Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations*

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May 26, 2020

Abstract

Microeconomic evidence on US corporate credit reveals a direct connection between firms' current earnings and their access to debt. This paper studies the macroeconomic implications of earnings-based borrowing constraints. In a theoretical model, earnings-based constraints imply that firms borrow more in response to positive investment shocks, whereas collateral constraints imply that they borrow less. The credit dynamics following identified investment shocks in both macro and firm-level data behave according to the predictions of the model with earnings-based borrowing constraints. In an estimated quantitative model with nominal rigidities, earnings-based constraints generate procyclical markups and imply a more important role for supply shocks than collateral constraints do.

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

*I am indebted to Silvana Tenreyro, Wouter Den Haan, Ricardo Reis and Per Krusell for continued advice and support. For useful comments, I thank Konrad Adler, Philippe Aghion, Andrea Alati, George-Marios Angeletos, Juan Antolin-Diaz, Boragan Aruoba, Adrien Auclert, Neele Balke, Miguel Bandeira, David Baqaee, Charlie Bean, Matteo Benetton, Adrien Bussy, Francesco Caselli, Laura Castillo, Alex Clymo, Pierre De Leo, Andy Ek, Neville Francis, Simon Gilchrist, Dan Greenwald, James Graham, John Haltiwanger, Jim Hamilton, Ben Hartung, Kilian Huber, Jay Hyun, Ethan Ilzetzki, Nir Jaimovich, Rustam Jamilov, Diego Kaenzig, Sebnem Kalemli-Ozcan, Nobu Kiyotaki, Felix Koenig, Sevim Koesem, Andrea Lanteri, John Leahy, Chen Lian, Ralph Luetticke, Yueran Ma, Davide Melcangi, Ben Moll, John Moore, Daniel Paravisini, Ivan Petrella, Jonathan Pinder, Lukasz Rachel, Morten Ravn, Soren Ravn, Claudia Robles-Garcia, Valerie Ramey, Federico Rossi, Felipe Saffie, Philipp Schnabl, John Shea, Kevin Sheedy, Lumi Stevens, Paolo Surico, Roman Sustek, Martin Uribe, Horng Wong, Mike Woodford, Jasmine Xiao, Shengxing Zhang, as well as seminar participants at Boston College Finance, CEBRA, the CEPR Financial Markets and Macroeconomic Performance conference, Columbia University, CREI, Duke Fuqua, the European Central Bank, the EDP Jamboree at EUI, the EEA in Cologne, the Federal Reserve Board, Georgetown University, George Washington University, Ghent University, the IMF, LBS TADC, LSE Economics, LSE Finance, the Midwest Macro Meetings in Madison, the New York Fed, Notre Dame University, the Ruhr Graduate School, the San Francisco Fed, the St. Louis Fed, UC San Diego, University of Copenhagen, University of Maryland Economics, University of Maryland Finance, University of Zurich, Warwick University, and the Young Economists Symposium at NYU. I acknowledge financial support from the Economic and Social Research Council, the Centre for Macroeconomics and the Sho-Chieh Tsiang scholarship.

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1 Introduction

Firm credit displays large swings which correlate with fluctuations in output, employment and investment. To understand this comovement, macroeconomists study the constraints to credit and how these constraints feed back to economic activity. This paper investigates the macroeconomic consequences of earnings-based constraints on firm borrowing. The focus on earnings-based credit constraints is in contrast with asset-based collateral constraints, which have become a cornerstone of many business cycle models. It is motivated by direct evidence on the importance of firms' current earnings flows for their access to debt. Micro data covering more than 50,000 loans to 15,000 US companies reveals the pervasive use of earnings-based loan covenants that make it difficult for firms to borrow when their current earnings are low.[1] The contribution of this paper is to develop a model-driven strategy to test for the economic relevance of earnings-based constraints in both macro and micro data, and to demonstrate that the constraint alters fundamental quantitative conclusions about US business cycles.

Earnings-based borrowing constraints imply credit dynamics that differ from the ones generated by collateral constraints. I study credit dynamics in a theoretical model in which debt can be restricted either by a multiple of the firm's current earnings or by a fraction of its capital. Depending on the 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 cause more investment, increased activity and stronger earnings, while they reduce the price of capital relative to other goods. As a consequence, the increase in earnings allows for more debt under the earnings-based constraint, whereas the lower value of capital reduces credit access with the asset-based collateral constraint.

I use the diverging predictions regarding the response of borrowing to investment shocks as a strategy to disentangle which type of credit constraint is more relevant empirically. In both macro and micro data, my findings establish the importance of earnings-based constraints. At the aggregate level, my empirical strategy is based on a structural vector autoregression (SVAR). I apply identification schemes in which investment shocks are identified from their low-frequency impact on the relative price of equipment investment. This follows the idea that low-frequency movements of the relative price of investment purely reflect technology.[3] Based on long-run restrictions (following Fisher, 2006), as well as medium-run restrictions (following Francis, Owyang, Roush, and DiCecio, 2014), I find that business sector debt increases in

[1] My motivating facts build on existing empirical studies on corporate credit constraints, in particular the work of Lian and Ma (2019). See also Greenwald (2018) for a discussion of the presence of income-based in addition to asset-based borrowing limits in mortgage contracts.

[2] My use of the term investment shock encompasses different variations, including investment-specific technology shocks and marginal efficiency of investment shocks. I provide details in the text. Justiniano, Primiceri, and Tambalotti (2010, 2011) show that these shocks are an important driver of business cycles.

[3] Specifically, the shock is identified from its impact on the price of new equipment. This is consistent with the loan-level data, where equipment is the largest category of collateral, ahead of real estate. I also verify that the shock reduces the price of *used* equipment goods, since in practice both new and used assets could serve as collateral.

response to a positive investment shock, supporting the economy-wide relevance of earnings-based constraints. In line with the model, earnings rise and the value of the capital stock falls.

At the firm-level, I study the borrowing response of individual firms to investment shocks for different borrower types. Using the merged Dealscan-Compustat quarterly database, I classify firms into those that face earnings-based covenants and those that borrow against collateral. Resorting to a panel-version of the local projection method of Jordà (2005), I regress individual firm borrowing on the macro investment shock extracted from the SVAR and allow for heterogeneous responses across earnings and collateral borrowers. To address endogenous selection into borrower types, I control for rich firm characteristics and use different fixed-effect specifications. The results show that earnings-based borrowers significantly and persistently increase borrowing in response to a positive investment shock. The credit response of collateral borrowers is either negative or flat depending on the specification, and the null hypothesis of equal responses across borrower types is always formally rejected. Similar findings hold for the response of firm-level investment, which highlights that identifying the relevant borrowing constraint is crucial for understanding fluctuations in economic activity.

Having established the empirical relevance of earnings-based borrowing constraints, I next study their quantitative implications for business cycles. Earnings-based constraints interact with the New Keynesian sticky price assumption much more directly than collateral constraints do. The New Keynesian transmission mechanism has the well-known feature that demand shocks imply countercyclical markups, whereas supply shocks imply procyclical markups (see e.g. Nekarda and Ramey, 2019). All else equal, higher markups translate into higher earnings, so the earnings-based borrowing constraint loosens when markups rise. Since credit is strongly procyclical empirically, the constraint represents a friction that renders procyclical markups more consistent with the data. Relative to a collateral constraint, its presence should thus imply that either prices are not sticky in a meaningful way or that supply shocks are quantitatively more important than demand shocks, or a combination of the two.

Earnings-based credit constraints therefore change fundamental quantitative conclusions about US business cycles. To verify the logic around sticky prices and markup cyclicality, I extend my model to a medium-scale New Keynesian dynamic stochastic general equilibrium (DSGE) model, which includes nominal rigidities as well as a host of other frictions alongside earnings-based constraints to firm borrowing. I estimate this model on US postwar data and compare its features to those of the same model estimated with traditional collateral constraints. I find three major differences between an earnings-based and a collateral constraint in the estimated model. First, a higher unconditional correlation between firms' price markups and output (+0.48 vs. -0.01). Second, a significantly lower estimate of price stickiness when firms borrow against earnings rather than collateral, and third, a larger contribution of supply shocks to output growth fluctuations (42% vs. 29%). The quantitative exercise thus demonstrates that the formulation of credit constraints not only matters for credit dynamics and the micro and macro level, but that it interacts in a substantive way with the central transmission mechanism of New Keynesian

DSGE models, which have become a key modeling framework in macroeconomics. 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 that studies the role of financial frictions in macroeconomics, which goes back to the seminal work of Bernanke and Gertler (1989), Shleifer and Vishny (1992), and Kiyotaki and Moore (1997).[4,5] In a retrospective on business cycle models, Kehoe, Midrigan, and Pastorino (2018) emphasize the importance of disciplining macro models with direct micro evidence. In this spirit, my paper builds on microeconomic evidence on firm credit to study macroeconomic fluctuations.

Second, the motivating evidence I build my analysis on draws on existing insights, mostly from the empirical corporate finance literature, on loan covenants and on the relevance of current earnings for credit access more broadly. Important contributions are Chava and Roberts (2008) and Sufi (2009), who emphasize the widespread use of covenants in corporate debt contracts.[6] Based on a comprehensive empirical analysis, Lian and Ma (2019) propose that the key constraint to firm debt are cash flows measured by earnings and causally identify the extent to which increases in earnings as opposed to assets relax borrowing constraints at the micro level.[7] They also show theoretically that cash-flow based lending may dampen financial accelerator effects. More recently, 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 theoretical insight to verify the relevance of earnings-based constraints in both macro and micro data. Moreover, I build a quantitative DSGE framework that encompasses additional frictions, which I use to study how different constraints affect fundamental conclusions about the macroeconomy, such the strength of price rigidities and the relative importance of supply and demand shocks.

Third, there are a few existing papers with models in which flow variables rather than assets restrict borrowing, including Kiyotaki (1998). My paper explicitly compares the consequences

[4] Quadrini (2011) provides a survey on financial frictions in macro. Recent research includes Geanakoplos (2010), Rampini and Viswanathan (2010, 2013), Gertler and Karadi (2011), Liu, Wang, and Zha (2013), Khan and Thomas (2013), Buera and Moll (2015), Azariadis, Kaas, and Wen (2016), Cao and Nie (2017) and Guerrieri and Lorenzoni (2017). Kocherlakota (2000) and Cordoba and Ripoll (2004) investigate the quantitative importance of collateral constraints. While collateral constraints are typically based on limited contract enforcement, another class of financial frictions is based costly state verification, in particular Carlstrom and Fuerst (1997) and Bernanke, Gertler, and Gilchrist (1999). For a quantitative application see Christiano, Motto, and Rostagno (2014).

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

[6] Other papers that focus on covenants include Dichev and Skinner (2002), Roberts and Sufi (2009a, 2009b), Nini, Smith, and Sufi (2012), Bradley and Roberts (2015) and Falato and Liang (2017). Chodorow-Reich and Falato (2017) study empirically how bank health transmitted to the economy via covenants during the 2008-09 financial crisis.

[7] An earlier paper that aims to identify the determinants of borrowing constraints at the micro level, but does not focus on earnings constraints, is Chaney, Sraer, and Thesmar (2012). Recent work by Adler (2018) studies the impact of covenants on investment, by focusing directly on covenant breaches as well as on precautionary motives.

of different flow-related and collateral constraints on firms. In particular, I provide a detailed theoretical exploration to show that the difference between earnings-based and collateral constraints is not driven by the flow vs. stock distinction, but by the definition of earnings as opposed to other financial flow indicators.[8] Greenwald (2018) proposes a model with both (flow-based) payment-to-income limits and (collateral-based) loan-to-value constraints on household mortgage borrowing.[9] I focus on corporate debt rather than on household mortgages.

Fourth, my paper relates to the literature on investment shocks, which includes theoretical work such as Greenwood, Hercowitz, and Krusell (2000), and papers that identify investment shocks in SVARs building on Fisher (2006). Justiniano, Primiceri, and Tambalotti (2010, 2011) investigate the role of investment shocks in US business cycles and find them to be a key force behind output fluctuations.[10] I contribute to this literature by analyzing credit dynamics that arise from investment shocks. Furthermore, to the best of my knowledge, nobody has explored investment shocks as a tool to distinguish different forms of financial frictions.

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

Finally, the insights on the interaction between earnings-based borrowing constraints and sticky prices speak to a broader discussion around the cyclical behavior of markups in New Keynesian models and the data, as summarized by Nekarda and Ramey (2019). My analysis demonstrates that studying credit constraints sheds new light on this discussion, and on the implications of the New Keynesian transmission mechanism more broadly.

Structure of the paper. Section 2 presents microeconomic evidence motivating the focus on earnings-based borrowing constraints. Section 3 introduces a business cycle model that features an earnings-based constraint and discusses its implied dynamics in comparison to a collateral constraint. Section 4 verifies the model predictions for investment shocks using both SVAR analysis on aggregate data and panel local projections on firm-level data. Section 5 explains the interaction between earnings-based borrowing constraints, sticky prices and markups. Guided by this explanation, Section 6 presents a quantitative New Keynesian DSGE model estimated with different credit constraints and discusses the different results. Section 7 concludes.

[8] See also Jappelli and Pagano (1989) in the context of the permanent income hypothesis and Arellano and Mendoza (2002), Mendoza (2006), Bianchi (2011) and Korinek (2011) in the context of sovereign debt. Brooks and Dovis (2018) examine the sensitivity of credit constraints to profit opportunities in a trade framework. Li (2016) studies how the lack of pledgeability of both assets and earnings reduces aggregate productivity in Japan.

[9] A related study is Corbae and Quintin (2015). See also the constraint in Kaplan, Mitman, and Violante (2017). Earlier work on the role of mortgages in business cycle typically focuses on collateral, for example Iacoviello (2005).

[10] See also Schmitt-Grohe and Uribe (2012). Papanikolaou (2011) provides an application to asset pricing.

2 Motivating evidence on earnings-based corporate borrowing

This section presents motivating microeconomic evidence on corporate borrowing in the US economy. More than 50,000 loan deals issued to 15,000 firms reveal that earnings are the key indicator which determines firms' access to funds. This echoes the analysis of Lian and Ma (2019), who also present detailed evidence that US firms primarily borrow based on earnings.[11]

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 measurable indicators, for which a numerical maximum or minimum value is specified. For example, a covenant may state that "the borrower's debt-to-earnings ratio must be below 4". Covenant breaches lead to technical default, which gives lenders the right to call back the loan. In practice, a breach can lead to various outcomes, including renegotiations of higher interest rates or other changing conditions in the contract. Importantly, breaches have been shown to occur frequently with large economic effects. Roberts and Sufi (2009a) find that net debt issuing activity experiences a large and persistent drop immediately after a covenant violation.[12]

Table 1: LOAN COVENANT TYPES, VALUES AND FREQUENCY

	Covenant type	p25	Median	p75	Mean	Frequency
1	Max. Debt to EBITDA	3.00	3.75	5.00	4.60	60.5%
2	Min. Interest Coverage (EBITDA / Interest)	2.00	2.50	3.00	2.56	46.7%
3	Min. Fixed Charge Coverage (EBITDA / Charges)	1.10	1.25	1.50	1.42	22.1%
4	Max. Leverage ratio	0.55	0.60	0.65	0.64	21.3%
5	Max. Capex	6M	20M	50M	194M	15.1%
6	Net Worth	45M	126M	350M	3.2B	11.5%

Note: The table list the most pervasive covenant types, sorted by their frequency in the Dealscan loan data. Covenant types with a frequency above 10% are included. As there can be more than one covenant per loan, the frequency adds up to more than 100%. EBITDA abbreviates earnings before interest, taxes, depreciation and amortization. As indicated in brackets, a minimum interest coverage covenant links to the ratio of EBITDA to interest expenses and a minimum fixed charge coverage covenant to the ratio of EBITDA to fixed loan charges. The sample consists of loan deals with at least one loan covenant, issued between 1994 and 2015 by US nonfinancial corporations. The 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, sorted by their frequency of use, in the *ThomsonReuters LPC Dealscan* database. For the United States, this data covers around 75% of the total commercial loan market in terms of volumes.[13] The covenant frequency is calculated for loans that feature at least one covenant and contains the median,

[11]In addition to building a macro model that features this type of borrowing in the next section, I discuss theoretical microfoundations for the presence of earnings-based debt contracts in Appendix B.

[12]Chava and Roberts (2008) find strong effects of breaches on investment and Falato and Liang (2017) strong effects on employment. Chodorow-Reich and Falato (2017) show that one third of US nonfinancial firms breached their covenants during the 2008-09 financial crisis.

[13]The data contain rich information, including the identity of borrower and lender, the amount, maturity, interest rate and, importantly, loan covenants. The unit of observation is a loan *deal*, which consists of loan *facilities*. Appendix A contains further information and summary statistics. In Section 4.3, I merge the Dealscan data to *Compustat*.

25th and 75th percentile as well as the value-weighted mean of the covenant value, that is, the numerical maximum (minimum) that restricts a given indicator. The key take-away from the table is that the three most frequently used covenants are all related to earnings. The specific earnings measure is EBITDA, which measures earnings before interest, taxes, depreciation and amortization. EBITDA is a widely used indicator of a firm's economic performance. It captures firm profits 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 implies that the level of debt cannot exceed earnings by a multiple of 4.6 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. I interpret this widespread use of earnings-based covenants as evidence that the flow of current earnings is an important determinant of companies' access to debt. The key questions of this paper are whether credit dynamics observed in macro and firm-level data support this interpretation, and how it affects fundamental conclusions about aggregate fluctuations.

Further channels through which earnings affect debt access. Loan covenants are a direct manifestation of current earnings constraining access to debt, as they are explicitly written into contracts. 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.[14] Furthermore, scrutiny of earnings by lenders could come in the form of internal credit risk models that use earnings as an input or be based on reference levels in earnings ratios that lenders are accustomed to consider without explicitly using covenants. Accordingly, the model of Section 3 will not be a model of covenants, but will capture the broader interpretation that current firm earnings affect their access to credit.

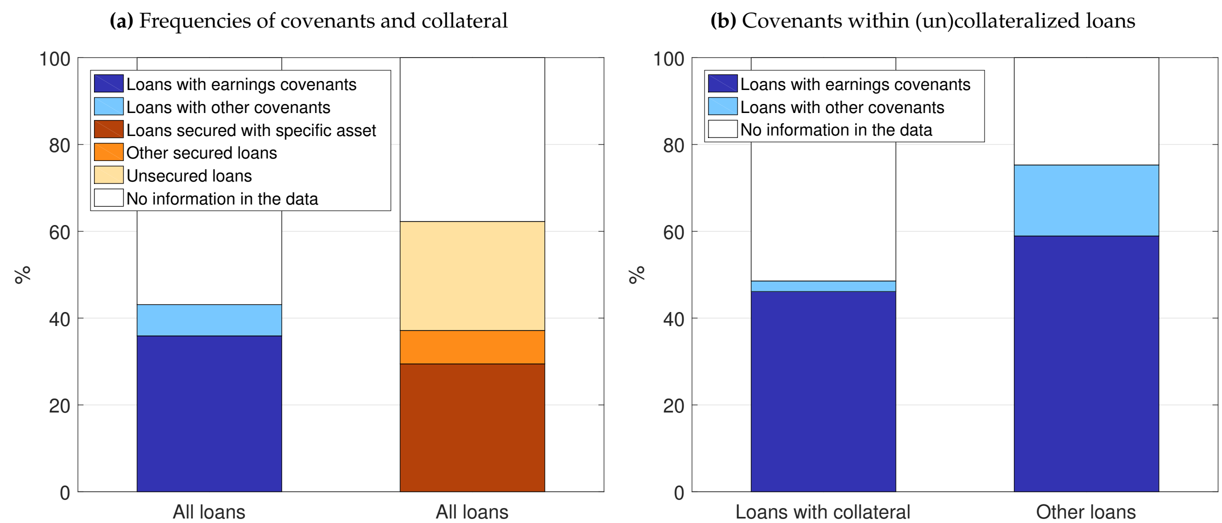
Earnings-based vs. asset-based lending. Figure 1 analyzes the value-weighted frequency of loan covenants and of collateral, that is, debt that is secured with specific assets. This is an important comparison, as business cycle research has put a strong emphasis on modeling credit frictions via collateral constraints. Panel (a) compares value-weighted shares of different loan characteristics. 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).[15] The left bar indicates that earnings-based covenants, which dominate

[14] According to Standard & Poor's Global Ratings (2013), the financial risk profile of corporations is assessed based on *core ratios*, which are the funds from operations (FFO)-to-debt and the debt-to-EBITDA ratio, as well as *supplemental ratios*, which relate to other operating cash flow measures.

[15] According to Lian and Ma (2019), loans secured with "all assets" in Dealscan should be classified as cash-flow based loans, 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 that are backed by "all assets" to the category called "Other secured loans". I thank Yueran Ma and Chen Lian for a helpful discussion.

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. 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.

Figure 1: THE IMPORTANCE OF EARNINGS-BASED AND ASSET-BASED DEBT IN COMPARISON



Note: 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. The sample consists of loan deals issued between 1994 and 2015 by US nonfinancial corporations.

Taking stock of the evidence. Detailed loan information at the micro level suggests that earnings-based borrowing is pervasive, likely exceeding the prevalence of asset-based borrowing. Lenders require that conditions on the borrower's EBITDA are fulfilled, directly linking firms' debt capacity to their current earnings. This happens via covenants, explicitly written into contracts, and potentially through additional channels such as credit ratings.

3 A business cycle model with earnings-based borrowing

This section introduces an earnings-based constraint on firm borrowing which formalizes the microeconomic evidence. I set up a prototype business cycle model to study the dynamics that arise from this constraint, in comparison with a traditional asset-based constraint, as it appears in many existing models. To derive differential predictions, I use the model to analyze a structural shock that moves earnings and the value of collateral in opposite directions: the investment shock. Section 6 extends the model to a quantitative framework with nominal rigidities.

3.1 Model environment

Time is discrete, denoted by t, and continues infinitely. The frequency is quarterly. The economy is populated by a representative firm and a representative household. There is a government which runs a balanced budget.

3.1.1 Firm problem

The firm produces a final consumption good using capital, which it owns and accumulates, and labor, which it hires on a competitive labor market taking the wage rate w_t as given. The consumption good is produced with a Cobb-Douglas production function

$$y_t = z_t k_{t-1}^{\alpha} n_t^{1-\alpha}, \tag{1}$$

and its price is normalized to 1. $\alpha \in (0,1)$ is the capital share in production. Total factor productivity (TFP), z_t, is subject to stochastic shocks. The firm's period earnings flow, or operational profits, is denoted as π_t and defined as

$$\pi_t \equiv y_t - w_t n_t. \tag{2}$$

This definition corresponds to EBITDA: sales net of overhead and labor costs, without subtracting investment, interest payments or taxes. Hence, the model definition of earnings is in line with the evidence provided in Section 2. π_t is the measure that will enter the firm's earnings-based borrowing constraint to be introduced below. Capital k_{t-1} is predetermined at the beginning of the period and its law of motion is

$$k_t = (1-\delta)k_{t-1} + v_t\left[1 - \Phi_t\left(\frac{i_t}{i_{t-1}}\right)\right] i_t, \tag{3}$$

where δ is the depreciation rate and the term $\Phi_t\left(\frac{i_t}{i_{t-1}}\right)$ introduces investment adjustment costs. I assume that $\Phi_t(1) = 0$, $\Phi'_t(1) = 0$, and $\Phi''_t(1) = \phi_t > 0$. The t subscript captures stochastic shocks to adjustment costs. Importantly, v_t is a stochastic disturbance. In the environment presented here, it captures both the level of the economy's investment specific technology (IST) as well as its marginal efficiency of investment (MEI). I refer to shocks to v_t simply as *investment shocks* and to the composite term $v_t\left[1-\Phi_t\left(\frac{i_t}{i_{t-1}}\right)\right]$ as the *investment margin*.[16] Both the presence of investment adjustment costs as well as v_t will lead to variation in the market value of capital. In the case of adjustment costs, this arises from the standard result that adjustment costs move the value of capital inside the firm relative to its replacement value, that is, they affect the ratio known as *Tobin's Q*. In the case of v_t, it is important to note that even in the absence of any adjustment costs, this disturbance will be inversely related to the relative price of k_t in consumption units. To see this, consider the flow of funds constraint of the firm, in units of the consumption good:

$$\Psi(d_t) + i_t + b_{\pi,t-1} + b_{k,t-1} = y_t - w_t n_t + \frac{b_{\pi,t}}{R_{\pi,t}} + \frac{b_{k,t}}{R_{k,t}}. \tag{4}$$

$\Psi(d_t)$ denotes the dividend (equity payout) function, and the b terms capture debt financing, both of which will be explained further below. Setting $\Phi_t(\cdot) = 0$ and substituting i_t from equation (3) into (4), it can be seen that the relative price of capital is the inverse of v_t:

$$\Psi(d_t) + \frac{k_t}{v_t} + b_{\pi,t-1} + b_{k,t-1} = y_t - w_t n_t + \frac{(1-\delta)k_{t-1}}{v_t} + \frac{b_{\pi,t}}{R_{\pi,t}} + \frac{b_{k,t}}{R_{k,t}}. \tag{5}$$

This observation about the inverse of v_t driving the relative price of capital will play a key role in the dynamics of debt following investment shocks under different borrowing constraints.

