Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations*

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Abstract

Microeconomic evidence reveals a direct link between firms' current earnings and their access to debt. This paper studies macroeconomic implications of earnings-based borrowing constraints. In a macro model, firms with earnings-based constraints borrow more in response to positive investment shocks, whereas firms with collateral constraints borrow less. Empirically, aggregate and firm-level credit responds to identified investment shocks according to the predictions with earnings-based constraints. Moreover, with sticky prices earnings-based constraints imply that supply shocks are quantitatively more important. This is validated in an estimated version of the model, highlighting the importance of carefully modeling credit constraints to understand policy tradeoffs.

JEL Codes: E22, E32, E44, G32.
Keywords: Collateral constraints; loan covenants; cash flow-based lending; financial frictions; investment-specific shocks; sticky prices.

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1 Introduction

Firm credit displays large swings over the business cycle. To understand this phenomenon, macroeconomists study the constraints to credit and how they interact with economic activity. This paper investigates the macroeconomic consequences of earnings-based borrowing constraints. These constraints are in contrast with asset-based collateral constraints, which have become a standard feature of business cycle models. Their presence is supported by direct evidence: microeconomic data reveals the pervasive use of loan covenants that make it difficult for firms to borrow when their current earnings are low.[1] The contribution of this paper is twofold. First, it develops a strategy to test for the relevance of earnings-based constraints in both macro and micro data. Second, it demonstrates that these constraints alter quantitative conclusions about US macroeconomic fluctuations and policy tradeoffs.

Motivated by micro evidence on US corporate loans, I develop a macro model with heterogeneous credit constraints. Firm credit can be restricted either by firms' current earnings or by the value of their capital. The first contribution of this paper is to combine predictions of this model with an econometric analysis of aggregate and firm-level data to distinguish the importance of different credit constraints. The model predicts that, depending on their constraint, firms either borrow more or borrow less in response to shocks that move earnings and the value of collateral in opposite directions. This is the case for investment shocks, which affect the ability of firms to turn resources into productive capital.[2] Positive investment shocks rise economic activity and earnings, while they reduce the relative price of capital. The increase in earnings allows for more debt under the earnings-based constraint, whereas the lower value of capital reduces credit access with the collateral constraint.

Based on these model predictions, I find that the earnings-based constraint is more relevant in both macro and micro data. At the macro level, I use a structural vector autoregression (SVAR) in which investment shocks are identified from their low-frequency impact on the relative price of equipment.[3] Business credit increases in response to a positive investment shock, evidence for the economy-wide relevance

[1]This motivating evidence echoes recent empirical research on corporate credit, in particular Lian and Ma (2021). See also Greenwald (2018) for a study of income-based in addition to asset-based borrowing limits in household mortgage contracts.

[2]The term investment shock encompasses different variations, including investment-specific technology and marginal efficiency of investment shocks, which Justiniano, Primiceri, and Tambalotti (2010, 2011) show are an important driver of US business cycles.

[3]The investment shock is identified from its negative impact on the price of new equipment. This is consistent with the loan-level data, where equipment is the largest category of collateral. I also verify that the shock reduces *used* equipment prices, as both new and used assets could serve as collateral.

of earnings-based constraints. At the firm level, I use the merged Compustat-Dealscan database to classify firms into those that face earnings-based loan covenants and those that borrow against collateral. I then run a panel local projection, regressing firm-level debt on the macro investment shock from the SVAR, allowing for heterogeneous responses across earnings-based and collateral borrowers. To take into account that firms operate different types of capital which may be affected by investment shocks in different ways, I weight the shock in the local projection with the sensitivity of each firms' industry-specific investment prices to aggregate investment shocks. The results at the firm level show that earnings-based borrowers significantly and persistently increase borrowing in response to a positive investment shock, while the credit response of collateral borrowers is significantly negative, consistent with the model predictions. Similar findings hold for firm-level investment, highlighting a tight link from financing decisions to economic activity.

Besides establishing the empirical relevance of earnings-based credit constraints, the second contribution of this paper is to study their quantitative consequences for business cycles and macroeconomic policy. The model features sticky prices, which allows me to study how different credit constraints affect stabilization tradeoffs. Broadly speaking, monetary policy can offset demand shocks, while supply shocks may lead to a stabilization tradeoff between inflation and activity. I derive analytically that with price rigidities earnings-based constraints imply that supply shocks should be important in driving business cycles. The reason is that when prices are sticky, demand shocks generate countercyclical markups, whereas supply shocks generate procyclical markups. All else equal, earnings move in the same direction as markups, so a constraint linked to earnings loosens when markups rise. Credit is procyclical empirically, so the earnings-based constraint, if binding, is a friction that renders countercyclical markups less consistent with the data in an environment price stickiness. Relative to a collateral constraint, its presence should therefore either increase the quantitative relevance of supply shocks, making markups less countercyclical, or it should imply low price rigidities so that markup variation is less important for earnings and credit dynamics.

To validate this theoretical implication of earnings-based credit constraints empirically, I estimate a quantitative version of my model on US data. The quantitative version features a variety of additional shocks and frictions typically included in medium-scale New Keynesian dynamic stochastic general equilibrium (DSGE) models, alongside earnings-based and collateral constraints to firm borrowing. I find that if a higher share of firms faces earnings-based constraints, there is a stronger contribution of supply shocks to output growth fluctuations than when a collateral constraint is the dominant credit friction among firms (76% vs. 37% at a two-year forecast error variance horizon). In addition, earnings-based credit constraints imply lower estimated price rigidities than collateral constraints, in fact muting the link from the cyclical movements in markups to earnings and debt. These findings demonstrate that the formulation of credit constraints not only matters for debt dynamics in the micro and macro level, but that it interacts with central conclusions drawn about the nature of US business cycles and ultimately the conduct of macroeconomic policy. The evidence provided in this paper as a whole makes the case for macroeconomists to change the benchmark way of modeling the credit constraints faced by firms in business cycle research.

Relation to the literature. First and foremost, this paper contributes to the literature on the role of financial frictions in macroeconomics, which goes back to the seminal work of Bernanke and Gertler (1989) and Kiyotaki and Moore (1997).[4] Nakamura and Steinsson (2018) emphasize the appeal of disciplining macro models with "micro moments." In this spirit, my paper builds on microeconomic evidence on firms' loan contracts to study financial frictions in macroeconomic fluctuations.[5]

Second, my motivating evidence connects to existing research on loan covenants and the micro-level details of firm debt.[6] Based on a comprehensive empirical analysis, Lian and Ma (2021) propose that the key constraint on US corporate debt are cash flows measured by earnings.[7] Greenwald (2019) studies the role of different covenant types in the transmission of monetary policy shocks at the firm-level. My contribution relative to these papers is twofold. I show that focusing on investment shocks provides a way to disentangle earnings-based from collateral constraints, and exploit this insight to verify the relevance of earnings-based constraints in both macro and micro data. Moreover, in a quantitative DSGE framework I study how different constraints affect fundamental conclusions about the macroeconomy, such as the

[4]Quadrini (2011) provides a survey on financial frictions. Some examples are Gertler and Karadi (2011), Liu, Wang, and Zha (2013), Khan and Thomas (2013), Rampini and Viswanathan (2013), and Guerrieri and Lorenzoni (2017). Collateral constraints derive from limited contract enforcement. Another class of financial frictions is based on costly state verification (Bernanke, Gertler, and Gilchrist, 1999).

[5]Papers that focus on corporate debt dynamics over the business cycle but do not highlight earnings-based constraints include Crouzet (2017) and Xiao (2018). Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova (2018) study leverage dynamics over the firm life-cycle.

[6]See for example Chava and Roberts (2008), Sufi (2009) and Chodorow-Reich and Falato (2021).

[7]These authors also show in a model that earnings-based constraints may insulate firms from fire sales. An earlier paper that aims to identify the determinants of credit constraints, but does not focus on earnings, is Chaney, Sraer, and Thesmar (2012).

relative importance of supply and demand shocks faced by policy makers. In more recent related work, Drechsel and Kim (2021) study the pecuniary externalities that arise from earnings-based borrowing constraints.

Third, there are existing models in which flow variables rather than assets restrict borrowing, including Kiyotaki (1998).[8] My paper explicitly compares the different consequences across constraint types. I show that differences between earnings-based and collateral constraints are not driven by the flow vs. stock distinction, but by the commonly applied definition of earnings. Greenwald (2018) studies both (flow-based) payment-to-income limits and (collateral-based) loan-to-value constraints on household mortgage borrowing.[9] I focus on firm rather than household credit.

Fourth, my paper relates to the literature on investment shocks, in particular papers that identify investment shocks building on Fisher (2006). Justiniano, Primiceri, and Tambalotti (2010, 2011) find investment shocks to be a key force behind US output fluctuations. My paper is the first one to use identified investment shocks as a tool to distinguish different forms of financial frictions.

Fifth, my econometric approach of studying firm-level responses to macro shocks using local projections in a panel data setting relates to work by Ottonello and Winberry (2020), Jeenas (2018) and Cloyne, Ferreira, Froemel, and Surico (2018). These authors all focus on monetary policy shocks, whereas I am the first to study investment shocks using this relatively novel panel local projection technique.

Finally, the interaction between earnings-based borrowing constraints and sticky prices relates to a broader discussion around how markups respond to different shocks in New Keynesian models, as summarized by Nekarda and Ramey (2020). My analysis demonstrates that credit constraints have direct implications for the New Keynesian transmission mechanism and the relative importance of supply and demand shocks.

Structure of the paper. Section 2 motivates the paper's focus on earnings-based borrowing constraints. Section 3 develops a macro model in which firms can face either earnings-based or collateral constraints. Section 4 uses the model's predictions on the dynamics following investment shocks to study the relevance of earnings-based constraints in aggregate and firm-level data. Section 5 examines the model's predictions on the interaction the importance of supply vs. demand shocks by estimating a quantitative version of the model. Section 6 concludes.

[8] See Mendoza (2006), among others, in a small open economy context. Brooks and Dovis (2020) examine the sensitivity of credit constraints to profit opportunities in a trade framework. Li (2022) studies how the lack of pledgeability of assets and earnings reduces aggregate productivity.

[9] Ingholt (2018) studies several occasionally binding credit constraints in mortgage contracts.

2 Microeconomic evidence on earnings-based credit

This section presents motivating microeconomic evidence on corporate credit in the US economy. Detailed loan-level data reveals that firms' current earnings are an important determinant of their access to credit.

The pervasive use of loan covenants. Loan covenants are legal provisions which a borrowing company is obliged to fulfill during the lifetime of a loan. They are usually linked to specific indicators, for which a numerical maximum or minimum value is set. For example, a covenant may state that "the borrower's debt-to-earnings ratio must be below 4." Covenant breaches lead to technical default, giving lenders the right to call back the loan. In practice, a breach can lead to various outcomes, including renegotiation of higher interest rates or other changes in the loan terms. Importantly, breaches significantly reduce the availability of credit to firms (Roberts and Sufi, 2009).

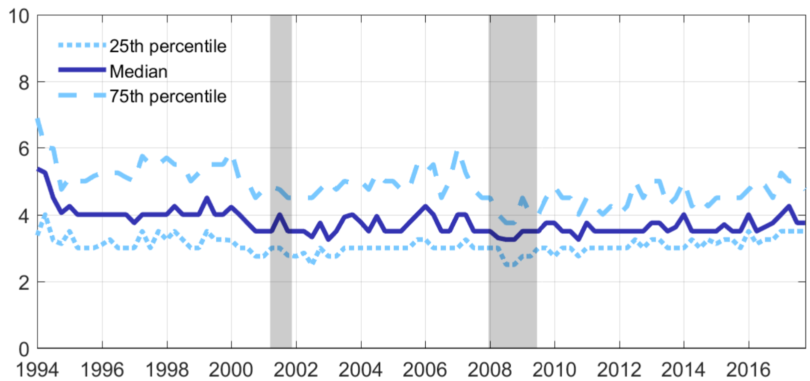
Table 1: MOST PERVASIVE LOAN COVENANT TYPES, VALUES AND FREQUENCY

	Covenant type	p25	Median	p75	Mean	Frequency
1	Max. Debt to EBITDA	3.00	3.75	5.00	4.58	60.9%
2	Min. Interest Coverage (EBITDA / Interest)	2.00	2.50	3.00	2.59	45.6%
3	Max. Leverage ratio	0.55	0.60	0.65	0.65	21.2%
4	Min. Fixed Charge Coverage (EBITDA / Charges)	1.10	1.25	1.50	1.43	20.9%
5	Max. Capex	6M	20M	50M	194M	13.6%
6	Net Worth	45M	128M	3500M	3.12B	10.4%

Notes. Loan covenant types sorted by their frequency in Dealscan. Covenants with a frequency above 10% are included. The sample consists of loan deals with at least one covenant, issued between 1994 and 2017 by US nonfinancial corporations (21,730 loan deals for 7,330 distinct borrowers). Mean and frequency are weighted with real loan size. 'M' and 'B' refer to million and billion of 2009 real USD.

The importance of earnings. Table 1 lists the most popular covenant types in the *ThomsonReuters LPC Dealscan* database. This data covers around 75% of the total US commercial loan market in terms of volumes. Appendix A presents further information and summary statistics. The table contains the frequency of each covenant, calculated for loans that feature at least one covenant. It also presents the median, 25th and 75th percentile as well as the value-weighted mean of the numerical maximum (minimum) that restricts a given indicator. The key insight from the table is that the three of the four most frequently used covenants are all related to earnings before interest, taxes, depreciation and amortization (EBITDA), a widely used performance indicator. It captures firm earnings that come directly from its regular operations and is readily available for scrutiny by lenders as part of standard financial reporting. The most popular covenant, present in over 60% of the value of loan debt, implies that the borrower's total level of debt cannot exceed earnings by a multiple of 4.58 at any given point in time. In other words, lenders *directly write into the contract* that earnings should fulfill a given target as a condition of the loan.

Figure 1: DEBT-TO-EBITDA COVENANT VALUES THROUGH TIME



Notes. Maximum debt-to-EBITDA ratio required in Dealscan loans issued by US nonfinancial corporations over time, calculated as percentiles across loan deals in each quarter. The sample restrictions are the ones applied to construct Table 1. The shaded areas represent NBER recessions.

Covenant values over time. Figure 1 examines the debt-to-EBITDA covenant over time, by showing the median value, and 25th and 75th percentile across loans issued in each quarter. The median appears to be quite stable around 3.5 to 4, with little change in recessions. It is common that macro models treat parameters that govern financial constraints as constant, and this pattern lends some justification for this modeling strategy. In the same vein, the focus of this paper is on the heterogeneity across types of credit constraints, whereas I treat constraint parameters as exogenous.[10] Interestingly, though out of the scope of my analysis, the figure reveals some fluctuations in the dispersion, with the 75th percentile rising and falling in the run-up to recessions.

Do covenants bind? The academic literature finds that covenants are violated frequently, with violations having a significant impact on the borrower. Roberts and Sufi (2009) find that net debt issuing activity experiences a large and persistent drop immediately after a covenant is breached. Chava and Roberts (2008) find strong effects of breaches on investment and Falato and Liang (2017) show strong effects on employment. Sufi (2009) finds that 35% of firms violate covenants over a period of 8 years. According to Chodorow-Reich and Falato (2021), one third of firms breached their covenants during the 2008-09 financial crisis. Furthermore, Adler (2020) shows that covenants drive borrowing and investment decisions even in the absence of a

[10]The estimated version of my model will allow for stochastic variation in covenant values over time.

violation, as firms try avoid costly future violations. To validate the estimated version of my model, I will study an empirical measure of covenant tightness.

Further channels through which earnings affect debt access. Loan covenants are a direct manifestation of current earnings constraining access to debt. There is also evidence of implicit debt constraints related to earnings. For example, lenders may base their decisions on credit ratings, which are typically constructed with a strong emphasis on EBITDA.[11] Furthermore, scrutiny of earnings by lenders could come as part of credit risk models (Carling, Jacobson, Linde, and Roszbach, 2007), or simply be based on reference levels in earnings ratios that lenders are accustomed to consider.

Earnings-based vs. asset-based lending. In addition to containing covenants, loans may be backed by assets, a feature that business cycle research has put a strong emphasis on. Based on a systematic classification of debt contracts, Lian and Ma (2021) conclude that 80% of the value of US corporate debt is earnings-based, whereas only 20% is asset-based.[12] The next sections of this paper distinguish different consequences of earnings-based as opposed to asset-based constraints, test their relevance in macro and micro data, and study how the different types of constraints affect fundamental conclusions about aggregate fluctuations and stabilization tradeoffs.

3 A macro model with heterogeneous credit constraints

This section formalizes the motivating evidence by introducing an earnings-based constraint on firm debt in a macro model. I use this model in two ways. First, to show that business cycle dynamics with this constraint are qualitatively different from those with a traditional asset-based constraint. Credit shows a diverging response to investment shocks, which move earnings and the value of collateral in opposite directions. This prediction will be tested in macro and micro data in Section 4. Second, I study how the earning-based borrowing constraint interacts with sticky prices, and the fact that price markups directly enter the earnings-based constraint. This interaction is examined in an estimated version of the model in Section 5.

[11] According to Standard & Poor's Global Ratings (2013), the financial risk profile of corporations is assessed based on *core ratios*, the funds from operations (FFO)-to-debt and the debt-to-EBITDA ratio.

[12] Lian and Ma (2021) use a variety of data sources including Dealscan. The Dealscan data alone also suggests that the share of earnings-based covenants is higher than the share of debt secured by specific assets. I show this in Appendix A.2. It is common for loans to include both covenants and collateral. My empirical firm-level analysis allows me to estimate marginal effects of each loan feature separately.

3.1 Model environment

Time is discrete, denoted by t, and continues infinitely. The economy is populated by firms, a representative household, and a government. The household and government are standard. In the firm sector, a final consumption good producer purchases inputs from monopolistically competitive intermediate input producers. Among these intermediate producers, some firms can borrow subject to earnings-based borrowing constraints while the remaining firms face collateral constraints.

Final good producer. The production function for the final consumption good is

$$Y_t = \left(\int_0^1 y_{i,t}^{\frac{1}{\eta}} di \right)^{\eta}, \tag{1}$$

where $y_{i,t}$ is the intermediate input purchased from producer i and η is the elasticity of substitution between different inputs. The optimality condition

$$p_{i,t} = P_t Y_t^{\frac{\eta-1}{\eta}} y_{i,t}^{\frac{1-\eta}{\eta}} \tag{2}$$

gives the demand function for intermediate producers. Intermediate prices aggregate to the economy's price level as $P_t = \left(\int_0^1 p_{i,t}^{\frac{1}{1-\eta}} di \right)^{1-\eta}$.

Intermediate producers. A continuum of size 1 of firms produce intermediate goods. They set prices subject to a Rotemberg adjustment cost. Within the continuum, there are two types of firms, $j \in \{\pi, k\}$. Firms with $j = \pi$ face an earnings-based borrowing constraint, while $j = k$ denotes firms that face a collateral-based borrowing constraint. The measure of type-π firms is χ. All intermediate producers operate the technology

$$y_{i,t}^j = z(k_{i,t-1}^j)^{\alpha}(n_{i,t}^j)^{1-\alpha}, \tag{3}$$

where $\alpha \in (0, 1)$ is the capital share in production, and $n_{i,t}^j$ denotes the amount of labor that firm i hires. z is total factor productivity (TFP), for simplicity assumed to be constant in this section. The firms' period earnings flow in real terms is defined as

$$\pi_{i,t}^j \equiv \frac{p_{i,t}^j y_{i,t}^j - w_t n_{i,t}^j}{P_t}. \tag{4}$$

Following the empirical evidence, this definition corresponds to EBITDA: sales net of labor costs, without subtracting investment, interest payments or taxes. For firm type

$j = \pi$, the variable $\pi^{\pi}_{i,t}$ enters the borrowing constraint introduced below. Capital $k^j_{i,t-1}$ is owned and accumulated by firms, and is firm type-specific. Its law of motion is

$$k^j_{i,t} = (1-\delta)k^j_{i,t-1} + v^j_t \left[1 - \Phi\left(\frac{i^j_{i,t}}{i^j_{i,t-1}}\right)\right] i^j_{i,t}, \tag{5}$$

where δ is the depreciation rate and the $\Phi(\cdot)$ function introduces investment adjustment costs. v^j_t is a stochastic disturbance, driven both by a common component and a component that is specific to firm type j. In the environment presented here, it captures both the level of investment-specific technology (IST) as well as the marginal efficiency of investment (MEI). I refer to shocks to v^j_t simply as *investment shocks*.[13] Both the presence of investment adjustment costs as well as v^j_t lead to variation in the market value of capital. In the case of adjustment costs, this arises from the standard result that the value of capital inside the firm differs from its replacement value, as captured by the ratio known as *Tobin's Q*. v^j_t is inversely related to the relative price of $k^j_{i,t}$ in consumption units and thus affects its value even in the absence of adjustment costs. To see this, consider the firm's flow of funds constraint, setting $\Phi(\cdot) = 0$:

$$\Psi(d^j_{i,t}) + \frac{k^j_{i,t}}{v^j_t} + \frac{b^j_{i,t-1}}{P_t} + \Upsilon(p^j_{i,t-1}, p^j_{i,t}, Y_t) = \frac{p^j_{i,t}y^j_{i,t} - w_t n^j_{i,t}}{P_t} + \frac{(1-\delta)k^j_{i,t-1}}{v^j_t} + \frac{b^j_{i,t}}{P_t R_t}. \tag{6}$$

All terms in (6) are denoted in real final consumption units. The scaling of the k terms makes clear that the relative price of capital is the inverse of v^j_t, which plays a key role in the dynamics of debt following investment shocks under different credit constraints. Following Jermann and Quadrini (2012), changes to equity payouts are costly:

$$\Psi(d^j_{i,t}) = d^j_{i,t} + \psi(d^j_{i,t} - \bar{d}^j)^2, \tag{7}$$

where $\bar{d}^j$ is the payout target (steady state level of $d^j_{i,t}$). Debt financing can be undertaken in the form of one-period risk-free bonds, denoted $b^j_{i,t}$. In an extension, I study debt with longer maturity. The effective gross interest rates faced by firms is R_t. Since debt is risk-free, both firm types face the same interest rate. Following Hennessy and Whited (2005), interest payments of firms are subject to a tax advantage τ, so that $R_t = 1 + r_t(1-\tau)$, where r_t denotes the interest rate received by lenders. τ creates a preference for debt over equity and makes firms want to borrow up to their constraint.

[13] IST captures the efficiency at which consumption is turned into investment, while MEI represents the efficiency at which investment is turned into installed capital. IST corresponds empirically to the inverse of the relative price of investment (see Section 4), while MEI does not have a clear empirical counterpart.

Households do not receive this tax rebate and thus lend funds in equilibrium. Finally, $\Upsilon(p^j_{i,t-1}, p^j_{i,t}, Y_t)$ denotes firm i's expenditure on price adjustment costs.

Alternative borrowing constraints. Both firm types $j \in \{\pi, k\}$ face borrowing constraints, which are formulated in consumption units and specified as

$$\frac{b^\pi_{i,t}}{(1+r_t)P_t} \leq \theta_\pi \pi^\pi_{i,t} \tag{8}$$

$$\frac{b^k_{i,t}}{(1+r_t)P_t} \leq \theta_k \mathbb{E}_t p^k_{k,t+1}(1-\delta)k^k_{i,t}. \tag{9}$$

In the earnings-based constraint (8), real debt is limited by a multiple $\theta_\pi > 1$ of current real earnings. An alternative formulation would capture the interest coverage ratio, that is, a constraint on $r_t b^\pi_{i,t}$ (see Greenwald, 2019). I focus exclusively on the debt-to-earnings formulation, as the corresponding covenant is the most popular one in the loan data, ahead of the coverage ratio (see Table 1). In equation (9) debt issued by the firm in t is limited by a fraction $\theta_k < 1$ of capital net of depreciation next period, valued at price $p^k_{k,t+1}$. The collateral of a given firm can be evaluated in different ways:

$$p^j_{k,t} = \begin{cases} Q^j_t & \text{if capital is priced at market value} \\ \frac{1}{v^j_t} & \text{if capital is priced at replacement cost.} \end{cases} \tag{10}$$

Q^j_t is the market price of capital, determined in equilibrium as the Lagrange multiplier on the capital accumulation equation. While I generally focus on the market value formulation, two observations are important. First, with investment shocks the replacement value of capital is not 1 but $1/v^j_t$, as it is denominated in consumption units. Q^j_t is also inversely related to v_t in equilibrium, but is additionally affected by adjustment costs. If adjustment costs are zero, the market value and replacement cost coincide at $1/v^j_t$. Therefore both the market value and the replacement cost would reflect the main mechanism in which an increase in v^j_t suppresses the price of collateral. Second, it may be possible that collateral is evaluated *at historical costs*, so that past prices of capital affect its value. I provide a robustness check in this direction. In the empirical analysis, I use aggregate as well as industry-level measures of $p^j_{k,t}$. I also study the difference between new and secondary market investment prices.

Rationalization. Borrowing constraints reflect deeper underlying frictions, such as information or enforcement limitations. Typically, a collateral constraint emerges as an optimal solution when borrowers can divert funds or withdraw their human capital from a project. For earnings-based constraints, one interpretation is that if the borrower diverts funds, then instead of seizing specific assets, the lender can take over and operate the firm herself. As the lender cannot perfectly predict the value of the firm when it is taken over, she estimates this contingent firm value as a multiple of current earnings, a valuation approach that is common in practice. A second interpretation is that the firm is able to directly pledge its earnings stream rather than an asset in return for obtaining debt access. A third interpretation is based on regulation: lenders require a different risk treatment of loans that feature a low earnings-to-debt ratio. In Appendix B, I discuss the existing literature on the microfoundation of loan covenants and provide details on relevant regulation. I also sketch out a formal environment that captures the first of these interpretations, where earnings-based constraints arise because lenders use current earnings as a predictor of future earnings. While the precise microfoundation is not key for the mechanisms studied in this paper, conclusions about optimal policy drawn in the context of earnings-based constraints may depend on whether current earnings constrain debt access because they are predictive of future profitably or for other reasons.

Firm optimality, household, and government. The objective of firm i is to maximize the expected stream of dividends, discounted at its owner's discount factor Λ_t:

$$\max \ \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_t d_{i,t}^{j} \tag{11}$$

subject to (2), (3), (4), (5), (6), (7), and either constraint (8) or (9). The firms' optimality conditions as well as the aggregation across the two borrower types are shown in Appendix C. The same appendix presents details on the household and the government. The household consumes the good produced by the firm and supplies labor. It does not receive the tax rebate on debt and therefore becomes the saver in equilibrium. The government is composed of a fiscal authority, which runs a balanced budget in every period, and a monetary authority, which targets inflation.

Model specification, parameterization, solution. I specify investment adjustment costs as quadratic in line with Christiano, Eichenbaum, and Evans (2005). The Rotemberg-type price adjustment costs are also quadratic, and calibrated following the estimates of Ireland (2001). I follow Jermann and Quadrini (2012) to set values for ψ and η. I set the household discount factor to match the corporate loan rate in

Dealscan. I also use Dealscan to calculate the dollar-weighted mean covenant value of the debt-to-EBITDA covenant, which gives a value of 4.6 (see also Table 1). As this value is for annualized EBITDA and my model is quarterly, I set $\theta_\pi = 4 \times 4.6$. I set the tightness of the collateral component to $\theta_k = 0.37$, which matches the average debt-to-asset ratio of firms with collateral constraints in the Compustat-Dealscan data. I study the model for different values of the share of earnings-based borrowers χ. Appendix C provides more details on the calibration. I solve the model with first-order perturbation techniques. This assumes shocks are "small," and the tax advantage makes the credit constraints bind at all times. While this is a strong simplification, I view the model as a framework to understand mechanisms that operate differentially through the heterogeneous credit constraints. As long as the relevant constraints bind sufficiently frequently to affect decisions of US firms in the data, the relative differences between the constraints should be picked up by empirical tests. Moreover, Adler (2020) shows that firms adapt their behavior in a precautionary manner to avoid covenant violations even when these do not bind. I further study the assumption of binding constraints in the estimation of the model in Section 5.

3.2 Distinguishing credit constraints using investment shocks

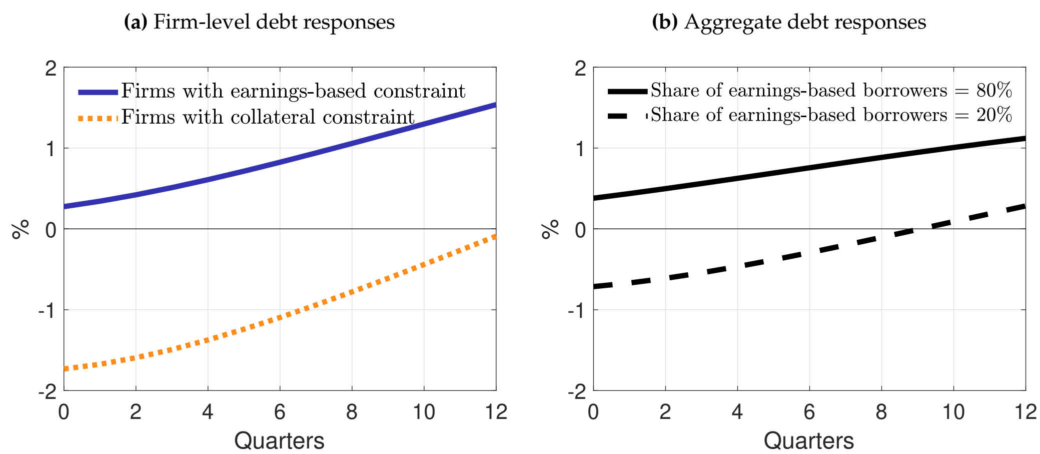
Whether earnings-based and collateral constraints imply different business cycle dynamics depends on which structural shocks hit the economy. A shock that moves earnings and the value of collateral in the same direction, all else equal, will also affect the debt capacity of firms in the same direction with either constraint. Therefore, such a shock does not imply credit dynamics that would allow me to distinguish different borrowing constraints. To derive predictions that do differ across the constraint types, I instead study a shock that has a positive impact on earnings but reduces the value of available collateral, the investment shock v_t^j in equation (5). I specify the process

$$\log(v_t^j) \quad = \quad \rho_v \log(v_{t-1}^j) + u_{v,t}^j, \tag{12}$$

where $u_{v,t}^j$ is iid, mean zero, normally distributed, with a standard deviation of 1. I focus on permanent investment shocks ($\rho_v = 1$), for which I can identify an empirical counterpart. I study shocks specific to firm type $j \in \{\pi, k\}$, as well as aggregate shocks that move $u_{v,t}^\pi$ and $u_{v,t}^k$ by the same unit.

Figure 2 presents impulse response functions (IRFs) of firm debt to positive investment shocks. Panel (a) shows separate IRFs for the two firm types, earnings-based borrowers in solid blue and collateral borrowers in dotted orange. The shock here is specific to each borrower type, and the share of earnings-based borrowers χ is simply set to 0.5. It is evident that the sign of the responses to the investment shock is flipped between one and the other borrower type. The intuition is as follows. An investment shock induces investment and stronger economic activity accompanied by growing earnings. As a consequence, a firm that faces of an earnings-based constraint is able to borrower more. However, the shock reduces the relative value of capital in consumption units. If a firm faces a collateral constraint that ties credit access to the real value of capital, it needs to reduce its debt level. Note that what matters for the firm-specific IRFs is the response of a firm's own price of investment to the investment shock, independent of whether the shock is specific to the firm or an aggregate shock. In Appendix C.2 I show that the IRFs to borrower type-specific investment shocks shown in Panel (a) are similar to those following an aggregate shock. In Section 4, I study debt IRF to investment shocks in firm-level data, using the sensitivity of industry-specific prices of equipment to identified aggregate investment shocks.

