et al. (2018), who observe that publicly listed firms are highly leveraged as they grow older.

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 disentangle the effects of credit crunches from the effects of housing net worth shocks. This allows me to analyze the relative importance of both shocks in explaining U.S. unemployment dynamics after the GFC.[27]

[27] 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).

Figure 11: 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 $K = 1$), and 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.

7.1 Effects of a Credit Crunch

Figure 11 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 an old firm (Y_O). Young firms face a stronger increase in their external finance premium compared to old firms due to their lower initial net worth and higher leverage, which leads to a larger perceived risk by lenders. As a result, young firms are forced to borrow at significantly higher interest rates, further constraining their capital investment and amplifying the reduction in employment. In contrast, old firms can substitute between debt and equity financing, lowering their borrowing needs and mitigating the impact of the credit shock. This is consistent with the findings of Begenau and Salomao (2018), who show that large firms tend to restructure their capital portfolios toward more equity and less debt in recessions. In contrast, smaller firms adapt their capital structure pro-cyclically. The aggregate results of a credit supply shock are illustrated in Figure 24 in Appendix E.3.

Although old firms have a higher debt-to-net worth ratio in steady state, younger firms reduce economic activity more strongly because old firms reshuffle their capital structure toward 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. The relatively quick employment recovery at old firms is consistent with empirical evidence from the Business Dynamics Statistics (BDS) data, which shows that employment in old firms began to recover after 2010. In contrast, employment in young firms only increased significantly around 2014. Table 5 compares the relative employment responses by firm age from my structural TVP-VAR model (first row), based on the median impulse responses depicted in Figure 2, to the relative employment reaction of young vs. old firms in my quantitative theoretical model (second row) for the same time period

(1.5 years after the shock).[28] However, the credit supply shock cannot fully explain the stronger employment contraction among young firms during and after the Great Financial Crisis (GFC). In the next subsection, I explore whether a decline in the value of collateralizable assets could help reconcile this discrepancy between the empirical and theoretical employment responses.

7.2 The Role of Collateralizable Assets for Young Firms

Figure 12 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 initial starting net worth (i.e. housing net worth). I follow Bernanke and Gertler (1989) in their interpretation of net worth of entrants as collateralizable assets, mainly tangible assets (such as buildings and land).

The simultaneous decline in young firms' collateralizable assets, particularly housing-based net worth, exacerbates the financial accelerator mechanism. As collateral values fall, young firms' borrowing costs rise, reducing their ability to secure loans. This decline in credit availability constrains their investment in capital, which in turn further reduces net worth and perpetuates the cycle of constrained borrowing and reduced economic activity. This feedback loop disproportionately affects young firms, as their reliance on external debt is greater, and their net worth is more sensitive to housing market shocks. As borrowing becomes more expensive, young firms reduce their demand for capital and labor, reinforcing the cycle of constrained investment and economic activity. 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 housing 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 more heavily on debt financing.

The second column of Table 5 compares the relative employment responses of young and old firms between the theoretical and empirical models, showing that the decline in house prices (i.e., entrants' collateralizable assets) plays a crucial role in matching the theoretical and empirical relative employment responses after the GFC. Once the house price decline is included, the theoretical model aligns closely with the empirical data, particularly in 2014/Q3.

