Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations*

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Abstract

Micro evidence on US corporate borrowing suggests a strong connection between firms' current earnings and their access to debt. This paper formalizes this link through an earnings-based constraint on firm borrowing and studies its macroeconomic implications. Introducing the proposed constraint in a business cycle model alters the transmission of shocks relative to an asset-based collateral constraint, which has become a standard building block in macroeconomics. In response to positive investment shocks, corporate debt expands when earnings-based constraints are present, while it contracts with collateral constraints. The paper empirically verifies these theoretical predictions using both aggregate and firm-level data. The responses of debt to investment shocks in the data support the aggregate relevance of the earnings-based constraint, and heterogeneous borrowing dynamics at the firm-level are in line with the mechanism. In an estimated quantitative model with nominal rigidities, earnings-based constraints dampen the output response to fiscal shocks, whereas monetary shocks have stronger but less persistent effects on inflation and activity relative to counterfactual estimations without the constraint.

JEL Codes: E22, E32, E44, G32. **Keywords:** Earnings-based borrowing constraints; cash-flow based lending; financial frictions; business cycles; investment shocks.

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1 Introduction

Firm credit displays large cyclical swings which correlate with fluctuations in output, employment and investment. Research on the drivers of this comovement has focused on how constraints to credit evolve over the business cycle and how this feeds back to economic activity.[1] This paper studies the macroeconomic consequences of an earnings-based constraint on firm borrowing. Formalizing such a constraint 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.[2] I show that incorporating the earnings-based constraint in business cycle analysis is crucial for correctly capturing aggregate and firm-level credit dynamics and for understanding the transmission of shocks in the macroeconomy.

Earnings-based borrowing constraints imply dynamics of firm debt that are different from the ones generated by asset-based collateral constraints, which have become a cornerstone of many business cycle models that incorporate credit.[3] I demonstrate this in a model in which firm debt can be restricted either by a multiple of the firm's current earnings or by a fraction of the expected value of its capital.[4] Under the alternative constraints, firm debt responds with opposite sign to structural shocks that move current earnings and the market value of collateral in different directions. This is the case for a positive investment shock, which improves the ability of firms to turn resources into productive investment. Such a shock causes stronger economic activity and larger earnings, while it reduces the relative value of capital. Larger earnings allow for more debt under the earnings-based constraint, whereas, in contrast, the lower market value of capital reduces debt access with the collateral constraint.[5] In other words, in an economy where fluctuations are driven by shocks to firm investment, earnings-based constraints imply a positive comovement of firm debt with the business cycle, whereas collateral constraints imply a negative one.

The corresponding dynamics of debt in the data are consistent with the earnings-based constraint, and not in line with the predictions implied by a collateral constraint. To verify the model predictions, I study the dynamics of debt, earnings and capital following investment

[1] Gertler and Gilchrist (2018) survey how research on the role of credit in macroeconomics has evolved since the 2008-09 global financial crisis, an event that marked a strong revival of this research agenda.

[2] My motivating evidence builds on existing empirical studies on corporate borrowing, in particular Lian and Ma (2018) who propose earnings-based constraints as a key determinant for firms' access to debt.

[3] Research on collateral constraints builds on the seminal work by Kiyotaki and Moore (1997). Examples include Jermann and Quadrini (2012) who study collateral constraints to firm borrowing in a macro model.

[4] I also discuss microfoundations for the presence of "asset-based" and "cash flow-based" lending.

[5] As an illustration, think about an airline and imagine a shock that makes the production of airplanes more efficient and lowers their relative price. The implication of this shock for borrowing differs sharply depending on the constraint. If airplanes serve as collateral, their falling relative value tightens the borrowing constraint. By contrast, the earnings-based constraint is relaxed as cheaper airplanes increase the airline's profitability.

shocks in both macroeconomic and firm-level US data. In addition to exploiting the sharp differential predictions under the alternative constraints, there are two key advantages of my focus on investment shocks. First, previous studies have highlighted that shocks to the investment margin of the economy are an important quantitative feature of business cycles in the United States (see for example Justiniano, Primiceri, and Tambalotti, 2010, 2011).[6] Second, investment shocks can be identified in the data, based on a well-defined empirical counterpart, the inverse of the relative price of investment goods. I exploit identification strategies using this observable to verify the differential model predictions stemming from earnings-based versus collateral constraints.

Debt dynamics in aggregate data support the relevance of earnings-based borrowing constraints for the economy as a whole. This finding is based on a structural vector autoregression (SVAR) for US time series. I identify investment shocks using two alternative identification schemes, based on long-run restrictions (following Fisher, 2006), as well as medium-run restrictions (in the spirit of Barsky and Sims, 2012). In both cases, the shock is identified based on its low frequency impact on the inverse relative price of equipment investment. I find that business sector debt increases in response a positive investment shock, in line with the model predictions under the earnings-based constraint, but inconsistent with the dynamics implied by the collateral constraint. In support of the model mechanism, business earnings rise and the value of the capital stock falls.

Debt dynamics in firm-level data are also in line with the model mechanism. I classify firms into those that face earnings-related covenants and those that borrow against collateral, and study their heterogeneous responses to investment shocks. Using a panel-version of the local projection method of Jordà (2005), I regress individual firm borrowing on the macro shock estimated from the SVAR, interacted with dummy variables that indicate earnings or 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 response of collateral borrowers is either negative or flat depending on the specification.[7]

Finally, earnings-based borrowing constraints also alter quantitative conclusions about US business cycles, in particular the transmission of policy shocks. I extend my model to incorporate features of a New Keynesian structural macroeconomic model. The extended model features a number of additional shocks and frictions, such as price and wage rigidities,

[6] My use of the term investment shock at this stage encompasses different variations of this shock, including investment-specific technology shocks, marginal efficiency of investment shocks, as well as shocks to investment adjustment costs. I provide more detail on the differences between these concepts throughout the paper.

[7] In a formal test, the null hypothesis of equal responses across borrower types is rejected. In an alternative setting I also show that firm-level responses of debt to a fall in the relative price of investment goods, using investment shocks as an instrumental variable (IV), are consistent with the proposed mechanism.

alongside a constraint which limits debt by a combination of an earnings-based and a collateral component. I estimate the weight between the components as well as other structural parameters of the model on US data. The results show that the data assigns a high weight on the earnings borrowing component. Counterfactual estimations indicate that the presence of earnings-based constraints dampens the output response of fiscal shocks, whereas monetary shocks have much stronger effects on inflation and somewhat stronger but less persistent effects on output. The intuition for the former result is that fiscal shocks crowd out investment to a larger extent when there is no additional benefit from building up collateral. The latter result is driven by a low degree of price rigidity that emerges in the presence of the earnings-based constraint. The estimated model also implies that investment shocks are the major driver of US output dynamics, which lends further support to my focus on this shock for verifying the relevance of earnings-based constraints in macro and micro data.