Figure 2: MODEL IRFS OF FIRM DEBT TO INVESTMENT SHOCKS UNDER DIFFERENT CONSTRAINTS



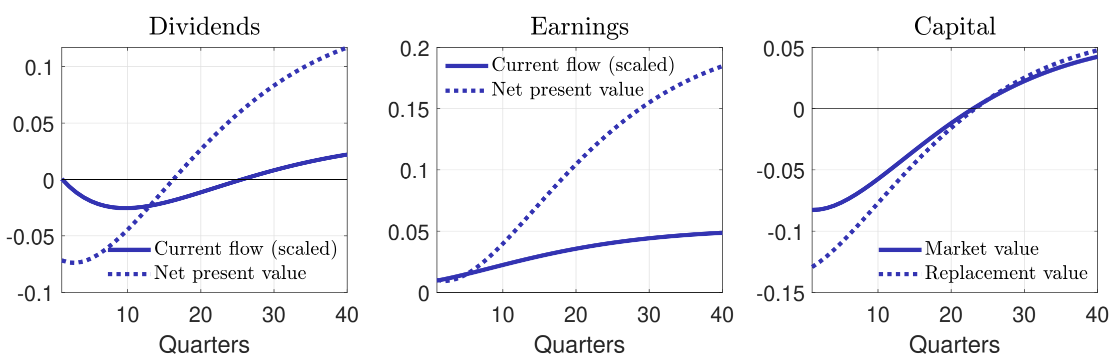
Notes. Model IRFs of firm debt to positive permanent investment shocks. Panel (a) shows the firm-level IRFs of different borrower types to investment shocks that are specific to each borrower type, computed in a model with equal shares of the two types ($\chi = 0.5$). Panel (b) presents the IRFs of aggregate debt to an aggregate investment shock, in two different calibrations where the share of earnings-based borrowers is $\chi = 0.2$ and $\chi = 0.8$. Overall, the figure highlights that the responses of debt to investment shocks have a different sign under the alternative borrowing constraints at the firm and the aggregate level.

Panel (b) of Figure 2 presents IRFs of total debt to an investment shock that is common to all firms in the economy. Here I vary the share of earnings-based borrowers χ from 0.2 (dashed line) to 0.8 (solid line). It is evident that when earnings-based constraints are the dominant credit constraint in the economy, aggregate debt responds positively to investment shocks, while aggregate debt falls when borrowing takes places predominantly against collateral. The intuition underlying this sign difference in the same as Panel (a): the shock raises earnings but reduces the value of collateral. The sign difference in the aggregate debt will allow me to make inference about which of the constraint is the more relevant force in the US economy, in addition to testing the model's predictions directly at the firm-level.

3.2.1 Discussion: borrowing against flow vs. stock variables

Earnings and the value of capital are a *flow variable* and a *stock variable*. Interestingly, the results above do not arise from the flow vs. stock distinction, but because earnings are a particular flow measure. To explain this, I begin with two observations, dropping indeces i and j for simplicity. First, the market value of a firm corresponds to the net present value (NPV) of *dividend* flows, that is, the infinite stream of d_t, discounted at the stochastic discount factor $m_{t+1} \equiv \frac{\Lambda_{t+1}}{\Lambda_t}$. We can define this market value recursively as $V_{d,t} = d_t + \mathbb{E}_t(m_{t+1}V_{d,t+1})$. Importantly, this value of flows is different from the current earnings flow π_t as well as from the NPV of earnings $V_{\pi,t} = \pi_t + \mathbb{E}_t(m_{t+1}V_{\pi,t+1})$. Second, in a neoclassical production economy, the market value of a firm is proportional to its capital under specific conditions (see Hayashi, 1982): if technology is constant returns to scale and adjustment costs are homogeneous of degree 1 in k, then $V_{d,t} = Q_t k_{t-1}$, with Q_t known as *Tobin's Q*. As a consequence of the two observations, the collateral constraint is equivalent to a constraint in which the firm's overall market value serves as collateral, and it has a flow-based equivalent, if all discounted future dividends enter the constraint.

Figure 3: IRFS OF DIFFERENT FLOW AND ASSET VALUE VARIABLES TO INVESTMENT SHOCK



Notes. Model IRFs of selected variables to a permanent investment shock, generated from a version of the model without any debt. This is intended to highlight the relation between alternative flows and asset values which may affect the right hand side of potential borrowing constraints. The unit of the IRFs is in levels of consumption units (current flows are additionally scaled by 10).

Earnings-based and collateral constraints are thus *not* equivalent for two reasons. First, they differ in terms of *flow definition*. The earnings-based constraint features earnings rather than dividends. Second, they differ in terms of *flow timing*. The earnings-based constraint features a current flow variable rather than the NPV of current and future flows. In the model, I can check which difference drives the results in Figure 2, by comparing the IRFs of d, V_d, π, V_π, Qk and k – variables that could potentially enter a constraint on debt – to an investment shock. For simplicity, I do so in a version of the model that does not feature any debt and all firms are the same. Figure 3 shows that both current earnings as well as the NPV of earnings rise in response to the shock. With any earnings-related constraint, additional debt could be issued in response to the investment shock and the timing of earnings by itself is not key. In contrast, dividends as well as the NPV of dividends, which equals the firm value and the value of the capital stock both decline. Hence, the results above arise not because debt is constrained by any flow instead of an asset value, but by EBITDA.

3.2.2 Additional investment shock results and robustness

A variety of additional model results and robustness checks are presented in Appendix C.2. Below I provide brief summaries of what I explore in this appendix.

Sticky vs. flexible prices. The IRFs in Figure 2 are generated in the presence of Rotemberg price adjustment costs. The sign difference in the debt response to investment shocks across earnings-based and collateral borrowers is similar when prices are fully flexible. As I show in the appendix, the main difference is that with flexible prices, the adjustment of borrowing is smaller on impact, while there is an immediate adjustment in borrowing in the sticky price model. The overall profile of the responses are otherwise almost identical. The next section studies how sticky prices interact with earning-based borrowing constraints more generally.

Short-term vs. long-term debt. I study an alternative version of the model in which firms use long-term debt, calibrated to the average maturity of 5 years in the Dealscan data. The responses of total real debt liabilities to investment shocks are very similar across a short-term and long-term debt formulation, but the difference lies on how net debt issuance, debt prices and equity issuance respond to the shock. In my empirical tests I always study the responses of total real debt liabilities.[14]

[14] Long-term debt might have a different impact in a model with default risk. Studying the interaction between default risk and different credit constraints is an interesting avenue for future research.

Other types of investment shocks. Shocks to v_t^j can capture both IST and MEI shocks. For the empirical verification of the mechanism in Section 4, I focus on that variation in v_t^j that captures IST shocks. The appendix shows that other types of disturbances that affect the relative price of investment, namely shocks to adjustment costs and non-permanent IST shocks, give rise to the same qualitative predictions.

Earnings timing. I analyze an alternative version of the earnings-based constraint in which current and three lags of earnings enter the constraint. This is based on the idea that covenants may in practice be evaluated based on a 4-quarter trailing average (see Chodorow-Reich and Falato, 2021). The results are similar to the ones shown in Figure 2. The debt response for earnings-based borrowers becomes a little more sluggish, but the sign difference in the responses across borrower types remains unchanged.

Collateral valuation at historical costs. Collateral may be at least in part evaluated based on historical costs (book value). I study an alternative version of the model in which the price of capital that enters the collateral constraint, $p_{k,t}^k$, is calculated as an average over past capital market prices $Q_{t-m}^k, m = 1, ..., 4$. The corresponding results show that the debt response under the collateral constraint is now more hump-shaped, as it takes time for the investment shock to be reflected in capital prices relevant for evaluation. The sign difference across the responses remains the same.

Dynamics of other variables. In deriving my testable model predictions for investment shocks, I focus on the IRFs of debt. The appeal of this strategy is that debt dynamics are tied very directly to the alternative constraint formulation and are not driven too much by further modeling choices. For completeness, the appendix shows the responses of other model variables to both borrower type-specific and aggregate investment shocks, across different settings for χ. In the data, I study the firm-level responses of both debt and investment. In the quantitative version of the model, I turn to studying other shocks and the dynamics aggregate output.

3.3 Credit constraints, sticky prices, and stabilization tradeoffs

In addition to deriving and testing *qualitative* predictions on firms' responses investment shocks, a distinct goal of this paper is to examine how different credit constraints affect broader *quantitative* conclusions about business cycles and macroeconomic policy tradeoffs. New Keynesian models have become perhaps the most widely used framework to tackle such quantitative questions. As their key element are nominal rigidities, this section examines the interaction between different credit constraints and nominal rigidities more closely.

Sticky prices and markup movements. Price rigidities affect the cyclicality of price markups over marginal costs: when prices are sticky, demand shocks imply countercyclical markups, while supply shocks imply procyclical markups. To see this, consider for simplicity a firm with decreasing returns to its production inputs and a fixed price. Suppose this firm is faced with a positive demand shock. Since it cannot adjust prices, it raises the quantity produced. To achieve this, it moves along its increasing marginal cost curve and thus reduces the ratio between the fixed price and its marginal cost: its price markup decreases in response to the positive demand shock. In other words, the markup is countercyclical conditional on demand shocks. The opposite is true for a positive supply shock. Suppose a technology shock enables the firm to produce output more efficiently. If the firm cannot adjust the price, it reduces its inputs down the marginal cost curve, raising its markup. Hence the markup is procyclical conditional on supply shocks. This logic generalizes to sufficiently rigid rather than fixed prices. If wages are sticky as well, the reasoning applies if prices are relatively more rigid than wages.[15]

Markups and earnings-based constraints. The behavior of markups conditional on different shocks interacts directly with earnings-based borrowing constraints, but only indirectly with collateral constraints. The reason is that firms' earnings are a function of their markup. Therefore, all else equal, a higher markup will translate into stronger earnings and will thus loosen the earnings-based constraint. To see this formally, consider a firm's markup, which is the ratio of price to marginal costs

$$\mathcal{M}_{i,t}^j = \frac{p_{i,t}^j}{mc_{i,t}^j}. \tag{13}$$

With the production technology in (3), nominal earnings can be rewritten as

$$p_{i,t}^j z (k_{i,t}^j)^\alpha (n_{i,t}^j)^{1-\alpha} \left(1 - (1-\alpha) \frac{w_t / p_{i,t}^j}{(1-\alpha) z (k_{i,t}^j)^\alpha (n_{i,t}^j)^{-\alpha}}\right) = p_{i,t}^j y_{i,t}^j \left(1 - (1-\alpha)(\mathcal{M}_{i,t}^j)^{-1}\right), \tag{14}$$

[15]Measuring markups directly in the data is challenging, as we typically observe only average costs and not marginal costs. Nekarda and Ramey (2020) provide a discussion.

which shows that firm earnings (EBITDA) are positively related to both the level of output and the markup. We can combine (8) and (14) to obtain

$$\frac{b^{\pi}_{i,t}}{P_t(1+r_t)} \leq \theta_{\pi}\frac{p^{\pi}_{i,t}}{P_t}y^{\pi}_{i,t}\left(1-(1-\alpha)(\mathcal{M}^{\pi}_{i,t})^{-1}\right). \tag{15}$$

This makes clear that an earnings-based credit limit is positive function of the markup. Such a direct relation is not present for a collateral constraint, in which the dynamics of capital and its price affect the tightness of the constraint. These variables are linked to price markups only through indirect equilibrium forces.

Earnings-based constraints in estimated New Keynesian models. The relation between markups and different credit constraints becomes particularly relevant when New Keynesian models are taken to the data. In the presence of an earnings-based borrowing constraint, countercyclical markups make it more difficult for the model to match the procyclical behavior of credit in the data: if markups move procyclically, earnings move procyclically (all else equal) and therefore credit becomes procyclical. It follows from the mechanics laid out above that a New Keynesian model can generate procyclical earnings in different ways. One way is if prices are sticky and supply shocks are more important than demand shocks. The other way is if prices are not meaningfully sticky, so that the core New Keynesian mechanism is muted, and the behavior of markups does not drive that of earnings and credit. How the relative strength of these forces plays out is a quantitative question, which I turn to by the estimating a quantitative version of the model in Section 5.

4 Distinguishing credit constraints in macro and micro data

This section uses the diverging model predictions on firms' responses to investment shocks, developed in Section 3.2, as a strategy to disentangle which type of credit constraint is more relevant in both aggregate and firm-level data. First, using an SVAR I identify investment shocks and examine the responses to these shocks in macro data. Second, I apply a panel local projection framework to study firm-level responses to investment shocks. At the firm level, I exploit industry-variation in the sensitivity of equipment prices to the aggregate investment shock, and I allow for heterogeneous responses across different borrower types. This paper is the first one to use identified investment shocks to disentangle between different types of financial frictions.

4.1 SVAR on aggregate data

Consider an n-dimensional vector of macroeconomic time series Y_t, written as the $MA(\infty)$-representation

$$Y_t = B(L)^{-1}u_t, \tag{16}$$

where L denotes the lag operator. The vector u_t contains the structural shocks with covariance matrix $\Omega_u = I_n$. These shocks are not identified unless additional restrictions are imposed. My identification scheme is based on long-run restrictions. Following Fisher (2006), I include as the first three variables in Y_t the log difference of the relative price of investment, the log difference in output per hour, and the log of hours. A recursive scheme on the long-run multiplier matrix $B(1)^{-1}$ identifies two shocks: the long-run level of the first variable is only affected by the first shock, and the long-run level of second variable is only affected by the first and second shock. The first shock is interpreted to induce investment-specific technological change, as the relative price of investment is only affected by this shock in the long run.[16] The model of Section 3 encompasses different variations of investment shocks, including such shocks investment-specific technology, so identifying it allows me to test the model's predictions. As an alternative identification scheme, I impose medium-run restrictions. Following Francis, Owyang, Roush, and DiCecio (2014), I identify the IST shock as the shock that maximizes the forecast error variance decomposition (FEVD) share of the relative price of investment at selected medium-term horizons (5 and 10 years). I found similar results using the cumulative variant of this procedure (Barsky and Sims, 2011).

Additional variables, data selection and specification. As I leave the remaining rows of $B(1)^{-1}$ unrestricted, I can add further variables to the system, for which the ordering becomes irrelevant to identification. I append the log differences in aggregate business earnings, the value of the capital stock and business sector debt. The inclusion of debt is key to validate the model predictions. Formally,

$$Y_t = [\text{dlog}(p_{k,t}) \;\; \text{dlog}(y_t/n_t) \;\; \log(n_t) \;\; \text{dlog}(\pi_t) \;\; \text{dlog}(p_{k,t}k_t) \;\; \text{dlog}(b_t)]'. \tag{17}$$

I use quarterly data from the US National Income and Product Accounts (NIPA) and the US Financial Accounts (Flow of Funds) from 1952 to 2017, and set $p = 4$. I deflate nominal data with the consumption deflator for nondurable goods and services. An important consideration lies in the choice of data for $p_{k,t}$, which corresponds to v_t^{-1}

[16]The second shock represents TFP, as it is the only driver that affects, other than IST, the economy's labor productivity in the long run.

if v_t captures IST. Following the literature, I use the relative price of equipment investment. I construct this from NIPA data but found very similar results using the Gordon-Violante-Cummins investment price. Furthermore, I explore the responses of secondary market equipment prices to the IST shock. In principle, one could also proxy the price of capital with stock prices. However, what matters for the model mechanism is not the firm value (or stock market) response, but the response of the value of assets that serve as collateral.[17] I therefore focus on the price of equipment, which is in fact the most important category of collateral in the loan-level data, ahead of real estate.[18] For debt I use the sum of loans and debt securities for the nonfinancial business sector. Appendix A.4 provides more details on the data.

4.2 Panel local projections in firm-level data

To study the responses of firm-level borrowing to identified investment shocks, I apply the local projection technique of Jordà (2005) to a panel setting. To the best of my knowledge, my paper is the first one to do so for investment-specific shocks.[19] I obtain average IRFs across all firms, as well as separate IRFs across heterogeneous borrower types. As investment shocks may affect firms differently depending on the type of capital they use, I scale the macro investment shock with the sensitivity of each firm's industry-specific equipment price to the shock. Formally, I construct the IRF of debt of firm i in industry s at horizon h to investment shocks by specifying

$$\log(b_{i,s,t+h}) = \alpha_h + \beta_h \hat{u}_{IST,s,t} + \boldsymbol{\gamma X_{i,s,t-1}} + \delta t + \eta_{i,s,t+h} \tag{18}$$

and obtaining estimates of β_h, $h = 0, 1, 2, \ldots, H$. $\hat{u}_{IST,s,t}$ is constructed as

$$\hat{u}_{IST,s,t} = \hat{\lambda}_s \hat{u}_{IST,t}, \tag{19}$$

where $\hat{u}_{IST,t}$ denotes the time series of the identified aggregate investment shock from the SVAR, and $\hat{\lambda}_s$ captures how the prices of equipment that is used in industry s responds to the shock $\hat{u}_{IST,t}$. The construction of $\hat{\lambda}_s$ is described in more detail below.

[17]In the data, the value of collateral and the market value of the firm in its entirety are different, for example due to the presence of human capital. Predictions for stock price responses to investment shocks are highlighted by Christiano, Motto, and Rostagno (2014).

[18]See the analysis provided in Table A.4 in the Appendix. After excluding non-informative categories such as "Other" or "Unknown", the category "Property & Equipment" is the largest type of collateral in the Dealscan data, three times as large as "Real Estate."

[19]Ottonello and Winberry (2020), Jeenas (2018) and Cloyne, Ferreira, Froemel, and Surico (2018), and various papers thereafter, apply panel local projection techniques to monetary policy shocks.

$\boldsymbol{X_{i,s,t-1}}$ is a vector that collects rich firm-level and industry-level controls, lagged by one quarter, as well as fixed effects. t is a linear time trend. Equation (18) gives an average IRF across *all* firms in the panel. Recall that my model predicts the response of debt to the investment shock in this regression to be positive if earnings-based constraints are more relevant in the economy on average ($\beta_h > 0$) and negative with collateral constraints being the relevant credit limit on average ($\beta_h < 0$).

Given the information in Dealscan, I can interact the shock with dummies that capture whether a firm is subject to earnings-based covenants or uses collateralized loans. This allows me to verify the proposed theoretical mechanism more directly:

$$\begin{aligned}\log(b_{i,s,t+h}) = \alpha_h + \beta_h \hat{u}_{IST,s,t} + \boldsymbol{\gamma X_{i,s,t-1}} \\ + \beta_h^{earn} \mathbb{1}_{i,s,t,earn} \times \hat{u}_{IST,s,t} + \alpha_h^{earn} \mathbb{1}_{i,s,t,earn} \\ + \beta_h^{coll} \mathbb{1}_{i,s,t,coll} \times \hat{u}_{IST,s,t} + \alpha_h^{coll} \mathbb{1}_{i,s,t,coll} + \delta t + \eta_{i,s,t+h},\end{aligned} \tag{20}$$

where $\mathbb{1}_{i,s,t,earn}$ and $\mathbb{1}_{i,s,t,coll}$ are dummies that capture if firm i is subject to earnings-related covenants or uses collateral. The IRF of an "earnings-based borrower" ("collateral borrower") at horizon h is given by the sum of the coefficients β_h and β_h^{earn} (β_h and β_h^{coll}). My model predicts that $\beta_h + \beta_h^{earn} > 0$ and $\beta_h + \beta_h^{coll} < 0$.

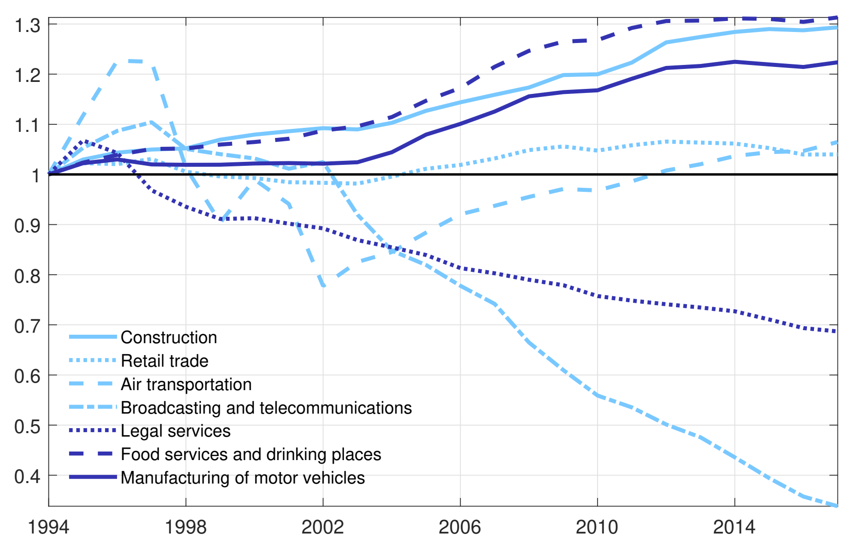
Data, specification, and borrower classification. I merge the Dealscan data set examined in Section 2 with balance sheet information from Compustat. The Compustat-Dealscan merged is enabled by a link file connecting the identifiers (see Chava and Roberts, 2008). The resulting data set covers more than 250,000 firm-quarter observations for more than 5,000 distinct firms from 1994 to 2017.[20] More details and summary statistics are provided in Appendix A.3. $b_{i,s,t}$ is the quarterly level of debt liabilities from Compustat. Consistent with the SVAR, I obtain a real series by deflating with the consumption deflator for nondurable goods and services. The firm-level classification into "earnings-based borrowers" and "collateral borrowers" is based on the information in Dealscan: $\mathbb{1}_{i,s,t,earn}$ is equal to 1 if a given firm issues a loan with at least one earnings covenant. $\mathbb{1}_{i,s,t,coll}$ is equal to 1 if the debt issued by the firm backed by collateral.[21] There may be omitted variables that affect both the left hand side and the endogenous selection of borrowers into a particular type. I address this

[20] These numbers reflect Compustat firms that have at least one appearance in the Dealscan data, and that can be merged to BEA data to construct industry-level sensitivities investment shocks (see further below). The number of observations used in the actual regressions varies depending on what information from the two data sets in used, e.g. because not all Dealscan loans contain covenant information.

[21] I use the classification of collateralized debt as secured revolvers following Lian and Ma (2021), and present results using an alternative classification in the appendix.

problem by controlling for omitted characteristics that may simultaneously be driving debt responses to investment shocks and selection into borrower types. Concretely, I use a specification with 3-digit industry-level fixed effects and firm size, as well as firm-level real sales growth to control for firm-specific cyclical conditions. There is little variation in the borrower type dummy within a given firm, which is appealing in the sense that the dummies are arguably more predetermined. Furthermore, as an alternative way to capture whether firms borrow based on earnings as opposed to assets, I provide the debt responses of large vs. small, high vs. low profit margin, and old vs. young firms, since large, high profitability and firm age are firm characteristics that the literature found to be correlated with the use of earnings-based credit (Lian and Ma, 2021). In all versions of (18) and (20) that I estimate, I include one lag of the left hand side variable, linear time trend, and add a control variable that captures macro shocks other than investment shocks, constructed from the SVAR residuals.[22] I set $H = 12$, and keep the firm composition constant when expanding h.[23]

Figure 4: REAL EQUIPMENT PRICE INDECES FACE BY SELECTED INDUSTRIES



Notes. Industry-specific real equipment investment price indeces ($1994 = 1$), plotted over the sample period 1994-2017. These are real equipment prices calculated based on each industry's real investment shares in 39 equipment categories in the BEA Fixed Asset Tables. The growth rates in these prices are used to estimate the industry sensitivity of equipment prices to aggregate investment shocks, $\hat{\lambda}_s$.

[22] I use the reduced form residuals of the debt equation in (16) and orthogonalize them with respect to the IST shock. The resulting series spans macro shocks to debt that are unrelated to IST.

[23] While debt liabilities are continuously recorded in Compustat, loan issuance in Dealscan is present only every other quarter. This means that the sample to estimate (20) is smaller than for (18). It also implies that estimating (20) is restricted to firms that issue any debt to begin with. While this potentially introduces an upward bias for both borrower types, I focus on sign and *relative* size of β_h^{earn} and β_h^{coll}.

Constructing industry-level equipment price sensitivities. I focus on the version of $\hat{u}_{IST,t}$ identified with long-run restrictions. To construct $\hat{\lambda}_s$ in (19), I use data from the BEA Fixed Asset Tables.[24] I proceed in two steps. First, I calculate real equipment investment price indices relevant to each of 58 BEA industries. A given industry's investment price index is obtained from the real prices of 39 equipment categories that firms in the industry invest in, ranging from mainframes to aircraft to furniture, weighted with the real investment shares in each category in a given year. Figure 4 shows that over the sample period used to estimate (18) and (20) the resulting real equipment price indeces faced by different industries display strong industry heterogeneity. For example, while the equipment purchased by construction companies and restaurants has become more expensive in real terms, prices of equipment used in telecommunications have fallen sharply. Second, I regress the inverse of each industry's equipment price index in log differences on $\hat{u}_{IST,t}$, to obtain $\hat{\lambda}_s$ and $\hat{u}_{IST,s,t}$.[25] These estimates can then be linked to the firm-level by merging Compustat-Dealscan and BEA industry identifiers. More details, as well as summary statistics of $\hat{\lambda}_s$ are provided in Appendix A.5. Note that all of the local projection results that follow look roughly similar when just using the aggregate shock $\hat{u}_{IST,t}$ in the local projection (that is, imposing $\hat{\lambda}_s = 1, \ \forall s$). I found that taking into account differences across industries in $\hat{\lambda}_s$ gives sharper effects of investment shocks at the micro level.

4.3 Results: macro and micro dynamics following investment shocks

Figure 5 presents the results that validate the importance of earnings-based relative to collateral constraints empirically. It shows the credit response to investment shocks across methods (SVAR and panel local projection), data sources (Flow of Funds and Compustat-Dealscan-BEA) as well as firm types (earnings-based and collateral borrowers). I discuss these different results in turn.

Aggregate debt responses. Figure 5, Panel (a) presents the IRF of aggregate business sector debt to a one standard deviation positive permanent IST shock in the SVAR identified with long-run restrictions, together with 90% bands. The key insight from the estimated IRF is that the response of firm credit to the investment shock is positive. This is in line with the model predictions with a sufficiently high share of firms that

[24] Another recent paper that uses this data is vom Lehn and Winberry (2021).

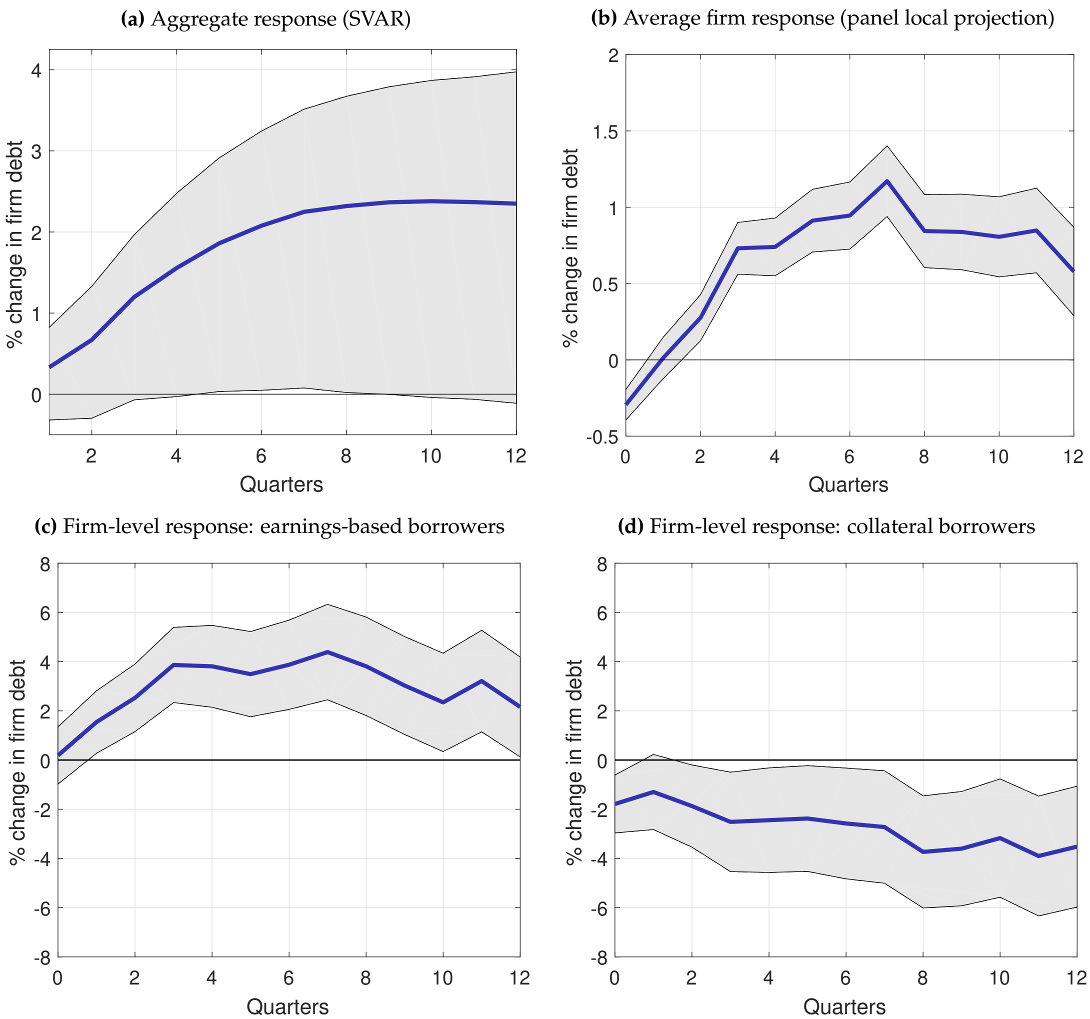
[25] These regressions mimic exactly how the aggregate equipment price series responds to the macro shock in the SVAR. Due to the structure of the BEA data, they are run at annual frequency. I use the same sample as for the SVAR, 1952-2017. The results are very similar when the sample stops in 1993, prior to the sample start for (18) and (20), in which case $\hat{\lambda}_s$ can be interpreted more closely to 'Bartik' weights.

borrow against earnings, but not when the dominant constraint across the firm sector is a collateral constraint. In fact, these results suggest that predictions from a model with only collateral constraints and investment shocks are at odds with aggregate data. The responses of the other variables in the SVAR, shown in Appendix D.1, are also consistent with the mechanics of the earnings-based borrowing constraint. In particular, the rise in debt is accompanied by growing earnings and a fall in the value of capital. The dynamics in aggregate US data, conditional on identified IST shocks, thus lend support to the importance of earnings-based borrowing for economy-wide debt dynamics in the US. The SVAR results based on the alternative, medium-horizon identification scheme are shown in Appendix D.2. The results are similar, with an even more significant increase in aggregate debt in response to the IST shock.

Average firm-level debt responses. Turning from macro to micro data, I first consider the average debt response to investment shocks across all firms in the Compustat-Dealscan-BEA panel, that is, the estimates of β_h in (18). In this regression, I do not add any controls other than lags of the left-hand-side variable and a time trend, and I use all firm-quarter observations the data, including those without information on borrower types. At the firm-level, the investment shock is now constructed using the industry-specific equipment price sensitivities. Figure 5, Panel (b) presents the results, with 90% bands based on two-way clustered standard errors by firm and quarter, following existing applications of local projections in panel settings (Ottonello and Winberry, 2020, Jeenas, 2018, Cloyne et al., 2018). After one quarter, the credit response is positive, in line with the aggregate debt response in the SVAR, and consistent with the model predictions when the more relevant credit constraint is earnings-based. While there is a slightly negative response on impact, the firm-level response otherwise matches the SVAR and relevant model responses in terms of the overall profile. This is reassuring, since Compustat firms are a specific subset of the total nonfinancial business sector for which I use data in the SVAR. Finally, it is evident that the additional micro-level information allows this IRF to be estimated with much tighter bands than the one in Panel (a). This highlights the econometric advantages of using micro moments to guide macroeconomic analysis.