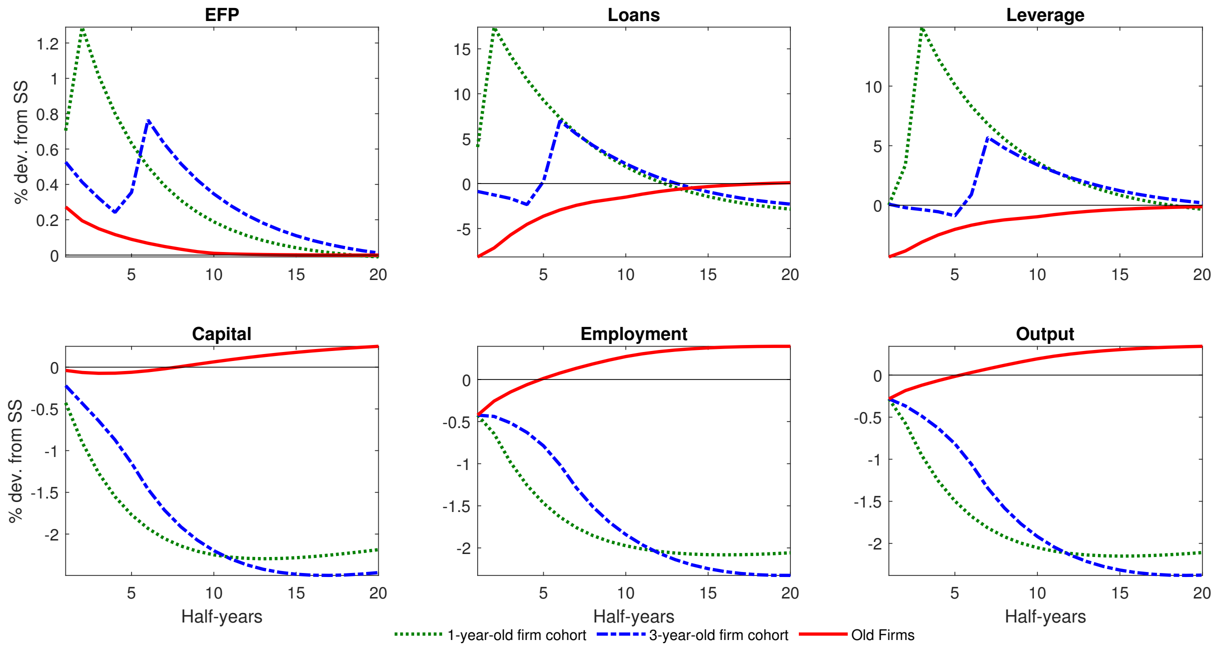
In summary, the simultaneous decline in collateralizable assets makes it even more difficult for young firms to access external finance. These challenges are intensified by the higher risk perceived by lenders and the resulting financial accelerator effect. The next subsection inspects the key economic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

7.3 Drivers of Heterogeneous Responses by Firm Age

Figure 13 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

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

Figure 12: Responses to a Credit Supply and House Price Shock: Young vs Old Firms



Notes: Responses to an unexpected contractionary credit supply shock and house price 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.

Table 5: Empirical IRFs vs. Theoretical IRFs: Employment effects, Young/Old Firms

	Employment Response of Young/Old Firm	
TVP-VAR Model	**2007/Q2**	**2012/Q1**
	1.83	5.79
Theoretical Model	**Credit Crunch**	**House Price Shock**
	1.88	5.79

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 house price shock).

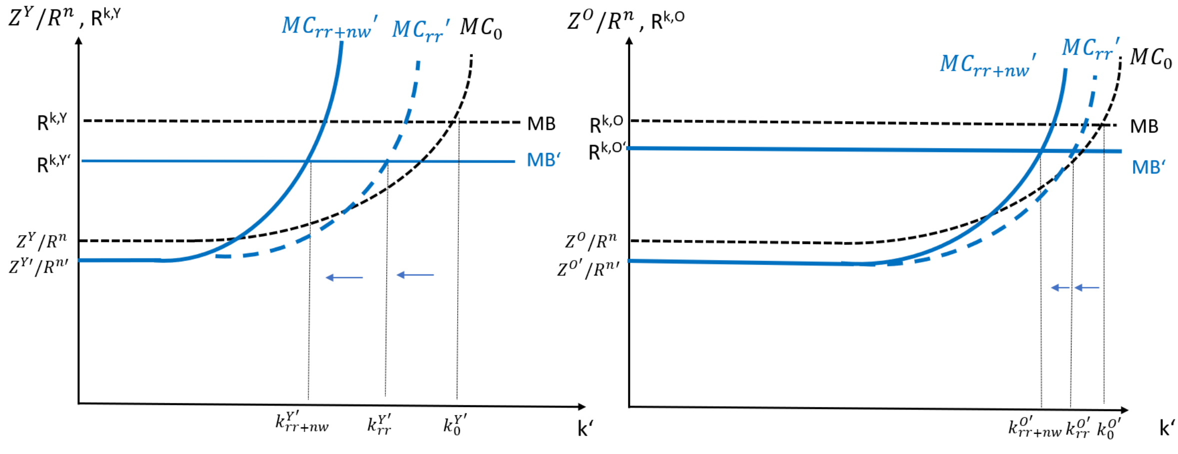
k'.[29]