The firm has two means of financing, equity and debt. d_t denotes equity payouts and $\Psi(d_t)$ captures costs related to equity payouts and issuance. Following Jermann and Quadrini (2012),

$$\Psi(d_t) = d_t + \psi(d_t - \bar{d})^2, \tag{6}$$

where $\bar{d}$ is the long run dividend payout target (the steady state level of d_t). Equation (6) captures in reduced form the fact that raising equity is costly and that there are motives for dividend smoothing.[17] Debt financing can be undertaken in the form of two alternative one-period risk-free bonds, denoted $b_{\pi,t}$ and $b_{k,t}$, where $b_{\pi,t-1}$ and $b_{k,t-1}$ are predetermined at the beginning of period t. The effective gross interest rates faced by firms are $R_{\pi,t}$ and $R_{k,t}$, and are both subject to a tax advantage, captured by τ_π and τ_k, of the following form:

$$R_{j,t} = 1 + r_{j,t}(1-\tau_j), \quad j \in \{\pi, k\} \tag{7}$$

where $r_{\pi,t}$ and $r_{k,t}$ are the interest rates received by lenders. This creates a preference for debt over equity and makes the firm want to borrow up to its constraint. The household does not

[16] IST captures the efficiency at which consumption is turned into investment, while MEI represents the efficiency at which investment is turned into installed capital. Both types of disturbances have been studied, e.g. by Greenwood, Hercowitz, and Krusell (2000) and Justiniano, Primiceri, and Tambalotti (2011). The key difference is that IST corresponds empirically to the inverse of the relative price of investment, while MEI does not have a clear empirical counterpart. This will come into play when taking my model predictions to the data in Section 4.

[17] Altinkilic and Hansen (2000) provide evidence of increasing marginal costs in equity underwriting. Discussions of dividend smoothing motives go back to Lintner (1956).

receive this tax rebate and thus wants to lend funds in equilibrium. This type of tax exists in many countries and the related modeling assumption follows Hennessy and Whited (2005).

Introduction of alternative borrowing constraints. Both types of debt are subject to borrowing constraints, which are formulated in consumption units and which I specify as

$$\frac{b_{\pi,t}}{1+r_{\pi,t}} \leq \theta_\pi \pi_t \tag{8}$$

and

$$\frac{b_{k,t}}{1+r_{k,t}} \leq \theta_k \mathbb{E}_t p_{kt+1}(1-\delta)k_t. \tag{9}$$

I will study calibrations in which firms borrow up to either one or the other constraint. In the earnings-based constraint (8), debt is limited by a multiple $\theta_\pi > 1$ of current earnings, π_t. I also allow a more general form, in which $f(\pi_{t-3}, \pi_{t-2}, \pi_{t-1}, \pi_t, \mathbb{E}_t\pi_{t+1})$ enters on the right hand side, and $f(\cdot)$ is a linear polynomial. This captures the idea that loan covenant indicators in practice are typically calculated as 4-quarter trailing averages (see Chodorow-Reich and Falato, 2017). An alternative formulation of the earnings-based constraint would be one that captures the interest coverage ratio, that is, a constraint on $r_{j,t}b_{j,t}$. 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).[18] 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 $p_{k,t+1}$. In the borrowing constraint, $p_{k,t+1}$ may reflect price of capital in different ways. Specifically,

$$p_{k,t} = \begin{cases} Q_t & \text{if collateral is priced at market value} \\ \frac{1}{v_t} & \text{if collateral is priced at replacement cost} \end{cases} \tag{10}$$

where Q_t is the market price of capital, to be determined in equilibrium. In the presentation of the main results, I will focus on the market value formulation. However, two observations are important to emphasize. First, in the presence of investment shocks the replacement value of capital is not 1 but $1/v_t$, as the contract is denominated in consumption units. The equilibrium value of Q_t will also be inversely related to v_t but will be additionally affected by adjustment costs. If adjustment costs are set to zero, the market value and replacement cost of capital coincide at $1/v_t$. This means that both the market value and the replacement cost reflect the main mechanism in which an increase in v_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. When studying the model, I provide a robustness check in this direction. In the empirical analysis, I use both new and secondary market investment goods prices as proxies for p_k.

[18]In a recent paper, Greenwald (2019) investigates the role of coverage ratio covenants in the transmission of monetary policy.

Rationalization of borrowing constraints. Borrowing constraints reflect underlying frictions which hinder debt issuance, such as information or enforcement limitations. Typically, a collateral constraint emerges as the optimal solution in a setting in which borrowers have the ability to divert funds or withdraw their human capital from a project (see for example Hart and Moore, 1994). In the case of the earnings-based borrowing constraint, one interpretation is that the borrower has the ability to divert funds, in which case the lender can seize 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, something very 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 sketch out a specific formal environment that captures the first of these interpretations. In that appendix, I also discuss the existing literature on the microfoundations of loan covenants and provide additional details on relevant regulation.

Naturally, the formalization of the constraints ignores some differences between asset-based loans and loans subject to earnings covenants. For example, while collateral is pledged upon origination and may be seized in the case of default, covenants can be exercised at any point during the lifetime of a loan. I abstract from these differences on two grounds. First, the fact that only the variable entering the right hand side of the debt limit differs between (8) and (9) allows for transparency in characterizing the consequences. Second, the Dealscan data shows that the maturity of corporate debt is relatively short, in particular compared to household debt.[19]

Firm's maximization problem. The objective of the firm is to maximize the expected discounted stream of the dividends paid to its owner, that is, its maximization program is

$$\max \ \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_t d_t \tag{11}$$

subject to (1), (2), (3), (4), (6), and either of the borrowing constraints (8) or (9). The term Λ_t in the objective function is the firm owner's stochastic discount factor between periods 0 and t. The firm's optimality conditions are shown in Appendix C.1.

3.1.2 Household, government and equilibrium

Details on the household problem, the government and the definition of the equilibrium can be found in Appendix C.2. 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 runs a balanced budget in every period.

[19] In Dealscan, the average (median) maturity of loans in 52 (60) months, and the value-weighted share of loans that refinance a previous loan is 83%. For a treatment of long-term debt, see Gomes, Jermann, and Schmid (2016).

Table 2: MODEL PARAMETERIZATIONS

Parameter	Value	Details on parameterization
		(a) Structural parameters
α	0.33	Capital share of output of 1/3
δ	0.025	Depreciation rate of 2.5% per quarter
$\overline{\phi}$	4	Smets and Wouters (2007)
β	0.9752	Steady state annualized corporate loan rate of 6.6%*
χ	1.87	Target $n = 0.3$ in steady state
ψ	0.46	Jermann and Quadrini (2012)
		(b) Model with earnings-based constraint
θ_k	0	Shut off collateralized borrowing
τ_k	0	Shut off collateralized borrowing
θ_π	4.6×4	Average value of debt-to-EBITDA covenants*
τ_π	0.35	Following Hennessy and Whited (2005)
		(c) Model with collateral constraint
θ_k	0.817	Same steady state debt-to-output ratio as Panel (b)
τ_k	0.35	Following Hennessy and Whited (2005)
θ_π	0	Shut off earnings-based borrowing
τ_π	0	Shut off earnings-based borrowing

Note: Panel (a) describes the parameterization of the structural parameters which are the same independent of which type of constraint is specified to feature in the model. Panels (b) and (c) present the parameterizations that ensure that the firm faces either one or the other constraint. * indicates parameters that are calculated directly from Dealscan.

3.2 Model parameterization and specification

The stochastic processes are autoregressive of order one in logs. See Appendix C.3 for details. I specify the investment adjustment costs as a quadratic function that satisfies the functional form assumptions introduced by Christiano, Eichenbaum, and Evans (2005), that is,

$$\Phi_t\left(\frac{i_t}{i_{t-1}}\right) = \frac{\phi_t}{2}\left(\frac{i_t}{i_{t-1}} - 1\right)^2. \tag{12}$$

This specification gives a steady state market value of capital of 1. Furthermore, in steady state, $\Phi''(1) = \overline{\phi}$. Panel (a) of Table 2 summarizes the values I set for the structural parameters of the model. Most parameter values are standard in business cycle research for the US case or match standard moments in US macroeconomic data. I set $\overline{\phi} = 4$ in line with Smets and Wouters (2007). To parameterize β, I calculate the average interest rate faced by firms in the Dealscan database. Panels (b) and (c) of the table show the calibration of the parameters that are related to the alternative borrowing constraints (8) and (9). I investigate model dynamics using the simplification that either one or the other constraint is faced by the firm, exploiting the fact that the model nests these special cases. Each constraint can be shut off by parameterizing $\theta_j = \tau_j = 0$, for $j \in \{k, \pi\}$ and $\forall t$. In this case debt type j is in zero net supply and the other constraint binds at all times.[20] I set the tax advantage of debt τ_j to 0.35 following Hennessy and Whited (2005).

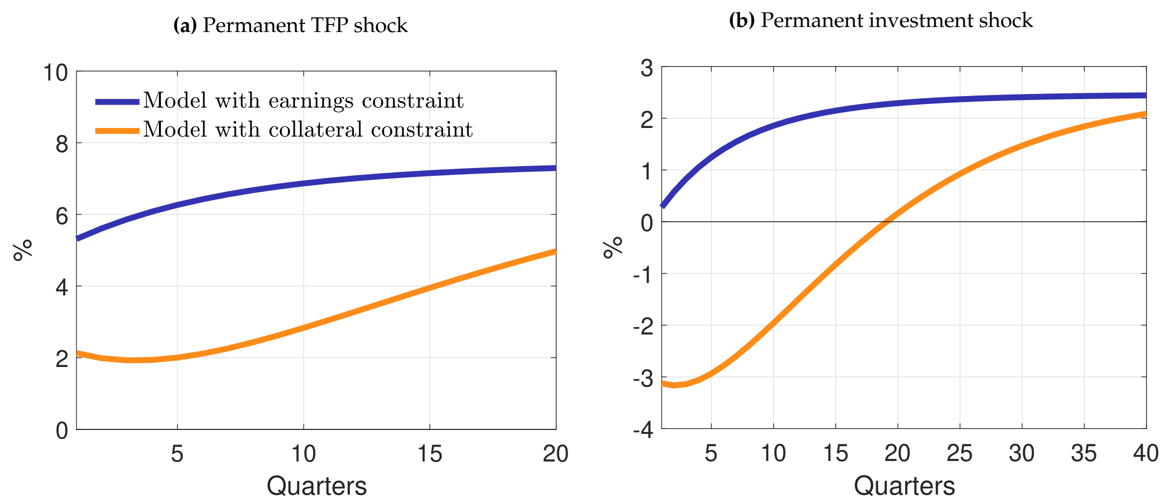
[20]Throughout my analysis I focus on binding borrowing constraints. This assumes that shocks are small enough in magnitude to keep the Lagrange multiplier on the constraint positive, that is, $\mu_{jt} > 0$, $j \in \{k, \pi\}$, $\forall t$. Modifying my

Regarding the tightness parameters of the constraints I proceed as follows. Using the Dealscan data I calculate the dollar-weighted mean covenant value of the debt-to-EBITDA covenant, which gives a value of $\theta_\pi = 4.6$ (see Table 1). As this value is for annualized EBITDA and my model is quarterly, I multiply by four. I then set the tightness of the collateral component to that value which achieves the exact same steady state debt-to-output ratio, which gives $\theta_k = 0.817$.

3.3 Credit dynamics implied by earnings-based vs. collateral constraints

Whether earnings-based and collateral constraints imply different credit dynamics depends on which shocks hit the economy. This is illustrated in Figure 2, which plots the IRFs of firm debt to a positive TFP shock and a positive investment shock.[21] The dark blue lines correspond to the model in which firms face the earnings-based constraint (see Panel (b) of Table 2), while the light orange lines are generated with a collateral constraint (see Panel (c)). While the responses of firm debt to the TFP shock are positive under both alternative borrowing constraints, the sign of the responses for the investment shock flip between one and the other parameterization. This implies the opposite comovement of debt with the shock. In other words, diverging conclusions about the dynamics of firm borrowing are drawn depending on the borrowing friction of the firm.

Figure 2: MODEL IRFS OF FIRM DEBT UNDER DIFFERENT BORROWING CONSTRAINTS



Note: The figure displays model IRFs of firm debt to different shocks, under two alternative calibrations in which only the earnings-based constraint (dark blue line) or only the collateral constraint (light orange line) is present. Panel (a) show the debt IRF to a positive TFP shock and Panel (b) to a positive investment shock. The parameters to generate these IRFs are shown in Table 2. I set $\rho_z = \rho_v = 1$ and $\sigma_z = \sigma_v = 0.05$. The figure highlights that the responses of debt to investment shocks have a different sign under the alternative borrowing constraints.

model to feature occasionally binding constraints would be relatively straightforward. This would make it feasible to also study possible switching effects between different types of borrowing constraints over the business cycle, similar to what Greenwald (2018) and Ingholt (2018) emphasize for the case of household mortgages.

[21] I show the results for permanent shocks since the SVAR methodology in Section 4 will allow me to identify permanent rather than transitory shocks in the data. The qualitative conclusions regarding the sign of the responses on impact are similar with transitory shocks. See also Figure 4 further below.

The intuition is as follows. The TFP shock raises both the firm's earnings as well as the market value of capital, supporting more debt under both constraints. While the magnitudes differ, the sign of the debt responses to this shock are therefore the same under the alternative constraints. This is different for the investment shock, which leads to higher efficiency in the economy's investment margin. This induces investment and stronger economic activity accompanied by growing earnings. However, the shock reduces the relative value of capital in consumption units. As a consequence, if the firm faces a collateral constraint, it needs to reduce its debt level, while it is able to borrow more in the face of an earnings-based constraint. This sign difference in the debt response will provide the testing ground for my empirical analysis in Section 4.

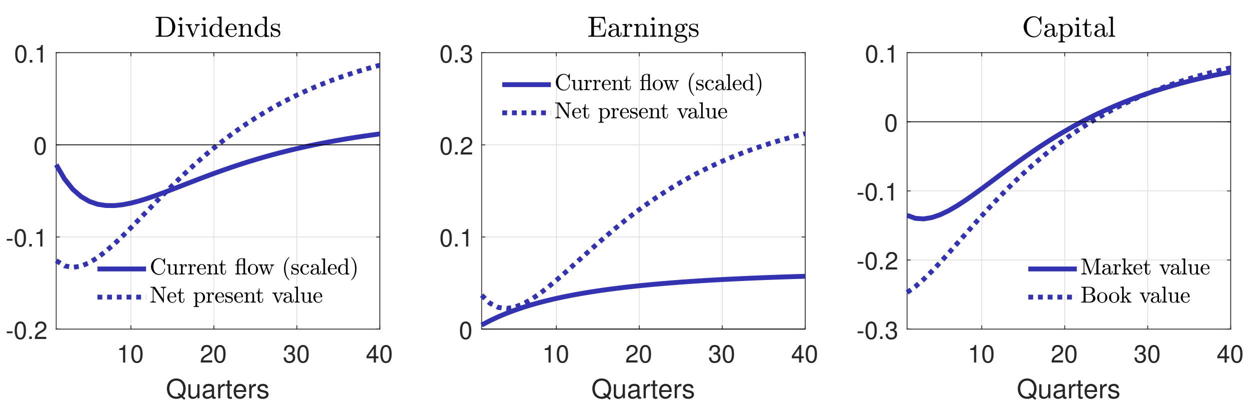
As an illustration of the mechanism, consider an airline. Imagine a scenario in which a shock – an exogenous technological innovation – makes the production of airplanes cheaper, which lowers their price relative to other goods in equilibrium. The implication of this shock for borrowing differs sharply depending on the relevant constraint. If airplanes serve as collateral, their falling relative value tightens the borrowing constraint. By contrast, the earnings-based borrowing constraint is relaxed as cheaper airplanes increase the airline's profitability.

3.4 Discussion: borrowing against flow vs. stock variables

The analysis above reveals the differences between two variables limiting the access to debt for firms: earnings and the value of capital, a *flow variable* and a *stock variable*, respectively. To further characterize the results, I highlight that the differences in the results do not arise from the flow vs. stock distinction, but from the fact that earnings are the specific flow measure that enter in the constraint. I begin with several observations that can be made on how the firm's market value and the flows to its owner relate to the specific variables entering the alternative credit constraint. First, in the equilibrium of the model, the market value of the firm corresponds to the NPV of *dividend* flows. That is, the firm's overall value is the infinite stream of d_t, discounted at the stochastic discount factor of the household $SDF_{t,t+1} \equiv \frac{\Lambda_{t+1}}{\Lambda_t} = \frac{\beta u_{c_{t+1}}}{u_{c_t}}$. We can define the market value of the firm recursively as $V_{d,t} = d_t + \mathbb{E}_t(SDF_{t,t+1}V_{d,t+1})$. Importantly, this value of flows is different both from the current earnings flow π_t as well as from the NPV of earnings flows, which can also be recursively defined as $V_{\pi,t} = \pi_t + \mathbb{E}_t(SDF_{t,t+1}V_{\pi,t+1})$. Second, in a neoclassical production economy, the market value of a firm is proportional to the capital it owns if specific conditions on technology are satisfied (see Hayashi, 1982): if technology is constant returns to scale and adjustment costs are homogeneous of degree 1 in k, it is the case that $V_{d,t} = Q_t k_{t-1}$. In this context Q_t is known as *Tobin's Q*. As a consequence of the two observations, if the conditions of Hayashi (1982) hold, the collateral constraint is equivalent to a constraint in which the firm's overall market value serves as collateral. In turn, this constraint would have an equivalent flow-related analogue, if the flows entering the constraint are all discounted future dividend flows. In this case, the two borrowing limits would be equivalent.

In light of these insights, we can see that the earnings-based borrowing constraint (8) and the collateral constraint (9) are *not* equivalent for two reasons. First, they differ in terms of the *flow* *definition*. The earnings-based constraint features earnings rather than dividends. Second, they differ in terms of the *flow timing*. The earnings-based constraint features a current flow variable rather than the NPV of all current and future flows. In the model, I can check directly which of these two differences drives the results in Figure 2, by comparing the responses of d_t, $V_{d,t}$, π_t, $V_{\pi,t}$ and $Q_t k_{t-1}$ to the investment shock. Figure 3 displays these IRFs as a comparison of different variables that could potentially limit borrowing. The figure 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 under the Hayashi conditions, both decline.[22] This leads to the counterfactual debt response with the collateral constraint. Hence, for the investment shock the difference in the debt response is driven by the flow *definition*. The main results of the model arise not because debt is constrained by a flow instead of by an asset value *per se*, but by the specific variable that defines this flow, current earnings.

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



Note: The figure displays 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 in the model (earnings and dividend flows are additionally scaled by 10). The net present values (NPVs) are recursively computed in the model using the household's stochastic discount factor.

3.5 Different shocks to the investment margin and other robustness

As discussed above, a shock to v_t can capture both an investment-specific technology (IST) and a marginal efficiency of investment (MEI) shock. For the purpose of the empirical verification of the mechanism in Section 4, I will focus on that component of v_t that captures IST. This allows me to establish a mapping of v_t to the data. In terms of the basic model mechanism, the distinction between these refined concepts is not of first order importance. To demonstrate this, Figure 4 plots

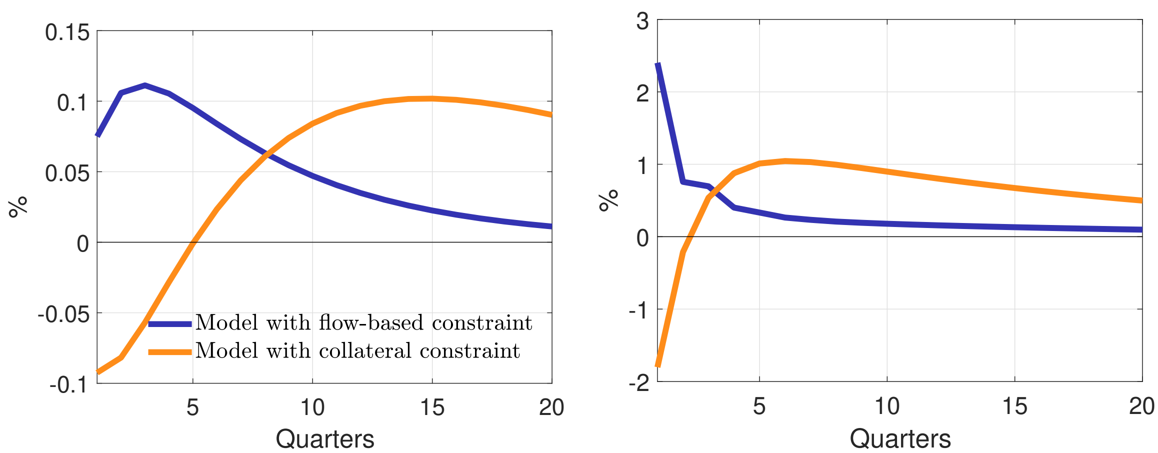
[22] Under the functional form chosen in (12), the Hayashi conditions are not satisfied (see also Jaimovich and Rebelo, 2009). However, in the calibration the numerical difference between NPV of dividends and the market value of capital is very small. In general, the specific form of adjustment costs is not crucial for my results.

two more sets of IRFs. In Panel (a), the IRFs to a negative transitory adjustment cost shock for the two model versions are plotted. It is evident that 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 Figure 2, 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 under the earnings constraint and a negative with the collateral constraint.

Figure 4: MODEL IRFS OF FIRM DEBT: ADDITIONAL INVESTMENT MARGIN SHOCKS

(a) Persistent adjustment cost shock

(b) Persistent investment shock



Note: The figure displays IRFs of firm debt to additional investment margin shocks generated from the model, under the two alternative calibrations in which only the earnings-based constraint (dark blue line) or only the collateral constraint (light orange line) is present. Panel (a) plots the IRFs to a negative adjustment costs shock with $\rho_\phi = 0.5$, $\sigma_\phi = 1$. Panel (b) repeats the investment shock IRFs from Figure 2 as a transitory but persistent rather than permanent shock ($\rho_v = 0.5$, $\sigma_v = 0.05$). The different signs across models show that the proposed mechanism is broad enough to carry through to different types of shock to the investment margin.

Robustness to earnings timing and to using historical costs. In Appendix C.5 I analyze a 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 of the indicator. The results for this specification are similar to the ones shown in Figure 2. The shape of the IRF changes due to the fact that current earnings will affect the borrowing ability also in future periods, but the sign of the response remains unchanged.

Both the market value of capital and its replacement cost are suppressed when v_t increases. In practice, some types of collateral may be at least in part evaluated based on historical costs (book value). To examine this idea, I study an alternative version of the model in which $p_{k,t}$ is calculated as an average over past capital prices $Q_{t-j}, j = 1, ..., 4$. The corresponding results are presented in Appendix C.6. The debt response under a collateral constraint is now more sluggish, as it takes time for the investment shock to be reflected into capital prices relevant for evaluation. The sign of the response, however, remains the same.

The dynamics of other variables. In deriving testable model predictions, I focus on the IRFs of debt and show the IRFs of remaining model variables in Appendix C.7. The appeal of this strategy is that debt dynamics are tied very directly to the alternative constraint formulation and are not driven by further modeling choices on the structure in which they operate. Interestingly, in a prototype neoclassical setting under standard calibrations, debt constraints themselves typically do not have strong effects on the model's overall dynamics.[23] Cordoba and Ripoll (2004) provide a detailed exploration of this insight. I show the responses of other variables only insofar as they help me to understand the different debt dynamics across parameterizations of the model. In the quantitative extension of the model in Section 6, I also study output dynamics.

4 Verifying the model predictions for investment shocks

This section uses the diverging predictions on the borrowing response to investment shocks as a strategy to disentangle which type of credit constraint is more relevant empirically. I resort to both aggregate and firm-level data, using an SVAR (Section 4.1 and 4.2) as well as a panel regression framework that allows for heterogeneous responses to shocks across borrower types (Section 4.3 and 4.4). Investment shocks can take the form of shocks to investment-specific technology (IST) as well as to marginal investment efficiency (MEI). The former type is directly tied to a readily available empirical counterpart, the inverse relative price of investment goods. While the interpretation of my model mechanism can be applied to both concepts, for the purposes of verifying the predictions empirically, I focus on a specific component of the investment margin, a shock to IST.[24] Specifically, I use equipment prices to construct this relative price, which is in line with the micro data.[25] Observable time series of this price have been exploited by previous research to identify IST shocks. My paper is the first one to use identified IST shocks to disentangle between different types of financial frictions.

4.1 SVAR on aggregate data

I specify an SVAR to estimate the impact of IST shocks on the US economy as a whole, using two identification schemes. First, I identify IST shocks using long-run restrictions building on the work of Fisher (2006).[26] Second, I use medium-run restrictions following Francis, Owyang, Roush, and DiCecio (2014). In addition, I set up a Monte Carlo experiment in which I repeatedly

[23] This is different when raising the value of ψ or when introducing working capital as in Jermann and Quadrini (2012). The predictions on the qualitative dynamics of total firm debt are not altered by these modifications.