Heterogeneous firm-level debt responses by borrower types. The heterogeneous IRFs based on estimating equation (20) are presented in Panels (c) and (d) of Figure 5. These IRFs are based on a specification with 3-digit industry fixed effects, controlling for firm size and growth of real sales. As described above, I also control for other

Figure 5: IRFS OF DEBT TO INVESTMENT SHOCK ACROSS METHODS, DATA SOURCES AND FIRM TYPES

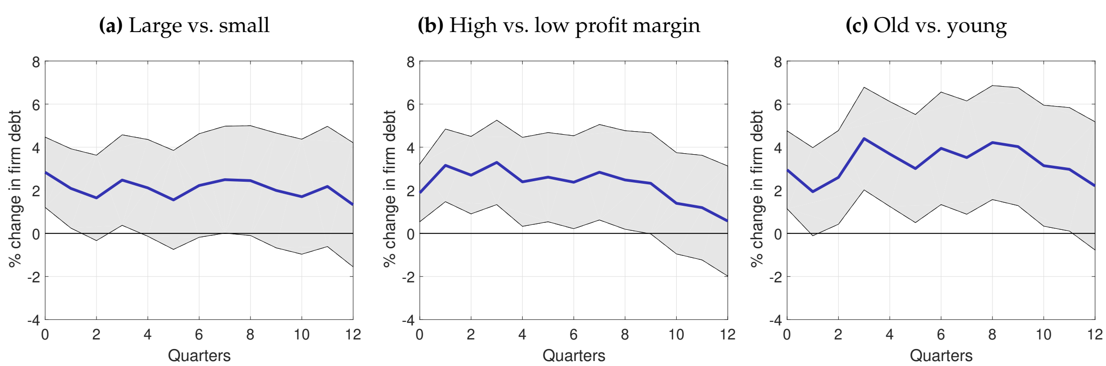


Notes. Empirical IRFs of firm debt to identified investment shocks. These empirical IRFs validate the mechanism behind the model IRFs shown in Figure 2 based on different methods, data sets and levels of aggregation. Panel (a) presents the response of aggregate business sector debt using Flow of Funds data. This is based on SVAR identified with long-run restrictions, as described in Section 4.1. The remaining panels show firm-level debt responses in the merged Compustat-Dealscan-BEA data, based on the panel local projections using investment shocks described in Section 4.2. Panel (b) plots the average IRF of firm debt to investment shocks across all individual firms (see equation 18). Panels (c) and (d) show the heterogeneous debt responses across borrower types, for earnings-based borrowers and collateral borrowers, respectively (see equation 20). These results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks) as well as a lag of the left hand side variable and a time trend. In all four panels, the IRFs are shown in percent and the gray shaded areas display 90% confidence sets. In the case of the firm-level regressions (Panels b, c, d), they are based on two-way clustered standard errors by firm and quarter. The size of the shock is one standard deviation.

macroeconomic shocks using the orthogonalized SVAR innovations, a lag of the left hand side variable and a linear time trend. Again, I plot 90% error bands constructed from standard errors that are two-way clustered by firm and quarter. Panels (c) and (d) reveal that the IRF of debt to the investment shock is positive for firms that face earnings-related covenants, but negative for firms that borrow against collateral. Hence the dynamics at the firm-level directly confirm the key prediction of the model mechanism. The null hypothesis of an equal response across the two borrower types is rejected over several horizons at the 1% significance level. This is not directly visible in the figure, but formally shown in Appendix E.2. Furthermore, Appendix E.3 shows the IRFs for the two additional firm groups that arise from the two-dummy specification of (20), which are firms subject to both earnings-based covenants and collateral, as well as firms that are subject to neither. These IRFs are both statistically insignificant.

The shapes of the IRFs in Panels (c) and (d) deserve some discussion. While the IRF for earnings-based borrowers is similar to the model – small on impact and then persistently increasing – the profile of the IRF of collateral borrowers differs from its model counterpart in that it displays a slower debt reduction. This may indicate an environment in which the value of collateral reflects prices of collateral and their responses to shocks with some delay. Indeed, an alternative version of the model, studied in Appendix C.2, generates a more sluggish response of debt with a collateral constraint if past capital prices are used to value collateral. Furthermore, the empirical responses of used equipment prices that I investigate in Appendix D.4 also show a negative but sluggish response, providing additional evidence for this interpretation.

Figure 6: RELATIVE RESPONSE OF DEBT TO INVESTMENT SHOCK FOR DIFFERENT FIRM CHARACTERISTICS

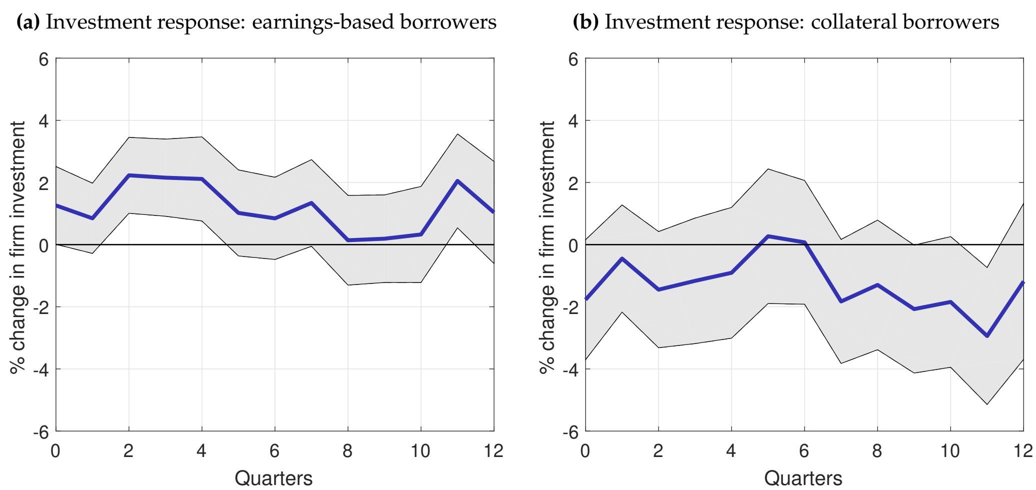


Notes. Estimated difference in the debt IRF to identified investment shocks between firm types. Large, high profit margin and old firms are associated with earnings-based credit, so a split across these dimensions provides an alternative way to test the model predictions. Large vs. small is a sorting above/below the median size as measured by number of employees; high vs. low profit margin above/below median EBITDA-to-assets ratio; old vs. young above/below median time since IPO date. The IRFs are shown in percent and the gray shaded areas display 90% confidence sets based on two-way clustered standard errors by firm and quarter. The size of the shock is one standard deviation.

Alternative borrower classification. The classification into borrower types that underlies my results uses direct information from firms' loan contracts. To further validate the mechanism, I construct analogous IRFs based on indirect information on other firm characteristics to classify heterogeneous borrower types. Specifically, I examine the debt response to investment shocks for large vs. small firms, high profit margin vs. low profit margin firms, as well as old vs. young firms. The literature has emphasized that large, high profit margin and old firms are more likely to borrow subject to earnings-based constraints (Lian and Ma, 2021). Figure 6 presents the results for these three alternative ways of constructing $\mathbb{1}_{i,s,t,earn}$ and $\mathbb{1}_{i,s,t,coll}$ in (20). For compactness the three panels of this figure present the estimate of the difference $\beta_h^{earn} - \beta_h^{coll}$. In line with the model predictions, I find that the (relative) debt response to investment shocks is significantly positive in all three categories, which provides additional evidence that validates the model predictions.

Appendix E.4 presents the results for a more demanding specification where the interactions with firm-level characteristics are included in addition to the interactions with the two borrower type dummies. The sign differences in the IRFs across earnings-based and collateral borrowers remains even controlling for the differential impact of the shock across size, profitability and age.

Figure 7: FIRM-LEVEL IRFS OF INVESTMENT TO INVESTMENT SHOCK FOR DIFFERENT BORROWER TYPES



Notes. Heterogeneous investment (capital expenditures) responses to identified investment shocks across borrower types, for earnings-based borrowers and collateral borrowers, respectively. These results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks) as well as a lag of the left hand side variable and a time trend. 90% bands are calculated using two-way clustered standard errors by firm and quarter. The size of the shock is one standard deviation.

Firm-level investment responses. I extend the analysis to study the response of firm-level investment. I modify equation (20) to have the log of $inv_{i,s,t+h}$ instead of $b_{i,s,t+h}$ on the left hand side, which measures capital expenditures from Compustat. The results, presented in Figure 7, line up with the dynamics of debt. Earnings-based borrowers significantly increase their investment in response to the shock, while collateral borrowers reduce investment. In line with the broad contours of the debt response, the negative response of firms that borrow against collateral is more sluggish. While capital expenditures are lumpy and volatile at the firm level and the IRFs look therefore much less smooth than for debt, a formal test rejects the null that the responses are equal across borrower types at various horizons (see Appendix E.2).

4.4 Additional empirical results and robustness

SVAR historical variance decompositions. My empirical strategy relies on the sign of credit IRFs and does not require that the IST shock explains a large fraction of economic fluctuations. To study whether investment shocks are in fact an important driver of macroeconomic dynamics according to the SVAR, Appendix D.3 provides historical variance decompositions. It is evident that IST shocks played a significant role in different episodes of the postwar US business cycle.

The response of used equipment prices. In practice, borrowers may pledge both new and used capital as collateral. This could be an issue for my empirical strategy, as I identify the investment shock from the price of new equipment. To address this concern, I show that the investment shock I identify above reduces the prices of *used* equipment goods. The results are presented in detail in Appendix D.4.

4.5 Key take-aways from the empirical analysis of investment shocks

The model mechanism I propose in Section 3.2 allows to test for the importance of earnings-based credit constraints by conditioning on investment shocks. The empirical response of credit to investment shocks in macro data indicates that the relevant firm credit constraint in the aggregate is an earnings-based one. A similar response is recovered in micro data for the average firm. Moreover, heterogeneous firm-level responses are directly in line with the mechanism: earnings-based borrowers increase their debt in response to an aggregate investment shock, firms subject to collateral constraints borrow less. Firm-level investment exhibits similar dynamics, highlighting the link from borrowing constraints to economic activity.

5 Credit constraints and supply vs. demand shocks

This section studies whether earnings-based credit constraints alter quantitative conclusions about US business cycles. I now move the focus to a broader set of macroeconomic shocks and to stabilization tradeoffs for macroeconomic policy. The theoretical predictions characterized in Section 3.3 guide this analysis.

5.1 Estimation of a quantitative version of the model

I extend the model of Section 3 to a New Keynesian medium-scale DSGE model in the spirit of Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). As in Section 3, there are two firm types, which borrow subject to earnings-based and collateral constraints, and which face capital adjustment and price adjustment costs. The estimated version of the model is generalized to also feature endogenous capital utilization, wage rigidities, habits in household preferences, and more general fiscal and monetary policy. I allow for the credit constraints to be subject to financial shocks by making the θ terms in equations (8) and (9) stochastic. In addition to financial shocks, the model features shocks to TFP, investment efficiency, price and wage markups, preferences, and monetary and fiscal policy. I categorize these shocks into supply and demand shocks below. More details are provided in Appendix F.

Borrower types. I set all parameters to be the same across borrower types $j \in \{\pi, k\}$, so that the only heterogeneity across firms is their credit limit. This assumption allows me to cleanly isolate the relevant effects of the constraints. In the same spirit, I focus on shocks that are common across all firms in the economy. I estimate two versions of the model. The first one features a high share of earnings-based borrowers of $\chi = 0.8$. This is motivated based on the evidence in Lian and Ma (2021) as well as the empirical results presented in the previous sections. In the second version, I set $\chi = 0.2$. This serves as a benchmark in which collateral constraints are important for a higher share of firms, closer to the typical setting previously considered in the literature.

Data and estimation procedure. I retrieve quarterly US data for the 7 observables used by Smets and Wouters (2007) (output, consumption, investment, employment, interest rates, wages and inflation) and add nonfinancial business sector debt as an eighth observable. I obtain real variables using the consumption deflator of nondurables and services, as in Section 4 and Justiniano, Primiceri, and Tambalotti (2011). Following the same authors, the sample is 1954:Q3 - 2009:Q1. Details on the data are provided in Appendix A.4. I use Bayesian methods. A subset of the parameters is calibrated as described in Section 3. For the estimated parameters, I use very similar priors as in the Smets and Wouters (2007)-style model of Jermann and Quadrini (2012). I obtain 1,000,000 draws from a Markov Chain Monte Carlo algorithm, discard the first 25%, and use the remaining ones to compute posteriors.

5.2 Main results from model estimation

A model as rich as the DSGE model estimated here in principle allows us to study a large variety of consequences of borrowing constraints: effects on parameter estimates, IRFs, moments or variance decompositions for many variables and shocks. I organize the results around the predictions about the implications of earnings-based borrowing constraints characterized analytically in Section 3.3. These predictions center around core elements of New Keynesian DSGE models, such as nominal rigidity estimates and the contribution of supply relative to demand shocks. My focus on these core elements represents a compact way to highlight the types of consequences of earnings-based constraints that should be relevant for a large class of models and questions.

Table 2: NOMINAL RIGIDITY ESTIMATES IMPLIED BY DIFFERENT CREDIT CONSTRAINTS

	(1) **more earnings-based ($\chi = 0.8$)**	**(2)** **more collateral ($\chi = 0.2$)**
Rotemberg price adjustment parameter	0.08	4.67
(90% HPD interval)	(0.04,0.11)	(4.29,5.01)
Calvo wage adjustment parameter	0.72	0.80
(90% HPD interval)	(0.68,0.75)	(0.78,0.81)

Notes. Posterior estimates for the price and wage rigidity parameters in the estimated model when the share of earnings-based borrowers is set to $\chi = 0.8$ (column 1) and to $\chi = 0.2$ (column 2).

Estimated nominal rigidities. Recall from the analytical results in Section 3.3 that earnings-based borrowing constraints should have one of the following consequences in an estimated New Keynesian macro model. First, supply shocks should be more important than demand shocks. Second, prices might not be meaningfully sticky. Table 2 investigates the latter of the two forces by presenting the posterior estimates of nominal rigidity parameters across the two estimated model versions. It is evident from column (1) that the model where earnings-based borrowing constraints are faced by the majority of firms, price rigidities are estimated to be low, in fact quite close to a flexible price model (posterior mean of the Rotemberg parameter of 0.08). The estimates in the model in which the collateral constraint plays a larger role, shown in column (2), imply a more rigid price setting environment for firms (posterior mean of 4.67). Interestingly, wage stickiness is weaker when the earnings-based constraint is more important (0.72 vs. 0.80). Recall that, strictly speaking, the arguments in Section 3.3 apply to price rigidity relative to wage rigidity. These relative rigidities across prices and wages, however, are difficult to interpret from Table 2 alone.[26] What is clear from Table 2 in and of itself is that the conclusions about one of the key ingredients of standard macro models, nominal rigidities, diverges between presence of earnings-based and collateral constraints. The consequences of these parameters for the quantitative importance of shocks can be investigated directly by analyzing variance decompositions.

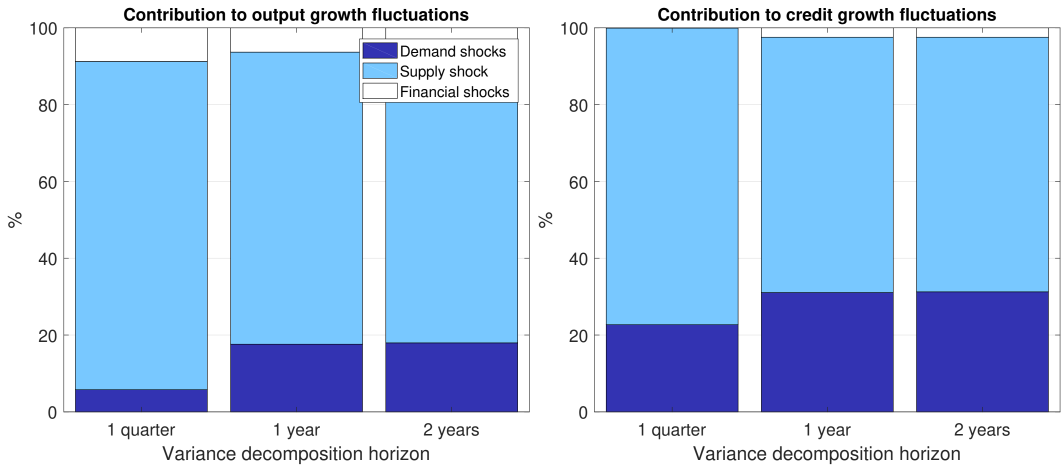
Supply vs. demand shocks. The most important quantitative result concerns the drivers of US business cycles. The estimated model features eight shocks that can be grouped into supply and demand shocks based on the comovement of output and prices they generate. Figure 8 presents variance decompositions of output growth and credit growth fluctuations into supply and demand shocks. It shows that the stronger presence of an earnings-based borrowing constraint implies a larger contribution of supply shocks to output growth fluctuations (76% vs. 37% at a 2-year horizon), as well as to credit growth fluctuations (66% vs. 34%) than the case where firms mainly borrow against collateral. With collateral constraints, demand shocks are more important. These diverging decompositions into demand and supply shocks reveal that considering earnings-based constraints is important for policy considerations: demand shocks are typically easier for monetary policy to offset, while several types of supply shocks rise to a more intricate tradeoff between price and activity stability. It is therefore of first order importance to gauge which shocks are the primary driver of a recession. Taking earnings-based credit into account changes such conclusions. My findings thus suggest that the presence of these constraints should be seriously considered in light of assessing macro stabilization policy using DSGE models.

Appendix F.2.2 presents additional model counterfactuals. These show that the differences in the contribution of different shocks are driven both directly by the presence of different borrowing constraints as well as by the different parameter estimates that result from firms facing mainly one or the other constraint.

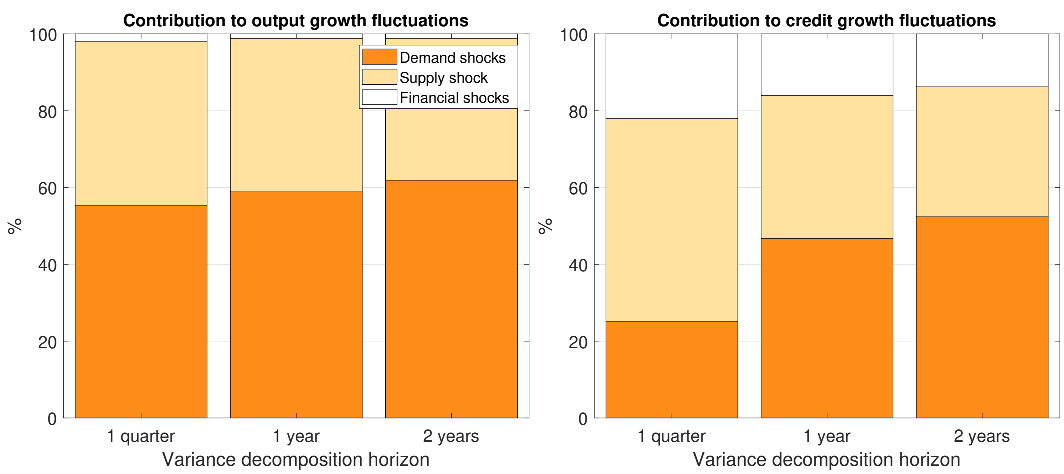
[26] The model features a Calvo setting for wages, but a Rotemberg setting for prices. The latter enables the aggregation of the decision of individual firms when financial frictions are present. For both model versions, the price rigidity estimates in Table 2 are much lower than the estimates of Ireland (2001) that I use to calibrate the model in Section 3. This is likely driven by the variety of other frictions, including wage rigidities, which are not present in Section 3 and in the model that Ireland (2001) estimates.

Figure 8: ESTIMATED IMPORTANCE OF SHOCKS WITH HETEROGENEOUS CREDIT CONSTRAINTS

(a) Decomposition into structural shocks with high share of earnings-based borrowers ($\chi = 0.8$)



(b) Decomposition into structural shocks with high share of collateral borrowers ($\chi = 0.2$)



Notes. Forecast error variance decomposition of fluctuations in output growth (left) and credit growth (right) into different types of structural shocks. Panel (a) is based on the model version estimated with a higher share of earnings-based borrowing constraints ($\chi = 0.8$), Panel (b) shows the corresponding results in the benchmark where more borrowers face collateral constraints ($\chi = 0.2$). In each panel, the decomposition is computed for a 1-quarter, 1-year and 2-year horizon. *Demand* shocks are MEI, preference, government spending and monetary policy shocks. *Supply* shocks are TFP, price markup and wage markup shocks. This is a traditional classification into demand (supply) shocks based on the positive (negative) comovement between output and prices implied by the respective shocks. *Financial* shocks are shocks to the respective credit constraint directly.

5.3 Further results from model estimation

Estimated markups. The results of the model estimation confirm the predictions of Section 3.3. Since the movements of markups in response to different shocks matter for these predictions, the implied markup cyclicality is another statistic that is interesting to analyze in the estimated model: I find that both with $\chi = 0.8$ and $\chi = 0.2$, average markups are estimated to be mildly countercyclical unconditionally. It is important to stress that this feature of the estimated model does not contradict the logic of Section 3.3 and interpretation of the results above. Recall that credit is used as an observable in the estimation. Since this variable is strongly procyclical, a model with earnings-based constraints can match the credit dynamics in the data better with procyclical earnings. This can happen in two ways. Either with sticky prices and procyclical markups (driven by supply shocks), or without sticky prices in which case the role of markups is generally muted, and in principle either supply or demand shocks could be important. In the estimation with a high share of earnings-based constraints, it turns out that price rigidities are estimated to be low (so markup movements are in fact less relevant), *and* supply shocks are important nevertheless.

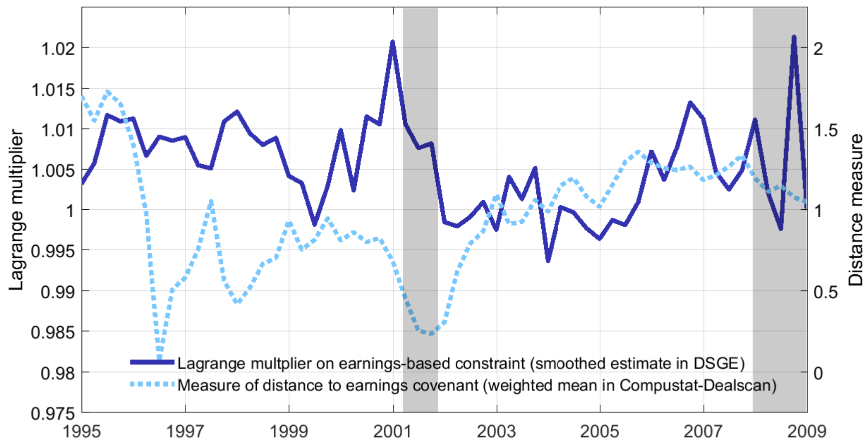
Investment shocks and local projections on simulated model data. Investment shocks imply a positive comovement of output and inflation, so are classified as demand shocks. The model estimated with $\chi = 0.8$ implies a lower importance of investment shocks than with $\chi = 0.2$. Given the importance of investment shocks in my empirical tests, this warrants some clarifying remarks. First, investment shocks in the estimated model are transitory, while the identified shocks in Section 4 are permanent. Second, my empirical strategy to distinguish the relevant credit constraint in micro data does not necessarily require a strong quantitative contribution of the investment shock, as long as it is correctly identified. To verify that the logic around investment shocks is consistent across the different parts of the paper, I study IRFs to permanent investment shocks in the estimated model in Appendix F.2.3. These IRFs show that the mechanism of Section 3 remains fully intact in the estimated version of the model. Furthermore, using simulated data from the estimated model, I show that the empirical techniques I apply in Section 4 can recover the different responses to investment shocks across borrower types when firms face other shocks, both transitory and permanent, as well as at the firm-level and in the aggregate. The simulation procedure and results are presented in Appendix F.2.4.

Financial shocks. In addition to supply and demand shocks, Figure 8 reports the contribution of financial shocks, which directly hit the θ-terms in equations (8) and (9). Earnings-based borrowing constraints attribute slightly more importance to these shocks for output growth fluctuations than collateral constraints. Interestingly, in the model with a higher share of earnings-based borrowers this type of shock has a meaningful role for business cycles even in the absence of working capital loans, an assumption commonly chosen generate amplification with credit constraints (for a discussion, see Quadrini, 2011). With a collateral constraint, credit variation itself is driven by the shock to the constraint, but there is less internal propagation to output.

Estimated Lagrange multiplier on earnings-based constraint. Figure 9 plots the estimated Lagrange multiplier on the earnings-based borrowing constraint, for the case $\chi = 0.8$ and the period in which the estimation sample overlaps with the micro data from Compustat-Dealscan. I compare this estimate to a micro data measure of the average distance of Compustat-Dealscan firms from the value specified in their debt-to-earnings covenants. This measure does not enter the estimation, so serves as an "untargeted moment." The estimation of the model relies on the simplification that credit limits bind at all times, so the Lagrange multiplier is always positive and captures only the intensive margin of how strongly the constraint binds. The two time series in Figure 9 should be negatively related in times of tight financial conditions: when firms' debt-to-earnings ratios are closer to their maximum (dotted line is low), the estimated model should imply a tight earnings-based constraint, that is, a high shadow price (solid line). The simplification of always binding constraints, however, has the disadvantage that the model may not accurately capture times when firms' debt-to-earnings ratios move far away for their maximum in the data (dotted line is high), but the model's Lagrange multiplier "incorrectly" stays above 0.

The figure shows that the Lagrange multiplier indeed reflects financially tight periods for Compustat-Dealscan firms, especially for several episodes in the 1990's and the 2001 recession, where downward swings in the empirical distance measure are mirrored by a higher shadow price on the constraint. The disadvantage of the binding constraint assumption is visible in the debt boom of the mid-2000s, where Compustat-Dealscan firms appear to be moving away from covenant limits, but the Lagrange multiplier does not drop to 0 as it might do in a model with occasionally binding constraints during that period. At the onset of the Great Recession when overall financial conditions started to deteriorate, the micro level measure begins to decline, while the multiplier, though volatile in this period, increases again.

Figure 9: EMPIRICAL ANALYSIS OF LAGRANGE MULTIPLIER ON EARNINGS-BASED CONSTRAINT



Notes. Smoothed posterior estimate of the Lagrange multiplier on the earnings-based constraint in the model with $\chi = 0.8$ (solid dark blue, left scale), compared to a measure of the distance of Compustat-Dealscan firms to their debt-to-earnings covenants (dotted light blue, right scale). The steady state value of the Lagrange multiplier is normalized to 1. The distance measure is constructed by subtracting, in each quarter, the sales-weighted ratio of debt to EBITDA across firms from the sales-weighted average of the maximum value in the debt-to-earnings covenants. For individual firms, this measure can be negative, in which case the firm is in violation. The distance calculated based on value-weighted means fluctuates between close to 0 and around 1.75. Shaded areas represent NBER recessions.

I use the estimated model to validate predictions on how different borrowing constraints interact differently with sticky prices and the relative importance of different shocks. The assumption behind my strategy is that as long as there are sufficiently frequent periods with tight financial conditions, then the estimation is informative about the predicted differences between the constraints. Figure 9 provides some support for this assumption, showing several increases in the tightness of covenants that the model's estimated Lagrange multiplier picks up.

5.4 Key take-aways from the model estimation

New Keynesian models are used to address a wide array of questions, ranging from their traditional purpose of assessing the effects of monetary policy, to more recent applications to housing markets or income inequality. My estimation results uncover that the earnings-based borrowing constraint interacts fundamentally with the New Keynesian transmission mechanism, and strongly alters conclusions about the shocks that drive macroeconomic fluctuations. This suggests that a variety of other applications of the New Keynesian DSGE framework can be revisited within the context of earnings-based credit constraints faced by firms.

6 Conclusion

Grounded on microeconomic evidence, this paper examines a debt limit that restricts firm borrowing to a multiple of current earnings. Model predictions that distinguish the relevance of earnings-based borrowing constraints relative to traditional asset-based constraints, are confirmed by aggregate and firm-level credit dynamics in US data. In addition, the way firm borrowing constraints are captured in quantitative DSGE models alters central conclusions relevant to macro policy tradeoffs. The insight that the consequences of earnings-based borrowing constraints lie so close to the core of the standard macro modeling framework makes the case for changing the way we think about firm credit constraints in business cycle research.

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APPENDIX FOR ONLINE PUBLICATION

Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations

by Thomas Drechsel

Contents

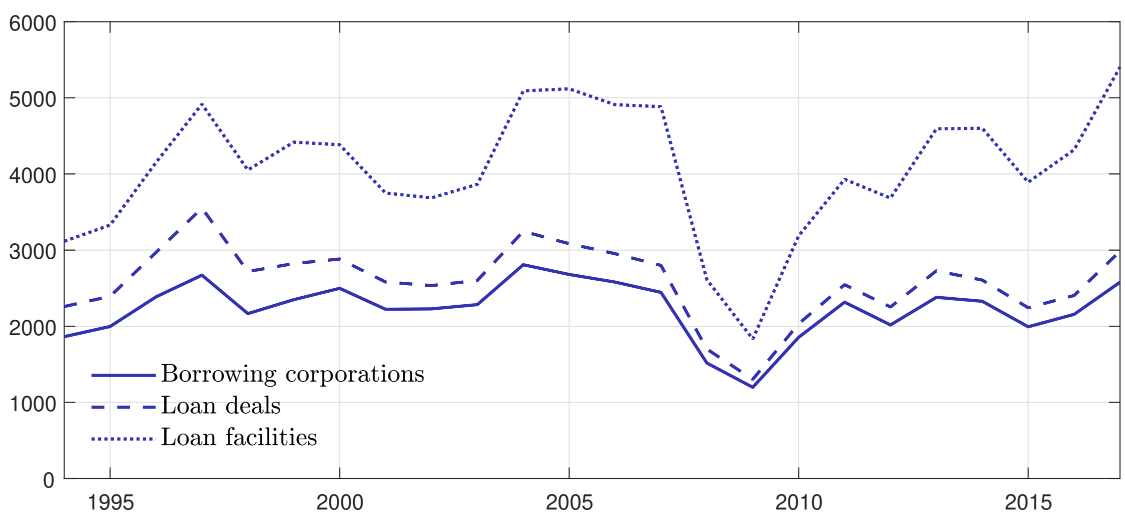
A Details on the data

This appendix provides details on the data sources used across all sections of the paper. First, Section A.1 describes the Thomson Reuters LPC Dealscan database and presents summary statistics. This data set is used for the motivational evidence in Section 2 of the main text. Second, the merged data set consisting of the Dealscan data, together with quarterly balance sheet information from Compustat is explained in Section A.3. This data is used in Section 4.2 of the main paper, for the local projections of the investment shock in panel data. Third, the construction of the time series data used for the estimation of the SVAR in Section 4.1 and the estimation of the quantitative model in Section 5 is laid out in Section A.4. Fourth, Section A.5 explains how the industry-specific equipment price sensitivities are constructed using BEA data.

A.1 Thomson Reuters LPC Dealscan data set

LPC Dealscan is a detailed loan-level database provided by Thomson Reuters. The data was retrieved through Wharton Research Data Service (WRDS). The unit of observation is a loan *deal*, sometimes called loan *package*, which can consist of several loan *facilities*. As explained in the main text, rich information is provided both and the deal and facility level. The information is collected at the time of origination but is then not followed over time, so that the data can be thought of as a large cross section with different origination dates.

Figure A.1: COVERAGE OF DEALSCAN SAMPLE BY ORIGINATION DATE



Notes. The figure plots the number of loan deals (or packages), loan facilities and borrowing corporations for the sample used in the main analysis of the paper, broken down by origination date since 1994. The sample covers USD denominated debt for US nonfinancial corporations.

Data coverage. For the main sample considered in the text I choose loan packages in which the lender is a US nonfinancial Corporation (excluding SIC codes 6000-6999) and the debt is US Dollar denominated. Following Chava and Roberts (2008), I start the sample with loans originated in 1994. I end the sample at the end of 2017, since 2017:Q4 is the last quarter in which I can merge the data with Compustat (see Section A.3). These sample restrictions result in a sample of 62,199 packages, 97,723 facilities and 17,904 unique borrowing corporations. The number of deals per borrower ranges from 1 to 48, with on average 7.59 deals per borrower. Figure A.1 summarizes the number of deals, facilities and borrowers split up by origination time. Note that this figure includes observations with and without information on covenants and collateral, so the number of observations used to produce individual statistics in the main text and this appendix can differ.

Summary statistics. Tables A.1, A.2, A.3 and A.4 provide further descriptive information on the data for the sample described above. Table A.1 provides summary statistics on the size of both deals and facilities and of the maturity of the loans, which is available at the facility level. As the table shows loans reach from single digit million amounts up to the size of a few billion dollars. Facility amounts are smaller on average, which is true by construction since a deal consists of at least one facility. The maturity of a facility is on average between 4 and 5 years (52 months). A.2 shows the coverage of the data across industries. Table A.3 lists the ten most frequently stated loan purpose, which is provided at the deal level. This information is available for every deal in the sample (no missing fields), although it is apparent that the number one category "corporate purpose" is relatively unspecific. Table A.4 lists the most common asset *types* of collateral pledged in secured loan facilities.

Table A.1: SUMMARY STATISTICS FOR DEALSCAN DATA

	Deal amount (mio 2009 USD)	Facility amount (mio 2009 USD)	Facility maturity (months)	Interest rate (drawn spread)
Mean	473.2	301.2	52	270
Standard deviation	1148.5	769.1	26	172
1st percentile	2.9	1.6	5	20
10th percentile	27.2	11.1	12	75
25th percentile	67.0	31.8	36	150
Median	168.8	98.3	60	250
75th percentile	447.2	283.7	60	350
90th percentile	1079.4	689.4	84	475
99th percentile	4728.7	3000.0	120	850
Observations	62,199	97,723	90,375	82,687

Notes. Summary statistics for Dealscan loan sample used for the main analysis in the paper. Real values were obtained using the US business deflator with base year 2009. The interest rate in the all-in spread for drawn facilities, expressed as a spread over LIBOR in basis points. Changes in the number of observation result from missing fields.