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 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, requiring 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

[29] This illustration is based on Bernanke et al. (1999) and has been adapted to illustrate the effects of monetary policy shocks by Ottonello and Winberry (2020) and Bahaj et al. (2022).

Figure 13: Inspecting the Mechanism: Young vs. Old Firms



a) Young Firm

b) Old Firm

Notes: Responses to a contractionary credit supply and house price 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 house price shock.

of k'. Second, the loan rate Z^Y_t reacts more strongly to shocks for young firms.

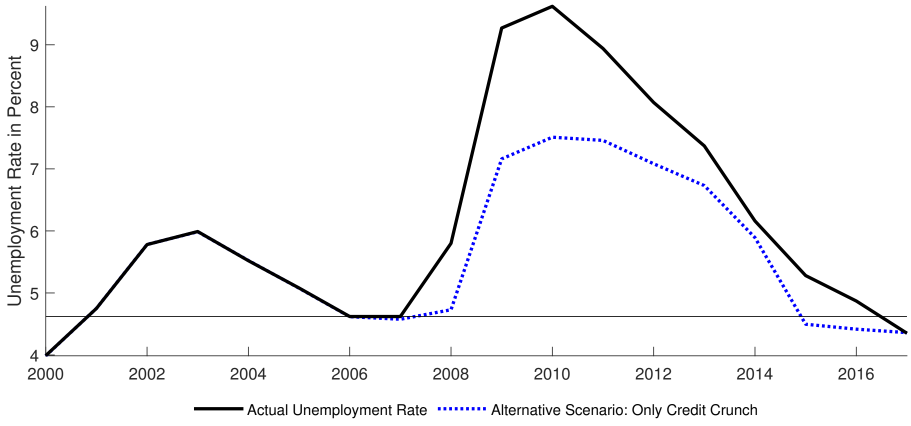
In response to a credit supply shock, both the marginal benefit curve and the marginal cost curve shift. The marginal benefit curve shifts down for both young and old firms as the return on capital $R^{k,j}$ decreases. However, the decline is more pronounced for young firms. The risk-free rate also declines, 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 $k^{j'}_0$ to $k^{j'}_{rr}$, 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+hp}, leading to even lower capital demand ($k^{j'}_{rr+hp}$).

Note that firm age serves as a proxy for underlying financial characteristics that evolve endogenously over the firm's life cycle. Young firms are more exposed to credit supply shocks not because of their age per se but because they typically have lower net worth and higher leverage and face steeper increases in borrowing costs when agency problems worsen. The results, therefore, generalize to other firms with similar financial vulnerabilities, even if they are not young, highlighting that it is financial fragility—proxied by age in the empirical analysis—that drives the differential responses. Nonetheless, as the empirical results in Section 3 show, age is a reliable proxy for identifying the firms most responsive to credit supply shocks.

7.4 The Relative Contribution of Shocks and Alternative Scenarios

To determine the extent to which the house price shock contributed to the decline in employment, I take two steps. First, I use the historical decomposition depicted in Figure 21 to gauge the contribution of financial shocks to U.S. unemployment dynamics. Second, I compute the relative con-

Figure 14: 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.

tribution of the house price shock to the overall decline in young firms' employment (weighted by their size) across the impulse response horizon based on my quantitative model.[30] According to my model, the house price 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 house price 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 house price shock during and after the GFC, compared to the pre-crisis year of 2006.[31] As shown in Figure 14, 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.[32] The results show that in the absence of the house price 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.