[24] Justiniano, Primiceri, and Tambalotti (2011) emphasize that MEI shocks are more important for business cycles than IST shocks. MEI shocks, however, are not as directly identifiable as IST shocks. I find the IST shock to be reasonably important in terms of the variance decomposition of debt implied by the SVAR (see Appendix D.3).

[25] In a subset of the loan-level data from Dealscan, it is possible to directly observe the *type* of collateral that is used in loan facilities. After excluding non-informative categories such as "Other" and "Unknown", the category "Property & Equipment" is the largest one, three times as large as "Real Estate". See Table A.4 in the Appendix.

[26] Long-run restrictions are the most common way to identify technology shocks in SVARs. Blanchard and Quah (1989) and Gali (1999) are early contributions which focus on TFP.

run the SVAR model on data that I generate directly from the model, in order to check the SVAR's ability to distinguish between the alternative borrowing constraints. Finally, I also verify that the shock I identify reduces the price of used (secondary market) equipment goods. This is to alleviate the concern that I identify the shock from its negative impact of the price of new equipment, while both new and used capital may be pledged as collateral in practice.

4.1.1 SVAR setting and identifying assumptions

I begin by formally introducing the general setting that encompasses both identification methods. Consider the n-dimensional vector of macroeconomic time series Y_t, which follows

$$B_0 Y_t = B_1 Y_{t-1} + ... + B_p Y_{t-p} + u_t, \tag{13}$$

where the vector u_t denotes the structural shocks with covariance matrix $\Omega_u = I_n$. The model can be rewritten in its $MA(\infty)$-representation as

$$Y_t = B(L)^{-1} u_t, \tag{14}$$

where L denotes the lag operator. The structural shocks u_t are not identified unless additional restrictions are imposed on the parameters of the system.

Identification using long-run restrictions. The idea is to impose identifying assumptions on the long-run multiplier $B(1)^{-1} = [B_0 - B_1 - ... - B_p]^{-1}$. Following Fisher (2006), I use as the first three variables 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 $B(1)^{-1}$ 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 has the interpretation of investment-specific technological change, as the relative price of investment is only affected by this shock in the long run. The second shock represents a concept akin to a TFP shock, as it is the only driver that affects, other than IST, the economy's labor productivity in the long run.[27] These restrictions are satisfied in the theoretical model of Section 3. I view the identification of the TFP shock as a by-product and mainly present the model results for the IST shock, as the latter shock implies sharply contrasting predictions under the alternative borrowing constraints.

Identification using medium-run restrictions. The idea is to identify a shock such that its forecast error variance decomposition (FEVD) share for a selected variable is maximized at a specific finite horizon h. These restrictions have been introduced to overcome weaknesses of the long-run identification method, such as their small sample properties (for details see Faust and

[27] Fisher (2006) also imposes the additional overidentifying restriction that labor productivity responds in a fixed proportion to the relative investment price. While this improves the precision of the estimates, I do not impose this restriction to remain as agnostic as possible.

Leeper, 1997). Based on the ideas of Uhlig (2003), Francis, Owyang, Roush, and DiCecio (2014) identify a technology shock as the shock that maximizes the FEVD share of labor productivity at horizons of 2.5 to 20 years. Barsky and Sims (2011) implement a variant of this method where the shock maximizes the *sum* of the FEVD up to a specific horizon. I follow the former authors' variant of this identification scheme, but found similar results using the cumulative variant. Using the same vector of observables Y_t, I identify the IST shock as the shock that maximizes the FEVD share in the relative price of investment at varying horizons h.

Variables in the system. As I only identify two shocks and leave the remaining rows of $B(1)^{-1}$ unrestricted, I can add further variables to the system, for which the ordering becomes irrelevant to the identification of IST and TFP. The additional variables are the log differences in aggregate business earnings, the relative value of the capital stock and business sector debt. In particular the inclusion of debt is key, as I have shown that in the model this variable responds with a different sign to investment shocks depending on the type of borrowing constraint that is present. For both identification schemes this gives, in line with the notation of the model,

$$Y_t = [\text{dlog}(p_{kt}) \ \ \text{dlog}(y_t/n_t) \ \ \log(n_t) \ \ \text{dlog}(\pi_t) \ \ \text{dlog}(p_{kt}k_t) \ \ \text{dlog}(b_t)]'. \tag{15}$$

p_{kt} is the relative price of investment, which corresponds to v_t^{-1} if v_t captures IST.

4.1.2 Data used for SVAR analysis

I use data from the US National Income and Product Accounts (NIPA) and the US Financial Accounts (Flow of Funds). Details can be found in Appendix A.3. I deflate nominal data with the consumption deflator for nondurable goods and services. An important consideration lies in the choice of data for p_{kt}. Following the literature on IST shocks, I use the relative price of equipment investment. I construct this from NIPA data and use the Gordon-Violante-Cummins (GVC) investment price for robustness.[28] Furthermore, I explore the responses of secondary market equipment prices to the IST shock, as in practice both new and used capital could serve as collateral (see Appendix D.6). In principle, one could also proxy the price of capital with stock prices. However, what matters for the mechanism I highlight in this paper is not the firm value (or stock market) response, but the response of the value of assets that serve as collateral. In the data, the value of collateral and the market value of the firm in its entirety are different.[29] I therefore focus on the price of equipment, which is the most important category of collateral in

[28] See Cummins and Violante (2002) and DiCecio (2009) for details. I test that both series are nonstationary in levels and stationary after first-differencing, see Gali (1996).

[29] An example for why there is a difference between collateral and firm values in practice is the presence of human capital, which is not pledged as collateral but that influence the market value of the firm. The predictions for stock prices responses to investment shocks is highlighted by Christiano, Motto, and Rostagno (2014). Studying the implications of risk shocks in the presence of different types of credit constraints would be an interesting extension to the framework presented in this paper. See also Furlanetto, Gelain, and Sanjani (2017) for a discussion of stock price comovement and the importance of investment-specific shocks at different frequencies.

the loan-level data (see Table A.4 in the Appendix). For debt I use the sum of loans and debt securities for the nonfinancial business sector. As some of the variables in (15), such as the log of hours, display low frequency movements, I detrend them before estimating the VAR. I compute 68% and 90% error bands using bootstrap techniques.

4.2 SVAR results: aggregate responses to investment shocks

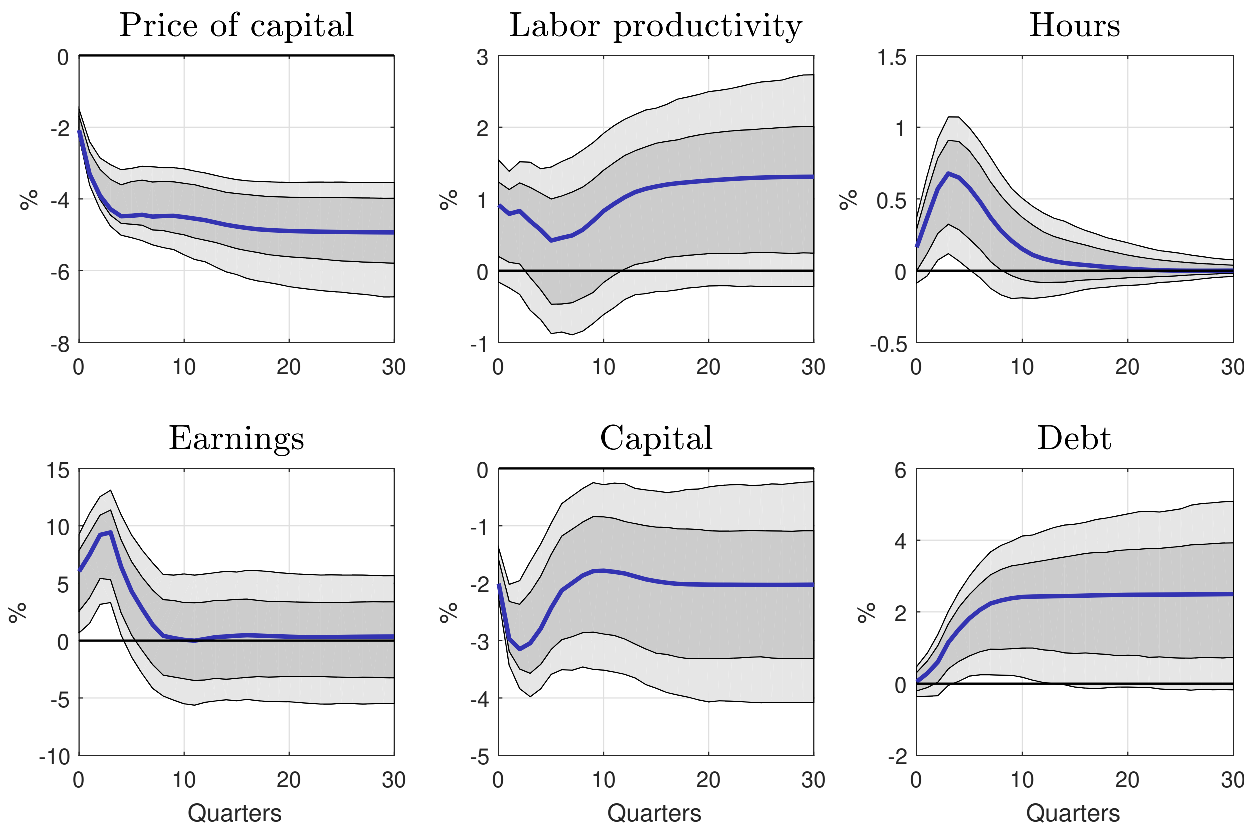
IRFs. The results for quarterly US data from 1952 to 2016 for $p = 4$ are shown in Figure 5. The figure presents the IRFs for a positive permanent IST shock identified based on its long-run impact on the relative price of investment. Appendix D.2 presents the analogous IRFs based on the medium-horizon identification scheme with $h = 20$ and $h = 40$, implying that IST is the main driver of the relative price of investment at a 5 and 10 year frequency, respectively. The key insight is that for both identification methods the SVAR estimates a positive response of debt. This is in line with the model predictions for the earnings-based constraint but not for the collateral constraint. Consistent with the mechanics of the earnings-based borrowing constraint, the rise in debt is accompanied by growing earnings and a fall in the value of capital. The dynamics in US data, conditional on identified shocks, thus lend support to the importance of earnings-based borrowing for debt dynamics in US business cycles.[30] In fact, these results show that the predictions from collateral constraints for investment shocks are at odds with the data.

Historical variance decompositions. My empirical strategy relies on the sign of the responses and does not require that the shock explains a large fraction of economic fluctuations. To study whether investment-specific shocks are in fact an important driver of macroeconomic dynamics according to the SVAR, Appendix D.3 provides the historical decompositions of the six macroeconomic variables in the system. The figures in this appendix show the contribution at each point in time of the different shocks (IST, TFP, other). It is evident that IST shocks played a marked role in different episodes of the postwar US business cycle. For example, consistent with the narrative around the tech boom, the 1990s expansion was strongly driven by IST.

Monte Carlo simulations. To verify the ability of the SVAR to distinguish between different constraints, I set up a Monte Carlo experiment in which I estimate the SVAR on simulated data generated from the model in Section 3. Specifically, I repeatedly create two types of data samples, each generated from one of the borrowing constraint specifications (Panel (b) vs. Panel (c) in Table 2). I do so by randomly drawing TFP, IST and additional shocks and then simulating the time series in (15) from the policy rules of the model. For each sample type I generate 10,000 repetitions on which I run the SVAR identified with long-run restrictions. The results, presented in Appendix D.4, are reassuring. In particular, the negative debt response generated from a collateral constraint model is fully contained in the 68% confidence set across repetitions.

[30] Appendix D.1 presents the IRFs to the TFP shock. As the constraints are not distinguishable conditional on this shock, my empirical analysis focuses on the IST shock.

Figure 5: SVAR IRFS TO POSITIVE INVESTMENT SHOCK IDENTIFIED WITH LONG-RUN RESTRICTIONS



Note: The figure displays the IRFs to an 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 2016: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 a earnings-based borrowing constraint in the theoretical macro model.

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 also demonstrate that the investment shock I identify above reduces the prices of *used* (secondary market) 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. The results are presented in detail in Appendix D.5.[31]

Additional robustness checks. I explore robustness of the SVAR results along a variety of dimensions. First, following Fisher (2006), I split the sample in the early 1980's to account for

[31]The fact that secondary market prices fall in response to an investment shock is plausible from a theoretical point of view. In a model with different (complementary) vintages of capital, one would expect that no-arbitrage restrictions between the different asset types ensure that prices qualitatively move in the same direction.

the change in the trend exhibited by the relative price of investment. In the first part of the sample the shapes of the IRFs are preserved, while the bands get wider. In the second part, the debt response to IST is again positive and significant, just more hump-shaped rather than settling at a permanent level. Second, I construct the business debt time series separately for loans and debt securities. This split reveals that the debt IRF in Figure 5 is mainly driven by loan dynamics, while the response for debt securities is noisy. Third, I use the Gordon-Violante-Cummins (GVC) relative equipment price series as opposed to the relative NIPA deflator as an alternative measure of the relative price of equipment. The results are very similar to the ones obtained using NIPA data. Finally, I also adjust the data for outliers as a robustness check.

4.3 Panel local projections in firm-level data

In this subsection, I exploit micro-level information on firms' debt contracts to directly validate the mechanism. I merge the Dealscan data set with balance sheet information from Compustat. This gives me a firm panel with information on earnings-based covenants and collateral as well as on rich firm characteristics. I regress firm-level borrowing on the investment shock obtained from the SVAR. This extends the local projection technique of Jordà (2005) to a panel setting, and is in similar spirit to Ottonello and Winberry (2018), Jeenas (2018) and Cloyne, Ferreira, Froemel, and Surico (2018), who all focus on monetary shocks. My paper is the first one to apply this technique to investment-specific shocks (and technological shocks more broadly). I obtain average IRFs across all firms, as well as separate IRFs for different borrower types, allowing me to verify whether my suggested mechanism is plausible. Furthermore, I study the firm-level debt responses to a fall in the relative price of investment goods, using an IV strategy. I also extend the analysis to study the response of firm-level investment.

4.3.1 Panel local projection setting and assumptions

I construct the IRF of borrowing of firm i at horizon h to the investment shock by specifying

$$\log(b_{i,t+h}) = \alpha_h + \beta_h \hat{u}_{IST,t} + \boldsymbol{\gamma X_{i,t-1}} + \delta t + \eta_{i,t+h} \tag{16}$$

and obtaining estimates of β_h, $h = 0, 1, 2, \ldots, H$. $\hat{u}_{IST,t}$ denotes the time series of the identified exogenous investment shock from the SVAR model above. $\boldsymbol{X_{i,t-1}}$ is a vector of rich firm-level and industry-level controls. Following Ottonello and Winberry (2018), these controls are lagged by one quarter. $\boldsymbol{X_{i,t-1}}$ also contains a lag of the left hand side variable, $\log(b_{i,t-1})$. t is a linear time trend. Equation (16) 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 on average ($\beta_h > 0$) and negative with collateral constraints being the relevant credit limit on average ($\beta_h < 0$).

Given the information in the Dealscan data, I can interact the shock with dummies that capture whether a firm is subject to earnings-based covenants or uses collateralized loans, obtaining heterogeneous IRFs across different borrower types. This allows me to verify the proposed theoretical mechanism more directly. Formally,

$$
\begin{aligned}
\log(b_{i,t+h}) = \alpha_h + \beta_h \hat{u}_{IST,t} + \boldsymbol{\gamma X_{i,t-1}} \\
+ \beta_h^{earn} \mathbb{1}_{i,t,earn} \times \hat{u}_{IST,t} + \alpha_h^{earn} \mathbb{1}_{i,t,earn} \\
+ \beta_h^{coll} \mathbb{1}_{i,t,coll} \times \hat{u}_{IST,t} + \alpha_h^{coll} \mathbb{1}_{i,t,coll} + \delta t + \eta_{i,t+h},
\end{aligned}
\tag{17}
$$

where $\mathbb{1}_{i,t,earn}$ and $\mathbb{1}_{i,t,coll}$ are dummy variables that capture whether the firm is subject to earnings-related covenants or uses collateral. Their data counterparts are discussed below. The IRF of an "earnings-based borrower" ("collateral-based borrower") at horizon h is given by the sum of the coefficients β_h and β_h^{earn} (β_h and β_h^{coll}).[32] My model predicts that $\beta_h + \beta_h^{earn} > 0$ and $\beta_h + \beta_h^{coll} < 0$. I discuss below how I address the endogenous selection into borrower types. An alternative version of (17) is based on an IV strategy. The idea is to study the responses to the relative price of investment goods, instrumented by the investment shock, rather than to the shock itself. The results are discussed below, with details in Appendix E.2. Finally, I also study the response of firm-level investment (real capital expenditures) rather than debt. The results are discussed below, with details provided in Appendix E.5.

4.3.2 Data and specification used for panel regressions

The Dealscan-Compustat merge is enabled by a link file connecting the identifiers in the two data sets, which has been created by Michael Roberts and collaborators (see Chava and Roberts, 2008). The resulting data set covers around 150,000 firm-quarter observations for more than 4,000 distinct firms from 1994 to 2015. $b_{i,t}$ is the quarterly level of debt liabilities from Compustat (calculated as the sum of the items 'dltq' and 'dlccq'). Consistent with the data treatment in the SVAR, I obtain a real series by deflating with the consumption deflator for nondurable goods and services. The firm-level classification into "earnings borrowers" and "collateral borrowers" based on the information in Dealscan is consistent with the aggregate shares I present in Figure 1. $\mathbb{1}_{i,t,earn}$ is equal to 1 if a given firm issues a loan with at least one earnings covenant. $\mathbb{1}_{i,t,coll}$ is equal to 1 if the debt issued by the firm is secured by specific assets (see the explanations provided in Section 2). As an alternative, I also construct a version of $\mathbb{1}_{i,t,coll}$ based on whether the firm uses a secured revolving line of credit. This follows Lian and Ma (2019), who point out that secured "revolvers" are typically asset-based. Summary statistics for the full data sample and conditional on the grouping by borrower type are provided in Appendix A.2.

I focus on the version of $\hat{u}_{IST,t}$ estimated using long-run restrictions in Section 4.1. To the extent that my identification in the SVAR is credible, this shock is a purely exogenous regressor, meaning that there are no endogeneity issues with respect to this variable in (16). Clearly, however, the dummy interactions to generate heterogeneous responses in equation (17) are a

[32] More precisely, the coefficients on the dummy variables capture the marginal effect of facing an earnings-based or a collateral constraint on borrowing, respectively. The dummies can both be 0 and both be 1, simultaneously.

cause for concern. 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 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. In an alternative specification, I also introduce firm-level fixed effects. In all versions of (16) and (17) that I estimate, I include one lag of the left hand side variable and a linear time trend to the regression. Furthermore, I add a control variable that is intended to capture macroeconomic shocks other than investment shocks, which I construct from the SVAR residuals.[33] I set $H = 12$, and keep the firm composition constant when expanding h.

While Compustat is a panel and debt liabilities are continuously recorded, loan issuance information in Dealscan is present only every other quarter. This has two consequences. First, sample to estimate (17) is smaller than the one I can use to estimate (16). Second, it also implies that the sample used to estimate (17) is restricted to firms that issue any debt to begin with. While I address the endogenous selection into debt types, I cannot address the endogenous extensive margin selection into being a borrower. While this potentially introduces an upward bias in the estimates for (17), I focus on the sign and *relative* size of β_h^{earn} and β_h^{coll}.

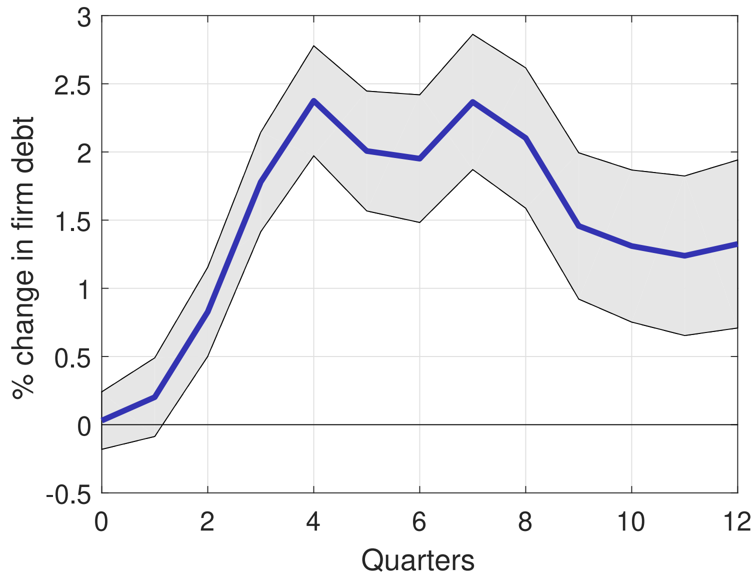
4.4 Firm-level results: heterogeneous responses to investment shocks

Average debt responses. I first present the debt response for all firm in the panel, that is, the estimates of β_h in (16), together with the associated 90% bands based on two-way clustered standard errors by firm and quarter. I also tried clustering standard errors at the 3-digit industry, which gives very similar results. In this regression I do not add any controls other than lags of the left-hand-side variable, a time trend and the exogenous shock itself. Figure 6 shows that the dynamic response of firm debt to an investment shock is positive, in line with the aggregate debt response in the SVAR, and consistent with the model in which the earnings-based constraint is the relevant debt limit. It matches the SVAR responses also in terms of the magnitude and persistence. This is reassuring, since Compustat-Dealscan firms are a specific but quantitatively meaningful subset of the total nonfinancial business sector for which I use data in the SVAR.

Debt responses by borrower types. The heterogeneous IRFs based on estimating equation (17) are presented in Figure 7. These results are based on a specification with 3-digit industry fixed effects, size as measured by number of employees and growth of real sales. As described above, I also control for other macroeconomic shocks using the orthogonalized SVAR innovations, as well as a lag of the left hand side variable and a linear time trend. Panel (a) shows the results based on the classification of collateralized debt is based on whether a given firm's borrowing is secured with specific assets (see Section 2 for details). Panel (b) shows the results using the

[33] I use the reduced form residuals of the debt equation in (14) and orthogonalize them with respect to the IST shock. The resulting series captures innovations to aggregate debt that unrelated to IST, which spans other structural shocks.

Figure 6: EMPIRICAL FIRM-LEVEL IRF OF DEBT TO AN INVESTMENT SHOCK

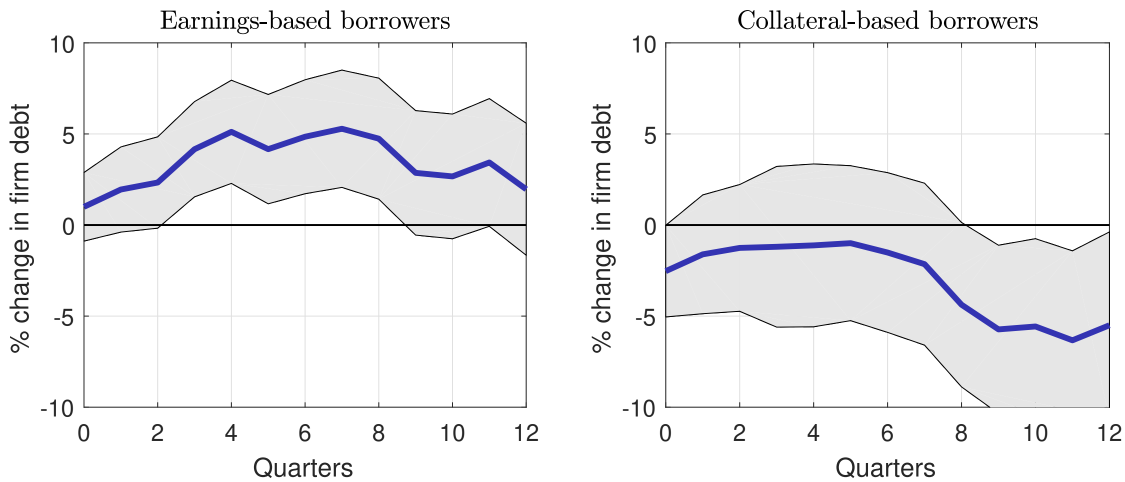


Note: The figure plots the average IRF of firm debt to a macro investment shock across individual firms, estimated using the method of Jordà (2005) in panel data, as formulated by equation (16). The macro shock has been identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). The data set used is a merge of Dealscan loan-level information with balance sheet variables from the Compustat quarterly database. The IRF is shown in percent. 90% bands are calculated using two-way clustered standard errors by firm and quarter. The figure shows that the debt IRF matches the one of aggregate debt in SVAR model and is in line with the predictions arising from an earnings-based borrowing constraint in the theoretical macro model.