Table A.2: INDUSTRY COVERAGE IN DEALSCAN DATA

Industry	No of firms	No of loan deals	Amount borrowed
Consumer Nondurables	1,287	4,927	2.23
Consumer Durables	501	2,010	1.22
Manufacturing	1,956	7,815	3.17
Oil, Gas, and Coal	969	4,024	2.25
Chemicals	428	1,911	1.13
Business Equipment	1,728	5,411	2.49
Telephone and TV	826	2,942	2.71
Utilities	929	4,560	2.83
Wholesale, Retail	2,650	9,977	3.74
Healthcare	1,254	4,132	2.28
Other	4,149	13,049	5.16
No SIC code available	1,226	1,441	0.21

Notes. Industries are based on the Fama-French 12 Industry Classification. (Finance and Utilities are excluded from the sample). The amount borrowed is in trillions of 2009 real USD. Note that the panel regressions on the merged Compustat-Dealscan data in the text use 3-digit SIC industry classification (for fixed effects etc.). The Fama-French classification is shown here just to provide a concise summary of the industry variation in the data.

Table A.3: FREQUENCY OF STATED DEAL PURPOSE IN DEALSCAN DATA

Deal purpose	Share (equal-weighted)	Share (value-weighted)
Corporate purposes	49.0%	46.6%
Working capital	11.2%	6.7%
Debt Repayment	10.6%	8.5%
Takeover	6.0%	14.0%
Acquisition line	5.5%	4.1%
LBO	4.7%	4.9%
CP backup	3.4%	7.2%
Dividend Recap	1.5%	1.2%
Real estate	1.3%	0.3%
Project finance	1.0%	0.8%

Notes. The table shows the ten most frequently stated ”deal purposes”. This information is available at the deal level for all observations in the US sample. The first column calculates the frequency by firm, the second one by (real) USD.

Table A.4: MOST FREQUENTLY PLEDGED ASSETS IN SECURED LOAN FACILITIES IN DEALSCAN DATA

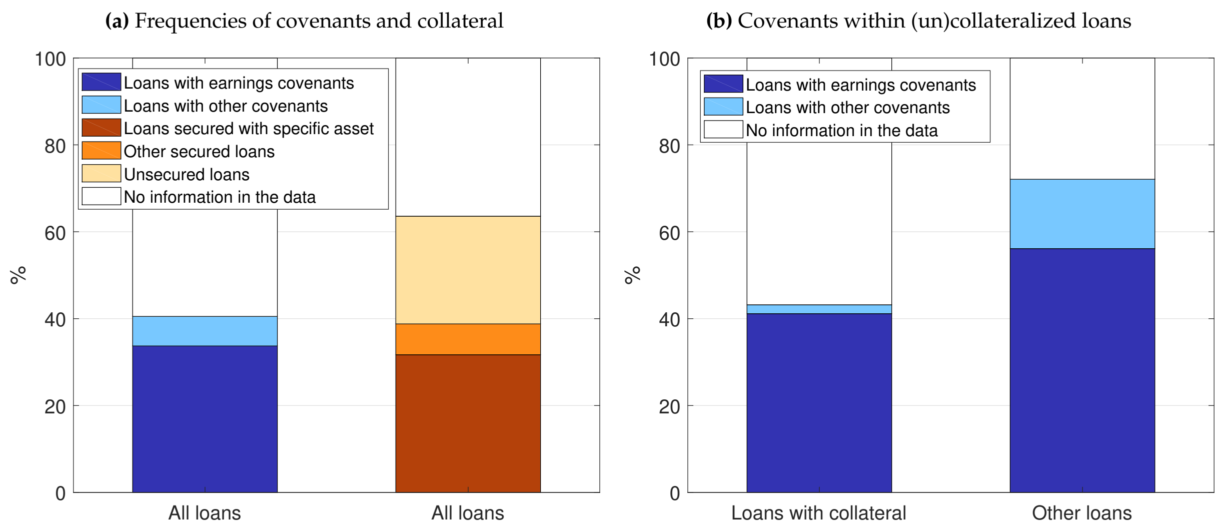
Collateral type	**Number of loan facilities**	**Volume in bn USD**
Property & Equipment	2356	427
Accounts Receivable and Inventory	1879	394
Intangibles	1398	268
Cash and Marketable Securities	1009	365
Real Estate	743	155
Ownership of Options/Warrants	104	20
Patents	81	12
Plant	51	14
Agency Guarantee	26	6

Notes. The numbers in this table are calculated by restricting Dealscan facilities to secured facilities and then calculating the frequencies of different security types. The table focuses on *specific* asset categories, i.e. excludes the categories "unknown", "all", and "other". According to Lian and Ma (2021), facilities secured by all assets (excluded in this table), can generally be classified as cash-flow based loans, as the value of this form of collateral in the event of bankruptcy is calculated based on the cash flow value from continuing operations. The key function of having security is to establish priority in bankruptcy.

A.2 Earnings-based vs. asset-based lending in Dealscan

Figure A.2 analyzes the value-weighted frequency of loan covenants and collateral. In Panel (a), the left bar presents the share of loans with at least one earnings-related covenant (dark blue area) and with only other covenant types (light blue area). For the remaining share, the information on covenants is not available (white area). The right bar presents the share of loans that are secured with specific assets, other secured loans, unsecured loans, and loans without information on whether they are secured (dark orange, medium orange, light orange, and white areas, respectively).[1] The left bar indicates that earnings-based covenants, which dominate within covenants overall, feature in around 35% of loans. This number is a lower bound, as the remainder of loans does not have any information on covenants. The key insight from the figure is that the share of earnings-based covenants is higher than the share of debt secured by specific assets, shown in the right bar. Finally, a sizable chunk of loans is unsecured.

Figure A.2: THE IMPORTANCE OF EARNINGS-BASED AND ASSET-BASED DEBT IN COMPARISON



Notes. Panel (a) displays the value-weighted shares of loan deals that contain covenants (left bar) and are secured/unsecured (right bar). In the left bar, the dark blue area represents the share with at least one earnings-based covenant. The light blue area covers loans with covenants unrelated to earnings. In the right bar, the different orange shades capture loans secured with specific assets (dark), other secured loans (medium) and unsecured loans (light). In both bars, loans without the relevant information are represented by the white area. Panel (b) repeats the left column of Panel (a), but breaks down the sample into loans secured with specific assets and other loans.

Panel (b) breaks down the frequency of covenants conditional on the loan being in two different groups. The first one is loans that are secured by specific assets while the second one is other loans, excluding loans without information on secured/unsecured. This shows that covenants are more likely to appear in a loan contract when specific collateral is not present, but loans backed by specific assets still have a reasonably high share of covenants. Hence, earnings-based covenants are used both in addition to and instead of collateral.

[1] Lian and Ma (2021) classify loans secured with "all assets" as cash-flow based, as the value in the case of bankruptcy is calculated based on the cash flows from continuing operations. Therefore, I define loans backed by *specific* assets as secured loans but assign those backed by "all assets" to the category called "Other secured loans".

A.3 Merged Compustat-Dealscan panel data set

Compustat Northamerica Quarterly. This data set provides accounting data for publicly held companies at quarterly frequency. The data was accessed through the Wharton Research Data Services (WRDS). I keep firms incorporated in the United States with positive assets and sales and exclude Financials (SIC codes 6000-6999). In addition, I generally exclude the sector of 'unclassifiable' firms (SIC codes starting with 99), since this sector contains very few large holding firms, which are typically financial firms (e.g. Berkshire Hathaway). Finally I drop firms that are present less than 5 years. These sample restrictions are typically made in papers that focus on nonfinancial Compustat firms, see for example Bates, Kahle, and Stulz (2009).

Merge of Dealscan with Compustat. I use Michael Roberts' identifier link, which is available on Michael Roberts' personal website, see also Chava and Roberts (2008). I am extremely grateful to these authors for publicly providing this link. The version of the link file which I retrieved is the April 2018 version, which contains matches through the end of 2017. I drop firms from Compustat that do not appear at least once in the Dealscan data and restrict the sample to the period covered by the link file. I deseasonalize the variables I use from Compustat by regressing them on quarter-dummies before using them in the actual regressions. The resulting merged data set covers more than 250,000 firm-quarter observations for more than 5,000 distinct firms from 1994 to 2017. (These numbers reflect also the merge with BEA data, see Appendix A.5). Note that the number of observations used in the actual regressions varies depending on what information from the two data sets in used, e.g. because only a subset of loans of covenant information. This becomes clear from the summary stats broken down by borrower type below.

Summary statistics for the merged data set. Table A.5 provides summary statistics for the firms in the full Compustat-Dealscan panel, which is used to estimate equation (18). Table A.6 presents the corresponding information for firms based on the baseline classification used in equation (20). Since firms can have several loan issuances, a given firm might appear in several panels of the table at different points in time. What the table shows is a mutually exclusive grouping of borrower types *in a given time period*, which is what is used in the estimation of (20).

Table A.5: SUMMARY STATISTICS FOR FULL COMPUSTAT-DEALSCAN PANEL ($N = 5,165$)

	Firm-qrt obs	Mean	SD	Min	Median	Max
Real total assets (bn 2009 USD)	289,371	4.1	15.7	0.0	0.6	583.8
Real sales (bn 2009 USD)	298,179	0.8	3.4	0.0	0.1	138.9
Real sales growth (percent)	289,418	3.2	17.8	30.8	1.8	46.2
Employment (thousands)	257,292	11.4	47.6	0.0	2.0	2300.0
Real debt liabilities (bn 2009 USD)	303,620	1.2	5.7	0.0	0.1	365.3
Cash ratio	289,064	0.1	0.2	0.0	0.1	0.8
Market-to-book ratio	261,325	1.8	1.0	0.8	1.4	4.7
Book leverage	289,112	0.6	0.2	0.2	0.6	1.1

Table A.6: SUMMARY STATISTICS FOR SUBGROUPS IN COMPUSTAT-DEALSCAN PANEL

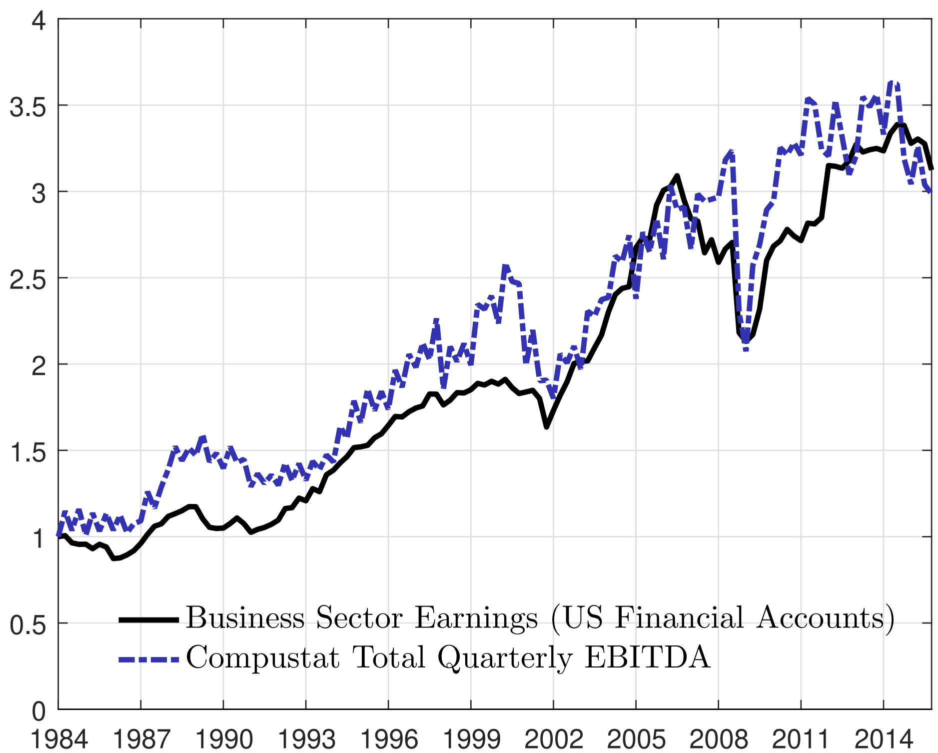
	Firm-qrt obs	Mean	SD	Min	Median	Max
Panel (a): Borrower-quarter observations in which loans have earnings covenants only ($N = 1,844$)						
Real total assets (bn 2009 USD)	53,136	7.5	21.7	0.0	2.1	552.7
Real sales (bn 2009 USD)	53,544	1.5	3.4	0.0	0.5	55.8
Real sales growth (percent)	53,304	3.9	16.3	-30.8	2.1	46.2
Employment (thousands)	48,552	21.8	45.3	0.0	6.8	707.9
Real debt liabilities (bn 2009 USD)	53,736	2.5	8.1	0.0	0.6	331.1
Cash ratio	53,088	0.1	0.1	0.0	0.0	0.8
Market-to-book ratio	49,500	1.9	0.9	0.8	1.6	4.7
Book leverage	53,136	0.6	0.2	0.2	0.6	1.1
Panel (b): Borrower-quarter observations in which loans have collateral only ($N = 2,188$)						
Real total assets (bn 2009 USD)	41,640	3.1	14.4	0.0	0.5	537.1
Real sales (bn 2009 USD)	43,704	0.7	3.0	0.0	0.1	92.8
Real sales growth (percent)	42,192	4.0	19.4	-30.8	2.3	46.2
Employment (thousands)	38,748	9.5	43.1	0.0	1.7	1900.0
Real debt liabilities (bn 2009 USD)	44,736	1.1	5.1	0.0	0.1	197.0
Cash ratio	41,592	0.1	0.1	0.0	0.0	0.8
Market-to-book ratio	37,104	1.7	0.9	0.8	1.4	4.7
Book leverage	41,628	0.6	0.2	0.2	0.6	1.1
Penal (c): Borrower-quarter observations in which loans have both ($N = 3,141$)						
Real total assets (bn 2009 USD)	96,024	2.1	7.6	0.0	0.6	490.4
Real sales (bn 2009 USD)	98,292	0.4	1.1	0.0	0.1	59.2
Real sales growth (percent)	97,056	5.8	18.7	-30.8	3.2	46.2
Employment (thousands)	90,840	7.4	19.7	0.0	2.3	487.9
Real debt liabilities (bn 2009 USD)	99,276	0.8	3.8	0.0	0.2	271.1
Cash ratio	96,000	0.1	0.1	0.0	0.0	0.8
Market-to-book ratio	86,832	1.6	0.8	0.8	1.3	4.7
Book leverage	95,976	0.6	0.2	0.2	0.6	1.1
Panel (d): Borrower-quarter observations in which loans do not have either ($N = 1,815$)						
Real total assets (bn 2009 USD)	43,296	12.0	25.5	0.0	3.4	404.3
Real sales (bn 2009 USD)	44,232	2.3	6.5	0.0	0.5	115.8
Real sales growth (percent)	43,212	4.4	18.7	-30.8	2.4	46.2
Employment (thousands)	32,784	32.9	109.4	0.0	6.3	2300.0
Real debt liabilities (bn 2009 USD)	44,820	3.8	9.1	0.0	1.1	232.9
Cash ratio	43,260	0.1	0.1	0.0	0.0	0.8
Market-to-book ratio	37,056	1.7	0.9	0.8	1.4	4.7
Book leverage	43,284	0.6	0.2	0.2	0.7	1.1

A.4 Aggregate data used for SVAR and model estimation

Data sources. The aggregate time series data used for the SVAR analysis and the estimation of the quantitative model come from a number of sources, including the Bureau of Economic Analysis, the Bureau of Labor Statistics and the US Financial Accounts provided by the Federal Reserve (also known as Flow of Funds). I retrieved these series using FRED and the data download program of the US Financial Accounts. In the treatment of relative prices in both panels, I closely follow Fisher (2006) and Justiniano, Primiceri, and Tambalotti (2011). The selection of variables for the New Keynesian model is similar to Jermann and Quadrini (2012). Table A.7 lists the time series and their construction, together with the specific identifiers.

Details on the earnings measure. To calculate an aggregate corporate earnings/profit measure, I use the item 'FA146110005.Q: Income before taxes' for the nonfinancial business sector, available from the table F.102 in the US Financial Accounts. I cross-checked the cyclical properties of this series with the 'ebitda' item from Compustat and found it to be relatively similar, see Figure A.3 for a comparison below:

Figure A.3: US FINANCIAL ACCOUNTS VS. COMPUSTAT



Notes. The figure shows a comparison of earnings measures from the US financial accounts and Compustat Quarterly. Both series are normalized to 1 in 1984:Q1. The Compustat series is not seasonally adjusted.

Table A.7: DETAILS ON AGGREGATE US TIME SERIES DATA

Panel (a): Data used in estimation of SVAR

Variable	Series sources and construction	Transform
Relative price of investment	Implicit price deflator of nonresidential fixed equipment investment (FRED: Y033RD3Q086SBEA), deflated with implicit price deflator of personal consumption expenditures of nondurable goods and services (FRED: CONSDEF)	log diff
Relative price of investment (alternative measure)	See DiCecio (2009) for details (FRED: PERIC)	log diff
Labor productivity	Nominal business sector value added (FRED: A195RC1Q027SBEA), deflated with consumption deflator (see above), divided by hours worked (see below)	logdiff
Hours worked	Hours of all persons in the nonfarm business sector (FRED: HOANBS)	log
Business sector earnings	Sum of nominal income before taxes in the nonfinancial noncorporate sector (USFA: FA116110005.Q) and corporate profits before tax excluding IVA and CCAdj (USFA: FA106060005.Q), deflated with consumption deflator (see above)	logdiff
Level of the capital stock	Constructed from capital expenditures in the nonfinancial business sector (USFA: FA145050005.Q) minus depreciation (consumption of fixed capital in the nonfinancial business sector, USFA: FA106300083.Q), valued at the relative price of investment (see above)	logdiff
Business sector debt	Level of debt securities and loans in the nonfinancial bussiness sector (constructed from USFA: FA104122005.Q and FA144123005.Q), deflated with consumption deflator (see above)	logdiff

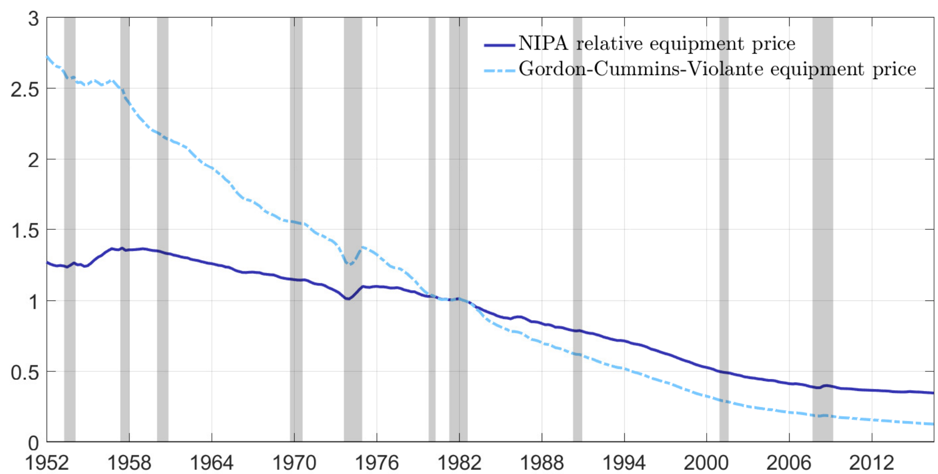
Panel (b): Data used in estimation of New Keynesian model

Variable	Series sources and construction	Transform
Output	Nominal GDP (FRED: GDP), divided by population (FRED: B230RC0Q173SBEA), deflated with consumption deflator (see above)	logdiff
Consumption	Real consumption expenditures of nondurable goods and services (FRED: PCNDGC96 and PCESVC96), divided by population (see above)	logdiff
Investment	Sum of nominal gross private domestic investment expditures (FRED: GPDI) and nominal private consumption expenditures on durable goods (FRED: PCDG), divided by population (see above), deflated with consumption deflator (see above)	logdiff
Hours worked	See above	logdiff
Real wage	Nominal compensation per hour in the nonform business sector (FRED: COMPNFB), deflated with consumption deflator (see above)	logdiff
Inflation	Percentage change in consumption deflator (see above)	none
Interest rate	Nominal effective Federal Funds Rate (FRED: FEDFUNDS)	none
Business sector debt	Level of debt securities and loans in the nonfinancial bussiness sector (constructed from USFA: FA104122005.Q and FA144123005.Q), deflated with consumption deflator (see above)	logdiff

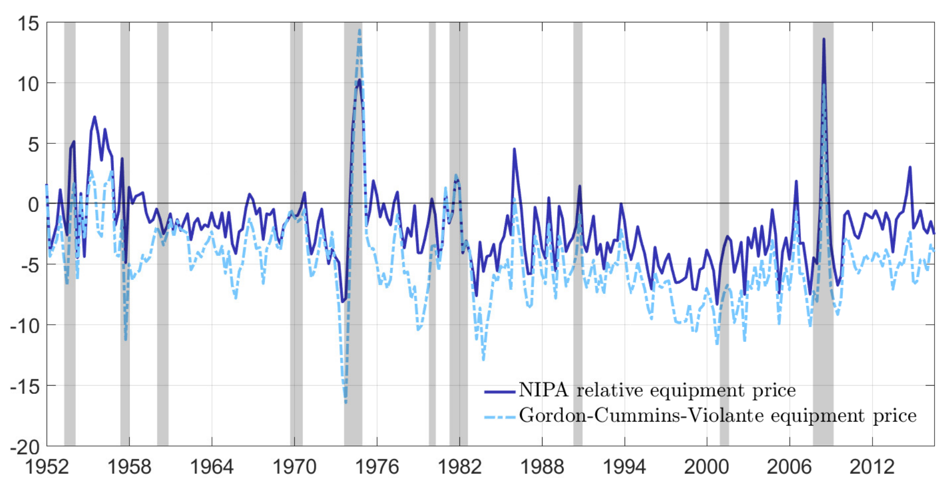
Details on relative equipment prices. Figure A.4 compares the two alternative measures used for the relative price of equipment investment. The first is the one based on NIPA data, constructed as the ratio between the equipment investment deflator and the deflator of consumption on nondurables and services. The second one is the Gordon-Violante-Cummins (GVC) relative equipment price, see Cummins and Violante (2002) and DiCecio (2009). Panel (a) plots the evolution in the level and Panel (b) plots the quarterly growth rates. More details can be found in Table A.7.

Figure A.4: MEASURES OF THE RELATIVE EQUIPMENT PRICE

(a) Levels (1982:Q3 = 100)



(b) Growth rates (annualized %)



Notes. Panel (a) plots the evolution in the level and Panel (b) the quarterly growth rates of the two alternative measures used for the relative price of equipment. The solid dark blue line shows the one constructed from NIPA deflators and the dashed light blue one the Gordon-Violante-Cummins (GVC) relative equipment price, see Cummins and Violante (2002) and DiCecio (2009). Table A.7 contains additional details.

Table A.8 reports the results from an augmented Dicker-Fuller (ADF) test on the two alternative equipment price series plotted in Figure A.4. The test is specified as in Gali (1996). The model under the null has a unit root, the alternative is the same model with drift and deterministic trend. The lag order is 4. Consistent with the assumptions required by the SVAR identification scheme, the test fails to reject a unit root in the level, but rejects a unit root in after first-differencing for both alternative measures.

Table A.8: RESULTS OF UNIT ROOT TESTS ON EQUIPMENT PRICE SERIES

	Test statistic	**5% critical value**	**Reject?**
NIPA levels	-3.34	-3.43	No
NIPA first differences	-5.40	-3.43	Yes
GVC levels	-0.15	-3.43	No
GVC first differences	-6.99	-3.43	Yes

Notes. Unit root test on alternative equipment price series in levels and first differences. See Table A.7 for details on the series. Following Gali (1996) the table reports the relevant t-statistics for the null hypothesis of a unit root in the level and the first difference of each time series, based on an augmented Dicker-Fuller (ADF) test with 4 lags, intercept and time trend.

A.5 Constructing industry-level equipment price sensitivities

Data source. I retrieve annual data on nominal and real equipment investment for different equipment categories and across industries from the Bureau of Economic Analysis (BEA) Fixed Asset tables. This is available on the BEA website at https://apps.bea.gov/national/FA2004/Details/Index.htm (see tables *Investment* and *Investment, fixed cost* in the category *Nonresidential Detailed Estimates*). See also vom Lehn and Winberry (2021) and the Online Appendix of their paper for very helpful explanations of the structure of the BEA Fixed Asset Tables. This data covers 39 equipment investment categories for 58 industries (I drop financial industries from the original 63 BEA industries, in line with the sample restrictions in Compustat and Dealscan).

Constructing equipment price indeces. Using the BEA data, I first compute deflators for the different investment categories, by dividing the nominal by the real investment series. I then divide these investment deflators by the consumption deflator of nondurable goods and services to obtain real equipment investment prices for each equipment category. Finally, I compute real investment shares across equipment categories for each industry using the industry's real investment expenditures, and then weight the real investment prices with those shares. In this way, I obtain one real equipment price index for each industry, $p_{k,s,t}$. Table A.9 presents real shares of different equipment categories for a selected subset of industries, showing the 10 equipment investment categories that are most important for the average industry. Figure 4 in the main body shows the real equipment price indeces faced by selected industries over the sample used to estimate the firm-level local projections. Both the table and the figure reveal meaningful heterogeneity in the equipment categories that different industries invest in, and the equipment prices that are relevant to them.

Constructing industry-level equipment price sensitivities. I regress, for each industry s, the negative of the log difference of $p_{k,s,t}$ on the investment-specific shock from the SVAR, $\hat{u}_{IST,t}$:

$$-\Delta \log p_{k,s,t} = \lambda_s \hat{u}_{IST,t} + \varepsilon_{s,t} \tag{21}$$

I take the negative because I would like to use estimates of λ_s to construct a regressor that enters in the local projections as an "industry-specific investment shock", that is, is a shock that is *inversely* related to the price of equipment in a given industry. I take the log difference, in line with the fact that the SVAR system is set up such that $\hat{u}_{IST,t}$ is defined as a permanent shock to the log difference of the aggregate equipment price. After estimating (21), I construct

$$\hat{u}_{IST,s,t} = \hat{\lambda}_s \hat{u}_{IST,t} \tag{22}$$

to estimate equations (18) and (20) in the main text. This requires linking the estimates $\hat{\lambda}_s$ and $\hat{u}_{IST,s,t}$ to the firm-level by merging Compustat-Dealscan and BEA industry identifiers (the BEA provides a bridge between NAICS codes and BEA industry codes).

Note that while the local projection are quarterly, I can only run (21) at annual frequency. Since $\hat{\lambda}_s$ is time-invariant, this should only affect the precision of the estimates but is not a conceptual issue. To estimate (21), I use the same sample as for the SVAR, 1952-2017. The results are very similar when I end the sample for (21) in 1993, prior to the sample start for (18) and (20) in 1994. In this case the $\hat{\lambda}_s$ coefficient can be interpreted more directly as 'Bartik' weights. My preferred version uses the longer sample as the baseline to increase the precision of the $\hat{\lambda}_s$ estimates at annual frequency.

Table A.10 provides a full list of all 58 BEA industries, together with the BEA sector code and the amount of firms in the Compustat-Dealscan data that are active in a given industry. (Note that the total number of 5,165 firms corresponds to the total number shown in Table A.5). Importantly, the table shows the estimate of $\hat{\lambda}_s$ for each industry. Note that these estimates are obtained from regressing a (negative) log-difference on another log-differenced object in (21), so can be interpreted as an *elasticity*. Using only aggregate investment shocks in the local projections would impose an elasticity of 1 across all industries. It is visible in the table that the elasticity is positive across almost all industries, which reflects that, at business cycle frequencies, the industry-specific impact of investment shocks goes in the same direction as aggregate investment shocks across a broad number of industries. This is the case despite the different lower frequency trends across industries that are visible in Figure 4 of the main text. The elasticities are particularly high in the manufacturing sector, where a lot of Compustat firms are active. They are weaker in some services industries, such as health care, and even negative in parts of the information sector.

Table A.9: REAL EQUIPMENT INVESTMENT SHARES ACROSS EQUIPMENT CATEGORIES - SELECTED INDUSTRIES, TOP EQUIPMENT CATEGORIES

Industry	General industr. equipment	Special industr. machinery	Other furniture	Autos	Metalworking machinery	Other trucks, buses, trailers	Communi-cations	Service ind. machinery	Aircraft	Other construct. machinery
Forestry, fishing, and related activities	3.87%	5.88%	1.12%	2.14%	0.01%	9.82%	0.50%	0.18%	9.27%	7.82%
Oil and gas extraction	7.15%	0.00%	1.28%	7.37%	0.87%	1.50%	0.81%	0.30%	2.50%	9.07%
Construction	3.75%	0.11%	1.63%	5.05%	1.80%	11.61%	0.68%	0.82%	0.22%	45.01%
Manufacturing: Motor vehicles	37.10%	15.23%	1.94%	3.53%	0.69%	0.77%	1.10%	0.80%	0.36%	0.50%
Manufacturing: Wood products	30.34%	25.82%	2.55%	2.72%	1.23%	5.62%	0.46%	5.86%	0.56%	0.41%
Manufacturing: Furniture, related	36.58%	22.33%	2.36%	2.55%	6.56%	11.26%	0.52%	0.51%	0.00%	6.16%
Manufacturing: Food, beverage, tobacco	15.28%	1.57%	2.19%	3.77%	58.50%	1.64%	0.46%	0.38%	0.14%	0.27%
Manufacturing: Paper products	31.92%	6.17%	2.64%	2.78%	27.20%	1.09%	1.83%	0.57%	0.13%	0.39%
Wholesale trade	12.29%	1.53%	8.61%	6.60%	2.50%	7.76%	2.40%	8.78%	1.21%	2.45%
Retail trade	10.04%	1.91%	28.44%	4.52%	0.86%	5.33%	2.95%	15.33%	0.21%	0.58%
Air transportation	1.87%	0.02%	1.76%	2.16%	0.05%	2.72%	2.87%	0.46%	82.19%	0.08%
Broadcasting and telecommunications	0.47%	0.09%	3.20%	10.77%	0.20%	7.57%	54.69%	0.29%	0.45%	1.62%
Legal services	0.06%	0.02%	47.63%	11.07%	0.00%	0.57%	6.11%	1.65%	0.00%	0.00%
Nursing, residential care facilities	3.06%	0.68%	14.71%	7.76%	0.00%	0.58%	3.59%	17.59%	0.07%	0.78%
Food services, drinking places	1.60%	3.06%	22.34%	3.77%	0.00%	1.04%	1.27%	53.14%	0.10%	0.01%

Notes. Across the columns of the table, the 10 most important (on average) equipment categories out of 39 categories are included for a selected subset of 58 industries, where each row represents one industry. For each industry, the shares across equipment categories are calculated year by year from the industry's real investment expenditures. Source: BEA Fixed Asset Tables.

Table A.10: ESTIMATES OF SENSITIVITY TO AGGREGATE INVESTMENT SHOCK ACROSS INDUSTRIES

Broad sector	Industry	BEA Code	# unique firms in Compustat-Dealscan	$\hat{\lambda}_s$
Agriculture, forestry, fishing	Farms	110C	13	1.20
	Forestry, fishing, related	113F	0	1.37
Mining	Oil and gas extraction	2110	217	0.72
	Mining, except oil and gas	2120	46	1.94
	Support activities for mining	2130	44	1.69
Utilities		2200	247	2.21
Construction		2300	82	1.71
Manufacturing - Durable	Wood products	3210	22	1.92
	Nonmetallic mineral products	3270	30	2.25
	Primary metals	3310	80	2.37
	Fabricated metal products	3320	91	1.83
	Machinery	3330	234	1.97
	Computer and electronic products	3340	526	2.26
	Electrical equipment	3350	80	1.97
	Motor vehicles, bodies, trailers, parts	336M	92	1.89
	Other transportation equipment	336O	52	2.50
	Furniture and related products	3370	33	1.58
	Miscellaneous manufacturing	338A	156	1.99
Manufacturing - Nondurable	Food, beverage, tobacco products	311A	136	2.41
	Textile mills, textile product mills	313T	34	1.98
	Apparel, leather, allied products	315A	85	2.11
	Paper products	3220	58	2.76
	Printing and relate	3230	35	1.84
	Petroleum and coal products	3240	38	0.85
	Chemical products	3250	343	2.12
	Plastics and rubber products	3260	69	3.13
Wholesale trade		4200	254	1.01
Retail trade		44RT	382	1.59
Transportation and warehousing	Air transportation	4810	31	2.06
	Railroad transportation	4820	12	2.22
	Water transportation	4830	13	-1.38
	Truck transportation	4840	36	1.45
	Transit, ground passenger transportation	4850	4	1.35
	Pipeline transportation	4860	53	1.26
	Other transportation, support activities	487S	33	1.37
	Warehousing and storage	4930	2	1.67
Information	Publishing industries (includ. software)	5110	232	0.84
	Motion picture and sound recording	5120	28	-0.96
	Broadcasting and telecommunications	5130	189	1.87
	Information and data processing	5140	129	-0.94
Real estate, rental and leasing		5320	52	0.33
Professional, scientific, technical services	Legal services	5411	2	0.08
	Computer systems design, related	5415	137	-0.01
	Miscellaneous	5412	143	1.35
Management of companies & enterprises		5500	0	0.48
Administrative & waste management	Administrative and support services	5610	135	-0.84
	Waste management, remediation	5620	33	2.13
Educational services		6100	27	1.53
Health care and social assistance	Ambulatory health care services	6210	93	0.49
	Hospitals	622H	23	1.42
	Nursing and residential care facilities	6230	28	0.25
	Social assistance	6240	4	1.73
Arts, entertainment, and recreation	Performing arts, sports, museums	711A	10	1.33
	Amusements, gambling, and recreation	7130	41	1.03
Accommodation and food services	Accommodation	7210	49	0.75
	Food services and drinking places	7220	118	1.29
Other services, except government		8100	29	1.96
			$\sum = 5{,}165$	

B Discussion of microfoundation

The two borrowing constraints introduced in Section 3 of the text are exogenously imposed on the firm. This appendix discusses a formal rationalization of these constraints. I lay out a setting in which the constraints are derived as the solution to an enforcement limitation, in which borrower and lender predict the renegotiation outcomes in the event of a default. The appendix also provides a further discussion of the potential frictions underlying the earnings-based constraint, by giving a summary of the literature on the microfoundations of loan covenants and presenting additional details on regulatory requirement in relation to earnings covenants.