8 Conclusion

Young firms play a significant role in overall job growth, making it crucial for economists and policymakers to understand the obstacles they face in creating jobs after economic downturns. One key challenge is young firms' access to credit, as they typically have lower net worth, shorter business histories, and higher bankruptcy risks, leading to more expensive borrowing and an increased likelihood of loan denials. While previous research has focused on microeconomic effects or assumed linear impacts over time, my paper contributes to the literature by examining the non-linear labor

[30] For this purpose, I compute the difference in employment responses with and without the house price shock.

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

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

market effects of financial market shocks by firm age and over time, from a macroeconomic perspective. Specifically, I disentangle the relative contributions of the credit supply and net worth channels.

Since the Great Financial Crisis (GFC), credit supply shocks have triggered more significant employment contractions among younger firms. Local house prices and fluctuations in young business owners' private home equity explain much of the age-based differences in job creation. To rationalize these findings, I develop a general equilibrium model that incorporates cohorts of young and old firms with financial market frictions. While the paper focuses on firm age as the key dimension of heterogeneity, the underlying mechanism is financial vulnerability, with age serving as a proxy for characteristics such as low net worth, high leverage, and limited credit history. The findings, therefore, speak more broadly to the role of capital structure and balance sheet strength in shaping firm-level responses to credit disruptions.

My model shows that the link between firms' net worth and the cost of external finance activates a financial accelerator mechanism that disproportionately impacts young firms with lower net worth. During the GFC, young firms not only faced tighter credit conditions but also a sharp decline in the value of their private real estate collateral. The interaction of these two shocks forced them to reduce economic activity and persistently cut labor demand. In contrast, older firms were less affected by the housing bust and were able to switch from debt to equity financing as credit supply tightened. My decomposition of the credit supply and net worth channels shows that without the bust in house prices, the U.S. unemployment rate during the GFC would have been almost two percentage points lower.

These findings suggest that targeted government support could help mitigate the financial constraints faced by young firms during downturns. Loan guarantee programs, for example, could alleviate credit constraints and encourage young firms to invest and create jobs. However, it is essential that such programs are well-targeted to firms with the highest growth potential. One possible solution is to pool funds at the bank level and allow banks to select beneficiaries, ensuring that loan guarantees are directed to firms most likely to benefit from the support.

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A Details on the Time-varying Parameter VAR

This section describes the priors and estimation algorithm used for the time-varying parameter estimations.[33]

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. 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 **A** denoting the lower-triangular matrix and $D^{\frac{1}{2}}$ is a diagonal matrix containing the standard deviations of residuals. The prior for log-volatilities is set to

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

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

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

where $\tilde{\alpha_0}$ is a stacked vector containing the diagonal elements of the inverse of the matrix **A**.

Regarding the priors for the hyperparameters, I assume that **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 **S** also follows an inverse Wishart distribution with

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

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

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

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 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 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 Further Empirical Evidence, Robustness, and Extensions