Relation to the literature. First and foremost, this paper contributes to the vast literature on the role of financial frictions in macroeconomics, going back to the seminal work of Bernanke and Gertler (1989), Shleifer and Vishny (1992), and Kiyotaki and Moore (1997).[8,9] In a retrospective on business cycle models, Kehoe, Midrigan, and Pastorino (2018) highlight the importance of disciplining macro models with direct micro evidence. In this spirit, my paper uses micro evidence on firm borrowing to capture firm debt dynamics more accurately in the context of studying macroeconomic fluctuations.

Second, the motivating evidence I provide builds on existing insights, highlighted by the empirical corporate finance literature, on the pervasive use of loan covenants. Important contributions are Chava and Roberts (2008) and Sufi (2009).[10] The focus of my paper is closely related to that of Lian and Ma (2018) who investigate the relevance of cash flow-based relative to asset-based firm borrowing. Based on a comprehensive empirical analysis, their paper proposes that the key constraint to firm debt are cash flows measured by operating earnings. These authors mainly focus on causally identifying the extent to which increases

[8] Research on borrowing constraints includes for example Lorenzoni (2008), Geanakoplos (2010), Gertler and Karadi (2011), Kiyotaki and Moore (2012), Jermann and Quadrini (2012), Liu, Wang, and Zha (2013), Buera and Moll (2015), Azariadis, Kaas, and Wen (2016), Del Negro, Eggertsson, Ferrero, and Kiyotaki (2016) and Cao and Nie (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 important class of financial frictions is based costly state verification problems in the spirit of Townsend (1979), see e.g. Bernanke and Gertler (1995), Carlstrom and Fuerst (1997) and Bernanke, Gertler, and Gilchrist (1999). Quadrini (2011) provides a survey on financial frictions in macroeconomics.

[9] Recent 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).

[10] Other papers that focus on covenants include Dichev and Skinner (2002), Roberts and Sufi (2009a, 2009b), Nini, Smith, and Sufi (2012), Murfin (2012), Bradley and Roberts (2015) and Falato and Liang (2017). In a recent paper Chodorow-Reich and Falato (2017) study empirically how bank health transmitted to the economy via loan covenants during the 2008-09 financial crisis. There are also important theoretical treatments of loan covenants, for example by Garleanu and Zwiebel (2009).

in earnings relax borrowing constraints at the micro level.[11] My paper embeds the relevance of borrowing based on current earnings into a macroeconomic model, verifies the predicted dynamics empirically and demonstrates quantitative consequences for business cycles.

Third, my model predictions and their empirical verification relate to the literature on investment shocks, which includes theoretical work by Greenwood, Hercowitz, and Huffman (1988) and Greenwood, Hercowitz, and Krusell (2000), and papers that identify investment shocks in SVARs building on the key contributions by 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. I contribute to this literature by analyzing borrowing dynamics that arise from investment shocks.[12,13]

Fourth, there are a few existing papers, within and outside the business cycle literature, in which flow variables rather than assets restrict borrowing (for example Kiyotaki, 1998).[14] My contribution relative to these papers lies in explicitly comparing theoretical and empirical differences between income flow-related and collateral constraints on firms.[15] I provide a detailed exploration of how different stock and flow borrowing constraints relate and demonstrate that the definition of earnings as opposed to other financial flows is key for characterizing empirically plausible debt dynamics with the earnings-based constraint.

Finally, in many countries mortgage contracts also contain income-related constraints, often directly imposed by the regulator. Greenwald (2017) formulates a payment-to-income limit in addition to a collateral (loan-to-value) constraint for mortgage borrowing and studies the transmission of macroeconomic shocks through the mortgage market.[16] My paper focuses on corporate debt rather than household mortgages, where the relevance of earnings-based constraints for business cycles is still understudied.

Structure of the paper. Section 2 presents microeconomic evidence that motivates the focus on earnings-based borrowing constraints for firms. Section 3 introduces a business cycle model that features an earnings-based constraint and discusses the resulting debt dynamics in

[11] Their paper also contains a detailed exploration of cash-flow based lending in a Kiyotaki-Moore economy. 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).

[12] See also Schmitt-Grohe and Uribe (2012) for a business cycle model with investment shocks. Other papers in the SVAR literature include Barsky and Sims (2012) and Francis, Owyang, Roush, and DiCecio (2014).

[13] My econometric approach to studying firm-level responses to investment shocks relates to work by Cloyne, Ferreira, Froemel, and Surico (2018) who study the heterogeneous firm-level effects of monetary policy shocks.

[14] 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.

[15] Constraints based on income flows often provide an ad-hoc way to restrict borrowing, for example if the model does not feature capital. Schmitt-Grohe and Uribe (2016) provide some discussion on stock versus flow constraints on sovereign debt. Diamond, Hu, and Rajan (2017) lay out a theory of firm financing in which control rights both over asset sales and over cash flows have varying importance over time.

[16] A related study is Corbae and Quintin (2015). Earlier work that studies household mortgages in business cycle models typically focuses on collateral, see for example Iacoviello (2005) and Iacoviello and Neri (2010).

comparison to a collateral constraint. Section 4 verifies the differential theoretical predictions for investment shocks using both SVAR analysis on aggregate data and panel projections on firm-level data. Section 5 turns to quantitative questions by estimating a New Keynesian model with earnings-based borrowing. Section 6 concludes.

2 Motivating evidence on earnings-based corporate borrowing

This section presents stylized evidence on corporate borrowing in the US economy. Using information from more than 50,000 loan deals issued to 15,000 firms, I document that earnings are a key indicator that determines the extent to which firms have access to loans.

Data source. I use the *ThomsonReuters LPC Dealscan* data base. For the United States, this data covers around 75% of the total commercial loan market in terms of volumes.[17] The unit of observation is a loan *deal*, which consists of loan *facilities*. Deal and facility can be the same unit, e.g. for a standard bank loan, or a deal can consist of a syndicated credit arrangement in which several lenders provide facilities of different types and conditions. The data contain rich information, including the identity of borrower and lender, the amount, maturity, and interest rate. I consider USD denominated loan originations since 1994 for US nonfinancial corporations. In Section 4.3, I merge the Dealscan data to the *Compustat Quarterly* data, which covers accounting information of listed US companies.[18]

The pervasive use of loan covenants. Loan covenants, sometimes referred to as nonprice terms, are legal provisions which the borrower 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. A covenant states for example that "the borrower's earnings-to-debt ratio must be above 4". Covenant breaches lead to technical default, which gives lenders discretion in taking contingent actions: calling back the loan, imposing a penalty payment, increasing the interest rate or changing other conditions in the contract. Breaches have been shown to occur frequently with large economic effects. Chodorow-Reich and Falato (2017) show for example that one third of nonfinancial firms breached their covenants during the 2008-09 financial crisis. Importantly, Roberts and Sufi (2009a) find that net debt issuing activity experiences a large and persistent drop immediately after a covenant violation.[19] These findings indicate that debt access is significantly reduced when the variable specified in the covenant moves above (below) its maximum (minimum) value.

[17] See Chava and Roberts (2008). The data does not include a big share of marketable debt instruments such as corporate bonds, a limitation which I will discuss later in this section.