B.1 A formal rationalization of the alternative borrowing constraints

Collateral constraint. I begin with this constraint, as it is more familiar in the literature. Consider the firm type $j = k$ as described in the text. For simplicity, I assume $P_t = 1$ and drop subscript i. Suppose that at the end of period t, when all transactions have been settled, the firm can default on its debt liabilities, which at this point amount to $\frac{b_t^k}{1+r_t}$. In the absence of any punishment, the firm would have an advantage from doing this, as the repayment of b_t^k would not reduce resources in its flow of dividends constraint (6) next period.

Suppose the legal environment surrounding this type of debt is such that in the event of default the lender can address a court which grants it the right to seize the firm's collateral at the beginning of $t + 1$. The lender will be able to re-sell this collateral after depreciation at market prices, but incur a transaction cost which is a fraction $(1 - \theta_k)$ of the resale value of capital. Hence, instead of having $\frac{b_t^k}{1+r_t}$ on the asset side of her balance sheet at the end of the period, the lender now has a legal claim on selling the asset tomorrow, which is valued as $\theta_k \mathbb{E}_t p_{k,t+1}^k (1 - \delta) k_t^k$. If the collateral is seized by the lender, the firm is required to stop operating.

Suppose that before going to the next period, lender and borrower are able to renegotiate. The borrower can offer a settlement payment s_t^k to the lender, in combination with a promise to repay the amount of liabilities she has defaulted on. Any settlement amount that the lender would agree to needs to satisfy

$$s_t^k + \frac{b_t^k}{1 + r_t} \geq \theta_k \mathbb{E}_t p_{k,t+1}^k (1 - \delta) k_t^k. \tag{23}$$

Now, for the firm to never choose to default, the value of operating in absence of default must exceed the value of the firm after successful renegotiation. In other words, as long as the required settlement payment is positive, the predicted outcome of renegotiation is such that the firm would never choose to default. Formally, from combining this non-negativity condition with (23), we obtain

$$
\begin{aligned}
s_t^k &\geq 0 && (24)\\
\theta_k \mathbb{E}_t p_{k,t+1}^k (1-\delta) k_t^k - \frac{b_t^k}{1+r_t} &\geq 0, && (25)
\end{aligned}
$$

which can be rearranged to equation (9) in the text.

Earnings-based constraint. Suppose that for the firm type $j = \pi$ the environment is such that when the firm defaults on its liabilities $\frac{b_t^\pi}{1+r_t}$ at the end of $t+1$, the court grants the lender the right to seize ownership of the entire firm. She can then either operate the firm herself or sell it on the market. Importantly, however, the lender is uncertain about the value of the firm in this case. Denote $\tilde{V}_{d,t}^{end}$ the end-of-period value of the firm after ownership rights have been transferred to the lender. In order to determine this uncertain value, the lender uses the common practice of valuation by multiples.[2] The lender evaluates firm ownership after default by using fixed multiple of the last available realization of a fundamental profitability indicator, EBITDA. The literature on credit risk models shows that EBITDA is a strong predictor of default and firm, also over and above a variety of other accounting metrics and macroeconomic indicators. See for example Carling, Jacobson, Linde, and Roszbach (2007). This is also reflected by the prominence of EBITDA in the methodology based on which big rating agents construct corporate credit ratings, see Standard & Poor's Global Ratings (2013).

Formally, the lender makes the approximation

$$
\tilde{V}_{d,t}^{end} \approx \theta_\pi \pi_t^\pi. \tag{26}
$$

In this case, the required settlement amount in the renegotiation process needs to satisfy

$$
\begin{aligned}
s_t^\pi &\geq 0 && (27)\\
\theta_\pi \pi_t^\pi - \frac{b_t^\pi}{1+r_t} &\geq 0. && (28)
\end{aligned}
$$

The last inequality can be arranged to (8) in the text.

Remarks. As shown above, both collateral and earnings-based borrowing constraint can arise in a world of limited enforcement. Specifically, they can be derived from a situation in which lenders and borrowers predict the outcome of a renegotiation process that would be triggered in the event of default. Based on the predicted outcomes of this renegotiation, the firm will not choose to default, but borrowing is subject to the respective limit on the debt liabilities.

In the setting laid out, the underlying contractual frictions behind equations (8) and (9) differ as follows. In the case of the earnings-based constraint, there is an informational friction

[2] For a textbook treatment on valuations, see Damodaran (2012).

regarding the contingent firm value. The transfer of ownership rights is not accompanied by a transaction cost, but by uncertainty that surrounds the value of the firm after ownership rights have been transferred. In the case of collateral, there is a rational prediction of the resale value, but a transaction cost needs to be incurred.

B.2 Further discussion of the earnings-based constraint

Microfoundation of loan covenants in the literature. Since I empirically motivated the earnings-based constraint based on the presence of loan covenants, studying the academic literature that has studied these covenants lets us get a sense of how researchers conceptualize earnings-based constraints at a micro level. As I stress in Section 2 of the text, however, covenants are one but not the only mechanism through which current earnings flows feed back to the ability to issues debt.

The literature on loan covenants can broadly be distinguished between two strands. The first are empirical papers that investigate covenants and their economic effects in firm-level data. This includes the papers that I have cited in Section 2 of the text. Key references are for example Chava and Roberts (2008), Roberts and Sufi (2009) and Bradley and Roberts (2015). These papers do not provide a fully fledged theoretical rationalization of why loans contain covenants, but mostly take them as a given empirical phenomenon and test their effects in the data. Nevertheless these papers typically do provide some remarks on the rationale for covenants to guide their analysis. The second strand is theoretical work in the (incomplete) contracts literature that directly addresses the microfoundation of covenants. This literature builds on seminal work of Aghion and Bolton (1992) and goes back at least to Jensen and Meckling (1976). One example that directly studies the contractual design of covenants is Garleanu and Zwiebel (2009). See also Diamond, Hu, and Rajan (2020) who lay out a theory of firm financing in which control rights both over asset sales and over cash flows have varying importance over time.

Both streams of work have generally highlighted moral hazard issues. A compact description is provided by Chava and Roberts (2008). According to the authors a key rationale for covenants is the allocation of contingent control rights over the firm. Adding covenants to a contract provide debt holders with the option to intervene in the companies management. In the same spirit, Dichev and Skinner (2002) refer to covenants as "trip wires". Such a contingent transfer of control rights provides an additional incentive to management behavior that is in line with the debt holders' objectives. While in my macro model these moral hazard problems are not explicitly present, the formal rationalization above has shown that is possible to generate the constraint from an enforcement issue. Furthermore, the earnings-based constraint introduces an important feedback between firms' earnings and their ability to borrow. The fact that the covenants literature finds large economic effects of covenants (and their breaches) on the borrowing firm suggests that such a feedback is a plausible empirical pattern.

Regulation. As mentioned in the main text, an alternative way to think about the earnings-based constraint is the presence of regulation that lenders, in particular banks, are subject to. For example, regulators in the US define "leveraged transactions", among other criteria, based on the debt-to-EBITDA ratio of borrowers.[3] Whether transactions are defined in this way in turn affects risk-weights and hedging requirements for lenders.

In the case of mortgages, regulatory requirements on income flows have been highlighted by Greenwald (2018), who also studies collateral (loan-to-value) and flow-related (payment-to-income) constraints. He imposes the two borrowing constraints household debt and refers to them as "institutional rules that are not the outcome of any formal optimization problem". Given that both collateral and the debt-to-EBITDA ratio also feature in the regulation of lenders that provide fund to nonfinancial firms, an alternative way to think about equations (8) and (9) is that they are the outcome of regulation rather than an underlying contracting frictions that lender and borrowing need to overcome.

[3]See for example the *US Interagency Guidance on Leveraged Lending (2013)*, which is available at https://www.federalreserve.gov/supervisionreg/srletters/sr1303a1.pdf. Similar definitions exist for the EU.

C Details on the model of Section 3

C.1 Model setup

C.1.1 Firm optimality conditions

For both firm types $j \in \{k, \pi\}$, the optimality conditions with respect to $d_{i,t}, p_{i,t}, i_{i,t}, b_{i,t}$, are

$$\lambda_{i,t} = \frac{1}{P_t \Psi_{d,i,t}} \tag{29}$$

$$P_t \left[\Upsilon_{2,i,t} + \mathbb{E} m_{t+1} \left(\frac{\Psi_{d,i,t}}{\Psi_{d,i,t+1}} \right) \Upsilon_{1,i,t+1} \right] - \zeta_{i,t} \Psi_{d,i,t} = 0 \tag{30}$$

$$Q_{i,t} v_t \Phi_{2,i,t} + \mathbb{E} m_{t+1} Q_{i,t+1} v_{t+1} \Phi_{1,i,t+1} - \frac{1}{\Psi_{d,i,t}} = 0 \tag{31}$$

$$\frac{\lambda_{i,t}}{R_t} - \frac{\mu_{i,t}}{P_t(1+r_t)} - \mathbb{E} m_{t+1} \lambda_{i,t+1} = 0 \tag{32}$$

where the superscript j is omitted for simplicity. $\lambda_{i,t}$ is the Lagrange multiplier on the firm's flow of funds constraint. Ψ_d denotes the derivative of the equity payout cost function. Υ_1 and Υ_2 are the derivatives of the price adjustment cost with respect to the past and the current price, respectively. $\zeta_{i,t}$ is the Lagrange multiplier on the firm's demand condition. $Q_{i,t}$ is the Lagrange multiplier on the capital accumulation equation and defines the market value of the capital stock. Φ_1 and Φ_2 are the derivatives of the investment adjustment cost with respect to the past and the current investment, respectively. $\mu_{i,t}$ is the Lagrange multiplier on the borrowing constraint. $m_{t+1} \equiv \frac{\Lambda_{t+1}}{\Lambda_t}$ is the stochastic discount factor between t and $t+1$.

The first order conditions for $n^j_{i,t}$ and $k^j_{i,t}$ are different for each type $j \in \{k, \pi\}$:

$$\frac{F^k_{n,i,t} - W_t/P_t}{\Psi^k_{d,i,t}} - \zeta^k_{i,t} D^k_{n,i,t} = 0 \tag{33}$$

$$\frac{F^\pi_{n,i,t} - W_t/P_t}{\Psi^\pi_{d,i,t}} - \zeta^\pi_{i,t} D^\pi_{n,i,t} + \mu^\pi_{i,t} \theta_\pi \left(F^\pi_{n,i,t} - W_t/P_t \right) = 0 \tag{34}$$

$$-Q^k_{i,t} + \mu^k_{i,t} \theta_k (1-\delta) \mathbb{E} p^k_{k,t+1} + \mathbb{E} m_{t+1} \left(\frac{F^k_{k,i,t+1}}{\Psi^k_{d,i,t+1}} - \zeta^k_{i,t+1} D^k_{k,i,t+1} + (1-\delta) Q^k_{i,t+1} \right) = 0 \tag{35}$$

$$-Q^\pi_{i,t} + \mathbb{E} m_{t+1} \left(\frac{F^\pi_{k,i,t+1}}{\Psi^\pi_{d,i,t+1}} + \mu^\pi_{i,t+1} \theta_\pi F^\pi_{k,i,t+1} - \zeta^\pi_{i,t+1} D^\pi_{k,i,t+1} + (1-\delta) Q^\pi_{i,t+1} \right) = 0 \tag{36}$$

where demand $D_{i,t}$ and real revenue $F_{i,t}$ are defined by:

$$p_{i,t} = P_t Y_t^{(\eta_t - 1)/\eta_t} \left[z k^\alpha_{i,t} n^{1-\alpha}_{i,t} \right]^{(1-\eta_t)/\eta_t} \equiv P_t D_{i,t} \tag{37}$$

$$p_{i,t} y_{i,t} = P_t Y_t^{(\eta_t - 1)/\eta_t} \left[z k^\alpha_{i,t} n^{1-\alpha}_{i,t} \right]^{1/\eta_t} \equiv P_t F_{i,t} \tag{38}$$

where the superscript j is again omitted for simplicity. $D_{n,i,t}$, $D_{k,i,t}$, $F_{n,i,t}$, and $F_{k,i,t}$ are the derivatives of demand and real revenue with respect to labor and capital, respectively. $p^k_{k,t}$ is the price used to evaluate capital in the collateral constraint. I set $p^k_{k,t} = Q^k_t$ to capture the market value formulation (see the discussion around equation (10) in the main text). In a robustness check I study a version of the model in which capital is evaluated at historical costs.

C.1.2 Aggregation

Aggregating across firms i and borrower types $j \in \{\pi, k\}$ gives

$$Y_t = \left(\int_0^1 y_{i,t}^{\frac{1}{\eta}} di \right)^{\eta} = \left((1-\chi)(y^k_t)^{\frac{1}{\eta}} + \chi (y^\pi_t)^{\frac{1}{\eta}} \right)^{\eta} \tag{39}$$

$$P_t = \left(\int_0^1 p_{i,t}^{\frac{1}{1-\eta}} di \right)^{1-\eta} = \left((1-\chi)(p^k_t)^{\frac{1}{1-\eta}} + \chi (p^\pi_t)^{\frac{1}{1-\eta}} \right)^{1-\eta} \tag{40}$$

$$N_t = (1-\chi) n^k_t + \chi n^\pi_t \tag{41}$$

$$I_t = (1-\chi) i^k_t + \chi i^\pi_t \tag{42}$$

$$B_t = (1-\chi) b^k_t + \chi b^\pi_t, \tag{43}$$

where capital letters denote aggregate variables, and lower case variables without subscript i indicate variables aggregated across firms within a type $j \in \{\pi, k\}$.

C.1.3 Household and government sector

Household. There is a representative household whose expected lifetime utility is

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} \right) \tag{44}$$

where β is the discount factor and the parameter ϵ denotes the elasticity of labor supply. The household invests in bonds b^j_t and equity shares s^j_t (at price $p^j_{f,t}$) of both firm types. The budget constraint is

$$C_t + \sum_{j[\chi]} \left\{ \frac{b^j_t}{(1+r_t)P_t} + p^j_{f,t} s^j_t \right\} + T_t = w_t N_t + \sum_{j[\chi]} \left\{ \frac{b^j_{t-1}}{P_t} + (d^j_t + p^j_{f,t}) s^j_{t-1} \right\}, \tag{45}$$

where $\sum_{j[\chi]}$ is a compact way to express the sum across firm types $j \in \{\pi, k\}$, weighted with χ and $1-\chi$. The household's optimality condition for bonds implies an Euler equation in which real returns $(1+r_t)\left(\frac{P_t}{P_{t+1}}\right)$ are priced with the stochastic discount factor $m_{t+1} \equiv \frac{\Lambda_{t+1}}{\Lambda_t} = \frac{\beta u_{c_{t+1}}}{u_{c_t}}$, where $u_{c_s} = c_s^{-\sigma}$.

Government (fiscal and monetary policy). The government's budget constraint reads

$$P_t T_t = \sum_{j[\chi]} \left(\frac{b_t^j}{R_t} - \frac{b_t^j}{(1+r_t)} \right), \tag{46}$$

where T_t are real lump sum taxes levied on households, and the terms $\frac{b_t^j}{R_t} - \frac{b_t^j}{(1+r_t)}$ reflect the tax subsidy given to firms that the government needs to finance.

The monetary authority follows an interest rate rule specified as

$$\frac{1+r_t}{1+\bar{r}} = \left(\frac{\pi_t^p}{\bar{\pi}^p} \right)^{\nu}, \tag{47}$$

such that interest rates react to deviations of inflation from steady state. Beware that I denote inflation by π_t^p, not to be confused with firm profits $\pi_{i,t}^j$.

C.1.4 Details on model parameterization and specification

Table C.1 summarizes the values I set for the structural parameters of the model. Several of these parameter values are standard in business cycle research for the US case or match standard moments in US macroeconomic data. I specify the investment adjustment costs as a quadratic function

$$\Phi\left(\frac{i_{i,t}^j}{i_{i,t-1}^j}\right) = \frac{\phi}{2}\left(\frac{i_{i,t}^j}{i_{i,t-1}^j} - 1\right)^2. \tag{48}$$

This functional satisfies the assumptions discussed by Christiano, Eichenbaum, and Evans (2005), $\Phi(1) = 0$, $\Phi'(1) = 0$, and $\Phi''(1) = \phi > 0$. It gives a steady state market value of capital of 1. I set $\phi = 4$ in line with Smets and Wouters (2007). I specify the price adjustment cost function as

$$\Upsilon(p_{i,t-1}^j, p_{i,t}^j, Y_t) = \frac{\upsilon}{2}\left(\frac{p_{i,t}^j}{p_{i,t-1}^j} - 1\right)^2 Y_t \tag{49}$$

and set $\upsilon = 77$ following the estimates Ireland (2001) for a simple NK model without any frictions apart from capital adjustment costs (so a structure fairly similar to the model in Section 3). (Note that this value is much smaller in the estimated version of the model in Section 5, which has features other frictions, including rigid wages). The results look very similar using a higher value of 90 as in Ottonello and Winberry (2020). I also analyze a flexible price version of the model ($\upsilon = 0$) as a robustness check.

I use the prior values of Jermann and Quadrini (2012) to parameterize ψ, η, σ and ϵ. To calibrate β, I calculate the average interest rate faced by firms in the Dealscan database. I set the tax advantage of debt τ to 0.35 following Hennessy and Whited (2005). Using the Dealscan data, I calculate the dollar-weighted mean covenant value of the debt-to-EBITDA covenant, which gives a value of 4.6 (see also Table 1). As this value is for annualized EBITDA and my model is quarterly, I set $\theta_\pi = 4 \times 4.6$. I set the tightness of the collateral component to $\theta_k = 0.37$, which matches the average debt-to-asset ratio of firms that face collateral constraints in the Compustat-Dealscan data. For the interest rate rule I set a value of $\nu = 1.5$ (a value larger than 1 is required for stability).

Table C.1: MODEL PARAMETERIZATION

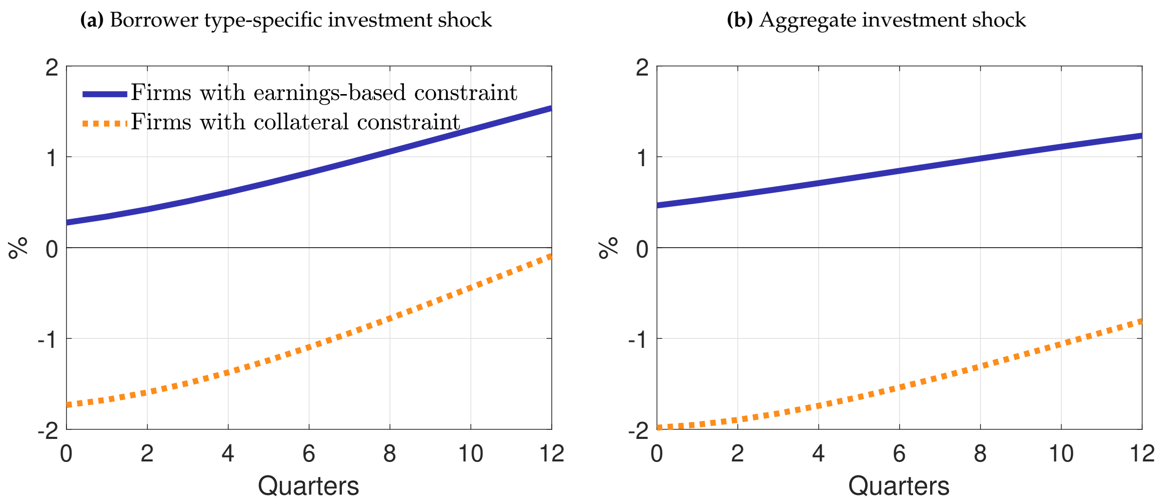
Parameter		Value	Details on parameterization / target
α	Capital share of output	0.33	Standard value for US data
δ	Capital depreciation rate	0.025	Standard value for quarterly US data
ϕ	Investment adjustment cost	4	Prior value in Smets and Wouters (2007)
υ	Price adjustment cost	77	Estimate by Ireland (2001)
ψ	Dividend adjustment costs	0.2	Prior value in Jermann and Quadrini (2012)
η	Elasticity of substitution	1.2	Prior value in Jermann and Quadrini (2012)
τ	Tax advantage of debt	0.35	Following Hennessy and Whited (2005)
θ_π	Tightness earnings-based constraint	4.6×4	Average value of debt-to-EBITDA covenants*
θ_k	Tightness collateral constraint	0.37	Average debt-to-asset ratio in Compustat-Dealscan*
β	Household discount factor	0.9752	Target steady state corporate loan rate of 6.6% ann.*
σ	Household intertemporal elasticity	1	Simplification: log-utility
ϵ	Household labor supply elasticity	2	Prior value in Jermann and Quadrini (2012)
ν	Interest rate rule feedback	1.5	Standard value

Notes. * indicates parameters that are calculated directly from Dealscan.

C.2 Additional model results

C.2.1 Borrower type-specific vs. aggregate investment shocks

Figure C.1: FIRM-LEVEL DEBT RESPONSES TO INVESTMENT SHOCKS UNDER DIFFERENT CONSTRAINTS

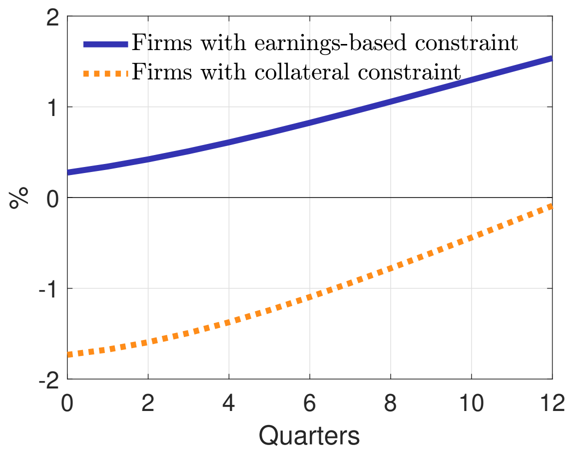


Notes. Panel (a) repeats Panel (a) of Figure 2 from the main text, which shows the debt IRFs for earnings-based borrowers and collateral borrowers to investment shocks that are specific to each borrower type. Panel (b) repeats the same IRFs, but for an aggregate investment shock, that is, an exogenous increase in the level of v_t^j by one standard deviation for both borrower types $j \in \{\pi, k\}$. This is the same shock that underlies the responses of total debt shown in Panel (b) of Figure 2 in the main text. In both panels here, I set the share of earnings-based borrowers to $\chi = 0.5$.

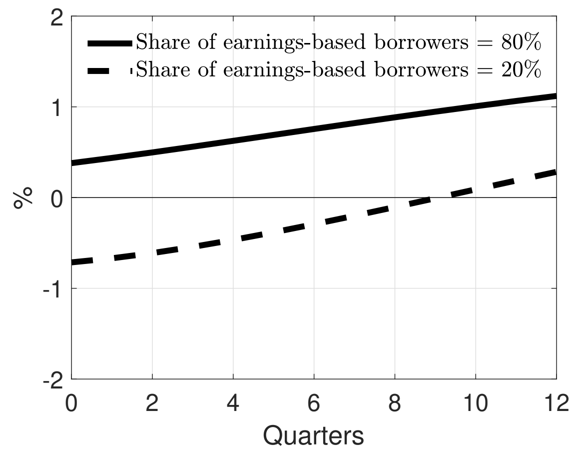
C.2.2 Sticky vs. flexible prices

Figure C.2: MODEL IRFS OF DEBT TO INVESTMENT SHOCKS: STICKY VS. FLEXIBLE PRICES

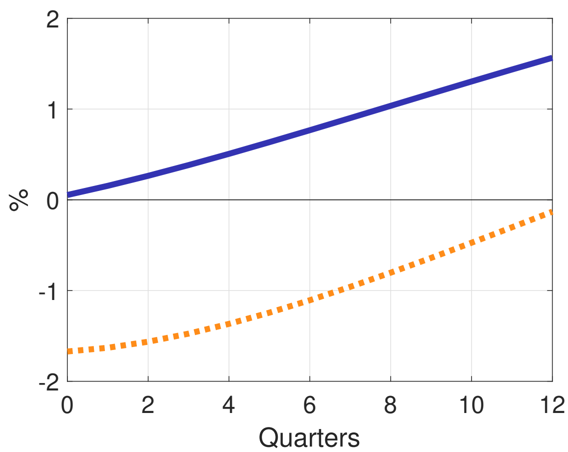
(a) Firm-level debt responses (sticky prices)



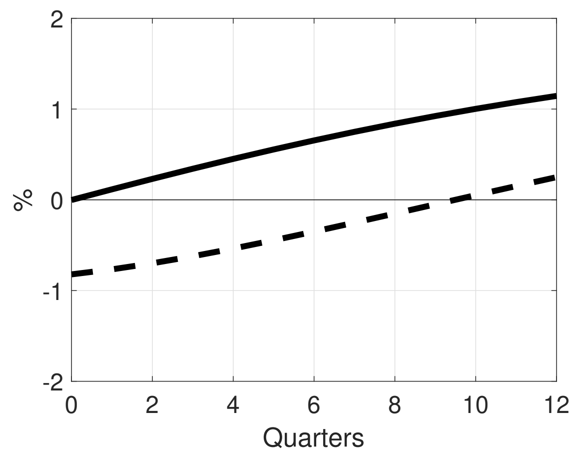
(b) Aggregate debt responses (sticky prices)



(c) Firm-level debt responses (flexible prices)



(d) Aggregate debt responses (flexible prices)



Notes. Panels (a) and (b) repeat Figure 2 from the main text. Panel (c) and (d) show the same responses to the same shocks, but for a version of the model where prices are fully flexible ($\upsilon = 0$). The comparison shows that the main difference lies in the response of debt on impact, where a positive jump is visible with price stickiness, but almost no response on impact is visible in the flexible price version. The profile of the responses is otherwise very similar.

C.2.3 Alternative version with long-term debt

Setting. In an alternative version of the model, I assume that firms issue risk-free long-term debt. In this setting, a firm pays a fixed coupon c per unit of its stock of debt at the beginning of period t, $\widetilde{b}_{i,t-1}$. In addition, the firm repays a fraction $\gamma \in (0,1)$ of the principal in period t. This computationally tractable specification of long-term debt goes back to Leland (1994). For recent applications see for example Gomes, Jermann, and Schmid (2016) and Jungherr and Schott (2021). Formally, the firms' flow of funds equation, omitting the investment adjustment costs and superscript j for notational ease, is modified to be

$$\begin{aligned} P_t\Psi(d_{i,t}) + P_t i_{i,t} + P_t\Upsilon(p_{i,t-1}, p_{i,t}, Y_t) + (c+\gamma)\widetilde{b}_{i,t-1} = \\ (p_{i,t}y_{i,t} - W_t n_{i,t}) + q_t(\widetilde{b}_{i,t} - (1-\gamma)\widetilde{b}_{i,t-1}) \end{aligned} \tag{50}$$

where q_t is the (tax-subsidized) price of long-term debt relevant to borrowers. The borrowing constraints of the two borrower types are given by

$$\bar{q}_t \frac{\widetilde{b}^{\pi}_{i,t}}{P_t} \leq \theta_\pi \pi^{\pi}_{i,t} \tag{51}$$

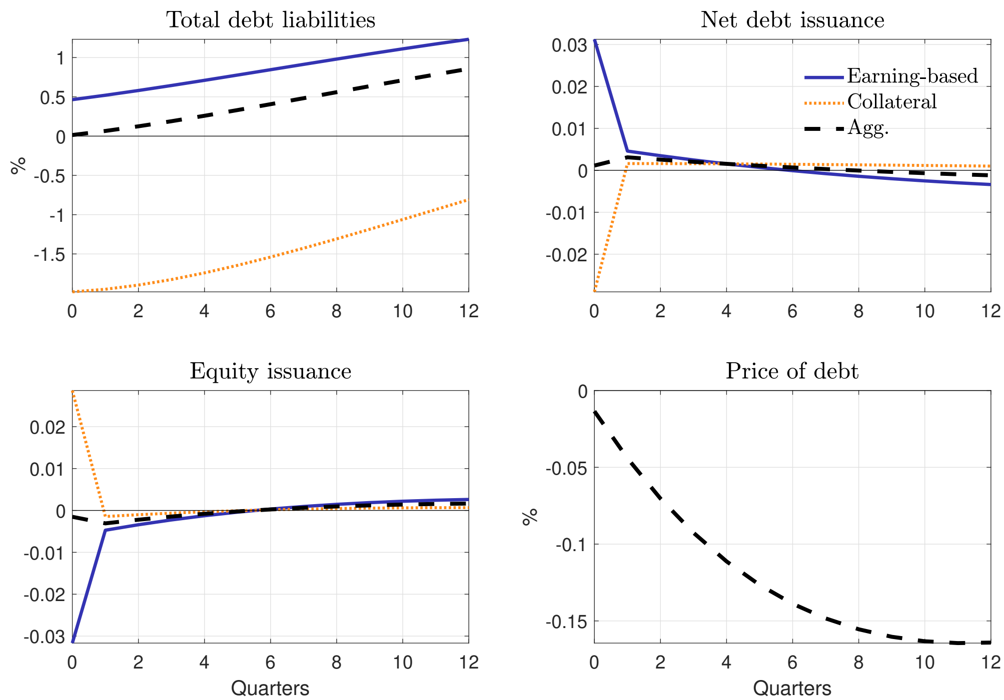
$$\bar{q}_t \frac{\widetilde{b}^{k}_{i,t}}{P_t} \leq \theta_k \mathbb{E}_t p^k_{k,t+1}(1-\delta)k^k_{i,t}, \tag{52}$$

where $\bar{q}_t$ is the bond price paid by the lenders. Equations (51) and (52) capture that the level of total liabilities is constrained by a multiple of earnings and a fraction of capital, respectively. This is in line with the empirical evidence, where covenant indicators, such as the debt-to-earnings ratio, are usually calculated based on *all* liabilities of the firm, including existing liabilities. Chava and Roberts (2008), among others, discuss how covenants are in fact imposed to avoid dilution of existing debt holders.