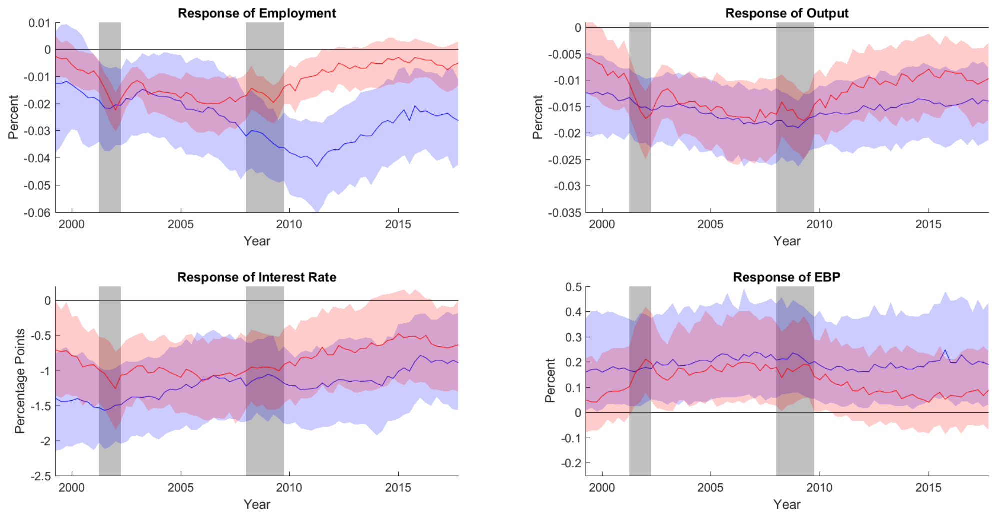
B.1 Different GIRF-horizons

This subsection displays generalized impulse responses to a credit supply shock i) 1 period after the shock (Figure 15), ii) 6 periods after the shock (Figure 16), and iii) 12 periods after the shock (Figure 17) for all endogenous variables, i.e. employment, output, the interest rate, and the EBP.

Figure 15: 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 the 16-th and 84-th percentiles of the posterior distribution for young (old) firms. Grey-shaded areas denote NBER recession periods.

Figure 16: Generalized Impulse Response Functions (GIRFs) in Response to a Credit Supply Shock: 6 Periods after the Shock



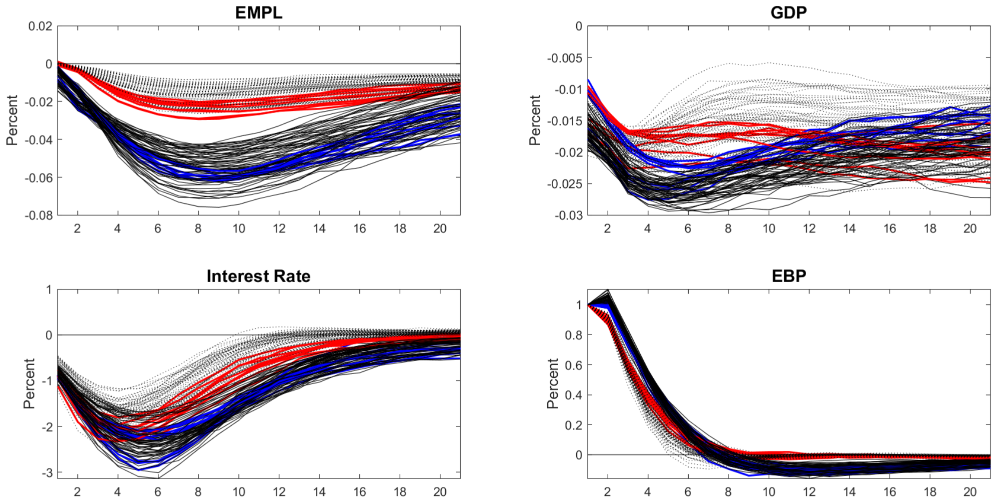
Notes: Responses of all four endogenous variables in the specification $[log(EMP)_t^j \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 6 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote the 16-th and 84-th percentiles of the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

Figure 17: 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 $[log(EMP)^j_t \quad log(GDP_t) \quad INT_t \quad EBP_t]$. The solid line illustrates median responses after 12 quarters to a 1 std. EBP shock (normalized to one), blue (red) shaded areas denote the 16-th and 84-th percentiles of the posterior distribution for young (old) firms. Grey-shaded areas denote NBER recession periods.