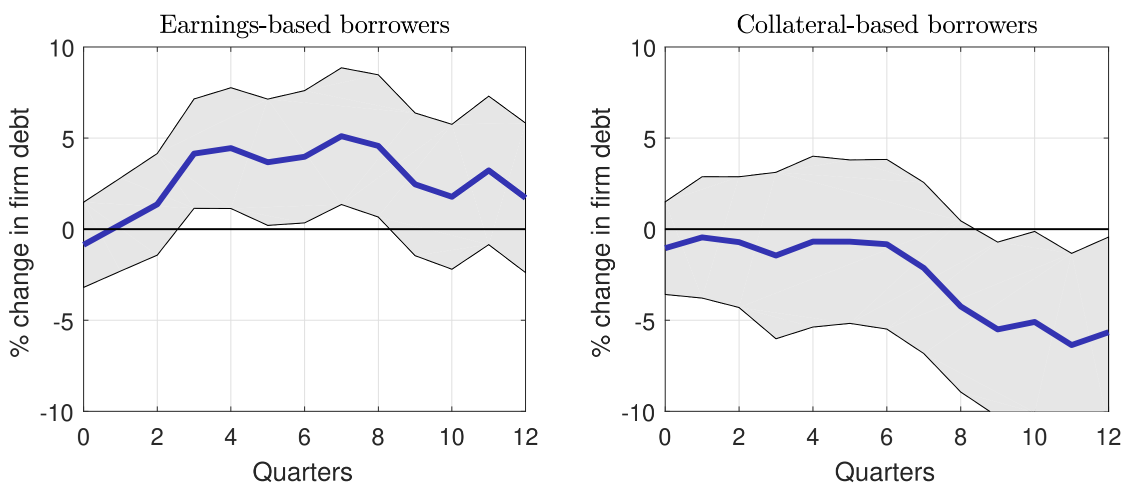
alternative classification of asset-based debt based on whether a firm uses secured revolvers following Lian and Ma (2019). Again, I plot 90% error bands constructed from standard errors that are clustered by firm and quarter. The bands across all four figures are wider than in Figure 6 due to the lower number of observations when using $\mathbb{1}_{i,t,earn}$ and $\mathbb{1}_{i,t,coll}$ in the regression. Both panels of Figure 7 show that the IRF of debt to an investment shock is positive for firms that face earnings-related covenants, but negative for firms that borrow against collateral. This confirms the key prediction of the model, as presented in Panel (b) of Figure 2. Reassuringly, the null hypothesis of an equal response across the two borrower types is rejected over several horizons at the 5% level. This is not directly visible in Figure 7, but is formally presented in the Appendix. Interestingly, while the shape of the IRF for earnings-borrowers is similar to the model prediction – small on impact and then increasing persistently – the IRF of collateral borrowers differs from its baseline model counterpart. The response on impact in Panel (a) is negative. However, it displays its most significant reduction only after around 2 years. This may indicate an environment in which the value of collateral reflects market prices with some delay. Indeed, an alternative version of the model, studied in Appendix C.6, generates a more sluggish response of debt with a collateral constraint if past capital prices are used to assess the value of collateral. Furthermore, the empirical responses of used (secondary market) equipment prices that I investigate in Appendix D.5 also show a negative but sluggish response, providing additional evidence for this interpretation.

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

(a) Using collateral classification based on specific assets



(b) Using collateral classification based on secured revolvers



Note: The figure displays average IRFs of firm borrowing within different firm groups, estimated using the method of Jordà (2005) in a panel context, as formulated by equation (17). 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) uses the collateral classification based on whether a loan is backed by specific assets or not (see details in Section 2). Panel (b) uses an alternative grouping where secured revolvers are categorized as collateralized debt (see Lian and Ma, 2019). The investment shock is identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). 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 IRFs shown in the figure are consistent with the model's prediction of a positive debt response under an earnings-based constraint and a negative one under a collateral constraint. A formal test rejects the null hypothesis of equal responses across the two firm types for various horizons, as shown in Table E.1 in the Appendix. The results for alternative specifications, as well as the responses for the remaining two borrower types are given in Appendix E.

IV strategy and robustness. Appendix E presents a host of additional results based on alternative variations of equation (17). First, I estimate the IRF to a fall in the relative price of equipment investment, instrumented by the investment shock (rather than the response to the investment shock directly). Second, the results for a specification based on firm fixed effects are presented. Finally, the appendix also shows the IRFs of Figure 7 for the two additional groups, which are firms subject to both earnings covenants and collateral, as well as firms that are subject to neither. Qualitatively, these results look very similar to the ones presented above. The exception is the firm fixed effect specification, where the debt response of collateral borrowers is flat, and the response of earnings borrowers is positive in just one out of the two classifications.

The response of firm-level investment. I extend the analysis to study the response of firm-level investment. The results, presented in Appendix E.5, line up with the dynamics of debt. Earnings 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 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 again rejects the null that the responses are equal across borrower types.

4.5 Take-aways from verifying the model predictions empirically

The proposed model mechanism allows to distinguish between alternative borrowing constraints by conditioning on investment shocks. The empirical responses of debt to investment shocks in macroeconomic data, shown above, indicate that the relevant one for aggregate debt dynamics is such an earnings-based constraint. Moreover, the heterogeneous firm-level responses are directly in line with the mechanism: earnings-based borrowers increase their debt liabilities in response to an aggregate investment shock, firms subject to collateral constraints do not.

5 Earnings-based borrowing, sticky prices and markup cyclicality

After verifying the relevance of earnings-based credit constraints using identified investment shocks in macro and micro data, the remainder of the paper investigates how the constraint fundamentally affects structural modeling in macroeconomics. A wide array of questions in business cycle research have been addressed using New Keynesian models. The connection between firm earnings and credit access implied by the earnings-based constraint goes right to the heart of the New Keynesian transmission mechanism, which relies on sticky prices.

New Keynesian models and price markups. In New Keynesian macro models, sticky prices affect the cyclicality of the price markups which firms charge over their marginal costs. In particular, when prices are sufficiently rigid, demand shocks imply countercyclical markups, while supply shocks imply procyclical markups.[34] To see this, consider 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 will raise the quantity of goods it produces. 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. Hence more demand results in a lower markup. In other words, the markup is countercyclical conditional on demand shocks. The opposite is true for a positive supply shock. Suppose the firm gets a shock that enables it to produce a larger quantity for given inputs. Since the firm cannot adjust the price, it will reduce its inputs down the marginal cost curve and thereby raise its markup. Hence improved supply conditions result in higher markups: the markup is procyclical conditional on supply shocks.

These mechanics generalize to sufficiently rigid rather than fully fixed prices and hold under production with constant returns to scale if one input (capital) is predetermined. If wages are sticky as well, the reasoning goes through as long as prices are relatively more rigid than wages. A recent discussion on the cyclicality of markups in New Keynesian models, as well as empirical estimates of markup cyclicality, are provided by Nekarda and Ramey (2019).[35]

Markup cyclicality and borrowing constraints. The New Keynesian sticky price mechanism interacts directly with earnings-based borrowing constraints but only indirectly with collateral constraints. The reason is that with an earnings-based constraint, firms' borrowing capacity is a function of the markup: *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 faced with an earnings-based limit on its real debt holdings:

$$\frac{b_t}{P_t(1+r_t)} \leq \theta_\pi \pi_t, \tag{18}$$

where b_t is nominal debt, r_t the nominal rate, P_t the price level and real earnings are given by

$$\pi_t = y_t - \frac{w_t}{P_t} n_t. \tag{19}$$

The firm's price markup is defined as the ratio of price to marginal costs

$$\mathcal{M}_t = \frac{P_t}{MC_t}. \tag{20}$$

which is the inverse of real marginal costs. Marginal costs are given by the wage relative to the marginal product of labor. With a Cobb-Douglas production technology, and assuming that wages are flexible, earnings can be rewritten as

[34] As commonly done in the literature, I generally refer to demand shocks as those structural shocks that imply a positive comovement between output and prices, and supply shocks to those that imply a negative comovement.

[35] Measuring markups to determine their cyclical properties directly in the data is challenging, as we typically observe only average costs and not marginal costs. Well-known earlier attempts have been made for example by Bils (1987) and Rotemberg and Woodford (1999).

$$\pi_t = z_t k_t^\alpha n_t^{1-\alpha}\left(1-(1-\alpha)\frac{w_t/P_t}{(1-\alpha)z_t k_t^\alpha n_t^{-\alpha}}\right) \tag{21}$$

$$\pi_t = y_t\left(1-(1-\alpha)\mathcal{M}_t^{-1}\right), \tag{22}$$

which shows that firm earnings (EBITDA) are positively related to both the level of output and the markup. Combining (18) and (22), the earnings-based borrowing constraint becomes

$$\frac{b_t}{P_t(1+r_t)} \leq \theta_\pi y_t\left(1-(1-\alpha)\mathcal{M}_t^{-1}\right). \tag{23}$$

This relation makes clear that borrowing can be written as a function of the markup, so that the slack in the constraint depends positively on the price markup. Such a direct link between markups and credit access 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, but only through indirect equilibrium forces.

This relation between markups and different credit constraints becomes particularly relevant when New Keynesian models are taken to the data, which is how they are ultimately applied to answer quantitative question about the macroeconomy. In the data, credit is a highly procyclical variable. In the presence of an earnings-based borrowing constraint, procyclical markups make it easier for a New Keynesian model to match this procyclical behavior of credit in the data. If markups move procyclically, earnings move procyclically (all else equal) and therefore credit becomes procyclical. Following the explanations above, a New Keynesian model can generate procyclical markups in different ways. One way is if supply shocks are more important than demand shocks. The other way is if prices are in fact not sticky in a meaningful way, so that the core New Keynesian mechanism is muted. It can also be a combination of the two. How the relative strength of these forces plays out is a quantitative question, which can be answered by the estimating a New Keynesian DSGE model with borrowing constraints on macroeconomic data that includes credit. This is done in the next section.

6 Earnings-based borrowing in a quantitative macro model

This section extends the model of Section 3 to a quantitative framework. To this end, I incorporate a number of shocks and frictions, such as price and wage rigidities, alongside credit constraints. I estimate the model on US data to investigate how earnings-based borrowing constraints relative to borrowing against collateral affect the quantitative conclusions of the model. The discussion of the results is guided by the insights around price stickiness and the cyclical behavior of markups provided in the previous section. It highlights how credit constraints interact fundamentally with the central New Keynesian transmission mechanism.

6.1 Structure of the quantitative model and its two alternative versions

The model is a New Keynesian medium-scale DSGE model in the spirit of Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). The philosophy behind this class of models is that in order to gauge the overall effect of any macroeconomic policy change, this policy change should be assessed net of all important forces that operate across the economy. For the purpose of adding borrowing constraints, I build on the Smets and Wouters (2007) framework in a similar way to Jermann and Quadrini (2012).[36] The details of the model are provided in Appendix F, and in what follows I elaborate on the borrowing constraints. There is a continuum of firms which have access to a nominal risk-free bond that is constrained (in real terms) by earnings or collateral. The interest rates paid on the debt is subject to a tax advantage of the type in equation (7). Formally, I estimate two versions of the exact same model, in which the borrowing constraint of firm i reads either

$$\frac{b_{i,t}}{P_t(1+r_t)} \leq \theta_{\pi,t}\pi_{i,t} \tag{24}$$

or

$$\frac{b_{i,t}}{P_t(1+r_t)} \leq \theta_{k,t}\mathbb{E}_t p_{kt+1}(1-\delta)k_{i,t}. \tag{25}$$

The θ terms are now allowed to vary with exogenous shocks to financial conditions. Their mean values are calibrated to match the debt-to-earnings ratio in the data with (24), and the debt-to-total assets ratio in the data with (25). In addition to financial shocks, the dynamics in the model are driven by TFP, investment and preference shocks, shocks to price and wage markups, as well as monetary and fiscal policy shocks.[37] Relative to Jermann and Quadrini (2012), I do not model working capital so that the constraints affect only intertemporal borrowing decisions.

6.2 Data and estimation settings for quantitative model

For the estimation of both model versions, I retrieve quarterly 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 credit as an eighth observable. I do not include the price of equipment as an observable, so that investment shocks have the interpretation of MEI shocks. I obtain real variables using the consumption deflator of nondurables and services, consistent with my SVAR and in the same way as Justiniano, Primiceri, and Tambalotti (2011). Following the same authors, the sample period is 1954:Q3 - 2009:Q1. I estimate the model with Bayesian methods. For comparability, I estimate the same set of parameters as Jermann and

[36] Apart from adding borrowing constraints, my 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.

[37] For the purpose of estimating the model, I define the investment shock as transitory. I verified that a permanent version of the shock gives similar debt dynamics as its counterpart in Sections 3 and 4.

Quadrini (2012) and use identical priors. I obtain 10,000,000 draws from a Markov Chain Monte Carlo (MCMC) algorithm, discard the first 25% and use the remaining ones to compute posteriors. Details on the data used for the estimation of the model are provided in Appendix A.3.

6.3 Model estimation results: a compact characterization of the differences

A model as rich as the DSGE model estimated here would in principle allow us to study a large variety of different consequences of the constraints. It is possible to compare parameter estimates, IRFs, moments or variance decompositions for many variables and shocks. One could focus on a wide range of macroeconomic questions, including the transmission of monetary and fiscal policy shocks. To streamline the discussion, I organize the results around the fundamental implication of earnings-based borrowing constraints discussed in Section 5: its interaction with price rigidity and markup cyclicality. The focus on this interaction demonstrates that the constraints differ at a level that is basic enough to potentially affect *any* macroeconomic question that an estimated New Keynesian model is applied to. In this sense, the discussion of the estimation results represents a compact way of highlighting the major implication of earnings-based credit constraints relative to traditional collateral constraints. Appendix F.2 contains additional estimation results.

Estimated markup cyclicality, price rigidity and importance of shocks. In support of the insights on the interaction between borrowing constraints and the New Keynesian mechanism, Table 3 presents a set of three key results. The first result is that the earnings-based constraint is associated with much more procyclical markups. The correlation between output and the markup is +0.48, which is in stark contrast with an acyclical markup implied by the model estimated with collateral constraints (correlation coefficient of -0.01), and which confirms the intuition laid out in Section 5. Since firm credit is used as an observable in the estimation, and since this variable is strongly procyclical, the model with the earnings-based constraint matches the dynamics in the data better when markups are procyclical. The reason is that earnings-based debt is a direct function of the firms' price markup over their marginal costs, as shown in equation (23). With a collateral constraint, there is no such direct relation and the procyclical pattern of credit can be consistent with acyclical markups. Of course, the direct link between markups and credit under the earnings-based constraint in (23) is an all-else-equal relation. The estimation of the model now allows us to conclude that this relation is quantitatively meaningful, also in the presence of a variety of shocks and frictions, leading to an unconditionally positive correlation between markups and the business cycle in the model with earnings-based borrowing constraints.

As explained in Section 5, New Keynesian models can generate procyclical markups through low price rigidities, through supply shocks playing an important role, or through a combination of the two. It is evident from the second and third results shown in Table 3 that the estimated DSGE model indeed features a combination of the two forces. The second result presented in the table is that earnings-based borrowing constraints give rise to a lower estimate of price stickiness than collateral constraints. In both model variants, the posterior of the Rotemberg price

Table 3: COMPARISON OF QUANTITATIVE MODEL FEATURES

Model with:	**earnings-based constraint**	**collateral constraint**
Correlation between price markups and output	+0.48	-0.01
Posterior estimate of Rotemberg price adjustment cost ($\tilde{\phi}$)	4.71	6.97
(90% HPD interval)	(4.51,4.95)	(4.97,8.50)
Contribution to output growth fluctuations:		
Demand shocks	42.1%	71.1%
Supply shocks	42.0%	28.8%
Financial shocks	15.9%	0.1%
Contribution to credit growth fluctuations:		
Demand shocks	57.0%	37.8%
Supply shocks	38.0%	29.8%
Financial shocks	4.9%	32.4%

Note: Selected results from two versions of the estimated New Keynesian DSGE model. *Demand shocks* are MEI, preference, government spending and monetary policy shocks. *Supply shocks* are TFP, price markup and wage markup shocks. This classification into demand (supply) shocks is based the positive (negative) comovement between output and prices implied by the respective shocks. Detailed estimation results can be found in Appendix F.2.

adjustment cost parameter has shifted away markedly from its prior (which I specify around a mean of 0.1), indicating that the data is generally informative about price stickiness. Importantly, the model with the collateral constraint implies a much more rigid price setting (posterior of 6.97) than the one with earnings-based borrowing constraints (4.71). The table also reports the corresponding credible 95% credible intervals, which do not overlap.[38] The quantitative strength of one of the key ingredients of standard macroeconomic models, sticky prices, is thus significantly reduced by the presence of earnings-based borrowing constraints relative to the more widely used type of borrowing constraint based on collateral.

The third result concerns the primitive drivers of US business cycles. DSGE models are commonly used to decompose the variation of macroeconomic variables into fundamental structural shocks. The model estimated here is driven by eight different shocks which can be grouped into supply and demand shocks based on the comovement of output and prices they generate. As Table 3 shows, the presence of an earnings-based borrowing constraint implies a larger contribution of supply shocks to output growth fluctuations (42% vs 29%), as well as to credit growth fluctuations (38% vs 30%).[39] Note that supply shocks include shocks that directly exogenously move the firm's markup, but also other type of supply shock such as TFP shocks, which generate procyclical markups endogenously. These variance decompositions again

[38]The model also features wage rigidities. As explained in Section 5, what matters for the arguments on markup cyclicality is in fact price rigidity *relative to the wage rigidity*. Interestingly, wage rigidities are estimated to be stronger with the earnings-based constraint, so the resulting relative price rigidity is even lower. See Appendix 6.3 for the posterior estimates of all parameters.

[39]More detailed decompositions are presented in Appendix 6.3. As shown there, the earnings-based borrowing constraint implies a somewhat lower importance of investment shocks than the collateral constraint. I emphasize that my empirical strategy to distinguish the relevant credit constraint in Sections 3 and 4 does not require a particular quantitative importance of the shock, as long as it is correctly identified. I verified that the mechanism of my model in Section 3 remains intact in the medium-scale DSGE.

validate the discussion of the interaction between credit constraints, different types of shocks and markup cyclicality in Section 5. They are consistent with the insight that procyclical markups are generated through the relevance of supply shocks. The diverging decomposition results between the alternative versions of the model are a way of demonstrating how earnings-based constraints affect the answer to one of the the most central questions business cycle research.

In addition to supply and demand shocks, the table also separately reports the contribution of financial shocks, which directly hit the θ-terms in equations (24) and (25). This type of shock has been emphasized by Jermann and Quadrini (2012) who estimate a similar DSGE model. Under either constraint formulation in my model, the contribution of this shock is lower than in their paper. This due to the fact that my model does not feature working capital, which is common way to generate stronger amplification from credit constraints. It is notable, however, that the earnings-based constraint attributes relatively more importance to these shocks for output fluctuations. This suggests stronger propagation from credit shocks to the real economy than with collateral constraints. Taken together, these decompositions highlight again the fundamental nature of the interaction between the constraint and the model's core mechanism.

Understanding credit constraints to understand business cycles. New Keynesian DSGE models are used to answer a wide array of questions, ranging from their traditional purpose of assessing the effects of monetary and fiscal policy, to more recent applications to macroprudential regulation, housing markets or income inequality. The presentation of my estimation results is tightly focused on just a handful of implied moments, which are presented to uncover that the earnings-based borrowing constraint interacts *fundamentally* with the New Keynesian transmission mechanism. While the scope of my analysis is to emphasize this interaction, it follows from these results that a variety of applications of the New Keynesian DSGE can be revisited within the context of this consequential effect of earnings-based credit constraints.

7 Conclusion

Grounded on microeconomic evidence, this paper studies a debt limit which restricts borrowing to a multiple of earnings. Theoretical predictions implied by such an earnings-based borrowing constraint are in line with both aggregate and firm-level credit dynamics in US data. Moreover, the way firm borrowing constraints are captured in DSGE models drives basic conclusions about the sources and propagation of business cycles. New Keynesian models have emerged as the major quantitative framework in macroeconomics, and my analysis reveals that firm credit constraints interact fundamentally with the central features of this framework. The consequences of earnings-based constraints lie so close to the core of our standard model that the evidence provided in this paper makes the case for macroeconomists to change the benchmark way of thinking about firm credit constraints.

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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, as well as some of the model calibrations in Section 3. Second, the merged data set consisting of the Dealscan data, together with quarterly balance sheet information from Compustat is explained in Section A.2. This data is used in Section 4.3 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 6 is laid out in Section A.3.

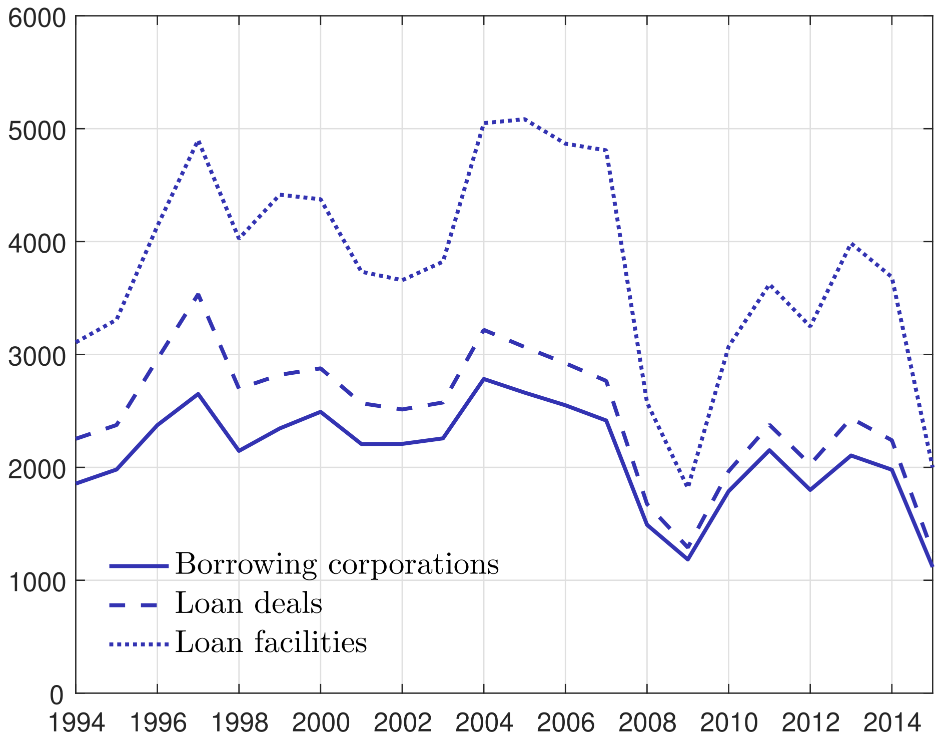
A.1 Thomson Reuters LPC Dealscan data set

LPC Dealscan is a detailed loan-level database provided by Thomson Reuters. The data was retrieved in March 2017 through the LSE Library Services and consists of a full cut of the entire database provided by Thomson Reuters as of October 2015. The data covers around 75% of the total US commercial loan market, see Chava and Roberts (2008). 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.

Data coverage. The raw data set retrieved contains 214,203 deals with 307,660 facilities for 78,646 unique borrowers globally. 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. These choices result in a sample of 54,400 packages, 83,290 facilities and 15,358 unique borrowing corporations. The number of deals per borrower ranges from 1 to 41, with on average 7.35 deals per borrower. Figure A.1 summarizes the number of deals, facilities and borrowers split up by origination time.

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.

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



Note: 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.

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	418.2	273.2	52	259
Std. deviation	1002.1	683.1	27	166
1st percentile	2.5	1.3	5	20
10th percentile	23.7	10.4	12	65
25th percentile	60.0	29.9	36	150
Median	151.2	92.2	60	250
75th percentile	395.8	257.4	60	330
90th percentile	951.1	619.4	84	450
99th percentile	4144.2	2750.0	120	830
Observations	54,397	83,288	76,205	70,282

Note: 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	1,120	4,420	1.83
Consumer Durables	424	1,738	0.80
Manufacturing	1,741	7,036	2.52
Oil, Gas, and Coal	805	3,479	1.78
Chemicals	382	1,699	0.91
Business Equipment	1,503	4,718	1.76
Telephone and TV	795	2,755	2.21
Utilities	767	3,964	2.27
Wholesale, Retail	2,216	8,579	2.83
Healthcare	1,003	3,469	1.65
Other	3,311	10,982	3.93
No SIC code available	1,290	1,560	0.25

Note: Industries are based on the Fama-French 12 Industry Classification. Finance and Utilities have been excluded. The amount borrowed is in trillions of 2009 real USD.

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

Deal purpose	Share (equal-weighted)	Share (value-weighted)
Corporate purposes	46.7%	44.0%
Working capital	12.3%	7.6%
Debt Repayment	11.9%	9.6%
Takeover	6.3%	13.8%
Acquisition line	5.3%	4.2%
LBO	4.4%	4.9%
CP backup	3.8%	8.1%
Dividend Recap	1.4%	1.1%
Real estate	1.3%	0.3%
Debtor-in-possession	1.0%	0.5%

Note: The table shows the ten most frequently stated ”deal purposes”. This information is available at the deal level for all 50,437 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	2292	353
Accounts Receivable and Inventory	1801	332
Intangibles	1367	238
Cash and Marketable Securities	989	328
Real Estate	737	142
Ownership of Options/Warrants	104	19
Patents	84	12
Plant	50	12
Agency Guarantee	25	6

Note: 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 (2019), 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 Merged Dealscan-Compustat panel data set

Compustat Northamerica Quarterly. This data set provides accounting data for publicly held companies in the US and Canada at quarterly frequency starting in 1960. The data was accessed through the Upenn Whartson Research Data Services (WRDS) in September 2016. 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 et al. (2009).