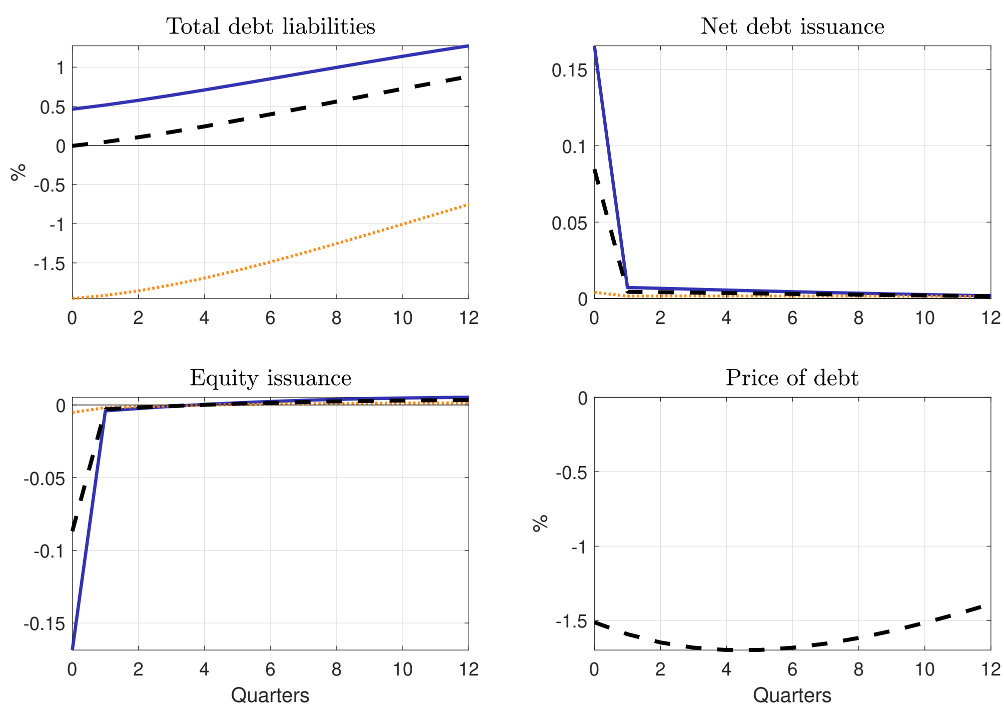
Comparison of investment shock dynamics. I set $\gamma = 0.05$ to match the average debt maturity of 5 years in Dealscan, and β and c to match the average interest rate (in the same way as for the baseline model in the text). Figure C.3 shows the responses of selected variables to an aggregate investment shock with short-term debt (Panel a) and the modified model with long-term debt (Panel b). In both panels, $\chi = 0.5$ and the solid blue line shows the responses of earnings-based borrowers, the dotted orange line those of collateral borrowers, and the dashed black line the aggregate responses. In both models, the main results are visible: the total level of real debt liabilities increases for earnings-based borrowers and decreases for collateral borrowers. Firms in both settings achieve the same level of total liabilities, since total liabilities are the quantity that is restricted by the constraint, and the tax advantage on debt makes firms always want to borrow up to their constraint. Therefore, as discussed in the main text, the response in debt is a direct consequence of how the variables that limit debt respond to the investment shock, with earnings increasing and the value of capital falling. Note that for the firm-level local projections in Section 4

Figure C.3: MODEL IRFS OF FIRM DEBT: SHORT-TERM VS. LONG-TERM DEBT

(a) Selected IRFs with short-term debt specification



(b) Selected IRFs with long-term debt specification



of the main text, I always compute the responses of total real debt liabilities in Compustat without using information on the maturity of the debt. In light of this empirical strategy, it is reassuring that the IRFs in Figure C.3 convey that the predictions for investment shocks are similar between a setting with one-period and a setting with longer maturity debt.

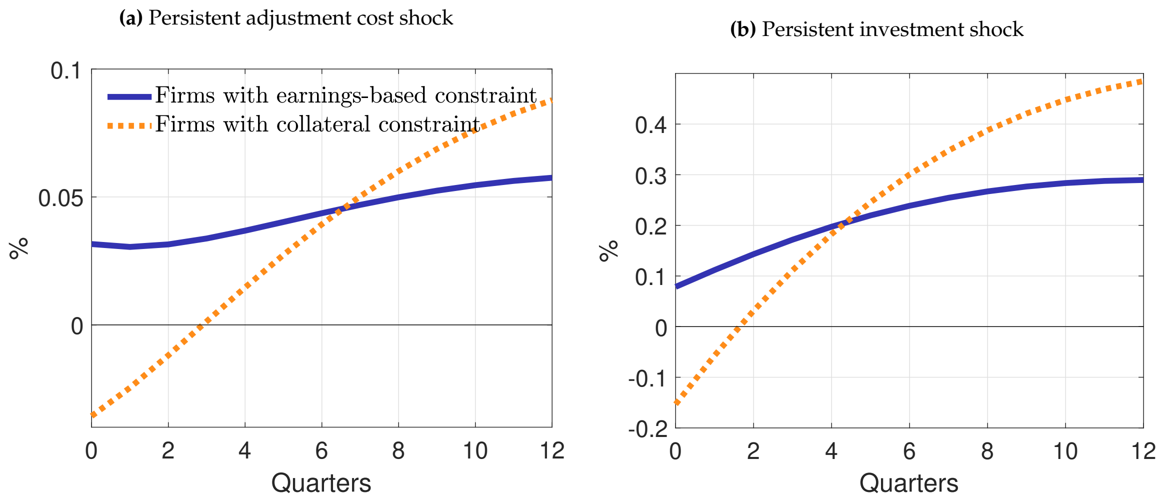
The main difference between the two settings lies in how net debt issuance, the price of debt, and equity issuance adjust to the shock. In Figure C.3, real net debt issuance is computed as $(q_t(\widetilde{b}_{i,t} - (1-\gamma)\widetilde{b}_{i,t-1}) - \gamma\widetilde{b}_{i,t})/P_t$, where for short term debt this collapses to $(q_t b_{i,t} - b_{i,t})/P_t = (b_{i,t}/R_t - b_{i,t})/P_t$, which is the measure of net debt issuance in the baseline model of the main text. It is visible that the net issuance response for earnings-based borrowers is stronger in the long-term debt setting, while net debt issuance moves little for collateral borrowers with long-term debt. This difference is driven in reduction of the price of debt (increase in interest rates) in response to the investment shock, which is much stronger in the economy with long-term debt, especially on impact. The value of total real debt liabilities, which is restricted by the constraint, moves in the same way across the two models. In the short-term debt model quantities adjust more, while quantities respond more sluggishly with long-term debt and prices instead exhibit a stronger adjustment.

It is possible that the differences between long-term and short-term debt would be more pronounced in a setting with firm default and risky debt contracts. The literature has examined various consequences of long-term debt contracts in settings with default. Gomes, Jermann, and Schmid (2016) show that with risky long-term debt the impact of unanticipated changes in inflation on the real debt burden impede investment decisions. Jungherr and Schott (2021) show that risky long-term debt renders recoveries from recessions generally more sluggish due to "debt overhang." Neither of these studies focuses on borrowing constraints or the consequences of different types of borrowing constraints, so studying the interaction between debt overhang mechanisms with risky debt and earnings-based constraints would be an interesting avenue for further research.

C.2.4 Different types of investment shocks

As discussed in the main text, shocks to v_t^j can capture both investment-specific technology (IST) and marginal efficiency of investment (MEI) shocks. For the purpose of the empirical verification of the mechanism in Section 4, I focus on that variation of v_t^j that captures IST. This allows me to establish a mapping of v_t^j to the data. In terms of the basic model mechanism, the distinction between these refined concepts is not of first order importance.

Figure C.4: MODEL IRFS OF FIRM DEBT: DIFFERENT INVESTMENT MARGIN SHOCKS



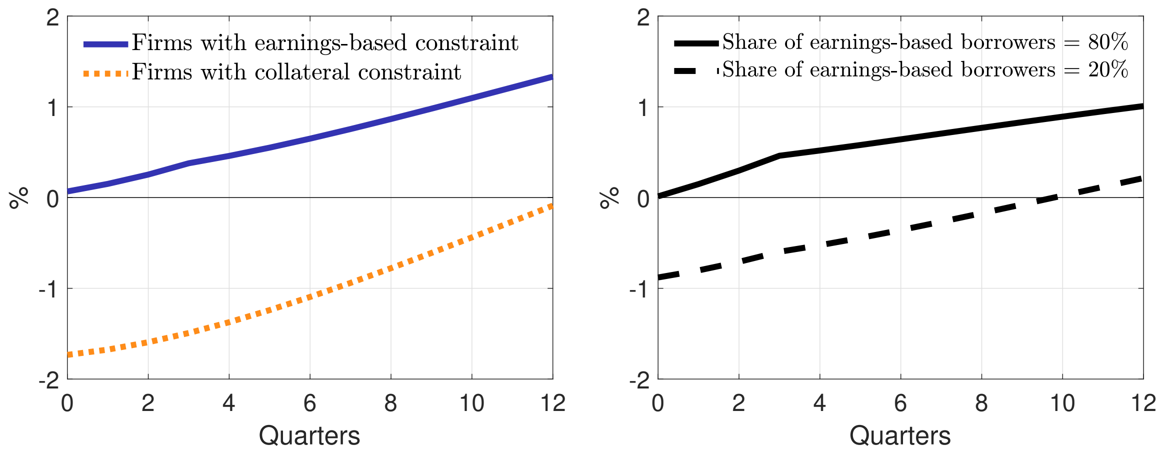
Notes. This figure repeats Panel (a) of Figure 2 from the main text, but instead of displaying IRFs to permanent investment-specific shocks, it studies other shocks that affect the relative price of investment. Panel (a) plots the IRFs to a negative adjustment costs shock. Panel (b) repeats the investment shock IRFs from Figure 2 as a transitory but persistent rather than permanent shock. I set the persistence of both disturbances to 0.75.

To demonstrate this, Figure C.4 examines IRFs to different shocks that all affect the relative price of investment. In Panel (a), the IRFs to a negative transitory adjustment cost shock across the two borrower types are plotted. To allow for a shock to adjustment costs I make the parameter ϕ time-varying, and specify $\log(\phi_t) = (1-\rho_\phi)\log(\overline{\phi}) + \rho_\phi \log(\phi_{t-1}) + u_{\phi,t}$. It is evident that at least on impact this shock also results in a different sign of the debt responses depending on which constraint is at play. In Panel (b), I repeat the IRFs to the investment shock from Panel (a) of Figure 2 in the main text, but specify the shock as transitory and persistent rather than permanent. There is again a different sign of the impact response, with a positive debt response for earnings-based borrowers and a negative for firms that borrow against collateral. These additional responses highlight that various types of disturbances that enter the same wedge in the capital accumulation equation, and thus lower the relative price of capital to consumption, gives rise to opposite qualitative predictions under the alternative credit constraints. When the relative price of capital falls, collateral constrained firms borrower less, but earnings-based borrowers increase there debt due to higher earnings.

C.2.5 Moving average formulation of the earnings-based constraint

Figure C.5: MODEL IRFS OF DEBT: MODIFIED EARNINGS-BASED CONSTRAINT

(a) Firm-level debt responses **(b)** Aggregate debt responses

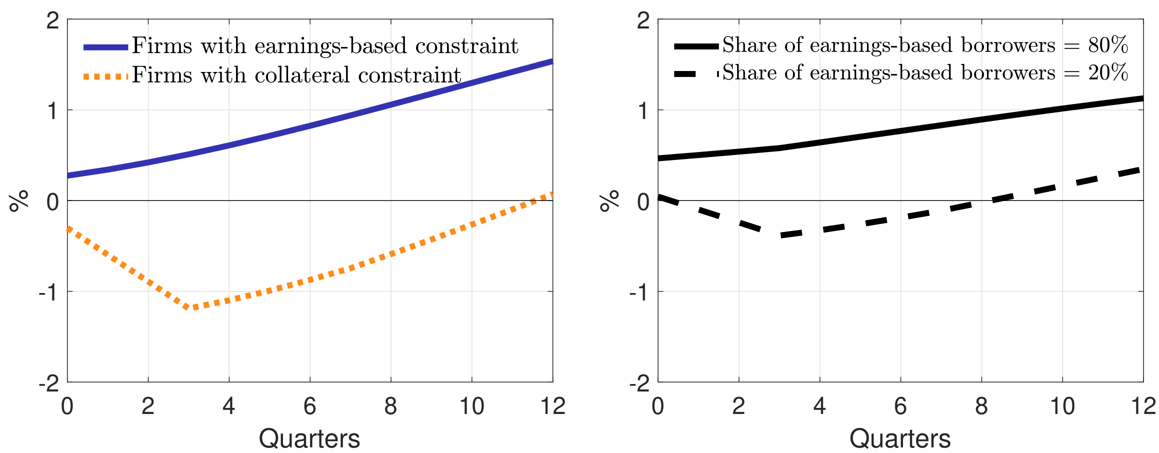


Notes. This figure shows the main model IRFs from the main text for a formulation of the earnings-based constraint in which current and three lags of earnings enter on the right hand side of equation (8). This is based on the idea that covenants may in practice be evaluated based on a 4-quarter trailing average of the indicator, see Chodorow-Reich and Falato (2021). The results for this specification are similar to the ones shown in Figure 2. The debt response becomes a little more sluggish, but the sign difference in the responses across borrower types remains unchanged

C.2.6 Collateral constraint with capital evaluated at historical costs

Figure C.6: MODEL IRFS OF DEBT: CAPITAL EVALUATED AT HISTORICAL COSTS

(a) Firm-level debt responses **(b)** Aggregate debt responses



Notes. This figure shows the main model IRFs from the main text for a formulation where the price of capital that enters the collateral constraint, $p^k_{k,t}$, is calculated as an average over past capital market prices $Q^k_{t-m}, m = 1, ..., 4$. The results for this specification are similar to the ones shown in Figure 2. The debt response under the collateral constraint is now more hump-shaped, as it takes time for the investment shock to be reflected in capital prices relevant for evaluation. The sign of the response remains the same.

C.2.7 Model IRFs of additional variables across different versions and shocks

Figure C.7: MODEL IRFS TO INVESTMENT SHOCK TO FIRM TYPE $j = \pi$ WITH $\chi = 0.5$

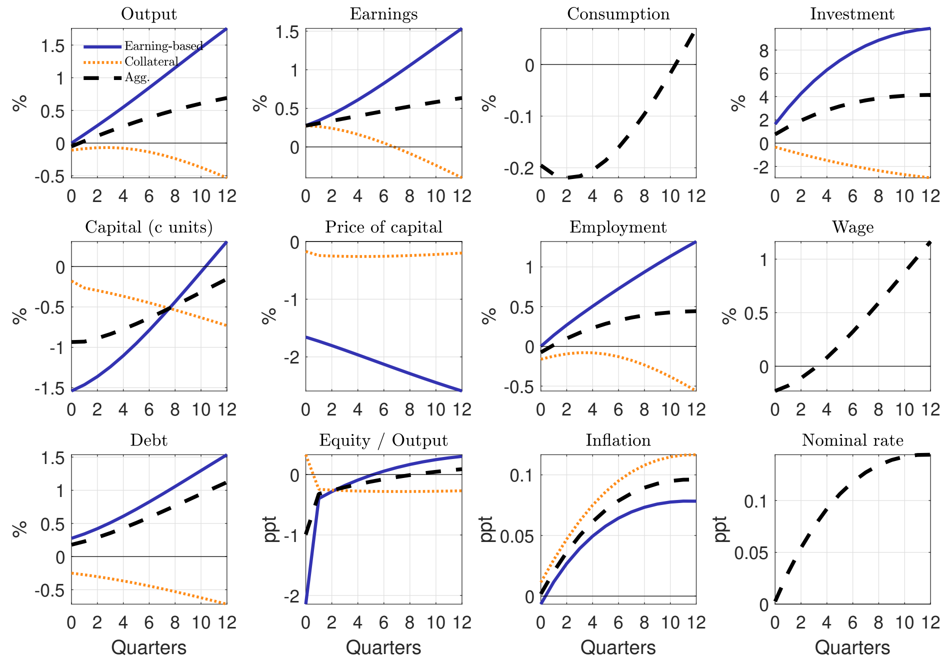


Figure C.8: MODEL IRFS TO INVESTMENT SHOCK TO FIRM TYPE $j = k$ WITH $\chi = 0.5$

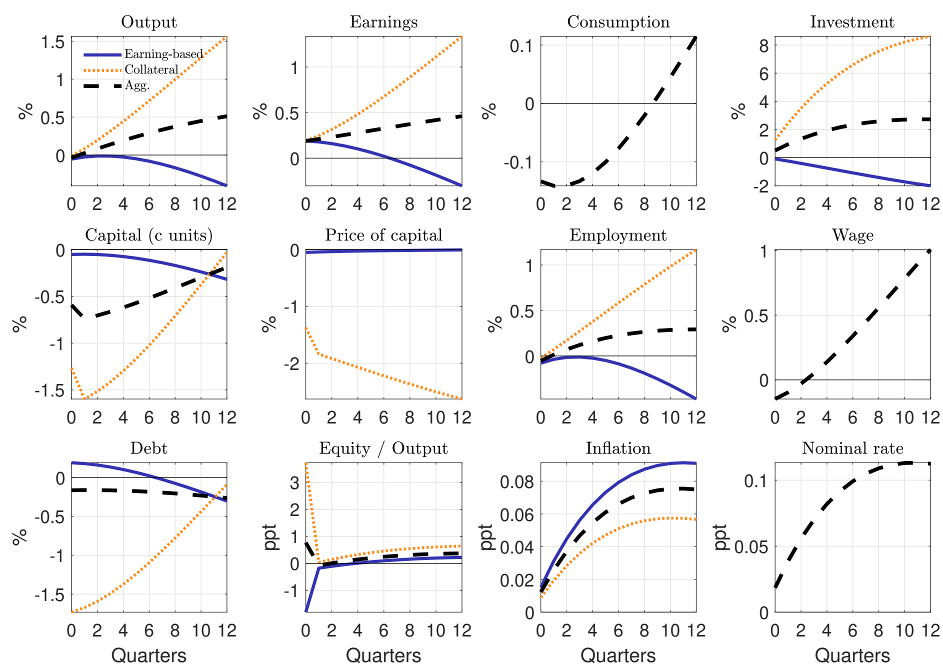


Figure C.9: MODEL IRFS TO AGGREGATE INVESTMENT SHOCK WITH $\chi = 0.2$

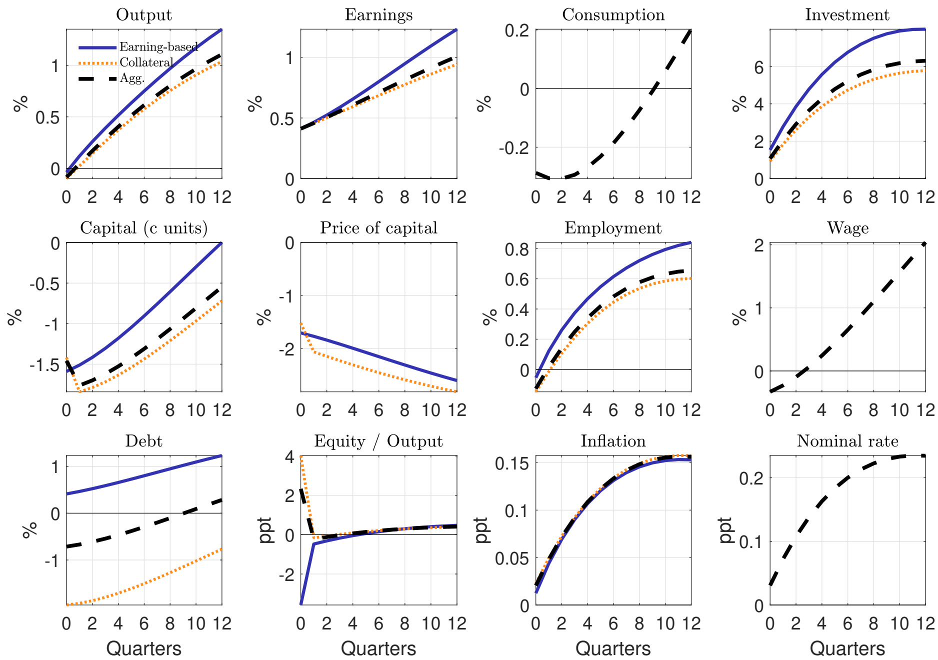
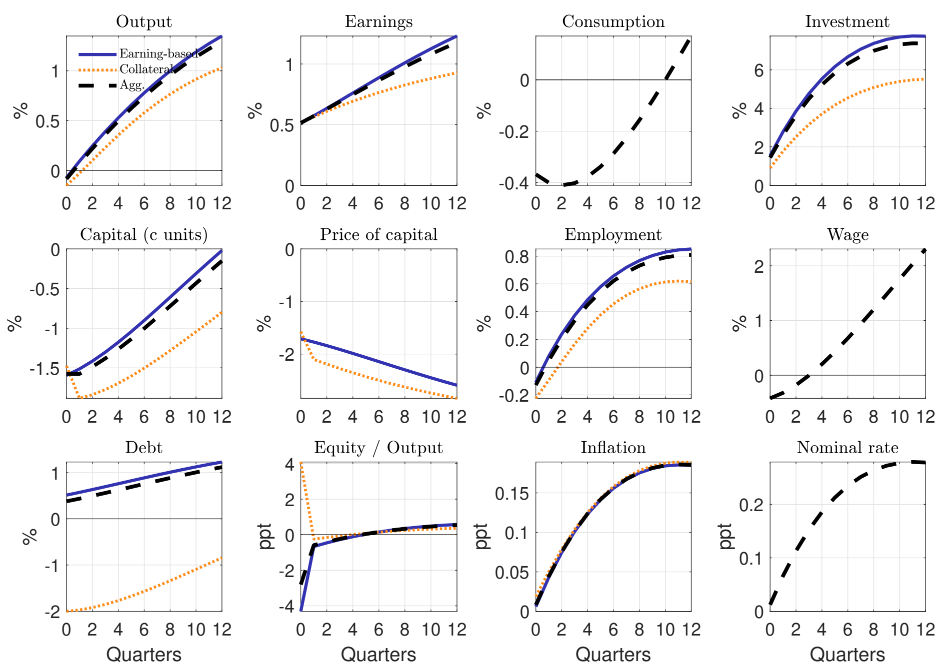


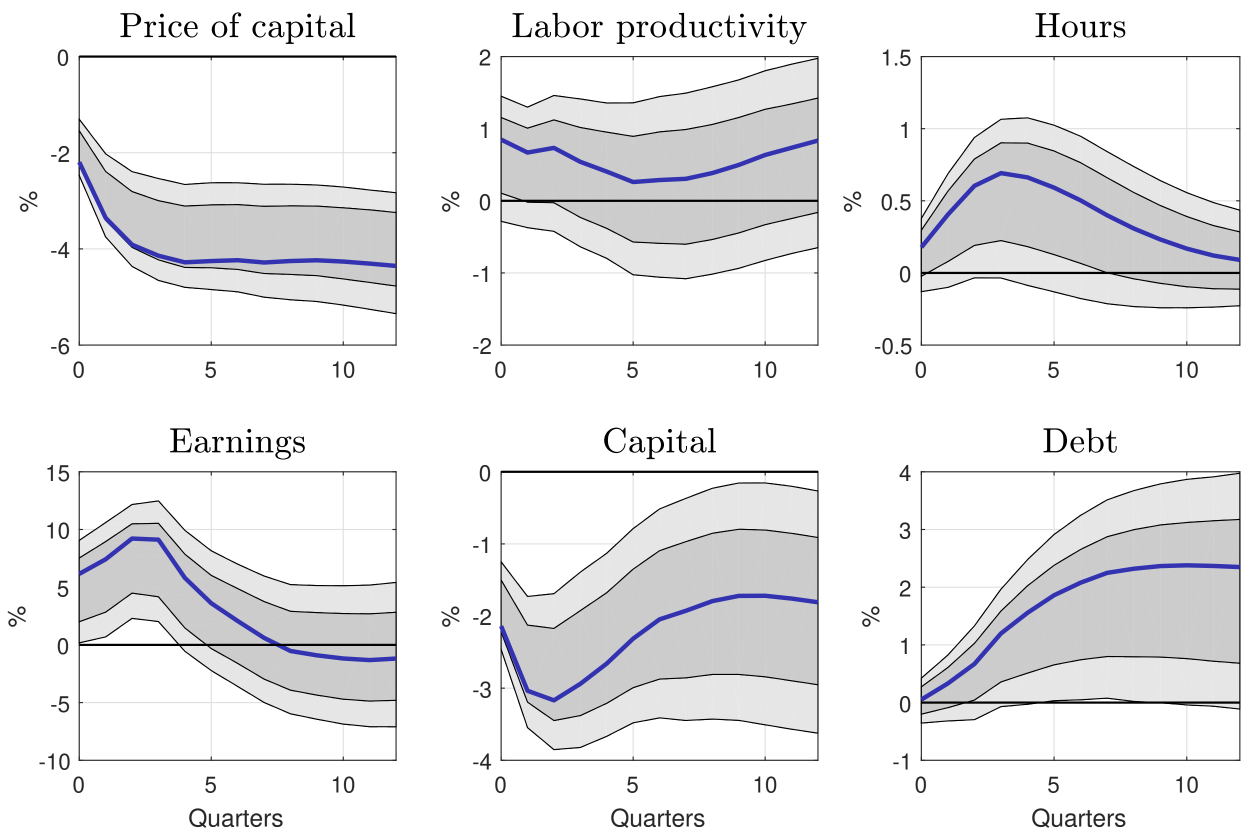
Figure C.10: MODEL IRFS TO AGGREGATE INVESTMENT SHOCK WITH $\chi = 0.8$



D Additional results for SVAR

D.1 SVAR IRFs of all variables to IST shock

Figure D.1: SVAR IRFS TO POSITIVE INVESTMENT SHOCK IDENTIFIED WITH LONG-RUN RESTRICTIONS

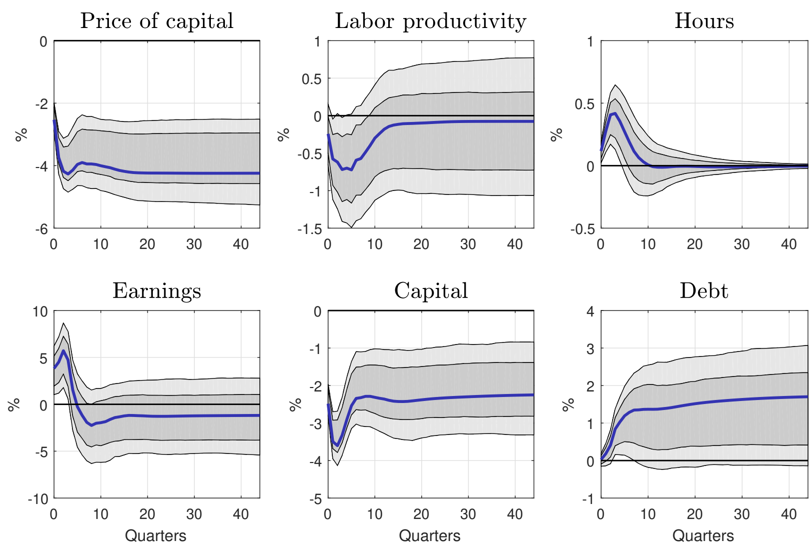


Notes. The figure displays the IRFs to a investment-specific shock identified from an estimated SVAR model using US data. The identification scheme relies on long-run restrictions following Fisher (2006). The responses are shown for all six variables included in the system, in percent. The unit of the shock is one standard deviation. The sample period used for estimation is 1952:Q2 to 2017:Q4. 68% (dark gray) and 90% (light gray) error bands are calculated using bootstrap techniques. The figure shows in particular a positive response of debt to an investment shock, which is in line with the model predictions arising from a earnings-based borrowing constraint in the theoretical macro model. The debt response corresponds to Panel (a) of Figure 5 in the main text.

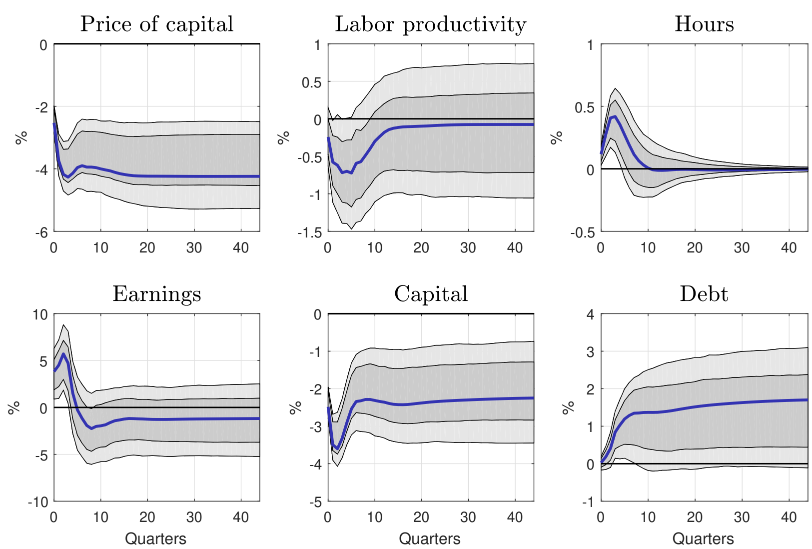
D.2 SVAR IRFs using medium-term restrictions

Figure D.2: SVAR IRFS TO INVESTMENT SHOCK IDENTIFIED WITH MEDIUM-HORIZON RESTRICTIONS

(a) Identification based on 5-year horizon



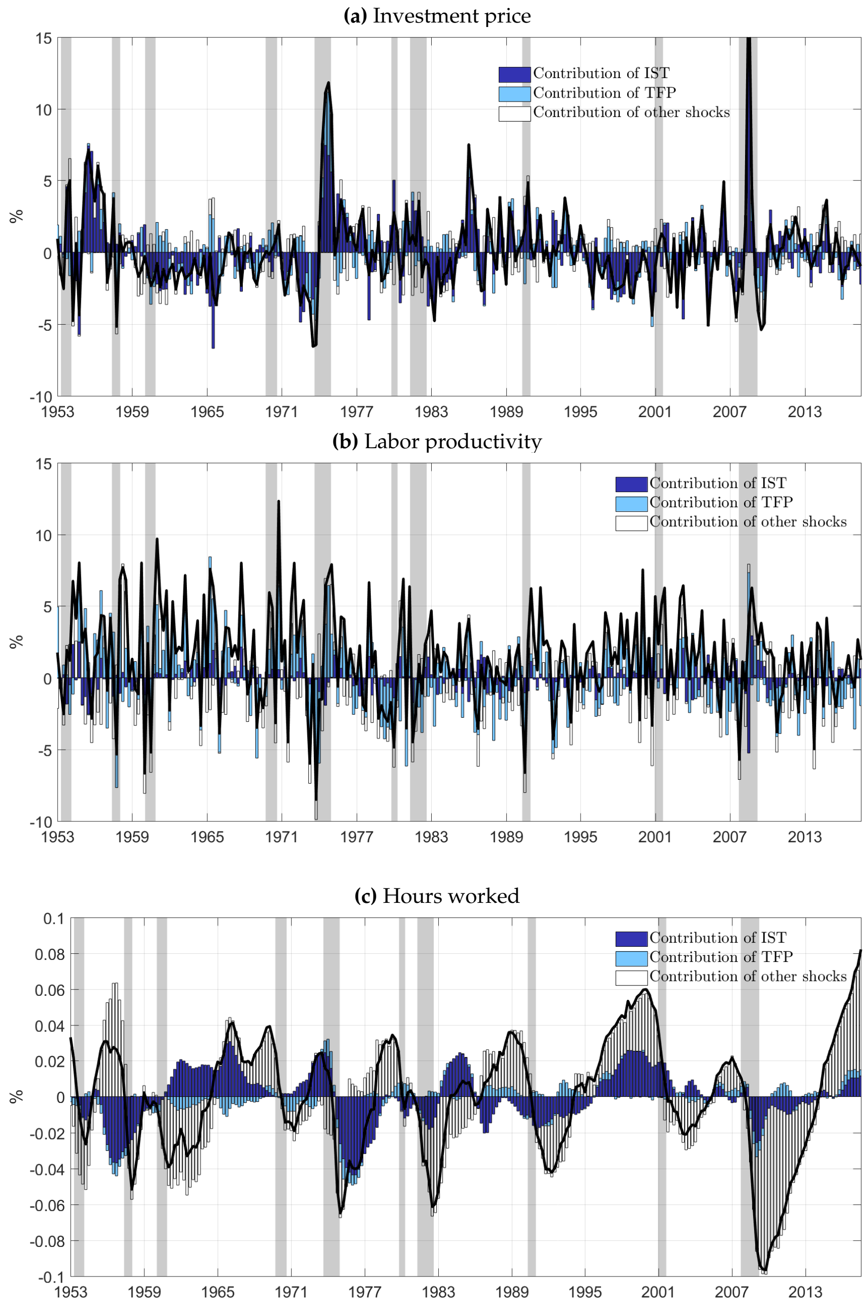
(b) Identification based on 10-year horizon



Notes. The figure has the same scope as Figure D.1 but uses a different identification scheme. This scheme is based on the method suggested by Francis, Owyang, Roush, and DiCecio (2014). Panel (a) shows the results for a 5-year horizon ($h = 20$) and Panel (b) for a 10-year horizon ($h = 40$). In both cases, the responses are shown for all six variables included in the system, in percent. The unit of the shock is one standard deviation. The sample period used for estimation is 1952:Q2 to 2017:Q4. 68% (dark gray) and 90% (light gray) error bands are calculated using bootstrap techniques. The figure shows a positive response of debt to an investment shock, which is in line with the predictions arising from an earnings-based borrowing constraint in the theoretical macro model.