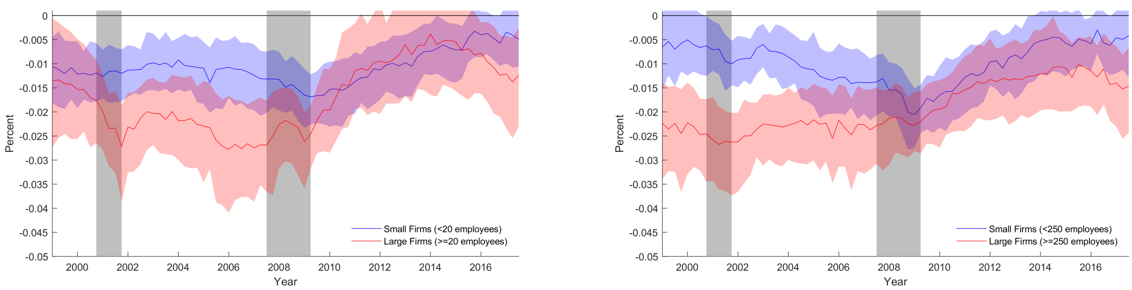
B.2 Further Robustness

Figure 18: 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 19: Firm Size: GIRFs of Employment in Response to a Credit Supply Shock



(a) Cutoff at 20 employees

(b) Cutoff at 250 employees

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

C 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:

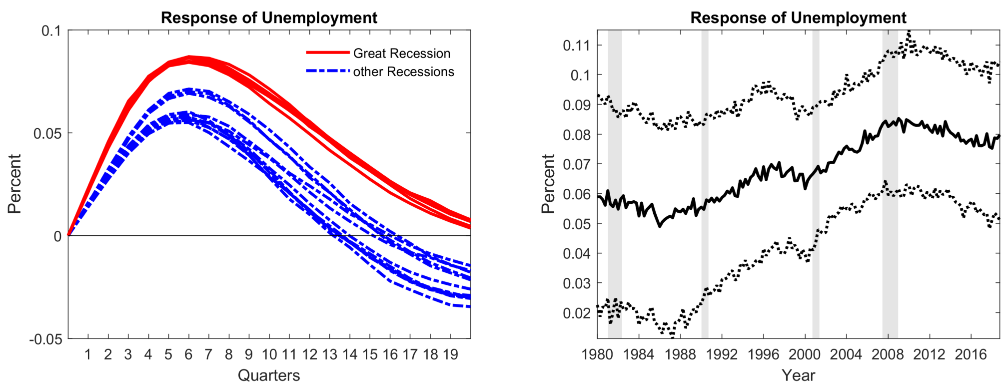
$$Y_t = [log(\text{unemp}_t)\ \ \Delta\text{GDP}_t\ \ \text{INT}_t\ \ \text{EBP}_t].$$

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.

C.1 Impulse Responses over Time

Figure 20 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.

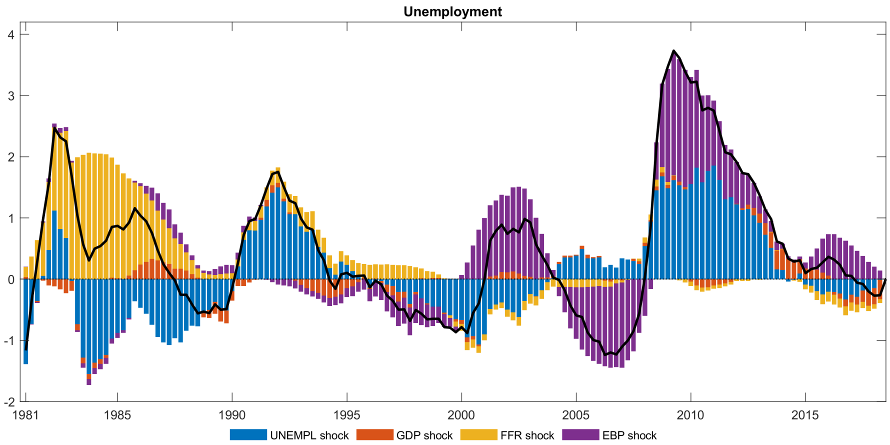
Figure 20: GIRFs of Unemployment in Response to a Credit Supply Shock (Long Horizon). Recessionary Periods and Over Time.