[18] Appendix A contains further information on the data set as well as summary statistics.

[19] Chava and Roberts (2008) find strong effects of breaches on investment and Falato and Liang (2017) strong effects on employment.

The importance of earnings. Table 1 lists the most popular covenant types, sorted by their frequency of use. The frequency is calculated for loans that feature at least one covenant and the table includes covenants which appear in more than 10% of these loans. Note that a given contract in the sample can have up to 8 covenants. The table also contains the median, 25th and 75th percentile as well as the value-weighted mean of the covenant value, that is, the numerical maximum or minimum value that restricts a given indicator.

Table 1: LOAN COVENANT TYPES, VALUES AND FREQUENCY OF USE

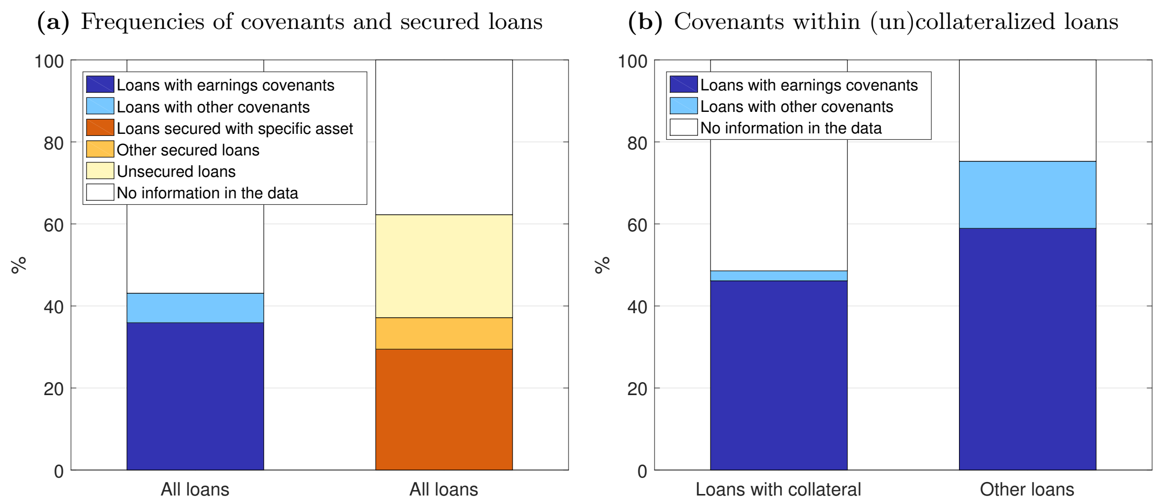
	Covenant type	p25	Median	p75	Mean	Frequency
1	Max. Debt to EBITDA	3.00	3.75	5.00	4.60	60.5%
2	Min. Interest Coverage (EBITDA / Interest)	2.00	2.50	3.00	2.56	46.7%
3	Min. Fixed Charge Coverage (EBITDA / Charges)	1.10	1.25	1.50	1.42	22.1%
4	Max. Leverage ratio	0.55	0.60	0.65	0.64	21.3%
5	Max. Capex	6M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

Note: The table provides a list of the most pervasive covenant types, sorted in descending order by their frequency of use in the Dealscan loan data. Covenant types with a frequency above 10% are included in the table. 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 typically 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 used to construct this table 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, respectively.

The table shows that the three most frequently used covenants are all related to earnings. The specific earnings measure is EBIDTA, 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 not confounded by accounting treatment of taxes and depreciation. It is also readily available for scrutiny by lenders as part of standard financial reporting. The most frequently occurring covenant implies that the lender requires the level of debt not to exceed this measure by a multiple of 4.6 on average at any given point in time. At this stage, I interpret the prevalence of earnings-based covenants as suggestive evidence that the flow of current earnings constitutes an important constraint on companies' access to debt. The subsequent sections of this paper will be dedicated to studying whether credit dynamics support this interpretation, and whether this affects conclusion that can be drawn about aggregate fluctuations.

Further channels through which earnings affect debt access. Loan covenants are a direct manifestation of current earnings potentially constraining access to debt, as they are explicitly written into contracts. There is also evidence of *implicit* debt constraints relating to earnings. For example, lenders may base their decisions on credit ratings, which are typically constructed with a strong emphasis on EBITDA. 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.[20]

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 (with any information on secured/unsecured). The sample used for both panels consists of loan deals issued between 1994 and 2015 by US nonfinancial corporations.

Earnings-based vs. asset-based lending. Figure 1 analyzes the frequency of loan covenants and of collateral, that is, debt that is secured with specific assets.[21] Panel (a) plots different value-weighted shares in the total number of loans. 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 and how they are secured (dark orange, medium orange, light orange, and white areas, respectively).[22] The left bar indicates that earnings-based covenants, which dominate

[20] According to Standard & Poor's Global Ratings (2013a, 2013b), 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. Together with the business risk profile (country risk, industry risk, competition) this determines the credit rating of a company.

[21] Since the information on secured/unsecured is at the facility-level, while the information on covenants is at the deal-level, I aggregate to the deal level, summing over the relevant facilities within deals.

[22] According to Lian and Ma (2018), loans secured with "all assets" in Dealscan should be classified as cash-flow based loans, as the value of this form of collateral in the case of bankruptcy is calculated based on

within covenants overall, feature in around 35% of loan debt. This is a lower bound, as the remainder of loans does not have any information, which does not necessarily mean that covenants are absent. The share of earnings-based covenants is higher than the share of debt secured by a specific assets, shown in the right bar.[23] Note that other secured debt is composed loans that are secured by the entire balance sheet of the borrower. Finally, it is noteworthy that a sizable chunk of loans are 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 provides evidence on the extent to which the use of loan covenants and collateral is related across loans. The panel shows that covenants overall are more likely to appear in a loan contract when specific collateral is not present. However, the loans backed by specific assets still have a reasonably high share of covenants. Taken together, the loan information suggests that earnings-based borrowing is pervasive, exceeding the prevalence of asset-based debt, and that earnings-based covenants are used both in addition to and instead of collateral.[24]

Existing evidence in the literature. Lian and Ma (2018) supplement the Dealscan data with a variety of data sources and present detailed evidence that US nonfinancial firms primarily borrow based on cash flows as measured by earnings. The magnitudes that Lian and Ma (2018) report paint a picture that is perhaps even stronger in favor of earnings-based borrowing, likely due to the fact that my analysis does not cover most marketable debt securities such as corporate bonds.[25] Other studies also resort to data sources different from Dealscan to study related questions. Azariadis, Kaas, and Wen (2016) use Compustat data to highlight the quantitative importance of firm borrowing without collateral.[26] While the focus on earnings-based constraints for firms is relatively novel, the fact that existing research using additional or other data sources has reached similar conclusions on the pervasiveness of such constraints lends further support to studying this microeconomic phenomenon in a business cycle context.

the cash flows from continuing operations. Therefore, I define loans backed by specific assets as secured loans but exclude those that are backed by "all assets". I assign the latter to the separate category called "Other secured loans". I thank Yueran Ma and Chen Lian for a helpful discussion on these differences.