D.3 SVAR historical decompositions

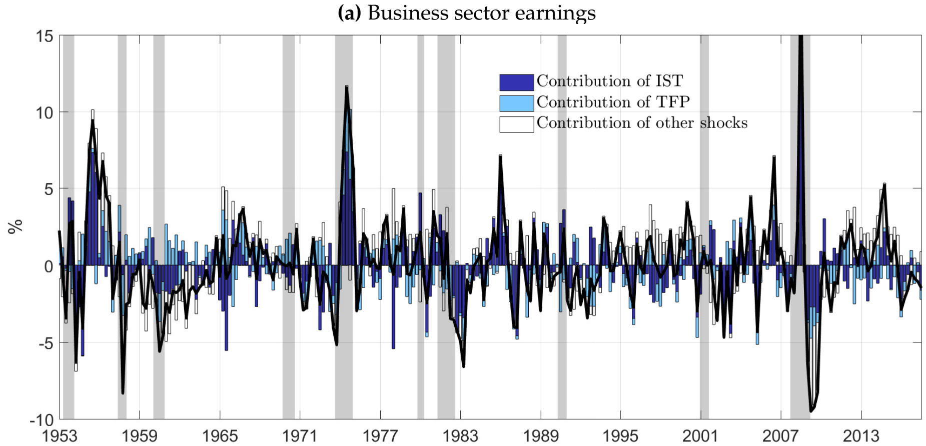
Figure D.3: SVAR: HISTORICAL VARIANCE DECOMPOSITIONS



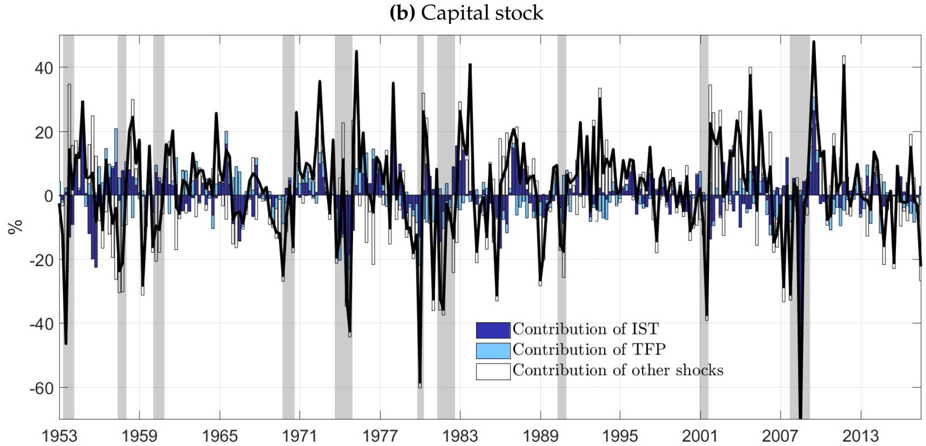
Notes. Historical variance decomposition of variables as estimated by the SVAR model identified with long-run restrictions. The black line is the actual (detrended) data series. The bars indicate the contribution of different structural shocks to the variance of the respective observable as estimated by the SVAR model. The dark blue bars represent investment shocks, the light blue ones TFP shocks, and the contribution of shocks that remain unidentified are shown by the weight bars. Shaded areas indicate NBER recessions.

Figure D.4: SVAR: HISTORICAL VARIANCE DECOMPOSITIONS (CONTINUED)

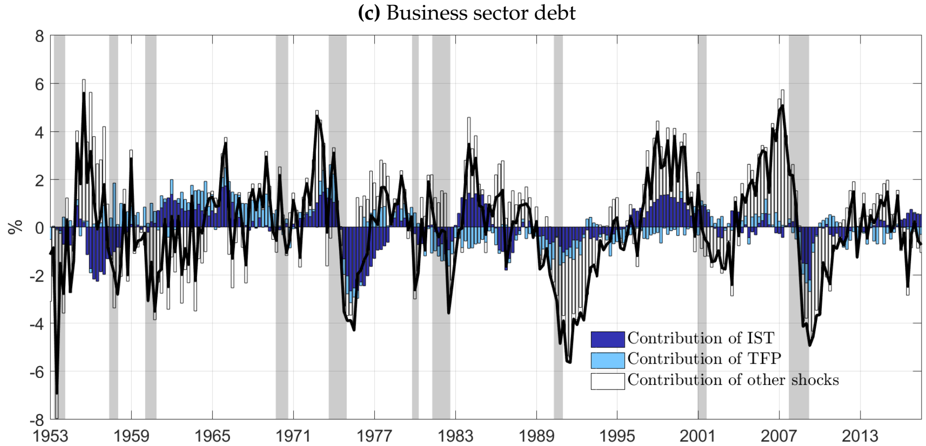
(a) Business sector earnings



(b) Capital stock



(c) Business sector debt

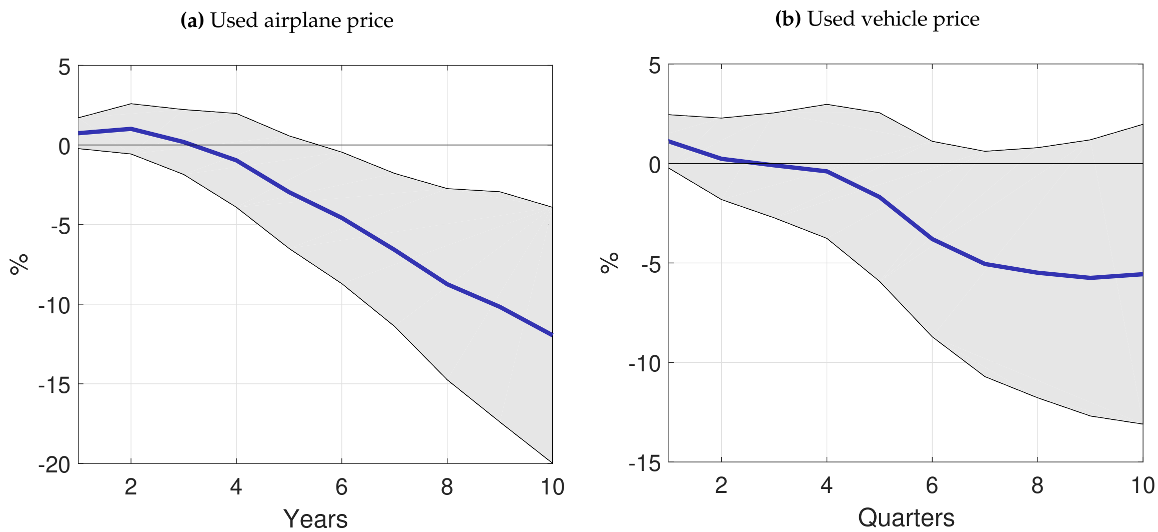


Notes. Historical variance decomposition of variables as estimated by the SVAR model identified with long-run restrictions. The black line is the actual (detrended) data series. The bars indicate the contribution of different structural shocks to the variance of the respective observable as estimated by the SVAR model. The dark blue bars represent investment shocks, the light blue ones TFP shocks, and the contribution of shocks that remain unidentified are shown by the weight bars. Shaded areas indicate NBER recessions.

D.4 SVAR IRFs of used equipment prices

The investment shock that is the focus of the main text is identified from its negative impact on the price of *new* investment goods. In the prototype business cycle model of Section 3, the prices of new and existing capital coincide. In practice, however, there is a difference in the dynamics of new and used equipment prices, and borrowers may pledge both new and used equipment goods as collateral. In this appendix, I demonstrate that the investment shock I identify in Section 4.1 also reduces the prices of *used* equipment goods. This means that the validation of the main mechanism of this paper also holds if secondary prices of capital were to predominantly determine the value of collateral in corporate debt contracts.

Figure D.5: RESPONSES OF USED EQUIPMENT PRICES TO IST SHOCK



Notes. The figure plots the responses of secondary market equipment prices to the investment shock identified in Section 4.1 of the main text. Panel (a) shows the IRF of used aircrafts constructed at annual frequency by Lanteri (2018). Panel (b) displays the analogous response for the quarterly price of used cars and trucks provided by the BLS. In both cases the IRFs are computed using a local projection that includes all variables from the original SVAR system. 68% error bands based on Newey-West standard errors are shown.

To compute these used price responses, I rely on two separate time series that are available for a sufficiently long period. The first price series captures the prices of used aircrafts and has been constructed by Lanteri (2018) at annual frequency from 1975 to 2009.[4] The second series is provided by the Bureau of Labor statistics (available via FRED) and captures the price of used cars and trucks at quarterly frequency from 1953. I run two separate local projections, in which I regress the respective price at an expanding horizon on the IST shock estimated in Section 4.1 as well as on all variables from the original SVAR system (and lags thereof). Since the errors of this regression will be serially correlated, I compute the confidence bands based on Newey-West standard errors.[5]

[4] I thank Andrea Lanteri for kindly sharing this airplane price series.

[5] I essentially follow Ramey (2016) in constructing the local projection. See also Jordà (2005), as well as Section 4.2 of the main text for additional remarks on local projection methods.

The resulting IRFs are shown in Figure D.5. Both price series show little movement on impact but a negative dynamic response to the investment shock. While the price of used airplanes is reduced significantly after around 5 years, the response of the used vehicle series is generally noisy and not significantly different from zero. In comparison to the IRF of new equipment prices shown in Figure D.1 of the main text, both series display a delayed response. Interestingly, this dynamic profile is consistent with the sluggish negative response of debt for collateral borrowers at the micro level in Section 4.2. This suggests that secondary market prices may play a relevant role in the Compustat-Dealscan data used for verification of the mechanism in micro data.

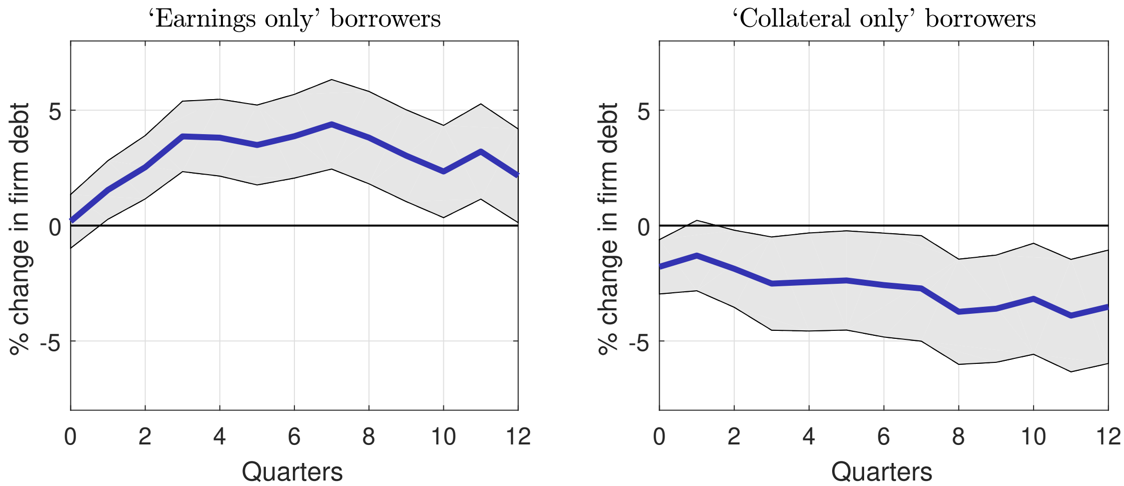
E Additional results for firm-level projections

This appendix presents additional results on the estimation of firm-level responses to investment shocks in Section 4 of the main text. Section E.1 of this appendix compares the firm-level responses from the main text based on a different definition of collateral borrowers. Section E.2 reports the coefficient estimates of the *difference* between earnings and collateral borrowers' debt IRFs and investment IRFs, and corresponding standard errors (horizon by horizon). This serves as a formal test of the difference between the IRFs shown in Panels (c) and (d) of Figure 5 and between the IRFs shown in Figure 7 in the main text. In Section E.3, the main results from the text are shown for the two additional groups, which are firms subject to both covenants and collateral, as well as firms that are subject to neither. Section E.4 analyzes alternative specifications where additional interactions of firm characteristics with the shock are included in the same regressions. In the next part of the Appendix, Section F.2.4 also shows results for firm-level local projections that are run on data that is simulated from the estimated macro model.

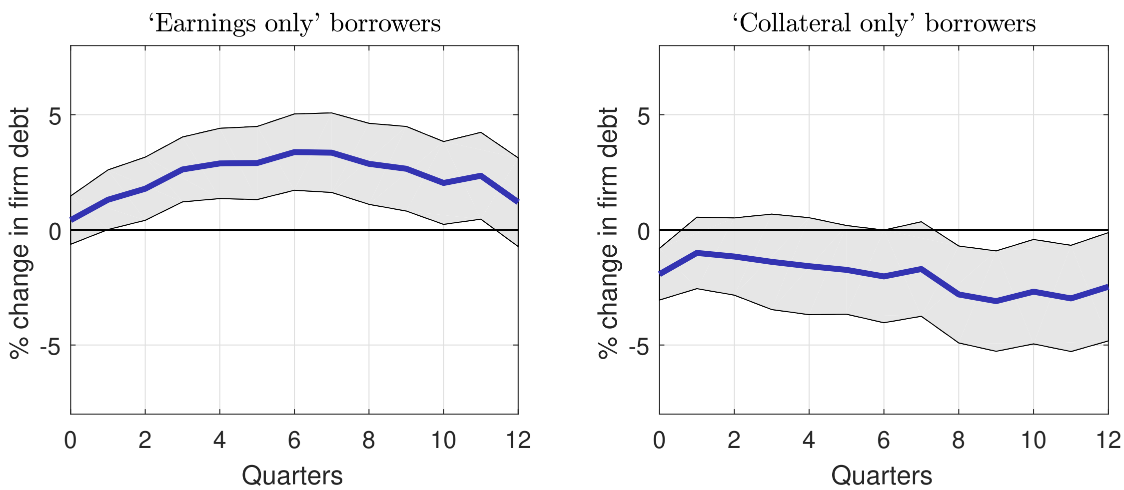
E.1 Alternative definitions of collateral borrowers

Figure E.1: FIRM-LEVEL IRFS OF DEBT TO INVESTMENT SHOCK FOR DIFFERENT BORROWER TYPES

(a) Using collateral classification based on secured revolvers (as in main text)



(b) Using alternative collateral classification based on specific assets



Notes. The figure displays average IRFs of firm borrowing to identified investment shocks across different firm groups, as formulated by equation (20). In both panels, the debt IRF for borrowers with earnings covenants and no collateral (left) and borrowers without earnings covenants but with collateral (right) are plotted. The results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks) as well as a lag of the left hand side variable and a time trend. Panel (a) repeats the results from Figure 5 in the main text, using a grouping where secured revolvers are categorized as collateralized debt (see Lian and Ma, 2021). Panel (b) uses the collateral classification based on whether a loan is backed by specific assets or not (see also Section A.2). 90% bands are calculated using two-way clustered standard errors by firm and quarter. The size of the shock is one standard deviation. The comparison across panels shows that the results are relatively similar across collateral borrower definitions.

E.2 Significance of the difference between heterogeneous debt IRFs

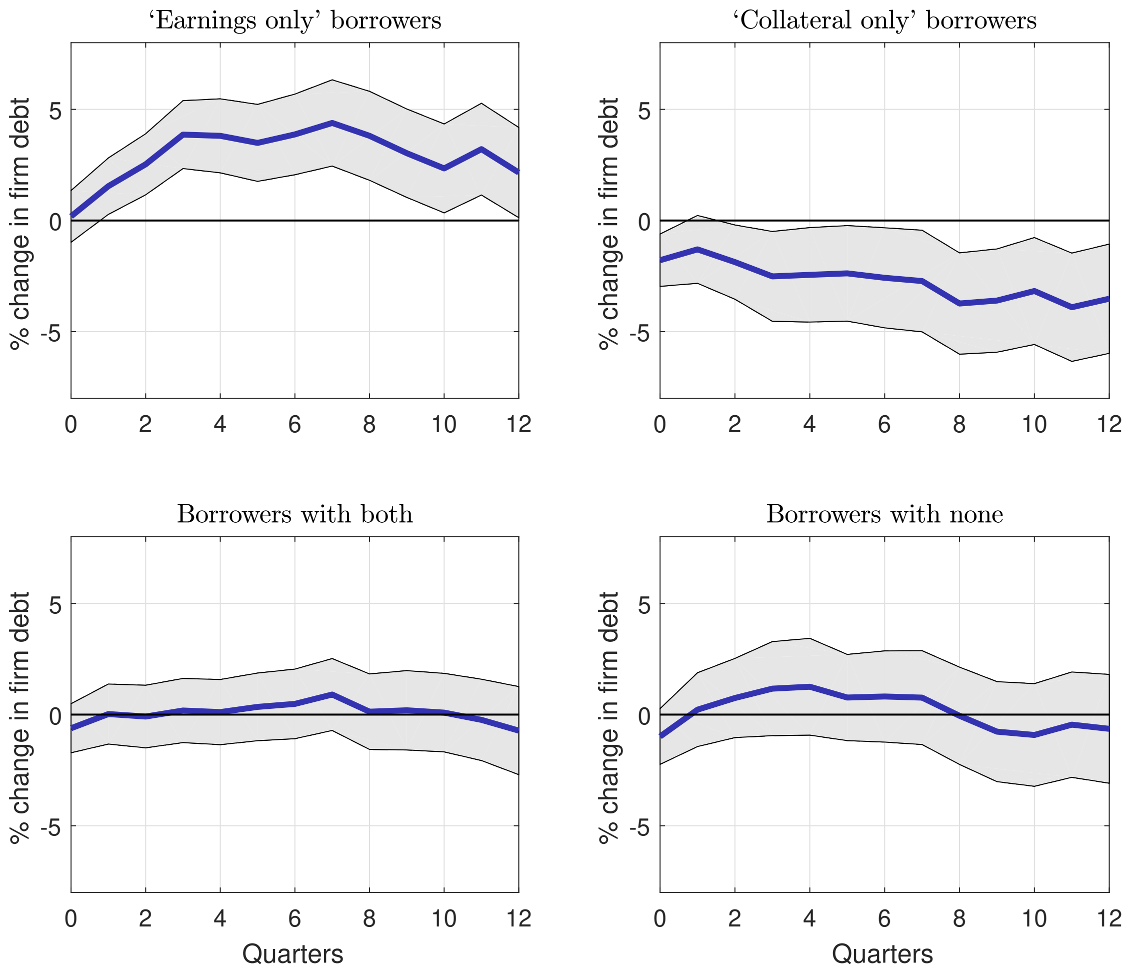
Table E.1: ESTIMATES OF THE DIFFERENCE BETWEEN IRF COEFFICIENTS

	Outcome variable is firm-level borrowing	Outcome variable is firm-level investment
$\beta_0^{earn} - \beta_0^{coll}$	0.0197*	0.0303*
	(0.0115)	(0.0161)
$\beta_1^{earn} - \beta_1^{coll}$	0.0284**	0.0130
	(0.0132)	(0.0140)
$\beta_2^{earn} - \beta_2^{coll}$	0.0440***	0.0368**
	(0.0145)	(0.0154)
$\beta_3^{earn} - \beta_3^{coll}$	0.0638***	0.0332**
	(0.0171)	(0.0162)
$\beta_4^{earn} - \beta_4^{coll}$	0.0625***	0.0302*
	(0.0184)	(0.0171)
$\beta_5^{earn} - \beta_5^{coll}$	0.0587***	0.0075
	(0.0195)	(0.0178)
$\beta_6^{earn} - \beta_6^{coll}$	0.0645***	0.0077
	(0.0204)	(0.0160)
$\beta_7^{earn} - \beta_7^{coll}$	0.0711***	0.0317*
	(0.0213)	(0.0166)
$\beta_8^{earn} - \beta_8^{coll}$	0.0754***	0.0144
	(0.0213)	(0.0174)
$\beta_9^{earn} - \beta_9^{coll}$	0.0663***	0.0226
	(0.0213)	(0.0168)
$\beta_{10}^{earn} - \beta_{10}^{coll}$	0.0551**	0.0217
	(0.0219)	(0.0179)
$\beta_{11}^{earn} - \beta_{11}^{coll}$	0.0711***	0.0499***
	(0.0222)	(0.0183)
$\beta_{12}^{earn} - \beta_{12}^{coll}$	0.0568***	0.0222
	(0.0218)	(0.0205)

Notes. The table shows estimates of the difference between the IRFs to investment shocks of earnings borrowers and collateral borrowers as estimated by equation (20), and shown in Panels (c) and (d) of Figure 5 and Panels (a) and (b) of Figure 7 in the main text. The left column shows these estimates for the specification where the left hand side is firm-level borrowing ($b_{i,s,t}$) and the right column where the response is firm-level investment ($inv_{i,s,t}$). Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table shows that the null hypothesis of equal responses across borrower types is rejected at various horizons and for both outcome variables.

E.3 Results for all four firm groups

Figure E.2: FIRM-LEVEL IRFS OF DEBT TO INVESTMENT SHOCK FOR ALL FOUR BORROWER CATEGORIES

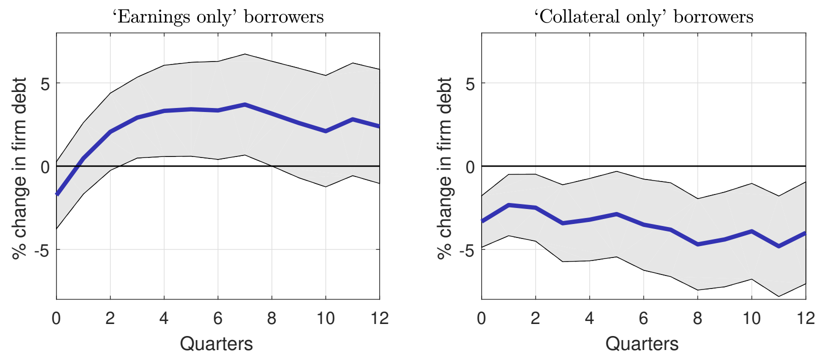


Notes. This figure repeats Panels (c) and (d) of Figure 5 in the main text, and additionally plots the IRFs of the remaining two firm groups: borrowers with both earnings covenants and collateral, and borrowers with neither. The results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks), as well as a lag of the left hand side variable and a time trend. The data set used is a merge of Dealscan loan-level information, with balance sheet variables from the Compustat quarterly database. 90% bands are calculated using two-way clustered standard errors by firm and quarter. The size of the shock is one standard deviation.

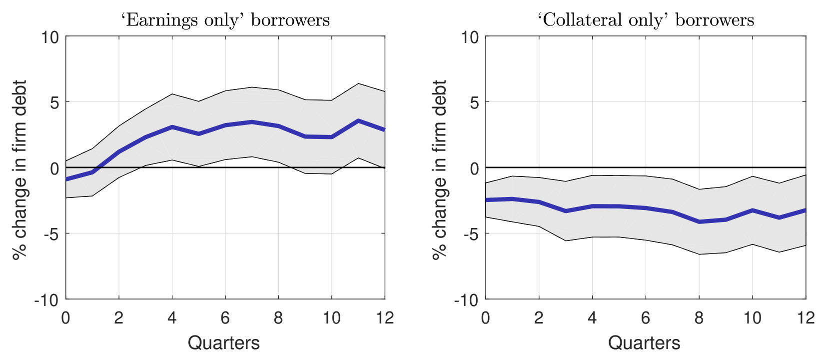
E.4 Results with several simultaneous interactions with the shock

Figure E.3: FIRM-LEVEL IRFS OF DEBT TO INVESTMENT SHOCK WITH ADDITIONAL INTERACTIONS

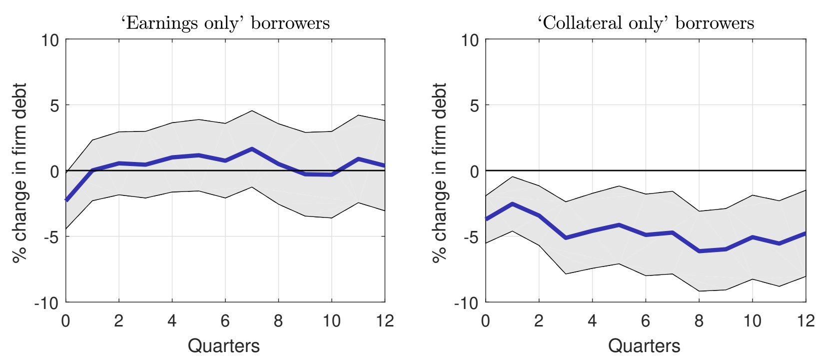
(a) Adding large vs. small interaction on top of borrower type interaction



(b) Adding high vs. low profitability interaction on top of borrower type interaction



(c) Adding old vs. young interaction on top of borrower type interaction



Notes. This figure repeats Panels (c) and (d) of Figure 5 in the main text for specifications where *additional* interactions of firm-level characteristics with the shock are included in the same regressions. Panel (a): large vs. small interaction based on a sorting above/below the median size as measured by number of employees. Panel (b): high vs. low profit margin interaction based above/below median EBITDA-to-assets ratio. Panel (c): old vs. young interaction based above/below median time since IPO date. In all cases, the regressions also contain 3-digit industry fixed effects, growth of real sales, and other macroeconomic shocks, as well as a lag of the left hand side variable and a time trend. The data set used is a merge of Dealscan loan-level information, with balance sheet variables from the Compustat quarterly database. 90% bands are calculated using two-way clustered standard errors by firm and quarter. The size of the shock is one standard deviation.

F Details on the estimated version of the model in Section 5

F.1 Model setup

To extend the heterogeneous credit constraint model of Section 3 to a quantitative version that I estimate on US data, I add various frictions and shocks that bring the framework close to a typical medium-scale New Keynesian model, such as the one introduced by Smets and Wouters (2007). To add credit constraint to a Smets and Wouters (2007)-type economy, I follow the model assumptions of Jermann and Quadrini (2012). Apart from adding borrowing constraints, the model differs from Smets and Wouters (2007) in the following ways. Firms rather than households own capital. Firms face Rotemberg price adjustment costs rather than Calvo pricing. The monetary policy maker targets output deviations from steady state rather than from the natural level. I add some corrections relative to the Jermann and Quadrini (2012) model that were suggested by Pfeifer (2016).

F.1.1 Firms

The problem of the final good producer is identical to Section 3 in the main text, with the exception that η_t is now stochastic and subject to price markup shocks. The intermediate good firms also face a very similar problem as in Section 3, but they have a slightly more general production function, which is (omitting the type-superscript j):

$$y_{i,t} = z_t(u_{i,t}k_{i,t-1})^{\alpha}n_{i,t}^{1-\alpha}, \tag{53}$$

where TFP, z_t, is common across firms and will be subject to stochastic shocks and $u_{i,t}$ is the utilization rate of capital, which is an endogenous choice taken subject to a cost. This capital utilization cost is specified as

$$\Xi(u_t) = \bar{\xi}(u_t^{1+\xi} - 1)/(1 + \xi) \tag{54}$$

The parameter $\bar{\xi}$ is calibrated to generate steady state utilization of 1, and ξ is estimated. Aggregation across the firm types j is as shown in Appendix C.1.2.

F.1.2 Households

There is a continuum of size 1 of households. Household ℓ's expected lifetime utility is

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \gamma_t \beta^t \left(\frac{(c_{\ell,t} - hc_{\ell,t-1})^{1-\sigma}}{1-\sigma} - \chi_n \frac{n_{\ell,t}^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} \right) \tag{55}$$

where γ_t is a preference disturbance and h captures external consumption habits. The parameter ϵ denotes the elasticity of labor supply. Households supply individual labor types $n_{\ell,t}$ and charge wage rate $w_{\ell,t}$. The budget constraint is

$$c_{\ell,t}+\sum_{j[\chi]}\left\{\frac{b^j_{\ell,t}}{(1+r_t)P_t}+p^j_{f,t}s^j_{\ell,t}\right\}+T_{\ell,t}+\int q^{\omega}_{\ell,t+1}a_{j,t+1}dw_{\ell,t}=w_{\ell,t}n_{\ell,t}+\sum_{j[\chi]}\left\{\frac{b^j_{\ell,t-1}}{P_t}+(d^j_{\ell,t}+p^j_{f,t})s^j_{\ell,t-1}\right\}, \tag{56}$$

where $\sum_{j[\chi]}$ is a compact way to express the sum across firm types $j \in \{\pi, k\}$, weighted with χ and $1-\chi$. $a_{\ell,t+1}$ are holdings of state-contingent claims with which households can insure against wage shocks. They are traded at price $q^w_{\ell,t+1}$. A labor agency supplies total labor N_t to firms, which is a composite of the different labor types ℓ supplied by households:

$$N_t=\left(\int_0^1 n_{\ell,t}^{\frac{1}{\vartheta_t}}\,dj\right)^{\vartheta_t} \tag{57}$$

where ϑ_t is subject to wage markup shocks. The demand for labor faced by individual households is therefore

$$n_{\ell,t}=\left(\frac{w_{\ell,t}}{W_t}\right)^{-\frac{\vartheta_t}{\vartheta_t-1}}N_t, \tag{58}$$

where W_t and N_t are the aggregate wage and employment level, respectively. (58) is taken as given by the household when choosing $n_{\ell,t}$ and $w_{\ell,t}$. Households face wage rigidities. A given household can only change their offered wage with probability $(1-\omega)$. From the optimization problem I derive a log-linear optimal wage equation. Given that all households make the same choices, this implies a sluggish low of motion for the aggregate wage rate W_t. For details, see Jermann and Quadrini (2012).

Household's optimality condition for bonds implies an Euler equation in which the real return $(1+r_t)\left(\frac{P_t}{P_{t+1}}\right)$ is priced with the stochastic discount factor $SDF_{t,t+1}\equiv\frac{\Lambda_{t+1}}{\Lambda_t}=\frac{\beta\gamma_{t+1}u_{c_{t+1}}}{\gamma_t u_{c_t}}$, where $u(\cdot)$ denotes the period utility function in (55).

F.1.3 Government

The government's budget constraint, in nominal terms, in similar to the model of Section 3,

$$T_t=\sum_{j[\chi]}\left(\frac{b^j_t}{R_t}-\frac{b^j_t}{(1+r_t)}\right)+P_t g_t, \tag{59}$$

with the addition of real government spending shocks to g_t.

F.1.4 Monetary policy

There is a Taylor rule specified as

$$\frac{1+r_t}{1+\bar{r}}=\left[\frac{1+r_{t-1}}{1+\bar{r}}\right]^{\rho_R}\left[\left(\frac{\pi^p_t}{\bar{\pi}^p}\right)^{\nu_1}\left(\frac{Y_t}{Y_{t-1}}\right)^{\nu_2}\right]^{1-\rho_R}\left[\frac{Y_t/Y^*_t}{Y_{t-1}/Y^*_{t-1}}\right]^{\nu_3}\varsigma_t, \tag{60}$$

such that interest rates react to deviations of inflation from steady state, output growth, and output growth in deviations from it steady state. See Jermann and Quadrini (2012) for a discussion. Beware that I denote inflation by π_t^p, not to be confused with firm profits $\pi_{i,t}$. $\rho_R > 0$ captures interest rate smoothing. ς_t is a stochastic disturbance that captures monetary shocks.

F.1.5 Stochastic processes

The model features eight structural disturbances, capturing shocks to TFP, investment, preferences, price markups, wage markups, fiscal policy, monetary policy and financial conditions. The processes are specified as in Smets and Wouters (2007):

$$\log(z_t) = (1-\rho_z)\log(\overline{z}) + \rho_z \log(z_{t-1}) + u_{z,t} \tag{61}$$

$$\log(v_t) = (1-\rho_v)\log(\overline{v}) + \rho_v \log(v_{t-1}) + u_{v,t} \tag{62}$$

$$\log(\gamma_t) = (1-\rho_\gamma)\log(\overline{\gamma}) + \rho_\gamma \log(\gamma_{t-1}) + u_{\gamma,t} \tag{63}$$

$$\log(\eta_t) = (1-\rho_\eta)\log(\overline{\eta}) + \rho_\eta \log(\eta_{t-1}) + u_{\eta,t} - \mu_p u_{\eta,t-1} \tag{64}$$

$$\log(\vartheta_t) = (1-\rho_\vartheta)\log(\overline{\vartheta}) + \rho_\vartheta \log(\vartheta_{t-1}) + u_{\vartheta,t} - \mu_w u_{\vartheta,t-1} \tag{65}$$

$$\log(g_t) = (1-\rho_g)\log(\overline{g}) + \rho_g \log(g_{t-1}) + \rho_{gz}\log(z_t) + u_{g,t} \tag{66}$$

$$\log(\varsigma_t) = (1-\rho_\varsigma)\log(\overline{\varsigma}) + \rho_\varsigma \log(\varsigma_{t-1}) + u_{\varsigma,t} \tag{67}$$

$$\log(\theta_{j,t}) = (1-\rho_\theta)\log(\overline{\theta_j}) + \rho_\theta \log(\theta_{j,t-1}) + u_{\theta,t} \quad j=\{\pi,k\} \tag{68}$$

The error terms follow standard deviations $\{\sigma_z, \sigma_v, \sigma_\gamma, \sigma_\eta.\sigma_\vartheta, \sigma_G, \sigma_\varsigma, \sigma_\theta\}$. I normalize $\bar{z} = \bar{v} = \bar{\gamma} = \bar{\varsigma} = 1$ and estimate $\bar{\eta}$ and $\bar{\vartheta}$. $\bar{g}$ is calibrated to the data (see below). $u_{\theta,t}$ is a common financial shock that hits both borrower types. $\overline{\theta}_\pi$ and $\overline{\theta}_k$ are different across borrower types and calibrated to the data (see below).