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 the 16-th and 84-th percentiles of the posterior distribution. Grey-shaded areas denote NBER recession periods.

Historical Decomposition: Figure 21 displays the historical contribution of credit supply shocks to unemployment. 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.

Figure 21: 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.

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.[34]

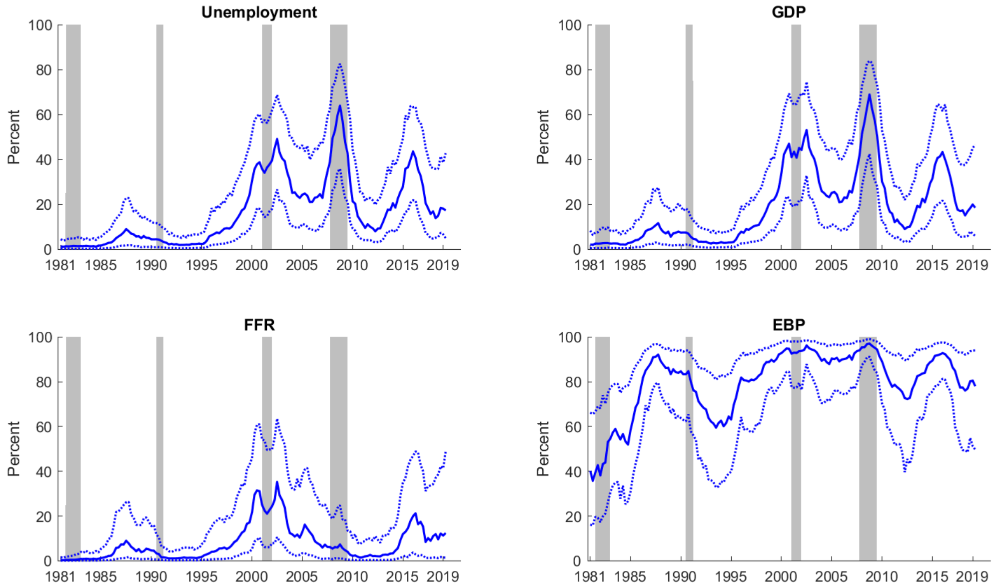
Forecast Error Variance Decomposition: In Figure 22, I present the contribution of credit supply shocks to the forecast error variance of all four endogenous variables six quarters after the shock (solid line) along with the sixteenth and eighty-fourth percentiles of the posterior distribution (dashed 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.[35] 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

[34] 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.

[35] 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 22: Forecast Error Variance: Contribution of Credit Supply Shocks



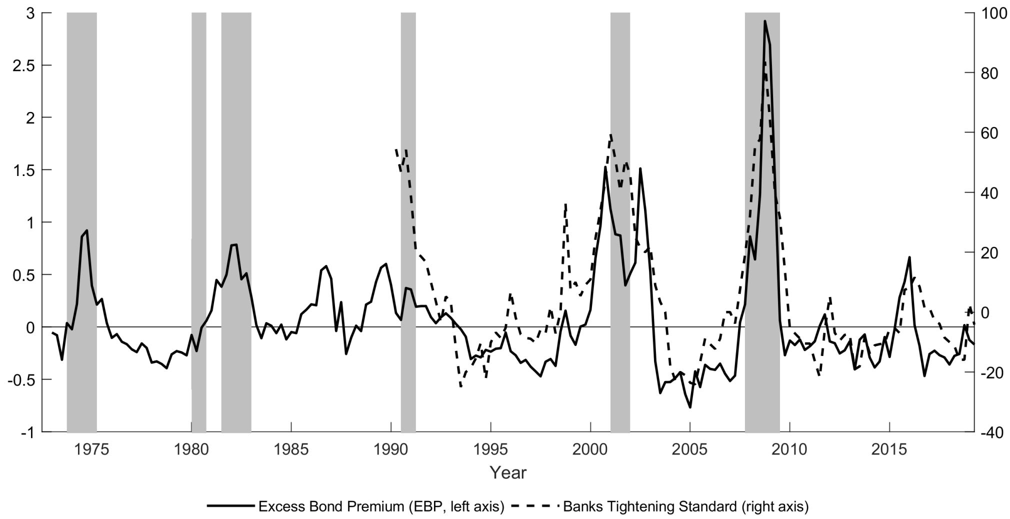
Notes: The solid line depicts the median of the contribution of credit supply shocks to the forecast error variance of all four endogenous variables 6 quarters after the shock. The dashed lines illustrate the 16th and 84th percentiles of the posterior distribution. FFR refers to the effective federal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