[23] Table A.4 in the Appendix lists the frequencies of different asset classes that are used as collateral.

[24] Figure B.1 in the appendix repeats the analysis with equal-weighted rather than value-weighted shares.

[25] This means that despite the comprehensive coverage of Dealscan within the universe of loans, a sizable chunk of aggregate corporate sector liabilities are not captured. To get a rough idea, I calculated using Flow of Funds data for 2016 that outstanding loans in the nonfinancial business sector amount to around 7.6 tn USD, while 5.8 tn USD of liabilities are in debt securities. The Dealscan data contains mostly syndicated loan deals and many of the facilities within a deal are credit lines (see also Appendix A). Ivashina and Scharfstein (2010) study the syndication aspect of corporate borrowing in more detail. For work with a more explicit focus credit lines see for example Sufi (2009) and Acharya, Almeida, and Campello (2013).

[26] Azariadis, Kaas, and Wen (2016) use a specific Compustat item which captures secured debt and calculate unsecured debt as a residual, subtracting it from total debt liabilities.

3 A business cycle model with earnings-based borrowing

This section proposes an earnings-based constraint on firm borrowing to formalize the microeconomic evidence. I set up a business cycle model in which the firm issues one of two debt types, which are constrained by current earnings and the value of collateral, respectively. This allows me to study the dynamics arising from the earnings-based constraint in comparison with a traditional asset-based constraint. To derive sharp differential predictions, the characterization of the model dynamics focuses on a structural shock that moves earnings and the value of collateral in opposite directions: the investment shock.

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, to be specified further below. 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 of earnings corresponds to *EBIDTA*, that is, sales net of overhead and labor costs, but without subtracting investment, interest payments or taxes. Hence, the model definition in (2) is consistent with the indicator that features in the most pervasive covenant according to the evidence provided in Section 2. π_t is the measure that will enter the firm's earnings-based borrowing constraint.

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 v_t is a stochastic disturbance, following a process specified further below. In the environment presented here, where the production of consumption, investment and capital goods is not decentralized into different sectors, v_t 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 the process of v_t simply as "investment shocks".[27] The term $\Phi_t\left(\frac{i_t}{i_{t-1}}\right)$ introduces investment adjustment costs. Following Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007) I assume that $\Phi_t(1) = 0$, $\Phi_t'(1) = 0$, and $\Phi_t''(1) = \phi_t > 0$. The t subscript captures the possibility of stochastic shocks to adjustment costs. I refer to the composite term $v_t\left[1 - \Phi_t\left(\frac{i_t}{i_{t-1}}\right)\right]$ as the *investment margin*. The results I characterize below will show that for the purpose of disentangling the two alternative borrowing constraints, different types of shocks to this margin work in similar ways.

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" (see for example Hayashi, 1982).[28] In the case of v_t, it is important to note that even in the absence of any adjustment costs, v_t 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, which reads

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

$\Psi(d_t)$ denotes the dividend (equity payout) function, and the b terms capture debt financing, both of which will be explained in more detail below. Setting $\Phi_t(\cdot) = 0$ and substituting i_t from equation (3) into equation (4), it can be seen that the relative price of capital directly varies with the inverse of v_t, a key property of models that feature such disturbances entering the investment margin:

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

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

[27] 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 extensively in business cycle research, 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 readily available empirical counterpart. This will come into play when taking my model predictions to the data in Section 4.

[28] In his original paper, Hayashi (1982) introduces a similar formulation as in equation (3) and refers to the composite term $\left[1 - \Phi_t\left(\frac{i_t}{i_{t-1}}\right)\right] i_t$ as the "installation function". In his setting, there is no variation in IST and the price of investment goods in consumption units is exogenously given.

The firm has access to two means of financing its operations, equity and debt. The variable d_t denotes equity payouts and the presence of the function $\Psi(d_t)$ 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.[29] 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 the period. 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 market interest rates received by lenders. This creates a preference for debt over equity and makes the firm want to borrow up to its constraints. Since the household does not receive this tax rebate, there is a heterogeneity in the desire to borrow and save across sectors of the economy, the household wants to lend funds, and debt is in positive net supply in equilibrium. This type of tax exists in many countries and the related modeling assumption follows Hennessy and Whited (2005).[30]

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

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

The θ parameters capture the exogenous tightness of the constraints.[31] In the earnings-

[29] Altinkilic and Hansen (2000) provide evidence of increasing marginal costs in equity underwriting. Lintner (1956) discusses dividend smoothing motives.

[30] See also Riddick and Whited (2009). Strebulaev and Whited (2012) provide a comprehensive review of the dynamic corporate finance literature. In effect, the tax advantage makes the firm "less patient" than the market, which discounts at rate $\frac{1}{1+r_{j,t}}$, and thus induces the firm to borrow up to its constraint. This outcome could be generated in alternative ways, for example by making the firm an entrepreneur household with a lower discount factor.

[31] In Section 5, I allow these parameters to be time-varying and subject to stochastic "financial shocks" in the spirit of Jermann and Quadrini (2012).

based borrowing constraint (8), debt is limited by a multiple $\theta_\pi > 1$ of current earnings, π_t.[32] I also allow a more general form of this constraint, 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 frequently used in the loan data, ahead of the coverage ratio (see Table 1).[33]

In equation (9) debt issued by the firm in t is limited by a fraction $\theta_k < 1$ of the capital stock net of depreciation next period, which is valued at price $p_{k,t+1}$. In the borrowing constraint $p_{k,t+1}$ could reflect either the book or the market price of capital. Formally,

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

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, but it is important to emphasize that in the presence of investment shocks the book price of capital is not 1 but $1/v_t$, as the debt contract is specified 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 and book value of capital coincide at $1/v_t$.

Discussion of borrowing constraints. Borrowing constraints reflect that the ability of a borrower to issue debt is limited due to an underlying friction such as information or enforcement limitations. In the case of collateral, a large body of work has shown how the market incompleteness implied by the constraint can be derived from such frictions. 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, but this withdrawal remains an off-equilibrium threat (see e.g. Hart and Moore, 1994).

In the case of the earnings-based borrowing constraint, one interpretation is that the firm is able to directly pledge its earnings rather than a physical asset in return for obtaining debt access. A second 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

[32] A constraint on $b_{j,t}$ rather than $\frac{b_{j,t}}{1+r_{j,t}}$ would capture a different timing of the interest payment and would not change the dynamics of the model in a meaningful way.