Merge of Dealscan with Compustat. As described in the text, I use Michael Roberts' identifier link, which is available on Michael Roberts' personal website and which is infrequently updated. 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. 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 150,000 firm-quarter observations for more than 4,000 distinct firms from 1994 to 2015.

Summary statistics for the merged data set. Table A.5 provides summary statistics for the firms in the full Compustat-Dealscan panel, which is constructed as described above, and used to estimate equation (16). Table A.6 presents the corresponding information for firms based on the baseline classification used in equation (17). Since firms can have several loan issuances, a given firm may appear in several panels of the table. For *a given time period* in the estimation of (17), the grouping is mutually exclusive.

Table A.5: SUMMARY STATISTICS FOR FULL COMPUSTAT-DEALSCAN PANEL ($N = 4,484$)

	Firm-qrt obs	Mean	SD	Min	Median	Max
Real total assets (bn 2009 USD)	153,554	4.6	16.2	0.0	0.8	542.7
Real sales (bn 2009 USD)	153,554	1.0	3.7	0.0	0.2	124.3
Real sales growth (percent)	149,049	3.4	16.6	-27.6	1.9	43.3
Employment (thousands)	136,575	14.3	53.5	0.0	2.8	2200.0
Real debt liabilities (bn 2009 USD)	153,554	1.4	6.4	0.0	0.2	339.6
Cash ratio	153,543	0.1	0.1	0.0	0.0	0.9
Market-to-book ratio	140,325	1.8	1.8	0.5	1.4	45.0
Book leverage (broad)	153,543	0.6	0.2	0.1	0.6	1.3
Book leverage (narrow)	153,543	0.4	0.2	0.0	0.3	0.9

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

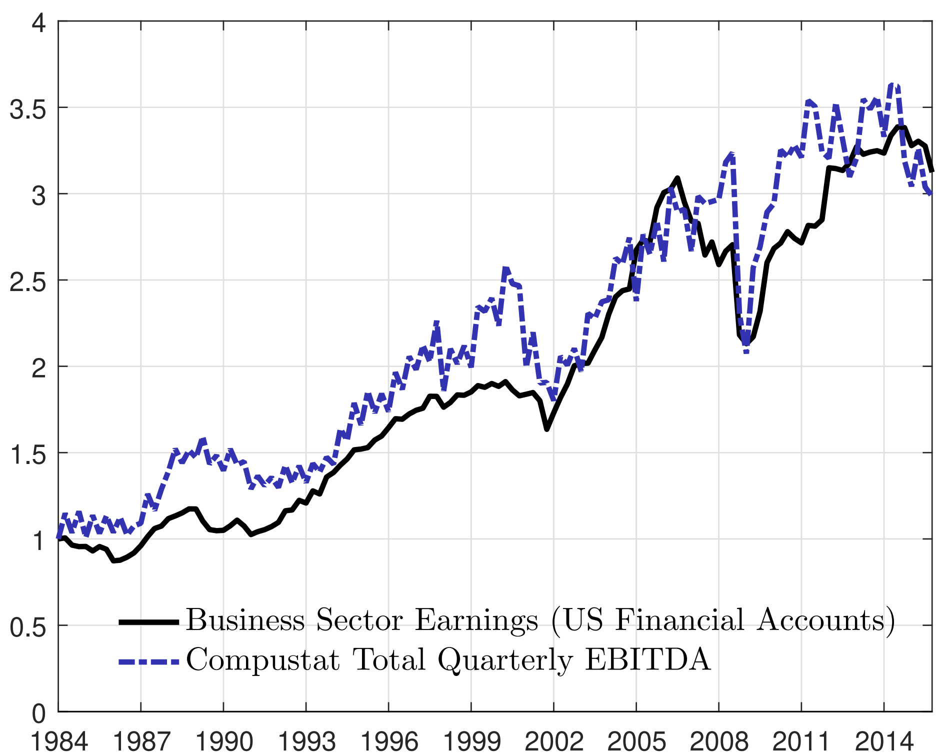
	Firm-qrt obs	Mean	SD	Min	Median	Max
Panel (a): Borrowers taking at least one loan with earnings covenants only ($N = 1,721$)						
Real total assets (bn 2009 USD)	46,680	5.4	17.2	0.0	1.6	455.6
Real sales (bn 2009 USD)	46,680	1.1	2.7	0.0	0.4	55.0
Real sales growth (percent)	46,044	4.9	16.3	-27.6	2.8	43.3
Employment (thousands)	43,164	17.7	40.8	0.0	5.4	707.9
Real debt liabilities (bn 2009 USD)	46,680	1.8	6.1	0.0	0.4	251.9
Cash ratio	46,668	0.1	0.1	0.0	0.0	0.9
Market-to-book ratio	43,848	1.7	1.0	0.5	1.5	16.8
Book leverage (broad)	46,668	0.6	0.2	0.1	0.6	1.3
Book leverage (narrow)	46,668	0.4	0.2	0.0	0.3	0.9
Panel (b): Borrowers taking at least one loan with specific collateral only ($N = 1,470$)						
Real total assets (bn 2009 USD)	28,128	3.5	10.2	0.0	0.6	192.8
Real sales (bn 2009 USD)	28,128	0.8	3.0	0.0	0.1	86.3
Real sales growth (percent)	26,652	4.7	17.6	-27.6	2.8	43.3
Employment (thousands)	25,860	12.5	52.6	0.0	2.1	1900.0
Real debt liabilities (bn 2009 USD)	28,128	1.5	4.4	0.0	0.2	131.1
Cash ratio	28,128	0.1	0.1	0.0	0.0	0.9
Market-to-book ratio	25,428	1.7	1.5	0.5	1.3	45.0
Book leverage (broad)	28,128	0.7	0.3	0.1	0.7	1.3
Book leverage (narrow)	28,128	0.5	0.3	0.0	0.4	0.9
Penal (c): Borrowers taking at least one loan with both ($N = 1,855$)						
Real total assets (bn 2009 USD)	44,124	2.2	9.8	0.0	0.6	513.3
Real sales (bn 2009 USD)	44,124	0.5	1.3	0.0	0.1	51.9
Real sales growth (percent)	42,864	6.0	17.8	-27.6	3.5	43.3
Employment (thousands)	41,652	9.2	24.0	0.0	2.6	355.0
Real debt liabilities (bn 2009 USD)	44,124	1.0	5.6	0.0	0.2	307.5
Cash ratio	44,124	0.1	0.1	0.0	0.0	0.9
Market-to-book ratio	40,764	1.6	0.9	0.5	1.3	12.0
Book leverage (broad)	44,124	0.6	0.2	0.1	0.6	1.3
Book leverage (narrow)	44,124	0.5	0.3	0.0	0.5	0.9
Panel (d): Borrowers taking at least one loan without either ($N = 844$)						
Real total assets (bn 2009 USD)	20,424	12.8	26.4	0.0	4.2	375.8
Real sales (bn 2009 USD)	20,424	2.6	5.6	0.0	0.7	66.0
Real sales growth (percent)	20,040	4.7	17.8	-27.6	2.7	43.3
Employment (thousands)	14,724	39.4	83.9	0.0	10.3	1383.0
Real debt liabilities (bn 2009 USD)	20,424	3.8	10.2	0.0	1.2	216.3
Cash ratio	20,424	0.1	0.1	0.0	0.0	0.9
Market-to-book ratio	18,048	1.7	1.0	0.5	1.4	12.7
Book leverage (broad)	20,424	0.6	0.2	0.1	0.6	1.3
Book leverage (narrow)	20,424	0.4	0.2	0.0	0.3	0.9

A.3 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.2 below:

Figure A.2: US FINANCIAL ACCOUNTS VS COMPUSTAT



Note: 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

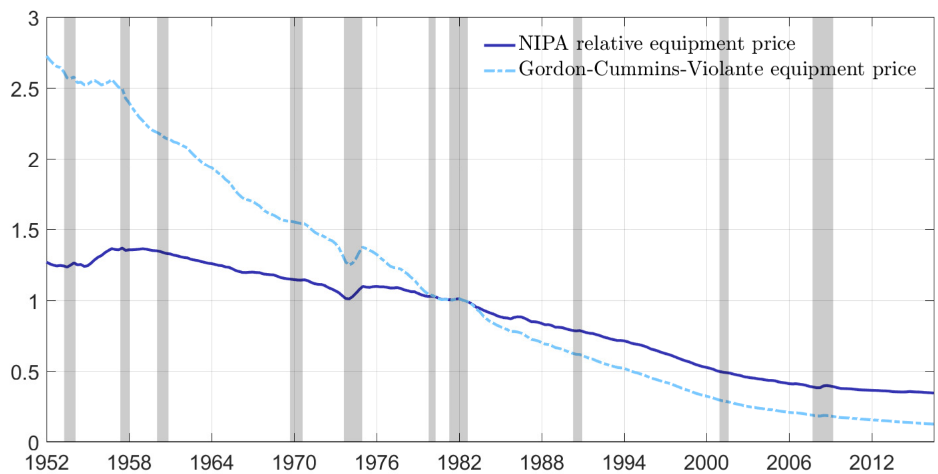
Panel (b): Data used in estimation of New Keynesian model

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

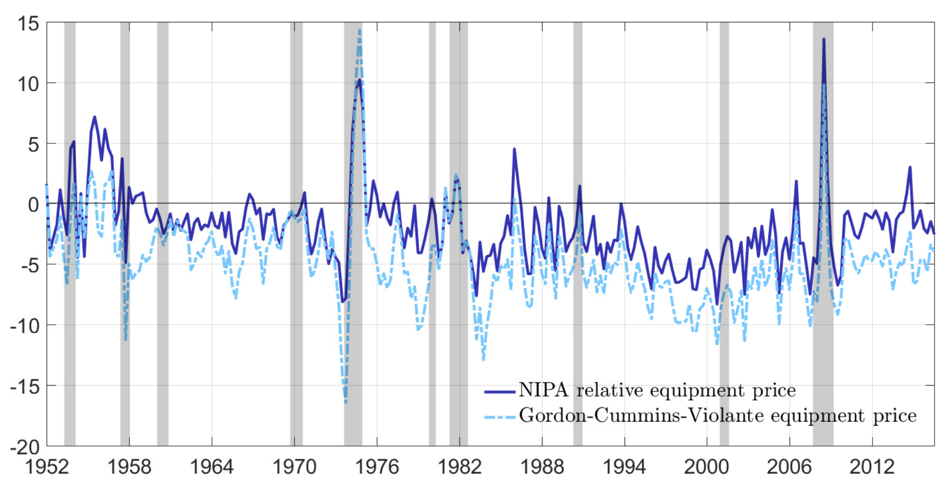
Details on relative equipment prices. Figure A.3 compares the two alternative measures used for the relative price of equipment investment. The first is the one based on NIPA data, constructed as the ratio between the equipment investment deflator and the deflator of consumption on nondurables and services. 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.3: MEASURES OF THE RELATIVE EQUIPMENT PRICE

(a) Levels (1982:Q3 = 100)



(b) Growth rates (annualized %)



Note: 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.3. 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

Note: 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.

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 renegociation 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 as described in the text and the first type of debt it has access to. 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 $\frac{b_{k,t}}{1+r_{k,t}}$. In the absence of any punishment, the firm would have an advantage from doing this, as the repayment of $b_{k,t}$ would not reduce resources in its flow of dividends constraint (4) 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 $\frac{b_{k,t}}{1+r_{k,t}}$ 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 $\theta_k \mathbb{E}_t p_{k,t+1}(1-\delta)k_t$. 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 $s_{k,t}$ 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

$$s_{k,t} + \frac{b_{k,t}}{1+r_{k,t}} \geq \theta_k \mathbb{E}_t p_{k,t+1}(1-\delta)k_t. \tag{26}$$

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 (26), we obtain

$$s_{k,t} \geq 0 \tag{27}$$

$$\theta_k \mathbb{E}_t p_{k,t+1}(1-\delta)k_t - \frac{b_{k,t}}{1+r_{k,t}} \geq 0, \tag{28}$$

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

Earnings-based constraint. Suppose that for the second debt type the environment is such that when the firm defaults on its liabilities $\frac{b_{\pi,t}}{1+r_{\pi,t}}$ 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.[1] Specifically, she evaluates firm ownership after default by using fixed multiple of the last available realization of a fundamental profitability indicator, EBITDA. Formally,

$$\tilde{V}_{d,t}^{end} \approx \theta_\pi \pi_t. \tag{29}$$

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

$$s_{\pi,t} \geq 0 \tag{30}$$

$$\theta_\pi \pi_t - \frac{b_{k,t}}{1+r_{k,t}} \geq 0. \tag{31}$$

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 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.

[1] For a textbook treatment, see Damodaran (2012).

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 (2009a) 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 (2017) 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.[2] Whether transactions are defined in this way in turn affects

[2] 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.

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 regulation rather than an underlying contracting frictions that lender and borrowing need to overcome.

C Details on the model of Section 3

C.1 Firm optimality conditions

The firm's optimality conditions with respect to n_t, $b_{k,t}$, $b_{\pi,t}$ and k_t and i_t are derived as follows[3]

$$F_{n,t} = w_t \tag{32}$$

$$R_{k,t}\mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}\right\} + \mu_{k,t}\frac{R_{k,t}}{1+r_{k,t}} = 1, \tag{33}$$

$$R_{\pi,t}\mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}\right\} + \mu_{\pi,t}\frac{R_{\pi,t}}{1+r_{\pi,t}} = 1, \tag{34}$$

$$Q_t = \mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}\left[(1-\delta)Q_{t+1} + F_{k,t+1} + \mu_{\pi,t+1}\theta_\pi F_{k,t+1}\right] + \mu_{k,t}\theta_k(1-\delta)p_{k,t+1}\right\} \tag{35}$$

$$Q_t v_t[(1-\Phi_t) - \Phi_{1,t}i_t] + \mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}Q_{t+1}v_{t+1}\Phi_{-1,t+1}i_{t+1}\right\} = 1 \tag{36}$$

where $F_{n,t}$ and $F_{k,t}$ denote the marginal products of labor and capital, respectively. The Lagrange multipliers on the borrowing constraints (8) and (9) are denoted by $\mu_{\pi,t}$ and $\mu_{k,t}$, respectively. Q_t is the Lagrange multiplier on the capital accumulation equation (3) and defines the market value of the capital stock, see Hayashi (1982). As is typical in models with adjustment costs, its dynamics are characterized by the first order condition of investment, equation (36). In this equation $\Phi_{1,t}$ and $\Phi_{-1,t+1}$ denote the partial derivatives of $\Phi_t\left(\frac{i_t}{i_{t-1}}\right)$ and $\Phi_{t+1}\left(\frac{i_{t+1}}{i_t}\right)$ to i_t, respectively. The capital price $p_{k,t}$ that is relevant in the collateral constraint is given by (10) in the main text.

C.2 Household, government, and definition of equilibrium

C.2.1 Household problem

The household's objective is to maximize expected discounted lifetime utility

$$\mathbb{E}_0\sum_{t=0}^{\infty}\beta^t u(c_t, n_t), \tag{37}$$

subject to the budget constraint

$$c_t + \frac{b_{\pi,t}}{1+r_{\pi,t}} + \frac{b_{k,t}}{1+r_{k,t}} + p_t s_t + T_t = w_t n_t + b_{\pi,t-1} + b_{k,t-1} + s_{t-1}(d_t + p_t). \tag{38}$$

[3] For ease of notation I focus on the case without dividend adjustment costs ($\psi = 0$).

Equity shares in the firm are denoted by s_t and evaluated at price p_t. T_t is a lump sum tax. I specify preferences using a log-log utility function in consumption and leisure

$$u(c_t, n_t) = \log(c_t) + \chi \ \log(1 - n_t), \tag{39}$$

where χ governs the relative utility of leisure. The household takes $r_{k,t}, r_{\pi,t}, p_t$ and w_t as given when maximizing her objective.

Household optimality conditions. The household's optimality conditions with respect to n_t, $b_{k,t}$, $b_{\pi,t}$ and s_t are

$$u_{c_t} w_t + u_{n_t} = 0 \tag{40}$$

$$u_{c_t} = \beta(1 + r_{k,t})\mathbb{E}_t u_{c_{t+1}} \tag{41}$$

$$u_{c_t} = \beta(1 + r_{\pi,t})\mathbb{E}_t u_{c_{t+1}} \tag{42}$$

$$u_{c_t} p_t = \beta\mathbb{E}_t(d_{t+1} + p_{t+1})u_{c_{t+1}}, \tag{43}$$

where u_{c_t} and u_{n_t} denote marginal utility of consumption and labor, respectively.

C.2.2 Government

The lump sum tax T_t is required to finance the tax advantage of debt that is given to the firm, which amounts to the difference between debt issued (valued at $R_{j,t}^{-1}$) and debt received (valued at $(1 + r_{j,t})^{-1}$) for both debt types $j \in \{k, \pi\}$. In principle this lump sum tax could be levied on the firm as well, which would not alter the results. For simplicity I assume that the government does not save or borrow. Taken together, budget balance requires

$$T_t = \frac{b_{k,t}}{R_{k,t}} - \frac{b_{k,t}}{(1 + r_{k,t})} + \frac{b_{\pi,t}}{R_{\pi,t}} - \frac{b_{\pi,t}}{(1 + r_{\pi,t})}. \tag{44}$$

C.2.3 Equilibrium

I collect the exogenous states of the model in the vector $\mathbf{x}_t = (z_t, v_t, \phi_t)'$. These variables are assumed to follow a stochastic process of the form $\mathbf{x}_{t+1} = \mathbf{A}\mathbf{x}_t + \mathbf{u}_t$, which will be specified in the parameterization section below. The endogenous states of the model are k_{t-1}, $b_{k,t-1}$ and $b_{\pi,t-1}$. A dynamic competitive equilibrium is then defined as a set of quantities $\{d_t, n_t, b_{k,t}, b_{\pi,t}, k_t, c_t, s_t, T_t\}_{t=0}^{\infty}$ and prices $\{w_t, Q_t, p_{k,t}, R_{k,t}, R_{\pi,t}, r_{k,t}, r_{\pi,t}, \mu_{k,t}, \mu_{\pi,t}, \Lambda_t\}_{t=0}^{\infty}$ such that:

1. $d_t, n_t, b_{k,t}, b_{\pi,t}$ and k_t solve the firm's maximization problem specified above
2. $c_t, n_t, b_{k,t}, b_{\pi,t}$ and s_t solve the household's maximization problem specified above
3. The household owns the firm: $\Lambda_t = \beta^t u_{c_t}$ and $s_t = 1$
4. The government's budget constraint holds

5. The exogenous disturbances follow $\mathbf{x}_{t+1} = \mathbf{A}\mathbf{x}_t + \mathbf{u}_t$
6. Markets clear

The equilibrium admits a recursive formulation, to which the solution is a set of policy functions that map state variables into endogenous controls. Section C.4 of this appendix contains details on the calculation of the model's steady state. I solve for the policy functions with standard first-order perturbation techniques.

C.3 Specification of stochastic processes

The stochastic processes underlying the exogenous disturbances are defined as

$$\log(z_t) = (1-\rho_z)\log(\overline{z}) + \rho_z \log(z_{t-1}) + u_{z,t} \tag{45}$$

$$\log(v_t) = (1-\rho_v)\log(\overline{v}) + \rho_v \log(v_{t-1}) + u_{v,t} \tag{46}$$

$$\log(\phi_t) = (1-\rho_\phi)\log(\overline{\phi}) + \rho_\phi \log(\phi_{t-1}) + u_{\phi,t} \tag{47}$$

where the structural shocks $\{u_{z,t}, u_{v,t}, u_{\phi,t}\}$ are uncorrelated, iid, mean zero, normally distributed random variables with standard deviations $\{\sigma_z, \sigma_v, \sigma_\phi\}$.

C.4 Sketch of analytical calculation of the steady state

To compute the steady state of the model, I proceed as follows:

1. Drop time subscripts, obtain a system in steady state variables.
2. Steady state must fulfill $r_j = (1-\beta)/\beta$, $R_j = 1 + r(1-\tau_j)$ and $\mu_j = (1+r_f)(1/R_j - \beta)$ from bond Euler equations for firm and household, that is, equations (33), (34), (41) and (42).
3. Steady state must fulfill $Q = 1$
4. Solve (35) for the steady state capital-labor ratio as a function of model primitives.
5. Calculate steady state wage rate w from (32) using steady state capital-labor ratio.
6. Combine the capital-labor ratio, the wage rate, (40) and the resource constraint to calculate n as a function of model primitives.
7. Recover k from the definition of the capital-labor ratio.
8. The calculation of the remaining variables is straightforward.

To match steady state moments, I run a minimization routine over the above steps, where the objective to be minimized is the Euclidean distance between model moments from their empirical targets.

To allow for adjustment cost shocks I introduce a small alteration to the model in which steady adjustment are non-zero. This is done in order to be able to compute IRFs to this shock as deviations from the nonstochastic steady state. In particular I define

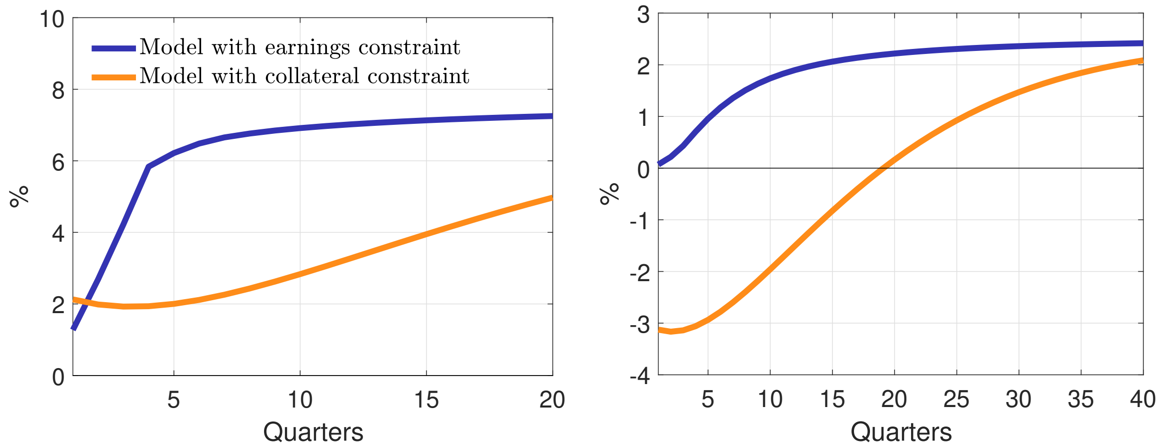
$$\Phi_t\left(\frac{i_t}{i_{t-1}}\right) = \frac{\phi_t}{2}\left(\frac{i_t}{i_{t-1}} - \iota\right)^2,$$

and set ι to 0.999.

C.5 IRF comparison with moving average earnings-based constraint

Figure C.1: MODEL IRFS OF DEBT: MODIFIED EARNINGS-BASED CONSTRAINT

(a) Permanent TFP shock **(b)** Permanent investment shock

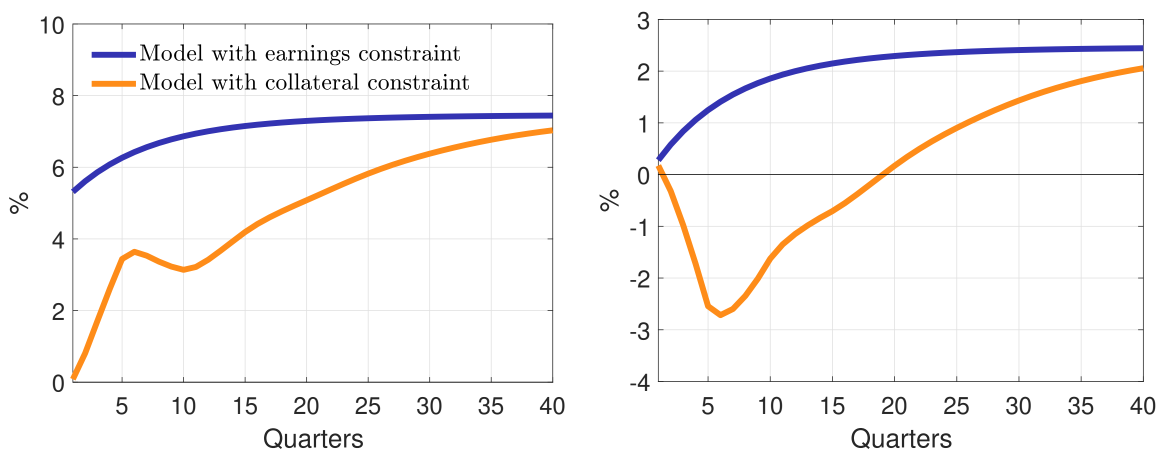


Note: This figure repeats Figure 2 for a formulation of the earnings-based constraint in which current and three lags of earnings enter in equation (8). It displays the IRFs of firm debt to different shocks generated from the model, under the two alternative calibrations in which only the (in this case modified) earnings-based constraint (dark blue line) or only the collateral constraint (light orange line) is present. Panel (a) show the debt IRF to a positive TFP shock and Panel (b) to a positive investment shock. The structural parameters to generate these IRFs are shown in Table 2. I set $\rho_z = \rho_v = 1$, and $\sigma_z = \sigma_v = 0.05$.