et al., 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.

D 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.

E Model Appendix

E.1 Firms' First Order Conditions

E.1.1 The Entrant

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

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

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

E.1.2 Age Cohort j

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

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

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

E.2 Household's First Order Conditions

The first-order conditions for the household's optimization problem, expressing the marginal utility of income as λ_t, are:

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

By forward substitution, the valuation of equity shares is captured by:

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

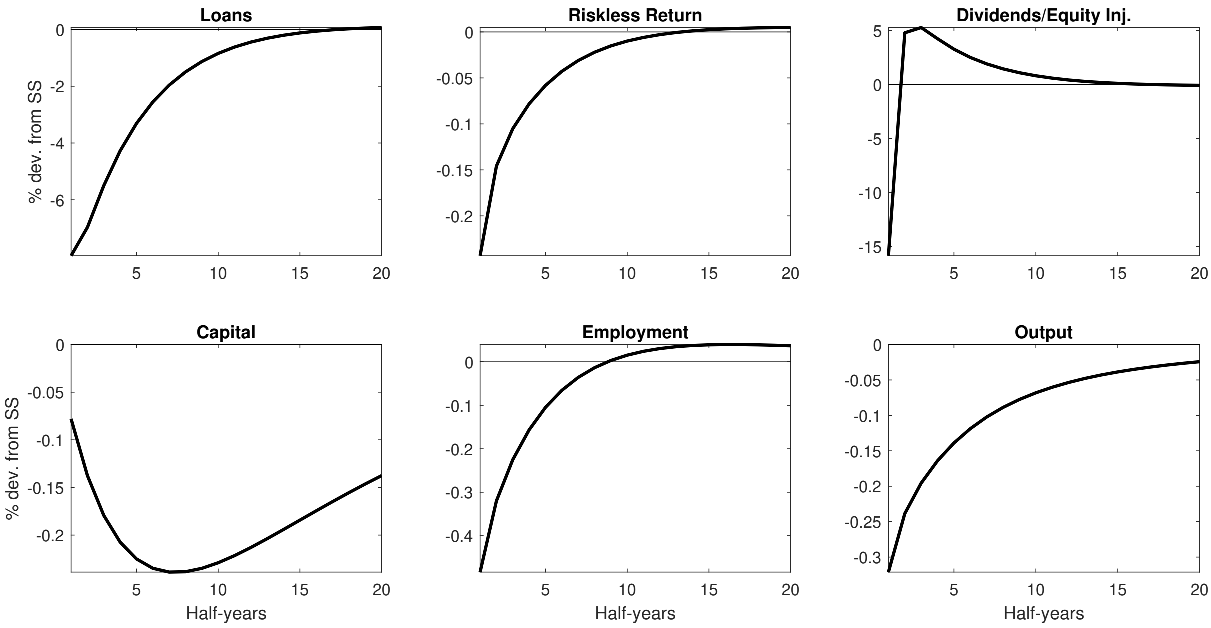
where the expected present value of future dividends is discounted by the household's stochastic discount factor $\beta^j \frac{\lambda_{t+j}}{\lambda_t}$. The household's decision on equity encompasses the total shares from all firms in the economy.

E.3 Further Simulation Results

E.3.1 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.

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.

F 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