[33] Lian and Ma (2018) emphasize the presence of both debt-to-earnings ratios as well interest coverage ratios in covenants. Daniel Greenwald's discussion of their paper at the NBER Monetary Economics Meeting, available online, contains some further thoughts on the differences between the two.

firm value as a multiple of current earnings.[34] A third interpretation is based on regulation. Regulatory requirements on lenders require a different risk treatment of loans that feature a low earnings-to-debt ratio. Exogenously imposed constraints that are not the outcome of a contracting problem could reflect such regulation.[35] In Appendix C, I sketch out a specific formal environment that captures the second of these three potential interpretations. In this 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 in reality. For example, while collateral is pledged upon origination and may be seized in the case of default, covenants can in principle 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 specific variable entering the right hand side of the debt limit is different between (8) and (9) allows for transparency in characterizing the implied differences in business cycle dynamics. Second, the Dealscan data shows that the maturity of corporate debt is relatively short, in particular compared to household debt, and that the relation between lenders and borrowers in the commercial loan market entails repeated interaction both in relation to covenant assessment and in relation to collateral.[36] The latter observation also justifies the simplification that both borrowing constraints affect one-period debt, which abstracts from considerations regarding maturity choice.[37]

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 D.1.

It is worth noting that the model presented here does not feature a *labor wedge*, as the marginal product of labor (MPN) equals marginal rate of substitution (MRS) between consumption and leisure in equilibrium. I have explored extensions of the model in which

[34]Valuation by multiples is a common practice for assessing various types of assets and investment opportunities, see Damodaran (2012) for a textbook treatment.

[35]Greenwald (2017) rationalizes borrowing constraints for household mortgages along similar lines.

[36]In the Dealscan data, the average (median) maturity of loans in 52 (60) months, and the value-weighted share of loans that refinance a previous loan is 83%.

[37]For a general equilibrium treatment of long-term debt, see for example Gomes, Jermann, and Schmid (2016). Cao and Nie (2017) provide a study of the role of market incompleteness implied by the non state-contingency of debt that is typically assumed alongside borrowing constraints.

the firm requires working capital loans to pre-finance expenditures. Since the results in this section are about *qualitatively* different borrowing dynamics arising from the alternative constraints, I stick to the simplest version in which $MRS = MPN$.[38]

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 D.2. The household consumes the good produced by the firm and supplies labor. She does not receive the tax rebate on debt and therefore becomes the saver in equilibrium. The government runs a balanced budget in every period.

3.2 Model parameterization and specification

The stochastic processes underlying the exogenous disturbances follow autoregressive processes of order one in logs. See Appendix D.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) and has been used in various subsequent papers on US business cycles, 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.[39,40] Furthermore, in steady state, $\Phi''(1) = \overline{\phi}$.

Table 2, Panel (a) 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 the prior used by Smets and Wouters (2007). To parameterize β, I calculate the average interest rate faced by firms in the Dealscan data base.[41] Panels (b) and (c) of the table show the calibration of the parameters that are related to the alternative borrowing constraints (8) and (9). In this part of the paper, I investigate model dynamics using the simplification that either one or

[38] The literature, in particular Jermann and Quadrini (2012), has advocated the working capital formulation as a way to introduce an interaction between the labor wedge and financial frictions as an important amplification mechanism that delivers quantitatively more elevated responses to shocks. See also Chari, Kehoe, and McGrattan (2007) for a general discussion of the labor wedge in business cycle models.

[39] For the result presented in this section the specific form of adjustment costs is not crucial. For example, the conclusions drawn from the results are the same with adjustment costs in capital rather than investment. I choose this specification mainly to be consistent with Section 5.

[40] In order to study the adjustment cost shock to ϕ_t I introduce a minor modification to (12) in which steady state adjustment costs exceed zero by an arbitrarily small magnitude. This is done in order to be able to compute IRFs to this shock as deviations from the nonstochastic steady state. See more in Appendix D.4.

[41] In particular I use the sum of the "All-in spread drawn", and add the 12-month LIBOR rate. I then calculate the mean over loan deals which feature either collateral, earnings-related covenants, or both.

the other constraint is faced by the firm. To do this, I exploit the fact that the model nests restricted versions in which only a collateral or only an earnings-based constraint are present. 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.[42]

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	Prior of Smets and Wouters (2007)
β	0.9752	Steady state annualized interest 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 only
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 only
θ_k	0.0485	Same steady state debt 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 achieve that the firm faces either one or the constraint. * indicates parameter values that are calculated directly from the micro data, using ThomsonReuters Dealscan.

I set the tax advantage of debt τ_j to 0.35 following Hennessy and Whited (2005). 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, the empirical counterpart of my earnings-based constraint. This gives a value of $\theta_\pi = 4.6$ (see Table 1). As this value is for annualized EBIDTA and my model is quarterly, I divide by four.

[42] Note that throughout the analysis I focus on binding borrowing constraints. This assumes that shocks are small enough in magnitude to keep the Lagrange multiplier on the constraint $\mu_{jt} > 0$, $j \in \{k, \pi\}$, $\forall t$. Modifying my model to feature occasionally binding constraints would be relatively straightforward. An extension in this direction would allow to study possible switching effects between different types of borrowing constraints, similar to what Greenwald (2017) emphasizes for household mortgages. I leave an extension along these lines for future work.

I then set the tightness of the collateral component to that value which achieves the exact same steady state debt level, which results in $\theta_k = 0.0485$. It should be emphasized that the results shown in the stylized model environment of this section are robust to variations in these parameter values. In particular, as the model is linearized and I focus on qualitative predictions, the results are not sensitive to varying the θ parameters across a range of values.

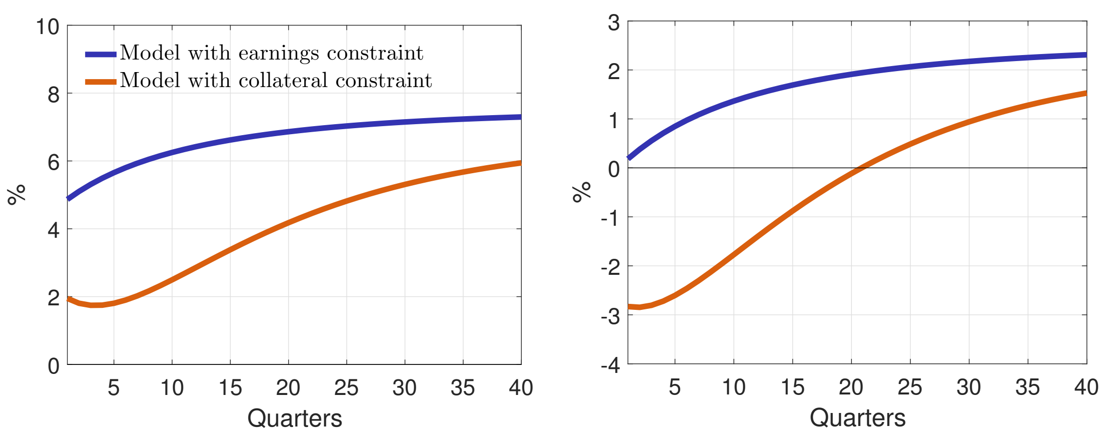
3.3 Macro dynamics implied by earnings-based vs. collateral constraints

Figure 2 plots the IRFs of firm debt to a positive TFP shock and a positive investment shock. Both shocks are permanent.[43] The blue lines corresponds to the model in which firms face the earnings-based constraint (parameterization shown in Panel (b) of Table 2), while the orange lines are generated in a model where the collateral constraint is present (see Panel (c)). The figure shows that while the responses of firm debt to the TFP are positive under both alternative borrowing constraints, the sign of the responses for the investment shock flip between one and the other parameterization, implying the opposite comovement of debt with the shock. In other words, different conclusions about the dynamics of firm borrowing are drawn depending on how the borrowing friction of the firm is formulated.