C.6 IRF comparison with capital evaluated at historical costs

Figure C.2: MODEL IRFS OF DEBT: CAPITAL EVALUATED AT HISTORICAL COSTS

(a) Permanent TFP shock **(b)** Permanent investment shock



Note: This figure repeats Figure 2 for a formulation of the collateral constraint in which an average of the 4 past prices of capital are used in (9). It displays the IRFs of firm debt to different shocks generated from the model, under the two alternative calibrations in which only the (in this case modified) earnings-based constraint (dark blue line) or only the collateral constraint (light orange line) is present. Panel (a) show the debt IRF to a positive TFP shock and Panel (b) to a positive investment shock. The structural parameters to generate these IRFs are shown in Table 2. I set $\rho_z = \rho_v = 1$, and $\sigma_z = \sigma_v = 0.05$.

C.7 Model IRFs of additional variables

Figure C.3: IRFS TO PERMANENT TFP SHOCK

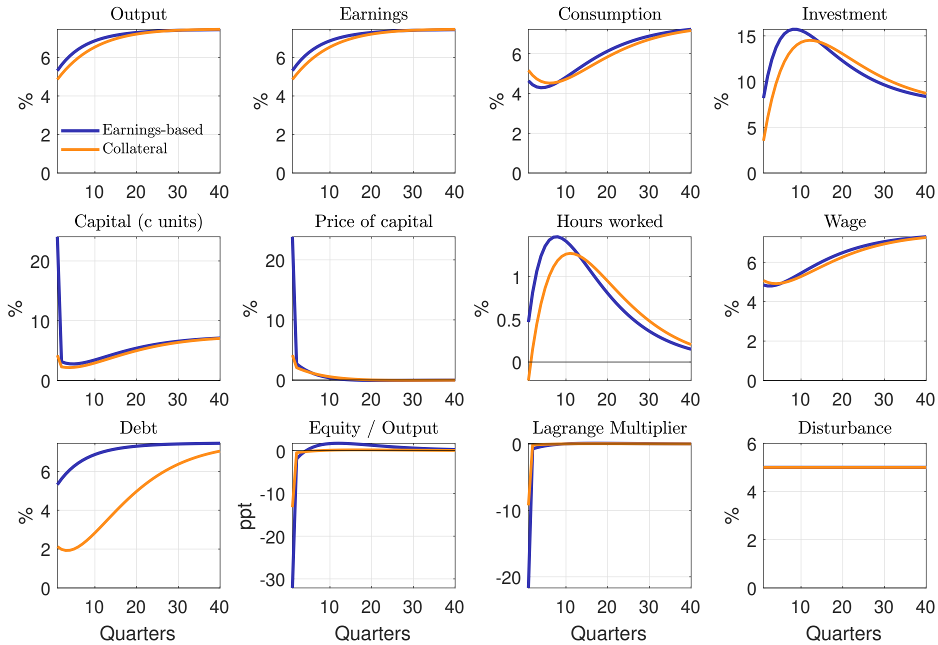
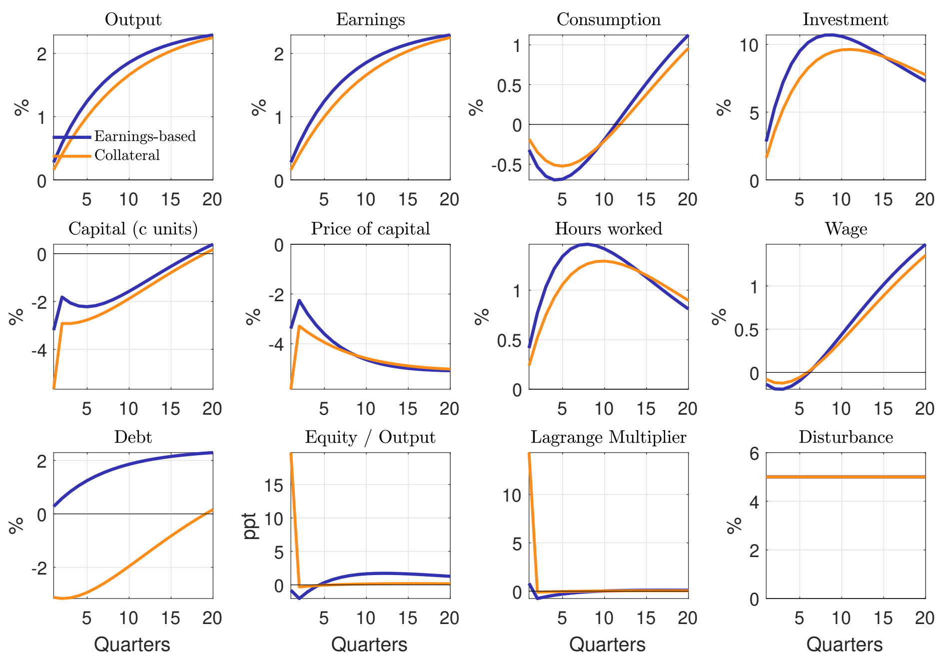


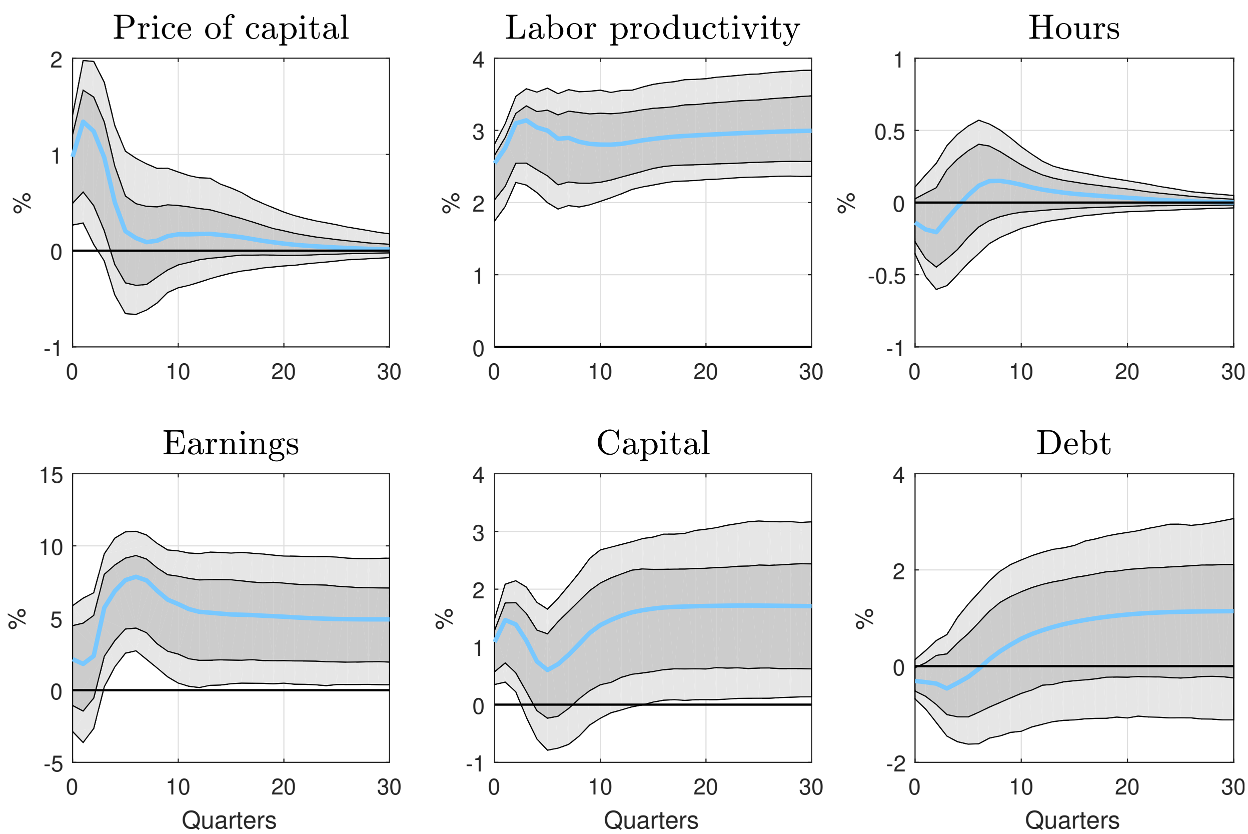
Figure C.4: IRFS TO PERMANENT INVESTMENT SHOCK



D Additional results for SVAR

D.1 SVAR IRFs to TFP shock

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

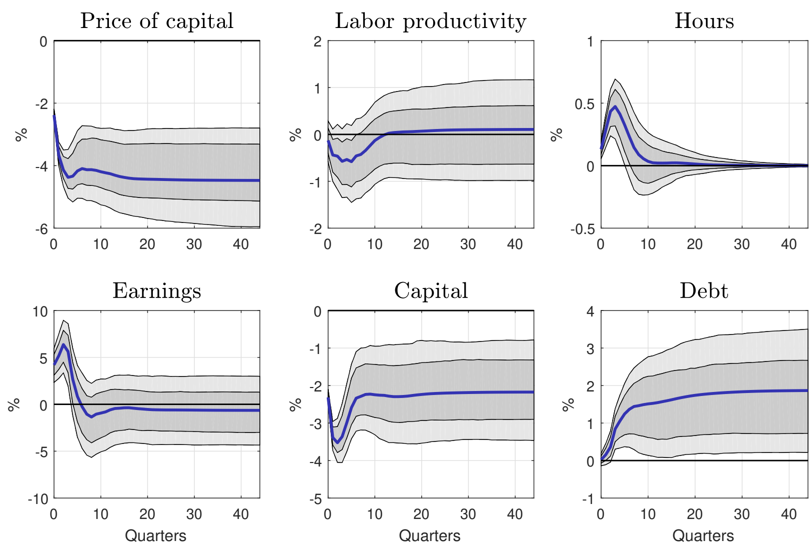


Note: The figure displays the IRFs to a TFP shock identified from an estimated SVAR model using US data. The identification scheme relies on long-run restrictions following Fisher (2006). The responses are shown for all six variables included in the system, in percent. The unit of the shock is one standard deviation. The sample period used for estimation is 1952:Q2 to 2016:Q4. 68% (dark gray) and 90% (light gray) error bands are calculated using bootstrap techniques. This shock is identified using the same estimation procedure and identification scheme as the investment shock in the main text, but is not used to verify predictions from the theoretical macro model.

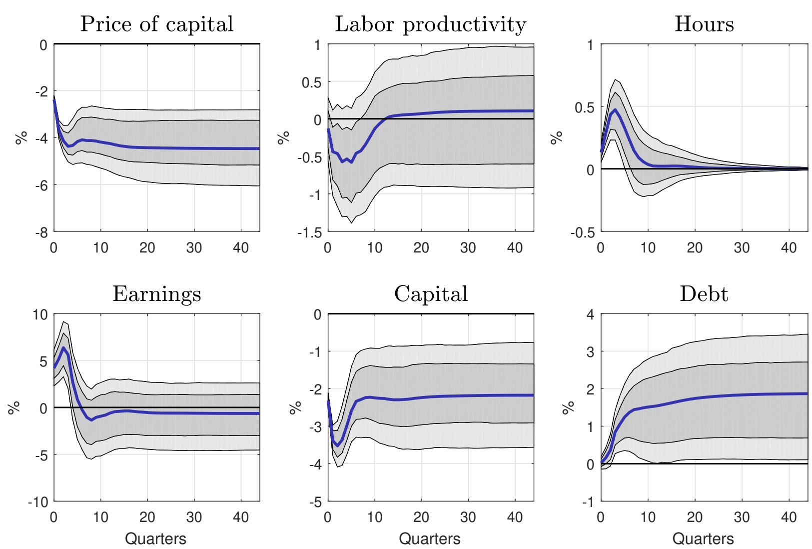
D.2 SVAR IRFs using medium-term restrictions

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

(a) Identification based on 5-year horizon



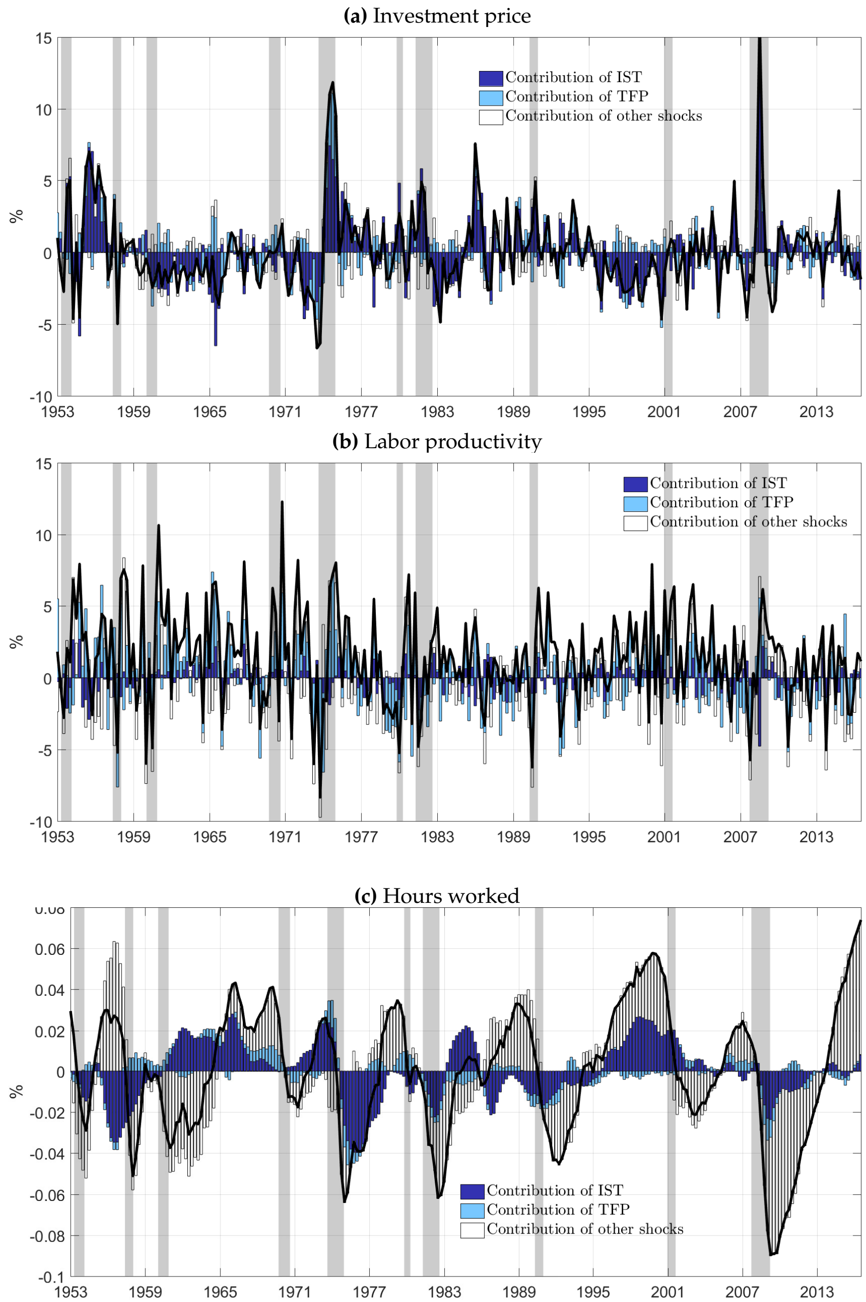
(b) Identification based on 10-year horizon



Note: The figure has the same scope as Figure 5 in the main text 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 2016: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

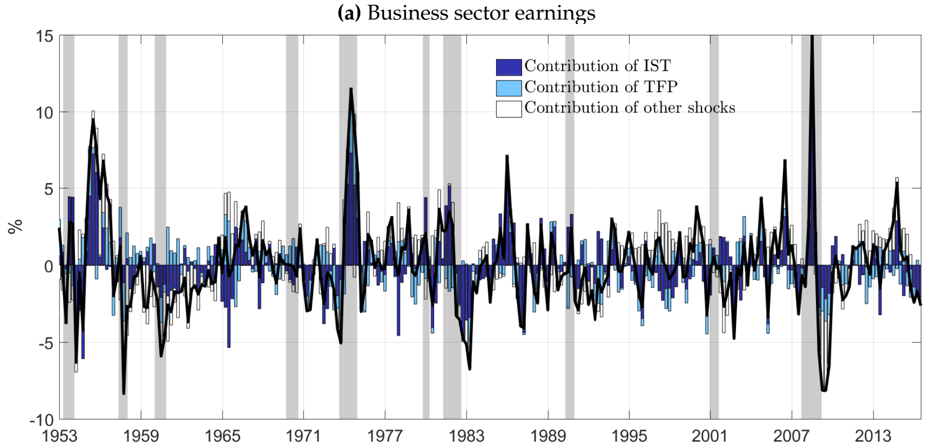
Figure D.3: SVAR: HISTORICAL VARIANCE DECOMPOSITIONS



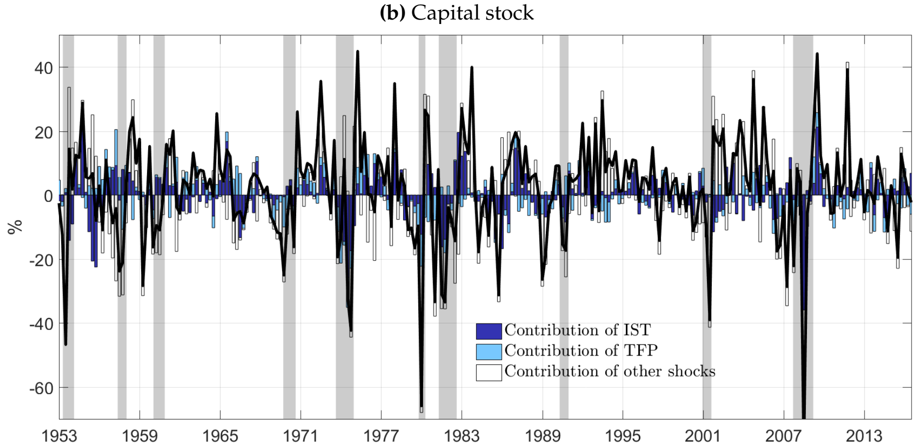
Note: Historical variance decomposition of variables as estimated by the SVAR model identified with long-run restrictions. The black line is the actual (detrended) data series. The bars indicate the contribution of different structural shocks to the variance of the respective observable as estimated 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 wight bars. Shaded areas indicate NBER recessions.

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

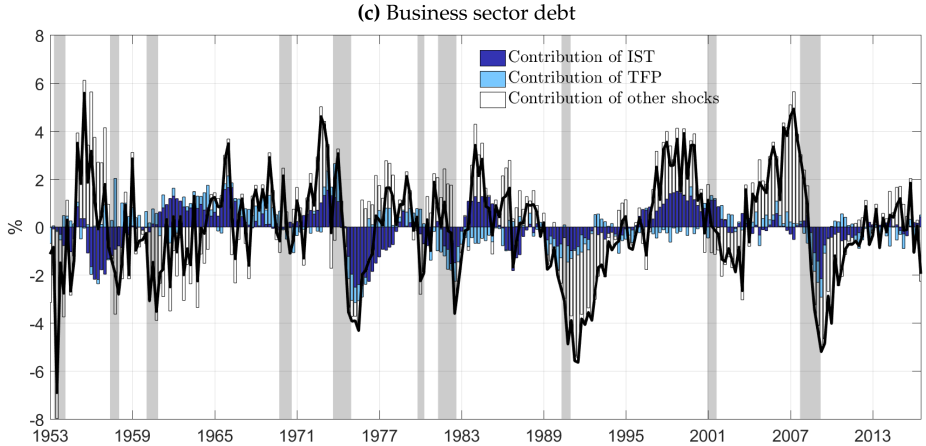
(a) Business sector earnings



(b) Capital stock



(c) Business sector debt



Note: 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 wight bars. Shaded areas indicate NBER recessions.

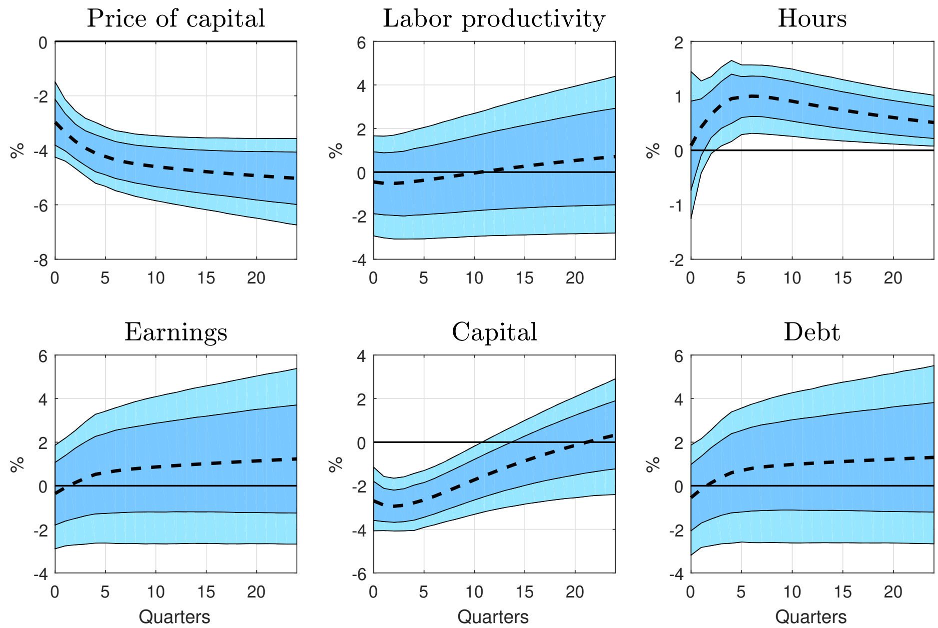
D.4 SVAR IRFs using simulated data

This appendix presents the results of a Monte Carlo exercise, which I set up as follows. I generate simulated data from the model in Section 3 and estimate the SVAR on this data. I repeatedly create two types of data samples, each generated from one of the two alternative borrowing constraint specifications (Panel (b) vs. Panel (c) in Table 2). I do so by randomly generating the time series in (15) from the model's solution. Specifically, I randomly draw permanent investment shocks, permanent TFP shocks, stationary government spending shocks (all with the same variance), and then plug them into the linearized policy rules of the model to generate observables. I then add iid measurement error to all series, calibrated to be 5% of the size of the structural shocks. For each sample type I generate 10,000 repetitions and run a SVAR identified with long-run restrictions on each of these samples. The identification procedure is carried out as described in the main text.

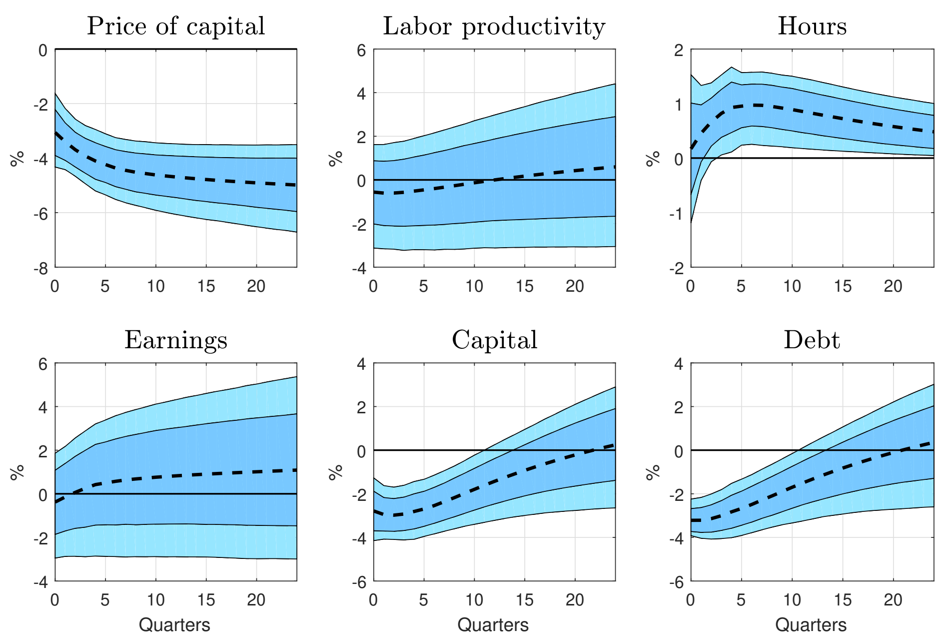
The results of this exercise are shown in Figure D.5. Panel (a) plots the IRFs from estimations on samples generated with the earnings-based constraint, Panel (b) the equivalent with the collateral constraint. Each subpanel shows the mean (dashed line) and and 68% confidence sets (light blue area) across Monte Carlo repetitions. The figure shows that the direction of the debt IRF implied by the model is correctly picked up by the SVAR on average. Interestingly, while the negative debt response arising from the collateral constraint is estimated to be statistically significant, the positive one implied by the earnings constraint model is imprecisely estimated.