F.1.6 Calibrated parameters

I calibrate α, β, δ, $\overline{\theta}_k$, $\overline{\theta}_\pi$ and τ the same way as in Table C.1. $\bar{g}$ is set to match the average US government spending-to-output ratio over the sample period. I estimate the remaining parameters, as shown below.

F.2 Additional results for estimated quantitative model

This Appendix presents additional results for the estimated quantitative model version introduced in Section 5.1 and the previous section of the Appendix.

F.2.1 Parameter estimates

Table F.1 shows the priors and posteriors for the model version where a higher share of firms face earnings-based borrowing constraints ($\chi = 0.8$). Table F.2 presents the analogous estimates for the case where more firms face collateral constraint ($\chi = 0.2$).

Table F.1: PRIORS AND POSTERIORS FOR ESTIMATED MODEL VERSION WITH $\chi = 0.8$

	Prior shape	Prior Mean	Prior Std	Post. mean	90% HPD interval	
σ	Normal	1.5	0.37	3.6092	3.4008	3.7879
ϵ	Normal	2	0.75	5.7268	5.2865	6.0628
h	Beta	0.5	0.15	0.0577	0.0216	0.0952
υ	Inv-Gamma	0.1	0.3	0.0809	0.0378	0.1145
ω	Beta	0.5	0.15	0.7172	0.6833	0.7499
ϕ	Inv-Gamma	0.1	0.3	1.1846	1.1134	1.2613
ξ	Beta	0.5	0.15	0.8618	0.7498	0.9855
ψ	Inv-Gamma	0.2	0.1	0.0534	0.0452	0.06
ρ_R	Beta	0.75	0.1	0.59	0.554	0.6267
ν_1	Normal	1.5	0.25	2.2777	2.1749	2.3685
ν_2	Normal	0.12	0.05	0.2777	0.2565	0.2955
ν_3	Normal	0.12	0.05	0.301	0.2865	0.3164
$\bar{\eta}$	Beta	1.2	0.1	1.1031	1.0786	1.1262
$\bar{\vartheta}$	Beta	1.2	0.1	1.0777	1.0641	1.0925
ρ_z	Beta	0.5	0.2	0.6684	0.5955	0.7425
ρ_{gz}	Beta	0.5	0.2	0.7579	0.6913	0.8301
ρ_υ	Beta	0.5	0.2	0.673	0.6311	0.712
ρ_γ	Beta	0.5	0.2	0.6678	0.604	0.7516
ρ_η	Beta	0.5	0.2	0.9837	0.9729	0.9946
μ_p	Beta	0.5	0.2	0.313	0.2539	0.3838
ρ_ϑ	Beta	0.5	0.2	0.9493	0.9299	0.9695
μ_w	Beta	0.5	0.2	0.8156	0.7565	0.8773
ρ_G	Beta	0.5	0.2	0.5209	0.492	0.557
ρ_ς	Beta	0.5	0.2	0.4433	0.4026	0.4793
ρ_θ	Beta	0.5	0.2	0.989	0.9809	0.9975
σ_z	Inv-Gamma	0.01	0.05	0.0251	0.0213	0.0286
σ_υ	Inv-Gamma	0.01	0.05	0.0627	0.0576	0.0678
σ_γ	Inv-Gamma	0.01	0.05	0.0883	0.0772	0.1034
σ_η	Inv-Gamma	0.01	0.05	0.0084	0.0077	0.0091
σ_ϑ	Inv-Gamma	0.01	0.05	0.1519	0.1296	0.1723
σ_G	Inv-Gamma	0.01	0.05	0.1077	0.0959	0.1235
σ_ς	Inv-Gamma	0.01	0.05	0.0091	0.0084	0.0098
σ_θ	Inv-Gamma	0.01	0.05	0.0183	0.0165	0.0200

Table F.2: PRIORS AND POSTERIORS FOR ESTIMATED MODEL VERSION WITH $\chi = 0.2$

	Prior shape	**Prior Mean**	**Prior Std**	**Post. mean**	**90% HPD interval**	
σ	Normal	1.5	0.37	0.6488	0.5659	0.7301
ϵ	Normal	2	0.75	4.7746	4.4151	5.4525
h	Beta	0.5	0.15	0.7868	0.7611	0.814
υ	Inv-Gamma	0.1	0.3	4.6719	4.2938	5.0095
ω	Beta	0.5	0.15	0.7984	0.7848	0.8122
ϕ	Inv-Gamma	0.1	0.3	3.0656	2.9129	3.1743
ξ	Beta	0.5	0.15	0.8113	0.6993	0.8838
ψ	Inv-Gamma	0.2	0.1	0.0891	0.0776	0.1025
ρ_R	Beta	0.75	0.1	0.5	0.476	0.5338
ν_1	Normal	1.5	0.25	1.8486	1.7994	1.8897
ν_2	Normal	0.12	0.05	-0.1343	-0.1507	-0.1158
ν_3	Normal	0.12	0.05	0.188	0.1761	0.1997
$\bar{\eta}$	Beta	1.2	0.1	1.2587	1.2215	1.2946
$\bar{\vartheta}$	Beta	1.2	0.1	1.2959	1.2677	1.3271
ρ_z	Beta	0.5	0.2	0.9884	0.9813	0.9961
ρ_{gz}	Beta	0.5	0.2	0.9619	0.9285	0.9957
ρ_v	Beta	0.5	0.2	0.8981	0.872	0.9232
ρ_γ	Beta	0.5	0.2	0.9041	0.8703	0.928
ρ_η	Beta	0.5	0.2	0.9343	0.9143	0.9567
μ_p	Beta	0.5	0.2	0.2717	0.1959	0.3867
ρ_ϑ	Beta	0.5	0.2	0.6451	0.6318	0.6567
μ_w	Beta	0.5	0.2	0.4812	0.4221	0.5393
ρ_G	Beta	0.5	0.2	0.9916	0.9844	0.999
ρ_ς	Beta	0.5	0.2	0.0725	0.0176	0.1191
ρ_θ	Beta	0.5	0.2	0.9866	0.9789	0.9944
σ_z	Inv-Gamma	0.01	0.05	0.0075	0.0068	0.0082
σ_v	Inv-Gamma	0.01	0.05	0.0477	0.0422	0.0532
σ_γ	Inv-Gamma	0.01	0.05	0.0135	0.0106	0.0157
σ_η	Inv-Gamma	0.01	0.05	0.0096	0.0086	0.01060
σ_ϑ	Inv-Gamma	0.01	0.05	0.2603	0.2463	0.2798
σ_G	Inv-Gamma	0.01	0.05	0.0199	0.018	0.0218
σ_ς	Inv-Gamma	0.01	0.05	0.0152	0.0142	0.016
σ_θ	Inv-Gamma	0.01	0.05	0.0136	0.0125	0.0147

F.2.2 Direct effects of constraints vs. indirect effects through parameter estimates

Table F.3 presents variance decompositions across different model versions. Panel (a) contains decompositions for output growth, and Panel (b) for credit growth, both for a 2-year horizon. In each panel, the first two models are the ones analyzed in Figure 8 of the main text. The third model corresponds to a counterfactual in which earnings-based constraints have a higher share ($\chi = 0.8$) but the parameters are set to those from the model estimated with a higher share of collateral constraints ($\chi = 0.2$). In that counterfactual, only the shock processes have been re-estimated to assess the resulting variance decompositions. Considering this counterfactual is insightful because differences between the two model versions analyzed in the main text are driven by *(i)* the direct mechanical difference between the two alternative borrowing constraints, and by *(ii)* the different parameter estimates that result from the estimation with a different importance of either of the two constraints. The third model can thus be studied to quantify the importance of *(i)* to the total difference in the contribution of supply and demand shocks to output and credit fluctuations across the two fully estimated models from the main text.

Table F.3: FORECAST ERROR VARIANCE DECOMPOSITIONS AT 2-YEAR HORIZON ACROSS MODEL VERSIONS

Panel (a): Output growth decomposition (%)	**Demand shocks**	**Supply shocks**	**Financial shocks**
Model with higher share of earnings-based constraints (fully estimated with $\chi = 0.8$)	17.96	75.7	6.34
Model with higher share of collateral constraints (fully estimated with $\chi = 0.2$)	61.94	36.94	1.12
Model with higher share of earnings-based constraints, parameter values from model with higher share of collateral constraints (set $\chi = 0.8$, fix parameters from $\chi = 0.2$ model, re-estimate shock processes)	49.36	41.88	8.77
Panel (b): Credit growth decomposition (%)	**Demand shocks**	**Supply shocks**	**Financial shocks**
Model with higher share of earnings-based constraints (fully estimated with $\chi = 0.8$)	31.25	66.29	2.46
Model with higher share of collateral constraints (fully estimated with $\chi = 0.2$)	52.39	33.84	13.77
Model with higher share of earnings-based constraints, parameter values from model with higher share of collateral constraints (set $\chi = 0.8$, fix parameters from $\chi = 0.2$ model, re-estimate shock processes)	55.84	39.17	4.99

Notes. Forecast error variance decompositions across different models. Panel (a) presents decompositions for output growth, Panel (b) for credit growth. In each panel, the first two models correspond to the ones described and analyzed in the text, see Figure 8. The third model corresponds to a model where earnings-based constraints have a higher share ($\chi = 0.8$) but the parameters are set to the ones from the model estimated with a higher share of collateral constraints ($\chi = 0.2$), and only the shock processes are re-estimated for the purpose of analyzing variance decompositions.

The findings presented in Table F.3 are the following. As discussed in the main text, the comparison between the two fully estimated models reveals that a higher share of earnings-based borrowing constraints implies a larger contribution of supply shocks to output growth fluctuations (76% vs. 37%) and a lower contribution of demand shocks (18% vs. 62%). The third model counterfactual presented in Table F.3 makes clear that this difference comes to a meaningful degree both from the direct effect of the borrowing constraints and from the different parameter estimates that are associated with the different constraints. Specifically, if we keep the parameter values as they are in the model with a higher share of collateral constraints but switch the main constraint to an earnings-based one, the contribution of supply shocks increases from 37% to 42% and that of demand shocks falls from 62% to 49%. The remaining difference – an increase in the importance of supply shocks from 42% to 76% and decrease in the importance of demand shocks from 49% to 18% – comes from changes in the parameter values that result from having a higher share of firms with earnings-based constraints in the estimation. This effect does come from the constraint, but indirectly through how it affects the estimation of the model.

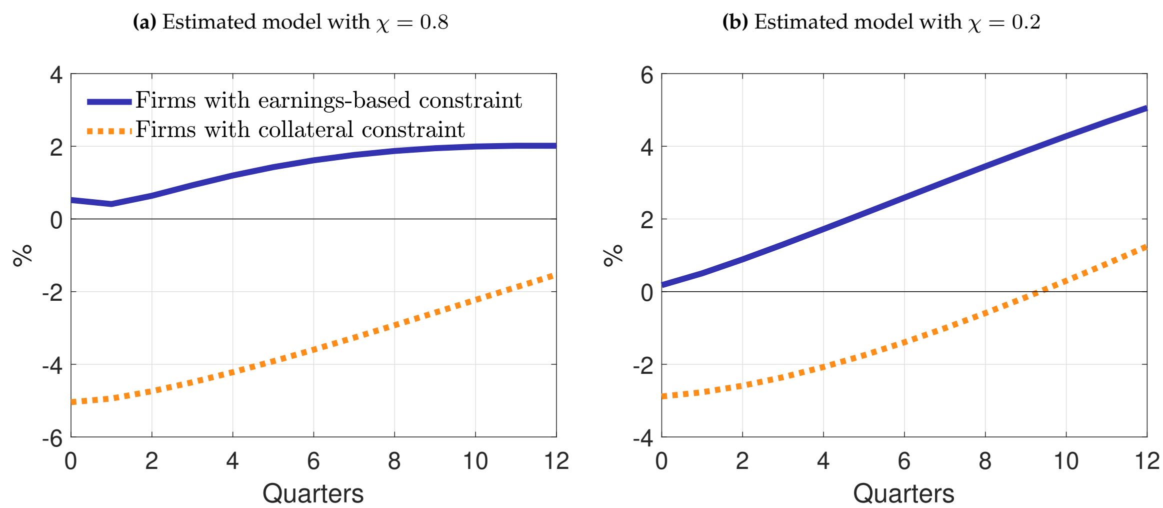
In the case of credit fluctuations, a roughly similar picture emerges, although it is a little bit less clear cut for demand shocks due to an offsetting change in financial shocks that occurs when re-estimating the shock processes in the model counterfactual. (Recall from the main text that I classify financial shocks as a separate category.) However, also in the case of credit growth variation, the direct effect coming from the earnings-based borrowing constraint itself already leads to an increase in the importance of supply shocks, from 34% to 39%, while the remaining increase in their importance from 39% to 66% can be attributed to different parameter estimates associated with a dominant earnings-based borrowing constraint.

Overall this analysis shows that the main results in the quantitative version of the model in Section 5 are driven both directly by the presence of different types of borrowing constraints, as well as by the different parameters estimates that result from having one or the other constraint in the estimation. Quantitatively, the majority of the difference appears to result from how the presence of the different constraints affect parameters estimates in the DSGE model.

F.2.3 Permanent investment shocks in the estimated model

Figure F.1 studies the real debt IRFs across borrower types to permanent aggregate investment shocks in the estimated model of Section 5. Panel (a) shows the IRFs in the model estimated with $\chi = 0.8$ and Panel (b) in the version with $\chi = 0.2$. The direct counterpart of these responses in the simpler version of the model in Section 3 is Panel (b) of Figure C.1. The comparison shows that while there are differences in magnitude and persistence of the IRFs, the main mechanism around permanent investment shocks – the sign different in the debt response across borrower types – remains intact also in the estimated version of the model, which features additional shocks and frictions, and which is estimated on US data. This is the case both when the majority of borrowers faces earnings-based constraints and when more firms borrow against collateral.

Figure F.1: IRFS OF REAL FIRM DEBT TO PERMANENT INVESTMENT SHOCKS IN ESTIMATED MODEL



Notes. Real debt IRFs across borrower types to aggregate investment (MEI) shocks in the estimated model of Section 5. The shocks here are permanent, that is, ρ_v is changed to 1 and all other parameters are set to their posterior mean. Panel (a) computes these IRFs in the model estimated with $\chi = 0.8$ and Panel (b) in the version with $\chi = 0.2$.

F.2.4 Local projections using simulated model data

This appendix examines the panel local projection methodology used in Section 4 in closer connection to the structural model. I estimate equation (20) from the main text on panel data that I simulate from the estimated version of the model presented in Section 5. Specifically, I generate simulated data for earnings-based borrowers and collateral borrowers that respond to a sequence of different aggregate and firm-level shocks, where the sample size is similar to my empirical application with Compustat-Dealscan data. This exercise helps to understand to what degree the different credit responses to permanent investment shocks across borrower types in the New Keynesian model economy – an environment with several other shocks and frictions that drive firms' decisions – can be recovered by the panel local projection technique.

Simulation procedure. I first solve the model of Section 5 at the estimated posterior means of all parameters and obtain the model's policy functions for real debt of both firm types $j \in \{\pi, k\}$.[6] Using these policy functions, I then simulate data from the model, by first generating random sequences of 5 types of shocks, and then feeding them into the policy functions: (1) permanent aggregate investment shocks; (2) permanent firm-specific investment shocks; (3) permanent aggregate neutral technology shocks; (4) permanent firm-specific neutral technology shocks; (5) transitory monetary policy shocks.[7] This set of different shocks is supposed to be representative of a variety of confounding factors that could make it difficult to recover the firm-level responses to the shock of interest in my empirical application, the aggregate permanent investment shock. These confounding factors are both permanent and transitory in nature, and include both aggregate and firm-level shocks.[8] On this simulated data set, I then run regressions similar to equation (20), using the true series of the permanent investment shock as a regressor and interacting it with dummy variables that capture each borrower type. I do not include any additional controls in these local projections.

Simulation settings. To calibrate the quantitative importance of the different structural shocks for the simulated data, I proceed as follows. For the aggregate shocks to investment and neutral technology, I use the standard deviations from the estimated model. For the respective firm-level shocks I use the same standard deviations, but scale them up by $\kappa_f > 1$. This captures the idea that firm-level shocks might be more important than aggregate shocks in firm-level data, and this could make it difficult to recover the IRFs to aggregate shocks. Furthermore, since there are many additional transitory business cycle shocks that may be driving credit variation in the data, and that I may not be able to fully control for in the estimation procedure, I use the monetary policy

[6] I use the model version estimated with $\chi = 0.8$. I found similar results using $\chi = 0.2$.

[7] The model, when estimated, contains only aggregate shocks and does not feature any (uninsured) idiosyncratic shocks at the firm level. However, after estimating the model, I can feed simulated shock processes into the policy function that is specific to an individual firm. In this way, I create "panel data" from an aggregate model.

[8] In the exercise using simulated data presented here, I abstract from the industry variation in the sensitivity of equipment prices to the aggregate shock that I use in Section 4.

shock as a representative "other macro shock" and scale up its standard deviation, taken from the estimated model, by $\kappa_{mp} > 1$. The persistence of monetary policy shocks is set equal to the posterior estimate from the model. I vary κ_f and κ_{mp} to obtain an understanding of how strong the confounding shocks need to be to harm the ability of my estimation procedure to retrieve the different IRFs to aggregate investment shocks across borrower types. I found that setting both of these scales to 1 allows the procedure to very precisely recover the IRFs shown in Figure F.1, so increasing them provides a challenge to the estimation. In the baseline setting, I set $\kappa_f = 5$, $\kappa_{mp} = 10$. I simulate a data set of $T = 96$ time periods, mimicking the application in Section 4 with quarterly data from 1994-2017. I set the number of borrower types to $N_k = 2,188$ and $N_\pi = 1,844$ again following the empirical application in Compustat-Dealscan where I estimate the marginal effect of having exclusively one type of borrowing with two dummy interactions (see also the summary statistics Table A.6).[9] Finally, to make the application more realistic, I generate the firm panel data to be highly unbalanced.[10]

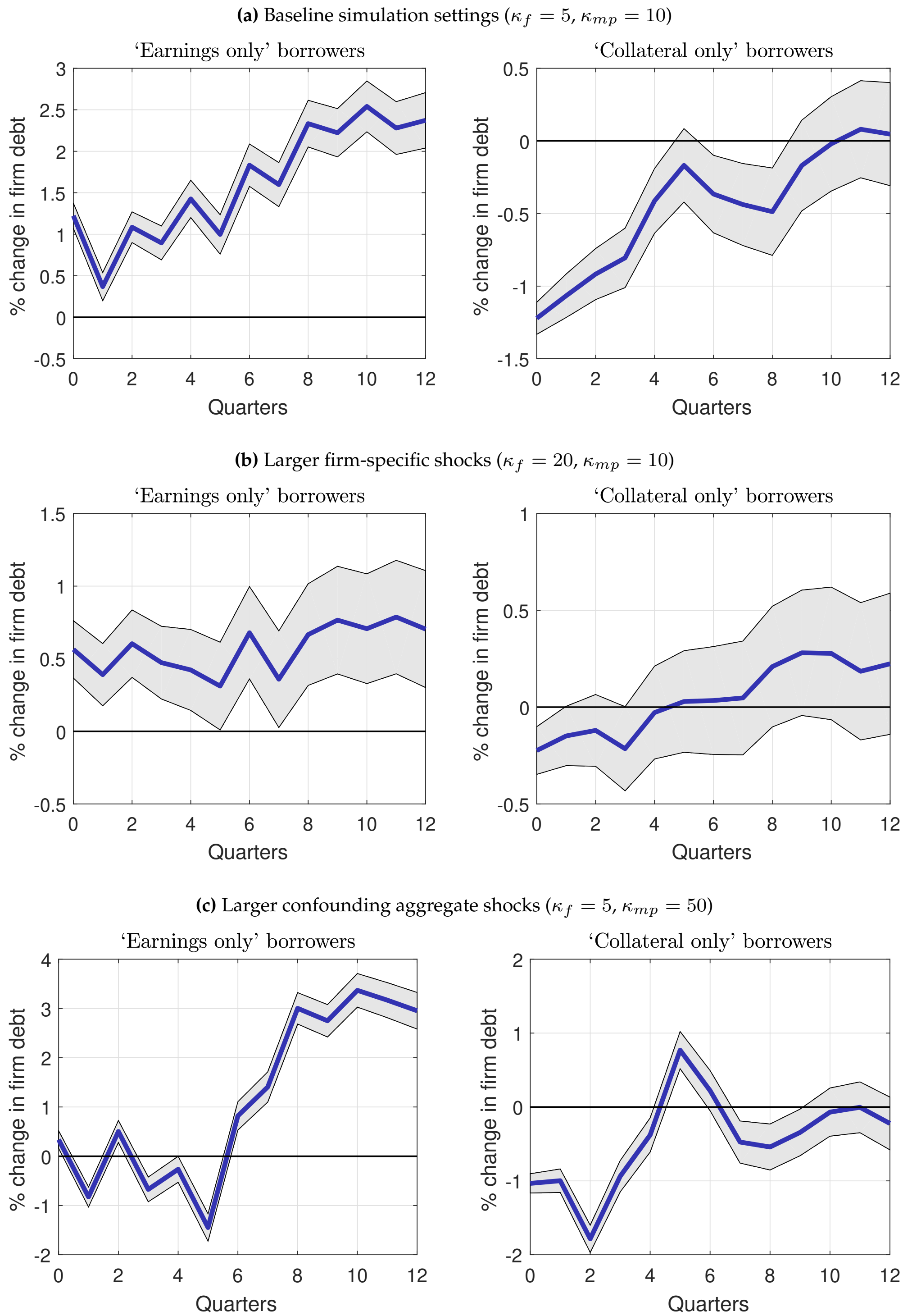
Local projection results in a simulated economy. Figure F.2 presents the estimated IRFs of real firm debt across the two borrower types, those with earnings-based constraints and those facing collateral constraints, for three different data generating processes that underlie the simulated data. These IRFs should be compared to the "true" underlying IRFs in the model of Section 5, which are shown in Figure F.1, Panel (a). Panel (a) of Figure F.2 presents the results for the scales $\kappa_f = 5$, $\kappa_{mp} = 10$, as explained above. Under this benchmark calibration, which already poses challenges to the estimation due to meaningful confounding shocks, it is evident that the panel local projection technique is able to correctly recover the different sign in the responses of firm debt across borrower types, key to my empirical strategy in Section 4. As in the model, earnings-based borrowers obtain more credit in response to the permanent shock, while collateral borrowers reduce their debt balance. Interestingly, I found that in the presence of the confounding shocks, in particular those at the firm-level, the magnitude of the responses is usually not estimated fully accurately in comparison to the model. This also becomes clear in the remaining panels of the figure.

Panels (b) and (c) of Figure F.2 vary κ_f and κ_{mp} in turn. Here I hand pick values that are high enough to illustrate at which point visible challenges for the estimation procedure start occurring. In Panel (b), κ_f is increased to 20 while $\kappa_{mp} = 10$ as in Panel (a). In other words, this is a setting where firm-specific shocks are by far the dominant source of fluctuations, explaining 20 times as much as their aggregate counterpart. It is visible that the bands across the IRFs to the aggregate

[9]Note that as long as I use the correct borrower type dummy as an observable in the regression, the relative shares are not too important as long as there are enough observations for each type. The results presented here look fairly similar when setting the shares for example to 80% and 20%.

[10]Since there are permanent shocks, the debt data for individual firms can drift to negative values. I set any negative value to missing, mimicking an environment in which firms drop out of (and come back into) the panel. Similar to my empirical application where there is likely nonrandom selection into the Dealscan data by firms that have the ability to borrow to begin with, this could introduce a general upward bias in debt IRFs across both firm types. Hence this is an issue that makes the setting more realistic and more challenging.

Figure F.2: RESULTS FROM LOCAL PROJECTIONS ON SIMULATED MODEL DATA



Notes. Debt IRFs across the two borrower types to permanent aggregate investment shocks, estimated on data that is simulated from the model in Section 5. The different panels capture different calibrations of the importance of confounding shocks in the underlying data generating process. κ_f governs how important firm-level shocks are relative to aggregate shocks. κ_{mp} governs the importance of other business cycle shocks (monetary policy shocks). The IRFs can be compared to those in the underlying model, see Figure F.1, Panel (a). The remaining settings of the simulation exercise are described in the text. The random shocks are generated with the same seed across the panels.

shock of interest get much wider and the estimates are generally closer to zero. Nevertheless, a significant qualitative difference across the two borrower types is recovered by the procedure. In Panel (c) κ_{mp} is increased to 50 while $\kappa_f = 5$ as in Panel (a). This is intended to capture a setting in which other aggregate business cycle shocks are much more important in the data. As the estimation procedure cannot control for these other aggregate shocks, the IRFs exhibit some confounding cyclical variation that the estimation wrongly attributes to investment shocks. However, it is still the case that the debt response of earnings-based borrowers is mostly positive, while that of collateral borrowers is mostly negative. Note that in the actual empirical application using Compustat-Dealscan data I do try control for other macroeconomic and firm-level shocks. See the discussion in Section 4.2.

Overall, the simulation exercises presented in this appendix demonstrate that the panel local projection procedure is able to robustly recover the sign difference in the debt response across borrower types, also in the presence of confounding aggregate and firm-level shocks that drive the data. This provides an additional validation of the empirical approach used in Section 4, in closer connection to the model.

F.2.5 Full variance decompositions

This section provides a more detailed breakdown of the variance decompositions presented in Figure 8 of the main text. Table F.4 corresponds to the version of the model estimated with a higher share of firms with earnings-based borrowing constraints ($\chi = 0.8$), Table F.5 the one with a higher share of firms facing a collateral constraint ($\chi = 0.2$).

Table F.4: VARIANCE DECOMPOSITION OF OBSERVABLES FOR ESTIMATED MODEL VERSION WITH $\chi = 0.8$ (IN %)

Variable	Horizon	TFP	Inv	Pref	Price	Wage	Gov	Mon	Fin
Output growth	1 quarter	64.22	0.14	2.48	20.18	1.06	3.16	0.00	8.76
	1 year	57.75	0.65	5.26	17.73	0.57	11.66	0.04	6.34
	2 years	57.49	0.73	5.38	17.65	0.56	11.81	0.04	6.33
Consumption growth	1 quarter	40.41	2.89	31.42	6.41	2.59	13.27	1.94	1.07
	1 year	44.73	2.18	22.68	7.56	1.72	18.44	1.42	1.27
	2 years	44.2	2.29	23.41	7.47	1.7	18.25	1.42	1.26
Investment growth	1 quarter	20.12	59.34	9.03	1.82	1.29	2.61	5.76	0.04
	1 year	17.93	60.56	8.18	1.50	2.03	2.96	6.41	0.42
	2 years	17.92	61.3	7.84	1.40	2.03	2.75	6.36	0.4
Inflation	1 quarter	58.84	0.16	9.97	10.65	0.74	14.98	1.78	2.87
	1 year	55.28	0.17	9.29	11.32	0.59	19.26	1.41	2.68
	2 years	55.2	0.19	9.29	11.33	0.67	19.23	1.41	2.69
Interest rate	1 quarter	53.72	0.57	14.54	6.85	0.59	22.52	0.07	1.14
	1 year	52.13	1.8	15.16	6.54	0.97	21.61	0.67	1.12
	2 years	51.69	2.11	15.06	6.53	1.33	21.41	0.74	1.13
Employment growth	1 quarter	17.07	3.92	11.51	12.51	4.43	43.53	5.32	1.72
	1 year	19.74	5.04	10.99	15.19	3.37	38.57	4.2	2.9
	2 years	20.43	6.17	11.01	14.48	3.22	37.64	4.28	2.77
Wage growth	1 quarter	61.33	0.28	6.71	11.3	0.01	16.47	0.91	2.99
	1 year	56.55	0.26	8.00	11.6	0.06	20.18	0.63	2.72
	2 years	56.53	0.32	7.99	11.57	0.06	20.12	0.68	2.72
Credit growth	1 quarter	67.87	0.01	8.43	8.54	0.84	14.06	0.19	0.06
	1 year	55.75	0.52	9.54	10.3	0.44	20.88	0.11	2.46
	2 years	55.59	0.55	9.62	10.26	0.44	20.96	0.12	2.46

Notes. Forecast error variance decomposition of the observables used for the estimation of the model, at different horizons. The decompositions are calculated at the estimated posterior means. Each row presents the decomposition for a given observable, columns correspond to different structural shocks that feature in the model: TFP-Total productivity shock; Inv-Investment shock; Pref-Preference shock; Price-Price markup shock; Wage-Wage markup shock; Gov-Government spending shock; Mon-Monetary policy shock; Fin-Financial shock. Appendix F.1 contains details on the model and specification of the structural shocks.

Table F.5: VARIANCE DECOMPOSITION OF OBSERVABLES FOR ESTIMATED MODEL VERSION WITH $\chi = 0.2$ (IN %)

Variable	Horizon	TFP	Inv	Pref	Price	Wage	Gov	Mon	Fin
Output growth	1 quarter	19.02	7.41	18.65	16.76	6.91	13.77	15.60	1.88
	1 year	20.57	15.49	26.64	11.55	7.78	7.85	8.90	1.23
	2 years	20.28	21.00	26.66	10.00	6.66	6.71	7.57	1.11
Consumption growth	1 quarter	11.40	12.72	35.12	7.42	13.28	1.43	18.40	0.22
	1 year	11.50	11.45	44.61	6.21	12.24	1.44	12.36	0.18
	2 years	11.26	17.23	42.61	5.51	10.87	1.29	11.08	0.17
Investment growth	1 quarter	9.24	74.54	3.70	3.89	3.56	0.28	4.71	0.08
	1 year	10.11	75.26	5.19	3.44	2.99	0.42	2.52	0.06
	2 years	11.56	73.07	6.61	3.35	2.63	0.55	2.15	0.07
Inflation	1 quarter	13.20	18.88	7.27	28.03	19.18	2.38	10.29	0.76
	1 year	10.58	34.75	15.84	14.41	10.17	2.15	11.75	0.35
	2 years	14.97	40.51	20.72	9.51	6.00	1.83	6.29	0.17
Interest rate	1 quarter	2.52	6.46	3.21	6.24	4.52	1.27	75.66	0.13
	1 year	2.52	28.18	12.69	4.01	5.09	1.58	45.77	0.15
	2 years	7.56	40.65	17.09	3.55	3.09	1.42	26.55	0.10
Employment growth	1 quarter	18.26	8.72	22.43	6.46	11.94	17.63	14.55	0.00
	1 year	19.17	12.40	30.13	6.40	10.92	10.94	10.03	0.01
	2 years	19.50	15.00	30.47	5.90	9.97	9.86	9.27	0.02
Wage growth	1 quarter	36.76	0.42	2.13	38.78	20.62	0.60	0.07	0.61
	1 year	38.86	0.59	2.74	35.47	20.05	0.57	1.11	0.60
	2 years	38.01	1.64	2.72	35.08	19.99	0.57	1.35	0.63
Credit growth	1 quarter	20.00	10.27	1.30	15.88	16.85	0.01	13.64	22.06
	1 year	13.56	17.84	5.78	11.98	11.64	0.58	22.56	16.06
	2 years	13.47	24.75	7.00	10.45	9.92	0.59	20.05	13.78

Notes. Forecast error variance decomposition of the observables used for the estimation of the model, at different horizons. The decompositions are calculated at the estimated posterior means. Each row presents the decomposition for a given observable, columns correspond to different structural shocks that feature in the model: TFP-Total productivity shock; Inv-Investment shock; Pref-Preference shock; Price-Price markup shock; Wage-Wage markup shock; Gov-Government spending shock; Mon-Monetary policy shock; Fin-Financial shock. Appendix F.1 contains details on the model and specification of the structural shocks.

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