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

(a) Permanent TFP shock

(b) Permanent investment shock



Note: The figure displays model IRFs of firm debt to different shocks, under two alternative calibrations in which only the earnings-based constraint (blue line) or only the collateral constraint (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 $\rho_z = \rho_v = 1$ (the shocks are permanent) 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.

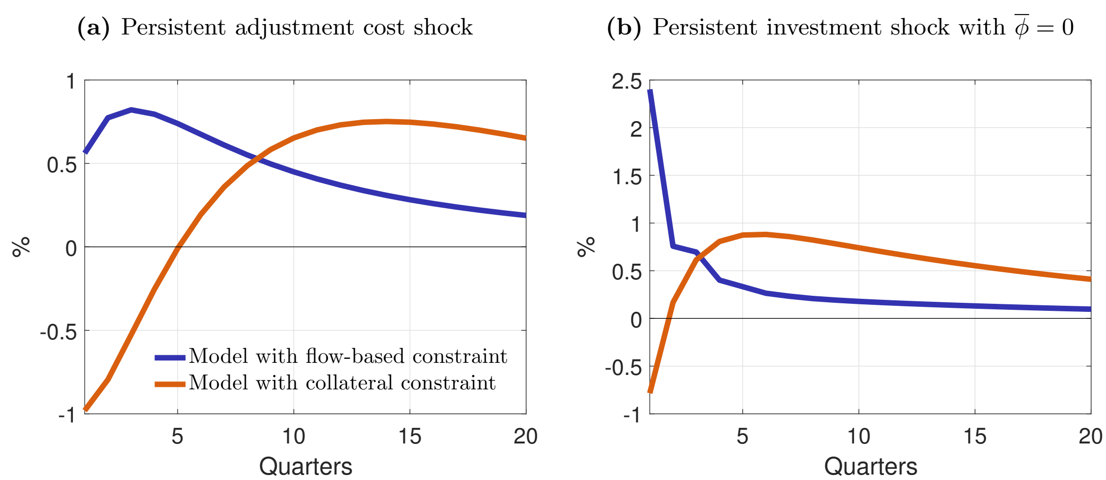
The intuition behind these dynamics is as follows. The TFP shock raises both the firm's earnings as well as market value of capital, supporting more debt under both constraint.

[43] 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 persistent shocks. See also Figure 3 further below.

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 reduce the relative value of capital in consumption units. This means that 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. The responses to this shock thus imply sharply different debt dynamics depending on the relevant borrowing constraint. These differences will provide the testing ground for my empirical analysis in Section 4.

As an illustration of the mechanism, think about an airline and imagine a shock – an exogenous technological innovation – that 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.

Figure 3: MODEL IRFS OF FIRM DEBT: ADDITIONAL INVESTMENT MARGIN SHOCKS



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 (blue line) or only the collateral constraint (orange line) is present. Panel (a) plots the IRFs to a negative adjustment costs shock with $\rho_\phi = 0.5$ and $\sigma_\phi = 1$. Panel (b) repeats the investment shock IRFs from Figure 2 as a transitory but persistent shock ($\rho_v = 0.5$ and $\sigma_v = 0.05$) and without investment adjustment costs ($\overline{\phi} = 0$). The different signs of the IRFs across models show that the proposed mechanism is broad enough to carry through to different types of shock to the investment margin.

As discussed above, when the production of capital and investment goods are not disaggregated into separate sectors, a shock to v_t can be thought of as both an investment-specific technology (IST) and a marginal efficiency of investment (MEI) shock.[44] At a later

[44] See the discussion below the introduction of equation (3) in Section 3.1. More details on this distinction is contained in Justiniano, Primiceri, and Tambalotti (2011) and Schmitt-Grohe and Uribe (2012).

stage in the analysis, for the purpose of the empirical verification of the mechanism in Section 4, I will narrow down the interpretation of v_t to capture IST. This allows me to establish a mapping of v_t to the data. At this stage, in terms of the main message behind the results, the distinction between these refined concepts is not of first order importance. In fact, the proposed mechanism has a broad interpretation which carries through to other shocks that affect the economy's investment margin. To demonstrate this, Figure 3 plots two more sets of IRFs. In Panel (a), the IRFs to a negative persistent adjustment cost shock for the two model versions are plotted. This is another disturbance that distorts the economy's investment margin as can be seen in equation (3). It is evident that this shock also results in a different sign of the debt responses on impact depending on which constraint is at play. In Panel (b), I repeat the IRFs to the investment shock from Figure 2, but shut off any adjustment costs to the model and specify the shock as persistent rather than permanent. This corresponds to a setting in which there are no fluctuations in the price of capital other than through the exogenous disturbance itself. As the panel shows, there is again a different sign of the impact response, with a positive debt response under the earnings constraint and a negative one when the collateral constraint is present. These additional responses highlight the broad scope of the key mechanism that the model delivers. Various types of disturbances that enter the investment margin give rise to the different implications under the two borrowing constraints.

In Appendix D.5 I repeat Figures 2 and 3 for a version of the earnings constraint in which current and three lags of earnings enter the constraint. This is based on the idea that covenants are often evaluated based on a 4-quarter trailing average of the indicator. The results for this specification are similar to the ones shown in the above figures. The shape of the IRFs changes due to the fact that current earnings will affect the borrowing ability in future periods. In particular, there is a delayed and hump-shaped response under this version of the earnings-based constraint, but the signs of the responses remain unchanged.

Note that in deriving testable model predictions I focus primarily on the IRFs of debt. I turn to selected additional variables in the next subsection, and show the IRFs of remaining model variables in Appendix D.6. 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. Cordoba and Ripoll (2004) provide a detailed exploration of this insight.[45,46] I therefore show the responses of other variables only

[45] A similar discussion is provided by Kocherlakota (2000), who shows that the amplification generated by credit constraints in a small open economy setting is sensitive to the quantitative specification of the underlying model structure, in particular factor shares. In related work, Fuerst (1995) shows that agency frictions in the spirit of Bernanke and Gertler (1989) also add little amplification in a basic business cycle model.

[46] As shown in Appendix D.6, apart from the debt IRFs the model behaves extremely similar under the

insofar as they help me to understand the different debt dynamics across parameterizations of the model. In Section 5 of the paper I do consider the dynamics of typical macroeconomic variables of interest. In that Section, I also introduce a number of additional shocks to feature in the model.

In summary, the results highlight the different *qualitative* conclusions that can be drawn about the dynamics of debt depending on the type of borrowing constraint. In the next subsection I provide a more in-depth characterization of these results with an explicit focus on the theoretical link between asset values, earnings and other flow variables. After this additional discussion I turn to verifying the model predictions in US data in Section 4.