Figure D.5: SVAR IRFS USING SIMULATED DATA

(a) SVAR IRFs to IST shock - Underlying data simulated with earnings-based constraint



(b) SVAR IRFs to IST shock - Underlying data simulated with collateral constraint



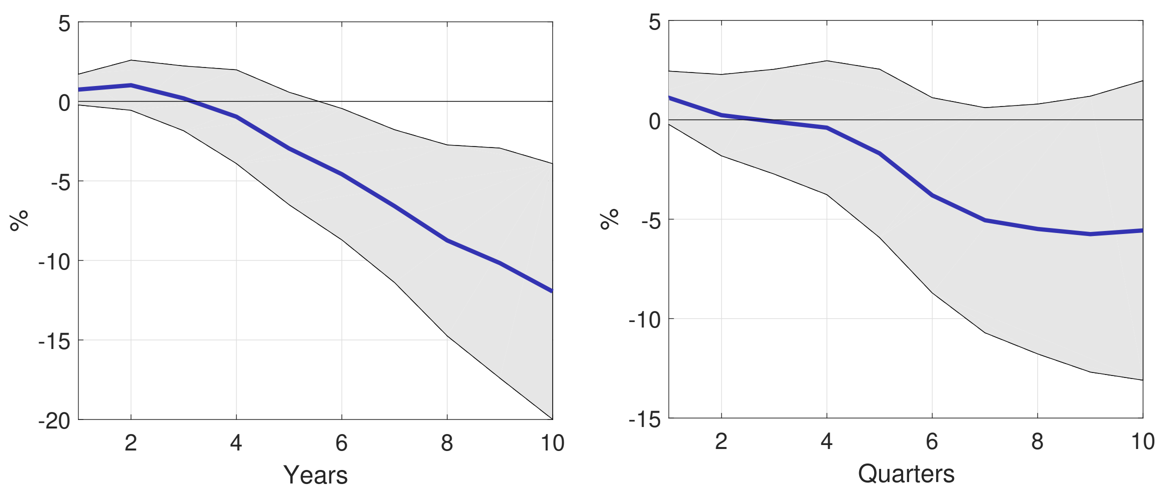
Note: The figure plots IRFs from an SVAR model estimated on data that is repeatedly simulated from the model in Section 3. Panel (a) uses the data generated with an earnings-based constraint, Panel (b) with a collateral constraint. In both cases, the data is generated from TFP shocks, investment shocks, an additional stationary demand shock. Normal iid measurement error is added to all series. 68% and 90% significance sets and means across 10,000 Monte Carlo repetitions are shown.

D.5 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.6: RESPONSES OF USED EQUIPMENT PRICES TO IST SHOCK

(a) Used airplane price **(b)** Used vehicle price



Note: 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 4.3 of the main text for additional remarks on local projection methods.

The resulting IRFs are shown in Figure D.6. 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 5 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 4.3. 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 a variety of additional results on the estimation of firm-level responses to investment shocks in Section 4.3 of the main text. Section E.1 of the appendix reports the coefficient estimates of the difference between earnings and collateral borrowers' debt IRFs and corresponding standard errors (horizon by horizn). This serves as a formal test of the difference between the IRFs shown in Figure 7. Section E.2 shows the results of Figure 7 for an alternative specification in which I estimate the IRF to a fall in the relative price of equipment investment, instrumented by the investment shock (rather than the debt response to the investment shock directly). Section E.3 contains the results for a firm fixed effects regression specification. Note that in the specification with firm fixed effects I cluster standard errors at the 3-digit industry level, rather than by firm and quarter. In Section E.4, the main results displayed in Figure 7 are shown also for the two additional groups, which are firms subject to both covenants and collateral, as well as firms that are subject to neither. Finally, Section E.5 presents results for the response of firm-level investment (capital expenditures) to investment shocks, separately for firms subject to earnings-based and collateral constraints.

E.1 Significance of the difference between heterogeneous debt IRFs

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

	Classification based on specific assets	Classification based on secured revolvers
$\beta_0^{earn} - \beta_0^{coll}$	0.0353*	0.0019
	(0.0208)	(0.0241)
$\beta_1^{earn} - \beta_1^{coll}$	0.0356	0.0070
	(0.0269)	(0.0294)
$\beta_2^{earn} - \beta_2^{coll}$	0.0359	0.0208
	(0.0287)	(0.0319)
$\beta_3^{earn} - \beta_3^{coll}$	0.0536	0.0559
	(0.0343)	(0.0385)
$\beta_4^{earn} - \beta_4^{coll}$	0.0623*	0.0513
	(0.0354)	(0.0408)
$\beta_5^{earn} - \beta_5^{coll}$	0.0516	0.0436
	(0.0346)	(0.0399)
$\beta_6^{earn} - \beta_6^{coll}$	0.0636*	0.0480
	(0.0358)	(0.0414)
$\beta_7^{earn} - \beta_7^{coll}$	0.0743**	0.0724*
	(0.0366)	(0.0422)
$\beta_8^{earn} - \beta_8^{coll}$	0.0912**	0.0881**
	(0.0372)	(0.0425)
$\beta_9^{earn} - \beta_9^{coll}$	0.0859**	0.0796*
	(0.0385)	(0.0432)
$\beta_{10}^{earn} - \beta_{10}^{coll}$	0.0824**	0.0687
	(0.0395)	(0.0442)
$\beta_{11}^{earn} - \beta_{11}^{coll}$	0.0976**	0.0959**
	(0.0404)	(0.0451)
$\beta_{12}^{earn} - \beta_{12}^{coll}$	0.0747*	0.0737
	(0.0417)	(0.0458)

Note: The table shows estimates of the difference between the debt IRFs to investment shocks of earnings borrowers and collateral borrowers as estimated by equation (17) in the main text. The left column shows these estimates for the specification corresponding to Panel (a) of Figure 7 and the right column for Panel (b). 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 alternative specifications.

E.2 IV strategy

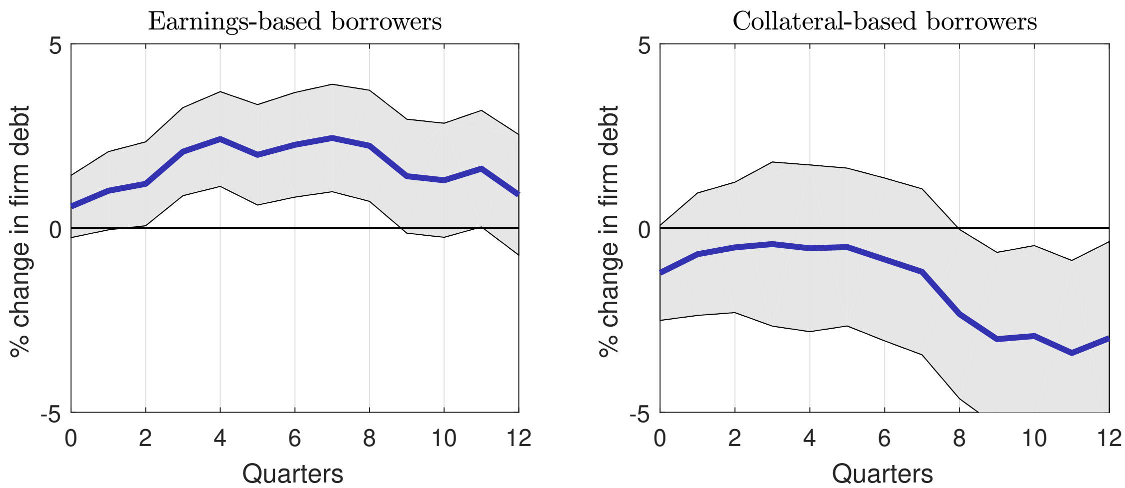
The results presented here study the responses of firm debt to a fall in the relative price of investment goods, instrumented by the exogenous investment shock, rather than considering the direct responses to the shock itself, as formulated by equation (17) and presented in the main text. To this end, equation (17) from the main text is modified to

$$\begin{aligned}\log(b_{i,t+h}) = \alpha_h + \beta_h p_{k,t} + \boldsymbol{\gamma X_{i,t-1}} \\ + \beta_h^{earn} \mathbb{1}_{i,t,earn} \times p_{k,t} + \alpha_h^{earn} \mathbb{1}_{i,t,earn} \\ + \beta_h^{coll} \mathbb{1}_{i,t,coll} \times p_{k,t} + \alpha_h^{coll} \mathbb{1}_{i,t,coll} + \gamma t + \eta_{i,t+h},\end{aligned} \tag{48}$$

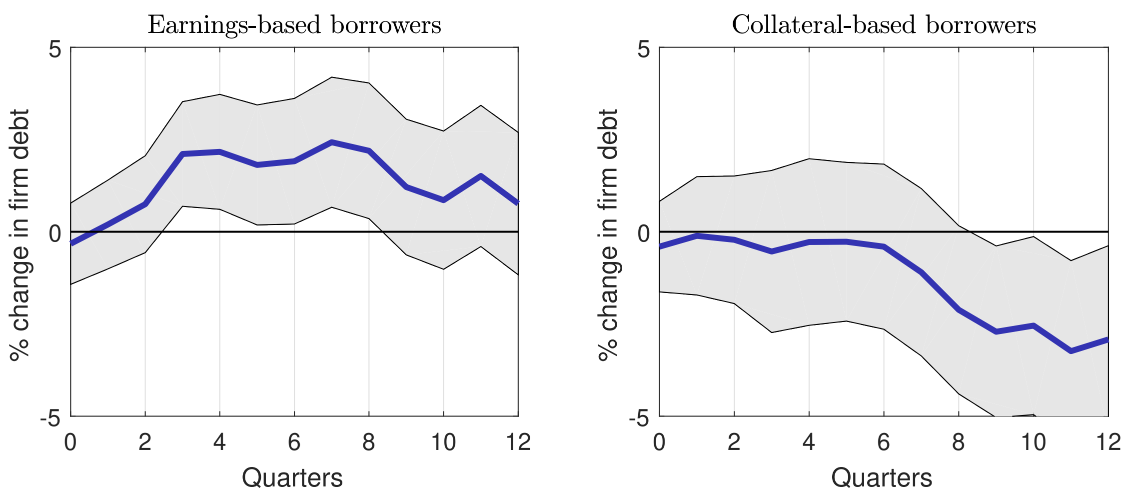
where $p_{k,t}$ is defined as in Section 4.1.2. Equation (48) is then estimated by using $\hat{u}_{IST,t}$ as an IV for $p_{k,t}$. The results for this specification, presented analogous to Figure 7, are shown in Figure E.1 below. They paint a very similar picture to the results in the main text. The responses are smaller in magnitude, and standard errors are lower relative to when the shock is used as a regressor directly.

Figure E.1: FIRM-LEVEL IRFS TO FALL IN INVESTMENT PRICE, INSTRUMENTED WITH IST SHOCK

(a) Using collateral classification based on specific assets



(b) Using collateral classification based on secured revolvers

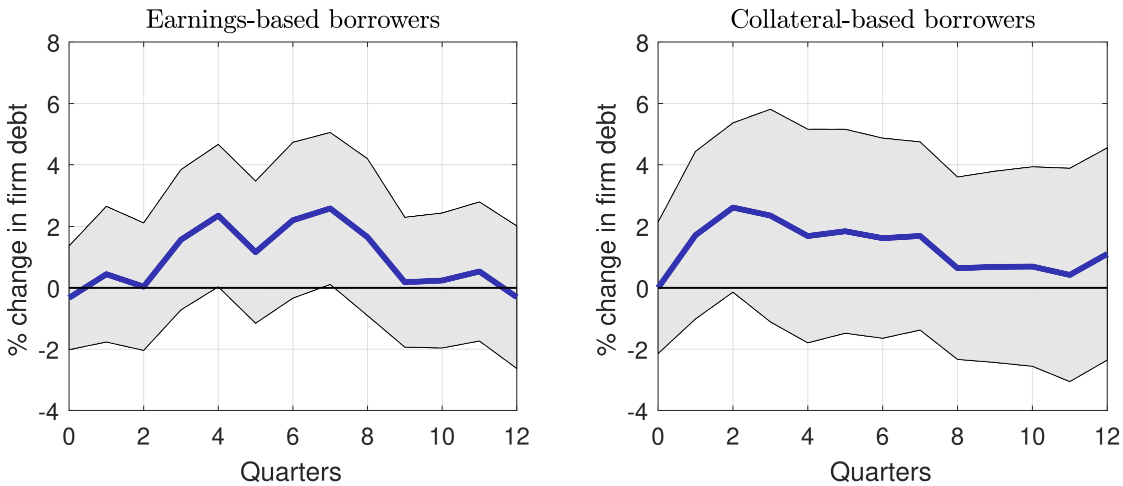


Note: This figure repeats Figure 7 from the text but instead plots the IRFs to a fall in the relative price of investment, instrumented with the investment shock, see equation (E.1) above. In both panels of the figure, the debt IRF for borrowers with earnings covenants and no collateral (left) and borrowers 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) uses the collateral classification based on whether a loan is backed by specific assets or not (see details in Section 2). Panel (b) uses an alternative grouping where secured revolvers are categorized as collateralized debt, see Lian and Ma (2019). The investment shock is identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). 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 IRFs shown in the figure are consistent with the model's prediction of a positive debt response under an earnings-based constraint and a negative one under a collateral constraint.

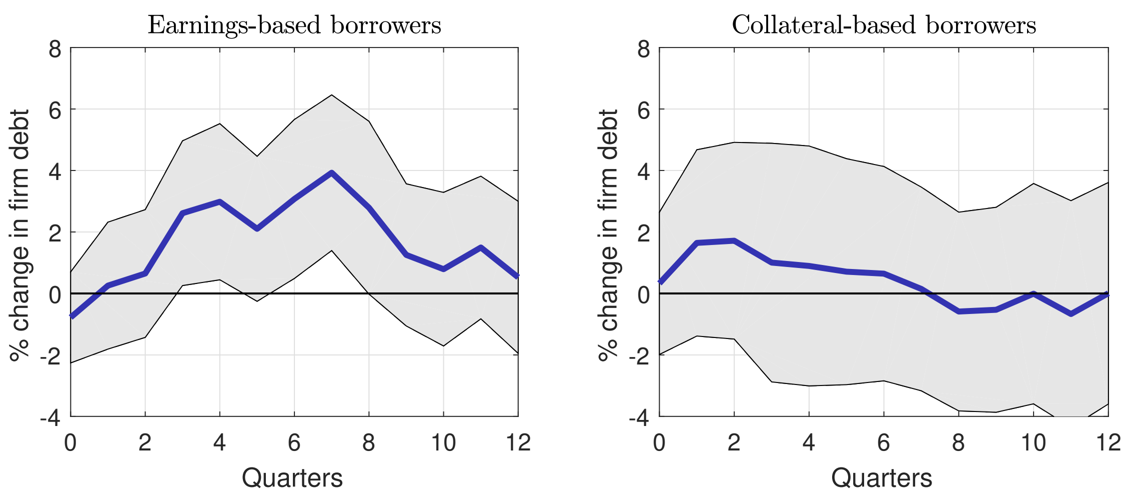
E.3 Results for specification with firm fixed effects

Figure E.2: FIRM-LEVEL IRFS INVESTMENT SHOCK: FIRM FIXED EFFECTS SPECIFICATION

(a) Using collateral classification based on specific assets



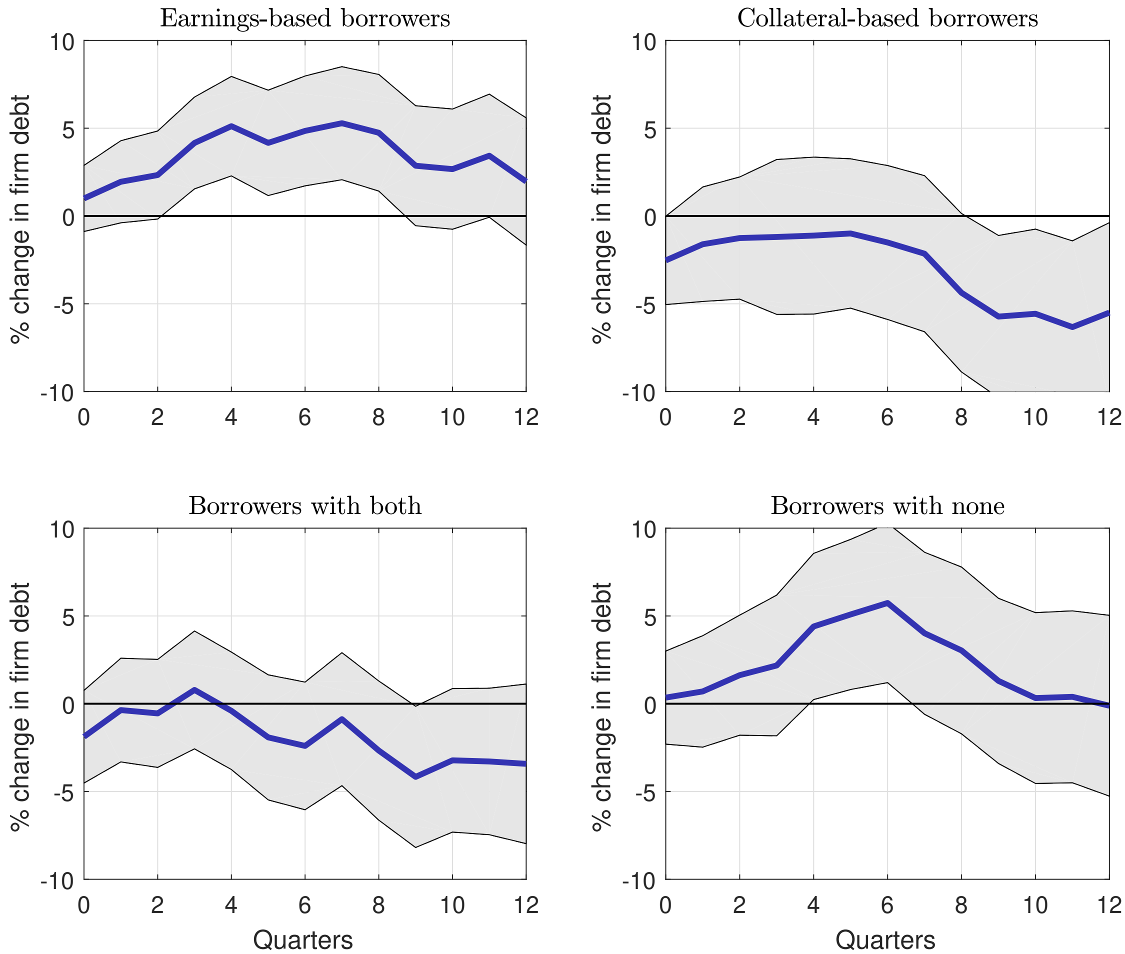
(b) Using collateral classification based on secured revolvers



Note: This figure repeats Figure 7 from the text for a regression specification with firm-fixed effects. The figure displays average IRFs of firm borrowing for different firm groups, estimated using the method of Jordà (2005) in a panel data context, see equation (17). In both panels of the figure, the debt IRF for borrowers with earnings covenants and no collateral (left) and borrowers without earnings covenants but with collateral (right) are plotted. Panel (a) uses the collateral classification based on whether a loan is backed by specific assets or not (see details in Section 2). Panel (b) uses an alternative grouping where secured revolvers are categorized as collateralized debt, see Lian and Ma (2019). The investment shock is identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). 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 standard errors clustered at the 3-digit industry level. The IRFs shown in the figure are consistent with the model's prediction of a positive debt response under an earnings-based constraint and a negative one under a collateral constraint.

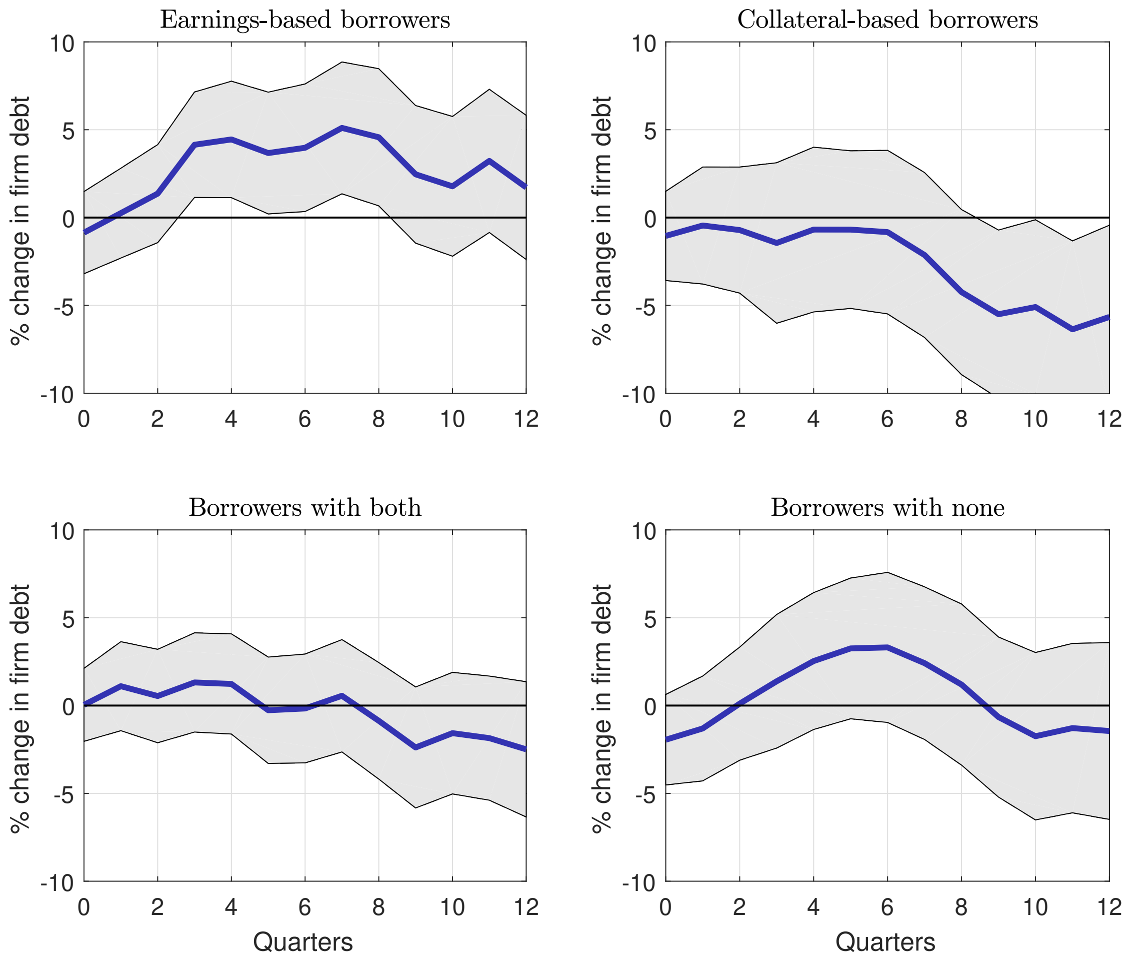
E.4 Results for all four firm groups

Figure E.3: IRFS FOR ALL FOUR CATEGORIES: COLLATERAL CLASSIFICATION BASED ON SPECIFIC ASSETS



Note: This figure repeats Panel (a) of Figure 7 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 investment shock is identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). 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.

Figure E.4: IRFS FOR ALL FOUR CATEGORIES: COLLATERAL CLASSIFICATION BASED ON SECURED REVOLVERS



Note: This figure repeats Panel (b) of Figure 7 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 investment shock is identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). 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.

E.5 The response of firm-level investment

In addition to the response of firm-level borrowing to investment shocks presented in the main text, in this appendix I also study the response of firm-level investment, separately for firms with earnings-based covenants and firms that borrow against collateral. To this end, I modify equation (17) in the main text to be

$$\begin{aligned}\log(inv_{i,t+h}) = \alpha_h + \widetilde{\beta}_h \hat{u}_{IST,t} + \boldsymbol{\gamma X_{i,t}} \\ + \widetilde{\beta}_h^{earn} \mathbb{1}_{i,t,earn} \times \hat{u}_{IST,t} + \alpha_h^{earn} \mathbb{1}_{i,t,earn} \\ + \widetilde{\beta}_h^{coll} \mathbb{1}_{i,t,coll} \times \hat{u}_{IST,t} + \alpha_h^{coll} \mathbb{1}_{i,t,coll} + \delta t + \eta_{i,t+h},\end{aligned} \tag{49}$$

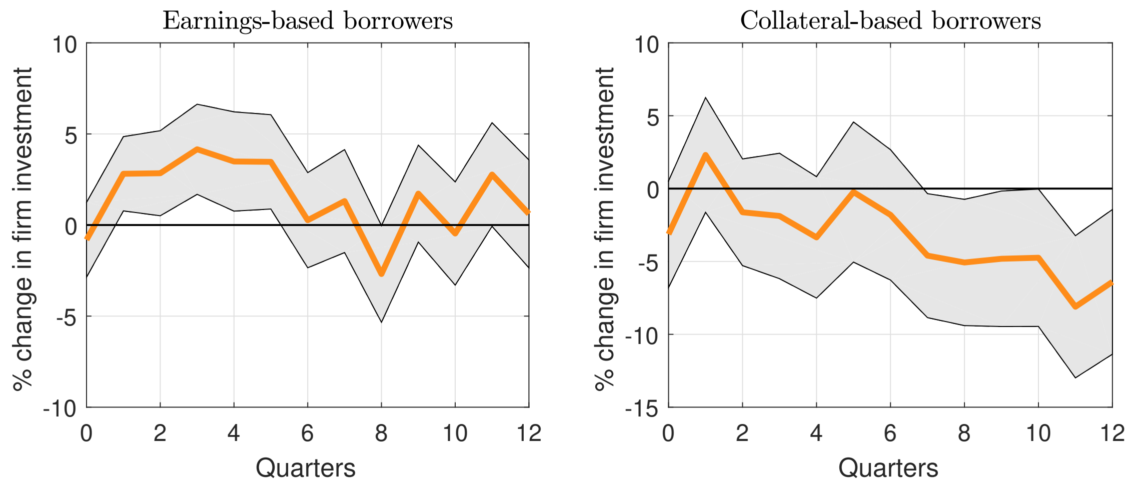
where $inv_{i,t+h}$ is capital expenditures ('capxq') from Compustat. In line with the data treatment described in the main text, I deflate this variable with the consumption deflator for nondurables and services.