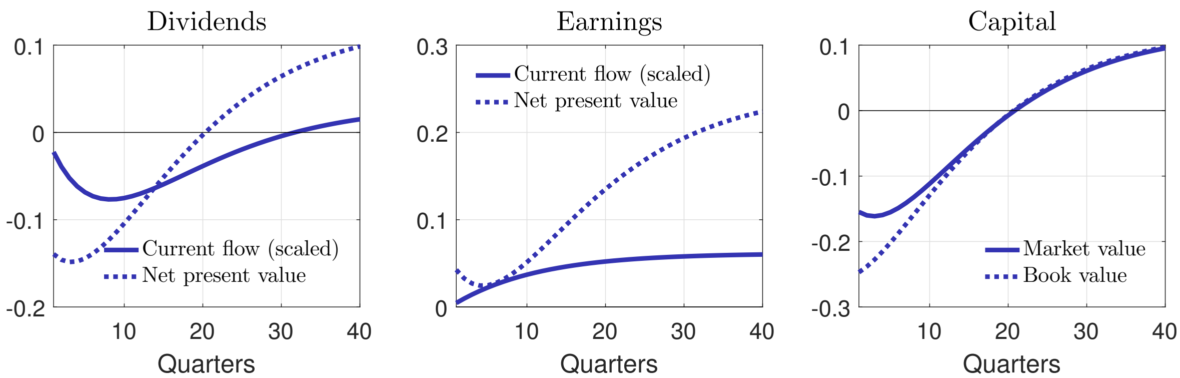
3.4 Discussion: borrowing against flow vs. stock variables

The model analysis highlights the differences between two variables limiting the access to debt for firms: earnings and the value of capital, which are a *flow variable* and a *stock variable*, respectively. To further characterize the results, this section analyzes to what extent this difference matters for the differential responses to investment shocks.

From a theoretical point of view, the market value of an asset corresponds to the net present value (NPV) of future flows that can be derived from that asset. In the context of a firm, its market value is equal to the flows that the firm generates for its owner. Several observations can be made on how the firm's market value and the flows to the owner relate to the specific variables constraining debt in my model. 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 on 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 were all discounted future dividend flows. In this case, the two borrowing limits would be equivalent.

two constraints. This is different for example when raising the value of ψ or when choosing a working capital formulation, as discussed after the introduction of the firm's maximization problem above. The predictions on the qualitative dynamics of total firm debt, however, are not altered by these modifications of the model.

Figure 4: 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 of different flows and asset values 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.

In light of these theoretical 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 the flows.[47] 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 4 displays these IRFs in a model without borrowing constraints. This is essentially a comparison of different variables that could potentially appear on the right hand side of a borrowing limit. The figure shows that both current earnings as well as the NPV of earnings rise in response to the shock. This means that with an earnings constraint additional debt could be issued in response to the investment shock and that timing of earnings by itself is not key in this case. However dividends as well as the NPV of dividends, which equal the firm value and the value of the capital stock under the Hayashi conditions, is reduced.[48] 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 results in Panel (b) of Figure 2 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.

[47] As shown in the previous section, I have explored sensitivity of the results to generalizations of the earnings-based constraint where lagged or one period ahead expected earnings can enter. These versions are still very different from the NPV, so the arguments made here again carry through.

[48] As the Hayashi conditions are satisfied in my model, the figure also shows that the IRFs of the NPV of dividends and the market value of capital to a given shock are identical (see the dashed line in the left chart and the solid line in the right chart for both panels).

4 Verifying the model predictions for investment shocks

This section empirically verifies the model predictions implied by the alternative borrowing constraints. First, I investigate which of the two borrowing limits, earnings-based or collateral constraint, is the *dominant friction* in driving the comovements we observe in US macroeconomic data. Second, I examine if the dynamics in the data are consistent with the *mechanism* through which the constraints on the firm operate in the model. I resort to both aggregate and firm-level data, using an SVAR (Section 4.1) and a panel regression framework that allows for heterogeneous responses to shocks (Section 4.3).

The empirical analysis focuses on the structural shock that has given different qualitative predictions in the model: the investment shock. As explained in Section 3, the disturbance v_t can capture both 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.[49] Observable time series of this price have been exploited by previous research to identify IST shocks. I build on this work to study the conditional dynamics of US data with a focus on the debt responses to investment shocks. That is, while the interpretation of the model mechanism can be broadly applied to different shocks to the investment margin, for the purposes of verifying the predictions empirically, I interpret v_t as a specific type of investment shock, a shock to IST.[50]

4.1 SVAR on aggregate US data

I specify an SVAR framework to estimate the impact of IST shocks on the US economy as a whole. The system includes variables that allow me to distinguish between dynamics that are supportive of either the earnings-based constraint or the collateral constraint: debt, earnings and capital. I use two different identification schemes. First, following the literature on technology shocks in SVARs, I identify IST shocks using long-run restrictions building on the work of Fisher (2006).[51] Second, I use medium-run restrictions following Barsky and Sims (2012), and Francis, Owyang, Roush, and DiCecio (2014).[52] I apply both identification methods to US postwar data. In addition, I set up a Monte Carlo experiment in which I

[49] 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”, both in terms of the number of facilities and the dollar volume. See Table A.4 in the Appendix.

[50] Justiniano, Primiceri, and Tambalotti (2011) emphasize that MEI shocks are more important than IST shocks for US business cycles. MEI shocks, however, are not directly identifiable the same way that IST shocks are. It will turn out that the IST shock I identify is reasonably important in terms of the historical variance decomposition of debt implied by the SVAR.

[51] 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 exclusively on TFP. Fisher (2006) and various subsequent papers also estimate the effect of IST shocks. A recent example is Ben Zeev and Khan (2015).

[52] Ramey (2016) provides a useful summary of the literature on both long-run and medium-run restrictions.

repeatedly 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.

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 times series Y_t, which is specified to follow

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

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 behind long-run restrictions is to impose identifying assumptions on the long-run multiplier $B(1)^{-1} = [B_0 - B_1 - ... - B_p]^{-1}$. Following the seminal study of 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. The idea is to identify two shocks, using a recursive scheme on $B(1)^{-1}$: 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 the 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.[53] It is important to highlight that these restrictions are satisfied in the model of Section 3. For the purpose of this paper, 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.