The results are shown in Figure E.5. This figure is constructed exactly like Figure 7 in the main text, with the two panels corresponding to the alternative ways of constructing the collateral borrower dummy. In both panels, it is visible that 'earnings borrowers' increase their investment in response to the shock, while 'collateral borrowers' reduce investment. In line with the broad contours of the debt response in the main text, the negative response of firms that borrow against collateral is sluggish. In general, these responses are less smooth than the ones for debt. This is unsurprising, given that I constructed $b_{i,t+h}$ in equation (17) from the stock of liabilities, but capital expenditures $inv_{i,t+h}$ are a volatile and lumpy flow variable.

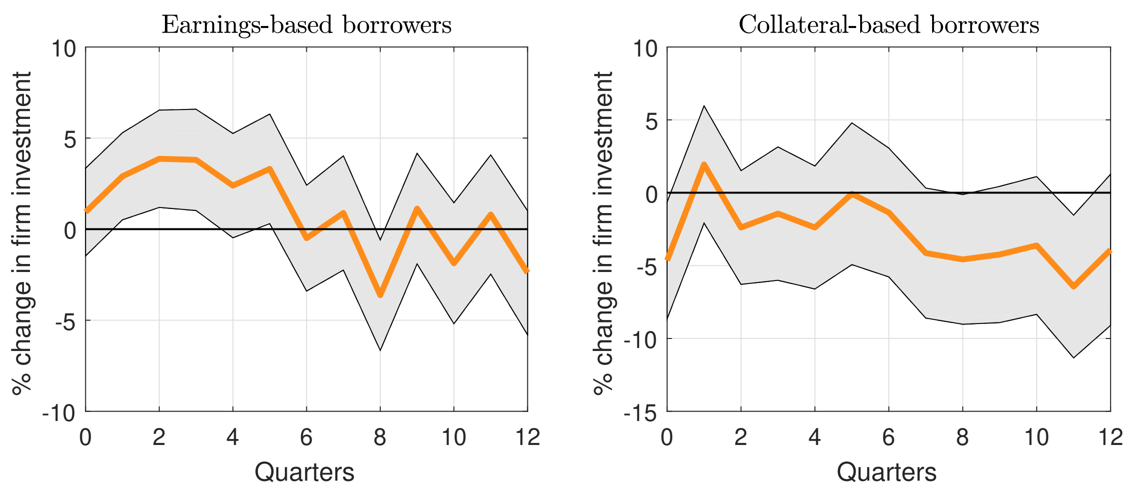
Table E.2 presents the coefficient estimates of the difference between earnings and collateral borrowers' debt IRFs ($\widetilde{\beta}_H^{earn} - \widetilde{\beta}_H^{coll}$), and the related standard errors horizon by horizon. This serves as a formal test of the difference between the IRFs shown in Figure E.5. These results show, similar to the results for debt in Table E.1, that the null hypothesis of equal responses across borrower types is rejected at various horizons and for both alternative ways of constructing the collateral borrower dummy.

Figure E.5: FIRM-LEVEL IRFS OF INVESTMENT TO INVESTMENT SHOCK FOR DIFFERENT BORROWER TYPES

(a) Using collateral classification based on specific assets



(b) Using collateral classification based on secured revolvers



Note: The figure displays average IRFs of firm investment (capital expenditures) within different firm groups, estimated using the method of Jordà (2005) in a panel context. In both panels, the investment 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) uses the collateral classification based on whether a loan is backed by specific assets or not (see details in Section 2). Panel (b) uses an alternative grouping where secured revolvers are categorized as collateralized debt, see Lian and Ma (2019). The investment shock is identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). 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 IRFs shown in the figure are consistent with the model's prediction of a positive debt response under an earnings-based constraint and a negative one under a collateral constraint. A formal test rejects the null hypothesis of equal responses across the two firm types for various horizons, as shown in Table E.2 below.

Table E.2: ESTIMATES OF THE DIFFERENCE BETWEEN INVESTMENT IRF COEFFICIENTS

	Classification based on specific assets	**Classification based on secured revolvers**
$\widetilde{\beta}_0^{earn} - \widetilde{\beta}_0^{coll}$	0.0232	0.0559*
	(0.0267)	(0.0325)
$\widetilde{\beta}_1^{earn} - \widetilde{\beta}_1^{coll}$	0.0050	0.0096
	(0.0289)	(0.0322)
$\widetilde{\beta}_2^{earn} - \widetilde{\beta}_2^{coll}$	0.0447	0.0625*
	(0.0281)	(0.0327)
$\widetilde{\beta}_3^{earn} - \widetilde{\beta}_3^{coll}$	0.0604*	0.0524
	(0.0321)	(0.0370)
$\widetilde{\beta}_4^{earn} - \widetilde{\beta}_4^{coll}$	0.0684**	0.0478
	(0.0327)	(0.0344)
$\widetilde{\beta}_5^{earn} - \widetilde{\beta}_5^{coll}$	0.0371	0.0338
	(0.0361)	(0.0397)
$\widetilde{\beta}_6^{earn} - \widetilde{\beta}_6^{coll}$	0.0207	0.0086
	(0.0342)	(0.0360)
$\widetilde{\beta}_7^{earn} - \widetilde{\beta}_7^{coll}$	0.0591*	0.0503
	(0.0333)	(0.0375)
$\widetilde{\beta}_8^{earn} - \widetilde{\beta}_8^{coll}$	0.0238	0.0095
	(0.0331)	(0.0369)
$\widetilde{\beta}_9^{earn} - \widetilde{\beta}_9^{coll}$	0.0654*	0.0537
	(0.0349)	(0.0378)
$\widetilde{\beta}_{10}^{earn} - \widetilde{\beta}_{10}^{coll}$	0.0428	0.0174
	(0.0361)	(0.0399)
$\widetilde{\beta}_{11}^{earn} - \widetilde{\beta}_{11}^{coll}$	0.1088***	0.0724*
	(0.0370)	(0.0405)
$\widetilde{\beta}_{12}^{earn} - \widetilde{\beta}_{12}^{coll}$	0.0701*	0.0152
	(0.0374)	(0.0429)

Note: The table shows estimates of the difference between the IRFs of firm-level capital expenditures to investment shocks of earnings borrowers and collateral borrowers as estimated by equation (17) in the main text. The left column shows these estimates for the specification corresponding to Panel (a) of Figure 7 and the right column for Panel (b). 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 alternative specifications.

F Details on the quantitative model of Section 6

F.1 Model setup

The model is a variant of the medium scale New Keynesian model introduced by Smets and Wouters (2007), similar to Jermann and Quadrini (2012).[6] The core of the model is that of Section 3 but a variety of additional frictions are added.

F.1.1 Final good firm

The final good firm produces a consumption good Y_t using inputs $y_{i,t}$ that are provided by intermediate producers. The production function is

$$Y_t = \left(\int_0^1 y_{i,t}^{\frac{1}{\eta_t}} \, di \right)^{\eta_t} . \tag{50}$$

η_t is a stochastic price markup disturbance. The final good is sold to households at price P_t and intermediate inputs are purchased at price $p_{i,t}$. The optimality conditions of the final good firm can be written as

$$p_{i,t} = P_t Y_t^{\frac{\eta_t - 1}{\eta_t}} y_{i,t}^{\frac{1-\eta_t}{\eta_t}} \tag{51}$$

which is the demand function that intermediate producers take as given, and intermediate prices aggregate to the economy's price level as $P_t = \left(\int_0^1 p_{i,t}^{\frac{1}{1-\eta_t}} \, di \right)^{1-\eta_t}$.

F.1.2 Intermediate goods firms

There is a continuum of size 1 of firms, which produce an intermediate good $y_{i,t}$ that is sold at price $p_{i,t}$ to a final good producer. The production of intermediate goods is based on a Cobb-Douglas production function

$$y_{i,t} = z_t (u_{i,t} k_{i,t-1})^{\alpha} n_{i,t}^{1-\alpha}, \tag{52}$$

where TFP, z_t, is common across firms and will be subject to stochastic shocks. $k_{i,t-1}$ is capital, which is owned and accumulated by firms and predetermined at the beginning of the period. $u_{i,t}$ is the utilization rate of capital, which is an endogenous choice taken subject to a cost to be specified further below. $\alpha \in (0,1)$ is the capital share in production. $n_{i,t}$ denotes labor used by firm i at the wage rate $w_{i,t}$, which is a composite of different labor types j that will be supplied by households:

$$n_{i,t} = \left(\int_0^1 n_{j,i,t}^{\frac{1}{\vartheta_t}} \, dj \right)^{\vartheta_t} , \tag{53}$$

[6] I add some corrections relative to the Jermann and Quadrini (2012) model that were suggested by Pfeifer (2016).

where v_t is stochastic shock that affects demand for labor. A firm's nominal period earnings flow, or operational profits, is denoted as $\pi_{i,t}$ and defined as

$$\pi_{i,t} \equiv y_{i,t} - w_{i,t} n_{i,t}. \tag{54}$$

As in the model in Section 3 the law of motion of capital is

$$k_{i,t} = (1-\delta)k_{i,t-1} + v_t \left[1 - \frac{\phi}{2}\left(\frac{i_{i,t}}{i_{i,t-1}}\right)^2\right] i_{i,t}. \tag{55}$$

MEI shocks enter via the disturbance v_t. In the quantitative application I do not allow for shocks to ϕ_t for comparability with previous studies.

Firms take (51) as given given when setting their price. Combining this equation with the production function, the price can be written as a function of aggregate variables and individual inputs, so that

$$p_{i,t} = P_t Y_t^{\frac{\eta_t - 1}{\eta_t}} \left(z_t (u_{i,t} k_{i,t-1})^{\alpha} n_{i,t}^{1-\alpha}\right)^{\frac{1-\eta_t}{\eta_t}}. \tag{56}$$

The capital utilization cost is specified as

$$\Xi(u_t) = \xi_1 (u_t^{1+\xi_2} - 1)/(1-\xi_2) \tag{57}$$

The parameter ξ_1 is calibrated to generate steady state utilization of 1.

Firms set prices subject to a Rotemberg adjustment cost. As discussed in detail by Jermann and Quadrini (2012), this approach to generating price rigidities – as opposed to, say Calvo pricing – substantially facilitates the aggregation of the decision of individual firms when financial frictions are introduced. Specifically, a firm that has previously set price $p_{i,t-1}$ faces the cost

$$\tilde{\Phi}(p_{i,t-1}, p_{i,t}, Y_t) = \frac{\tilde{\phi}}{2}\left(\frac{p_{i,t}}{p_{i,t-1}} - 1\right)^2 Y_t. \tag{58}$$

Finally, firms have access to debt, which is limited by weighting between an earnings-based and a collateral component. The details of this constraints are given in the main text, see the description of equations (24) and (25).

Firm maximization problem. The objective of firms is similar to what is descried in equation (11) in the more stylized model of Section 3. In the New Keynesian setting, firms maximize the flow of (nominal) dividends, discounted with the household's stochastic discount factor, subject the flow of dividends equation (which now contains also price adjustment and utilization costs), the borrowing constraint – either (24) or (25), the law of motion of capital (55) and the demand function given by (51). They now also choose their price $p_{i,t}$ and utilization rate $u_{i,t}$, in addition to $d_{i,t}$, $n_{i,t}$, $i_{i,t}$, $k_{i,t}$, and $b_{i,t}$.

F.1.3 Households

There is a continuum of size 1 of households. Household $j's$ expected lifetime utility is given by

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \gamma_t \beta^t \left(\frac{(c_{j,t} - hc_{j,t-1})^{1-\sigma}}{1-\sigma} - \chi \frac{n_{j,t}^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} \right) \tag{59}$$

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 $n_{j,t}$ and charge wage rate $w_{j,t}$. The budget constraint is

$$c_{j,t} + \frac{b_{j,t}}{1+r_t} + p_t^f s_{j,t} + T_{j,t} + \int q^{\bar{\omega}}_{j,t+1} a_{j,t+1} dw_{j,t} = w_{j,t} n_{j,t} + b_{j,t-1} + P_t d_{j,t} + p_t^f s_{j,t-1}. \tag{60}$$

$a_{j,t+1}$ are holdings of state-contingent claims with which households can insure against wage shocks. They are traded at price $q^w_{j,t+1}$. The notation in (60) is otherwise similar as in the stylized mode of Section 3.

The demand for labor coming from the intermediate goods firms is given by

$$n_{j,t} = \left(\frac{w_{j,t}}{W_t} \right)^{-\frac{\vartheta_t}{\vartheta_t - 1}} n_t, \tag{61}$$

where W_t and n_t are the aggregate wage and employment level, respectively. (61) is taken as given by the household when choosing $n_{j,t}$ and $w_{j,t}$.

Households face wage rigidities, which arise, in the spirit of Calvo, from the fact that a given firm can only change their wage with probability $(1 - \bar{\omega})$. 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 (59).

F.1.4 Government

The government's budget constraint, in nominal terms, reads

$$T_t = \frac{b_t}{R_t} - \frac{b_t}{(1+r_t)} + P_t G_t, \tag{62}$$

where T_t are nominal lump sum taxes levied on households, the term $\frac{b_t}{R_t} - \frac{b_{k,t}}{(1+r_{k,t})}$ is the tax subsidy given to firms, and G_t is a real spending shock that follows an exogenous stochastic process.

F.1.5 Monetary policy

There is a Taylor rule specified as

$$\frac{1+r_t}{1+\bar{r}} = \left[\frac{1+r_{t-1}}{1+\bar{r}}\right]^{\rho_R} \left[\left(\frac{\pi_t^p}{\bar{\pi}^p}\right)^{\nu_1} \left(\frac{Y_t}{Y_{t-1}}\right)^{\nu_2}\right]^{1-\rho_R} \left[\frac{Y_t/Y_t^*}{Y_{t-1}/Y_{t-1}^*}\right]^{\nu_3} \varsigma_t, \tag{63}$$

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 more details. 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 policy shocks.

F.1.6 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):

$$\log(z_t) = (1-\rho_z)\log(\bar{z}) + \rho_z \log(z_{t-1}) + u_{z,t} \tag{64}$$

$$\log(v_t) = (1-\rho_v)\log(\bar{v}) + \rho_v \log(v_{t-1}) + u_{v,t} \tag{65}$$

$$\log(\gamma_t) = (1-\rho_\gamma)\log(\bar{\gamma}) + \rho_\gamma \log(\gamma_{t-1}) + u_{\gamma,t} \tag{66}$$

$$\log(\eta_t) = (1-\rho_\eta)\log(\bar{\eta}) + \rho_\eta \log(\eta_{t-1}) + u_{\eta,t} - \mu_p u_{\eta,t-1} \tag{67}$$

$$\log(\vartheta_t) = (1-\rho_\vartheta)\log(\bar{\vartheta}) + \rho_\vartheta \log(\vartheta_{t-1}) + u_{\vartheta,t} - \mu_w u_{\vartheta,t-1} \tag{68}$$

$$\log(g_t) = (1-\rho_g)\log(\bar{g}) + \rho_g \log(g_{t-1}) + \rho_{gz}\log(z_t) + u_{g,t} \tag{69}$$

$$\log(\varsigma_t) = (1-\rho_\varsigma)\log(\bar{\varsigma}) + \rho_\varsigma \log(\varsigma_{t-1}) + u_{\varsigma,t} \tag{70}$$

$$\log(\xi_t) = (1-\rho_\xi)\log(\bar{\xi}) + \rho_\xi \log(\xi_{t-1}) + u_{\xi,t} \tag{71}$$

The error terms follow standard deviations $\{\sigma_z, \sigma_v, \sigma_\gamma, \sigma_\eta.\sigma_\vartheta, \sigma_G, \sigma_\varsigma, \sigma_\xi\}$. I normalize $\bar{z} = \bar{v} = \bar{\gamma} = \bar{\varsigma} = \bar{\xi} = 1$, calibrate $\bar{g}$ to match the US purchases-to-output ratio, and estimate $\bar{\eta}$ and $\bar{\vartheta}$.

F.2 Additional results for estimated quantitative model

This Appendix presents more detailed results for the estimated quantitative model version introduced in Section 6 and described in more detail in the previous sections of the Appendix.

F.2.1 Parameter estimates

Table F.1: PRIORS AND POSTERIORS FOR MODEL WITH EARNINGS-BASED CONSTRAINT

	Prior shape	Prior Mean	Prior Std	Post. mean	90% HPD interval	
$\tilde{\phi}$	Inv-Gamma	0.1	0.3	4.7082	4.5090	4.9534
σ	Normal	1.5	0.37	1.6637	1.3661	1.8700
ϵ	Normal	2	0.75	1.9358	1.6317	2.1930
h	Beta	0.5	0.15	0.9757	0.9707	0.9807
$\bar{\omega}$	Beta	0.5	0.15	0.8449	0.7805	0.8925
ϕ	Inv-Gamma	0.1	0.3	3.0692	2.3869	3.6814
ψ	Beta	0.5	0.15	0.8893	0.8173	0.9670
κ	Inv-Gamma	0.2	0.1	0.0923	0.0687	0.1159
ρ_R	Beta	0.75	0.1	0.7618	0.7304	0.7935
ν_1	Normal	1.5	0.25	1.3693	0.9789	1.9850
ν_2	Normal	0.12	0.05	0.0582	0.0038	0.1291
ν_3	Normal	0.12	0.05	0.4260	0.4109	0.4381
$\bar{\eta}$	Beta	1.2	0.1	1.0050	1.0013	1.0089
$\bar{\vartheta}$	Beta	1.2	0.1	1.1311	1.0201	1.2209
ρ_z	Beta	0.5	0.2	0.9952	0.9914	0.9992
ρ_{gz}	Beta	0.5	0.2	0.9081	0.8266	0.9873
ρ_v	Beta	0.5	0.2	0.5583	0.4359	0.6897
ρ_γ	Beta	0.5	0.2	0.3463	0.2488	0.4292
ρ_η	Beta	0.5	0.2	0.9752	0.9597	0.9908
μ_p	Beta	0.5	0.2	0.0738	0.0238	0.1199
ρ_ϑ	Beta	0.5	0.2	0.9517	0.9079	0.9857
μ_w	Beta	0.5	0.2	0.9223	0.8487	0.9789
ρ_G	Beta	0.5	0.2	0.0349	0.0027	0.0681
ρ_ς	Beta	0.5	0.2	0.1455	0.0599	0.2246
ρ_ξ	Beta	0.5	0.2	0.9154	0.8914	0.9400
σ_z	Inv-Gamma	0.001	0.05	0.0148	0.0124	0.0171
σ_v	Inv-Gamma	0.001	0.05	0.1421	0.0989	0.1766
σ_γ	Inv-Gamma	0.001	0.05	0.2939	0.2374	0.3469
σ_η	Inv-Gamma	0.001	0.05	0.0076	0.0070	0.0082
σ_ϑ	Inv-Gamma	0.001	0.05	1.3168	1.0634	1.5461
σ_G	Inv-Gamma	0.001	0.05	0.0603	0.0494	0.0715
σ_ς	Inv-Gamma	0.001	0.05	0.0099	0.0088	0.0110
σ_ξ	Inv-Gamma	0.001	0.05	0.0183	0.0168	0.0197

Table F.2: PRIORS AND POSTERIORS FOR MODEL WITH COLLATERAL CONSTRAINTS

	Prior shape	Prior Mean	Prior Std	Post. mean	90% HPD interval	
$\tilde{\phi}$	Inv-Gamma	0.1	0.3	6.9736	4.9745	8.5032
σ	Normal	1.5	0.37	1.5188	1.1494	1.9192
ϵ	Normal	2	0.75	1.2478	0.7588	1.7232
h	Beta	0.5	0.15	0.9016	0.8351	0.9413
$\bar{\omega}$	Beta	0.5	0.15	0.6924	0.6379	0.7487
ϕ	Inv-Gamma	0.1	0.3	1.7658	1.2091	2.2922
ψ	Beta	0.5	0.15	0.1336	0.0724	0.1894
κ	Inv-Gamma	0.2	0.1	0.4992	0.3734	0.6353
ρ_R	Beta	0.75	0.1	0.2376	0.1695	0.3040
ν_1	Normal	1.5	0.25	1.2516	1.1703	1.3314
ν_2	Normal	0.12	0.05	-0.0227	-0.0322	-0.0134
ν_3	Normal	0.12	0.05	0.1554	0.1068	0.2032
$\bar{\eta}$	Beta	1.2	0.1	1.7192	1.6509	1.7884
$\bar{\vartheta}$	Beta	1.2	0.1	1.1860	1.1022	1.2878
ρ_z	Beta	0.5	0.2	0.9903	0.9839	0.9968
ρ_{gz}	Beta	0.5	0.2	0.9269	0.8644	0.9910
ρ_v	Beta	0.5	0.2	0.5927	0.4866	0.6972
ρ_γ	Beta	0.5	0.2	0.4352	0.2904	0.6220
ρ_η	Beta	0.5	0.2	0.9922	0.9861	0.9986
μ_p	Beta	0.5	0.2	0.6454	0.5184	0.7753
ρ_ϑ	Beta	0.5	0.2	0.9808	0.9711	0.9905
μ_w	Beta	0.5	0.2	0.8687	0.8248	0.9141
ρ_G	Beta	0.5	0.2	0.9743	0.9567	0.9933
ρ_ς	Beta	0.5	0.2	0.1345	0.0556	0.2123
ρ_ξ	Beta	0.5	0.2	0.9976	0.9959	0.9995
σ_z	Inv-Gamma	0.001	0.05	0.0067	0.0062	0.0072
σ_v	Inv-Gamma	0.001	0.05	0.0576	0.0319	0.0813
σ_γ	Inv-Gamma	0.001	0.05	0.0667	0.0411	0.0849
σ_η	Inv-Gamma	0.001	0.05	0.0181	0.0135	0.0224
σ_ϑ	Inv-Gamma	0.001	0.05	0.2942	0.2257	0.3918
σ_G	Inv-Gamma	0.001	0.05	0.0184	0.0169	0.0198
σ_ς	Inv-Gamma	0.001	0.05	0.0197	0.0179	0.0216
σ_ξ	Inv-Gamma	0.001	0.05	0.0072	0.0062	0.0082

F.2.2 Full variance decompositions

Table F.3: VARIANCE DECOMPOSITION OF OBSERVABLES VERSIONS OF QUANTITATIVE MODEL (%)

(a): Model with earnings-based constraint								
	TFP	**Inv**	**Pref**	**Price**	**Wage**	**Gov**	**Mon**	**Fin**
Output growth	16.06	4.76	0.74	23.1	2.88	34.95	1.60	15.91
Consumption growth	13.65	4.85	74.33	1.18	1.80	1.39	2.30	0.50
Investment growth	7.93	72.08	1.76	2.94	1.84	1.01	11.46	0.97
Inflation	23.51	5.80	1.06	17.00	3.91	39.25	1.32	8.14
Interest rate	45.69	15.94	0.77	4.12	4.13	0.58	21.68	7.09
Employment growth	27.87	16.80	0.42	7.47	1.75	36.3	5.23	4.15
Wage growth	22.01	6.12	0.73	18.06	1.43	41.82	1.16	8.65
Credit growth	20.14	5.93	0.93	14.21	3.68	48.21	1.96	4.93
(b): Model with collateral constraint								
	TFP	**Inv**	**Pref**	**Price**	**Wage**	**Gov**	**Mon**	**Fin**
Output growth	8.08	29.95	13.61	6.23	14.52	14.02	13.53	0.06
Consumption growth	8.76	0.66	56.58	3.67	19.62	0.23	10.47	0.00
Investment growth	3.75	72.04	0.08	2.83	11.07	0.08	9.99	0.16
Inflation	18.72	12.45	11.55	23.97	23.02	5.74	4.43	0.12
Interest rate	4.05	3.81	3.43	4.70	6.04	1.58	76.35	0.03
Employment growth	27.84	24.78	9.11	1.24	14.52	12.02	10.44	0.05
Wage growth	25.97	0.39	3.45	35.15	34.36	0.00	0.67	0.00
Credit growth	5.35	13.46	4.07	10.71	13.74	0.71	19.59	32.37

Note: Infinite horizon forecast error variance decomposition of the observables used for the estimation of the model. 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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