As I only identify two first 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

[53] This identification scheme implies that the first row of $B(1)^{-1}$ is composed of zeros apart from the first element and the second row is composed of zeros apart from the first two elements. Fisher (2006) also imposes the additional, overidentifying restriction that labor productivity responds in a fixed proportion to movements in the relative investment price. While this improves the precision of the estimates, I do not impose this restriction to remain as agnostic as possible.

identification of IST and TFP. The additional variables are the log difference in aggregate business earnings, the log difference in the relative value of the capital stock and the log difference in 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 borrowing constraint component that is present. Together this gives, in line with the notation of the model,

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

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

Identification using medium-run restrictions. The idea behind medium-run restrictions is to identify a shock such that its forecast error variance decomposition (FEVD) share for a selected variable at a specific finite horizon h is maximized. 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 Leeper, 1997). Francis, Owyang, Roush, and DiCecio (2014), for example, 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 (2012) implement a variant of this method where the shock maximizes the *sum* of the FEVD up to a specific horizon.[54] I follow the latter authors' variant of this identification scheme. Using the same vector of observables Y_t, I identify the IST shock as the shock that maximizes the cumulative FEVD share in the relative price of investment over varying horizons h. Again, I leave the remaining shocks in the system unidentified.[55]

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) for the total nonfinancial business sector. Details can be found in Appendix A.3. To compute real variables I use nominal data which I deflate 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.[56] I construct this relative price from NIPA data and use the Gordon-

[54] Earlier work on these types of restrictions includes Uhlig (2004) and Faust (1998). They are also applied in recent paper by Angeletos, Collard, and Dellas (2018).

[55] To implement the medium-horizon identification, I begin by estimating the VAR in reduced form and calculating an initial estimate of the B_0^{-1} matrix, based on a simple Cholesky decomposition. I then take an orthonormal rotation of this matrix such that the identifying restriction is satisfied. In practice, this means that I run a constrained optimization routine over $n \times n$ matrices D, in which I calculate the FEVD implied by DB_0^{-1}, and the objective is to maximise the FEVD share of the first shock in the first variable. The constraint of the routine is that $D'D = I_n$ must be satisfied.

[56] Among different relative investment price categories, the equipment price is the one with a clear downward trend in US data based on which the IST shock can be identified. The deflator for total investment and for

Violante-Cummins (GVC) investment price for robustness.[57] For debt I use the sum of loans and debt securities for the nonfinancial business sector and also consider these debt categories separately for robustness. As some of the variables display low frequency movements after log differencing, I detrend some of the series before estimating the VAR.[58] I estimate the reduced form VAR using OLS, recover the IRFs from inverting (rotating) the relevant matrices under the identifying restrictions, and compute 68% error bands using bootstrap techniques.

4.2 SVAR results: aggregate responses to investment shocks

IRFs. The results on 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 capital. Section E.2 in the appendix 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. For both identification methods the figure shows a positive response of debt, which is in line with the model predictions for the earnings-based constraint but not for the collateral constraint. In line with the dynamics of the model, the rise in debt is accompanied by growing earnings and a fall in the value of capital.

To best interpret these results, suppose the model introduced in Section 3 of this paper is a good description of reality, that is, it approximates well the data-generating process behind the time series used in the SVAR. Given the positive debt response to the IST shock in Figure 5, the IRFs are supportive of the version of the model that features an earnings-based constraint and not a collateral constraints. 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.[59]

Historical variance decomposition. My empirical strategy only relies on the sign of the responses, and conceptually it does not require the importance of the shock in a variance decomposition sense to be large. However, if the shock is an important driver of macroeconomic dynamics, this means that the relevance of the earnings-based borrowing

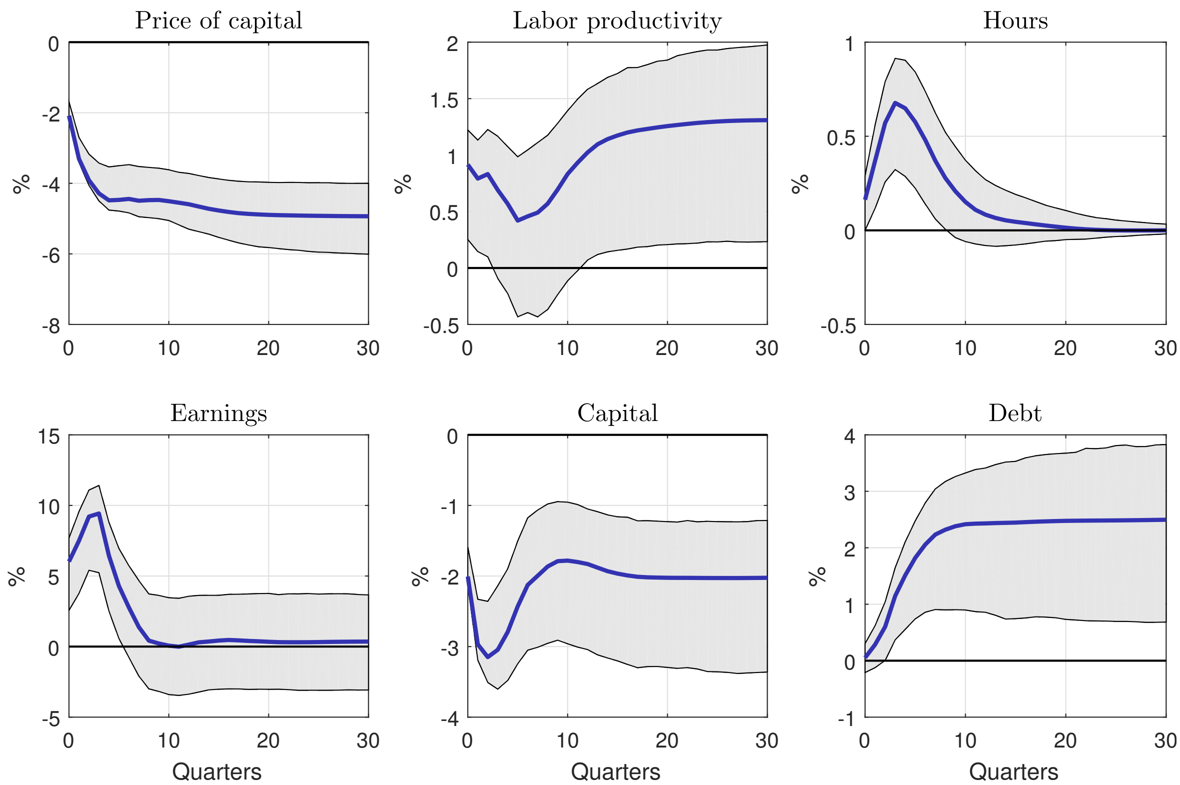
structures do not display as strong trends. Interestingly, the Dealscan data set provides information on the type of collateral used in loan contracts: "property and equipment" is the top category of specific assets pledged as collateral, which further supports this choice. See Table A.4 in the Appendix.

[57] Appendix A.3 contains a figure comparing the two alternative series. I also run a unit root test to confirm that both series are nonstationary in levels and stationary after first-differencing, as required by the identification scheme of the SVAR. See also Gali (1996) for details.

[58] Blanchard and Quah (1989) provide a related discussion. The detrending mostly increases the precision of the estimates but has little influence on the shape of the estimated IRFs.

[59] Appendix E.1 presents the IRFs to the TFP shock. Consistent with the model, this shock has an expansionary effect, raising the variables in the system, despite hours. Debt also rises (albeit not significantly). For TFP shocks, however, it did not make a big difference which constraint is relevant to begin with, so the empirical verification of the specification of the borrowing constraint relies on the responses to the IST shock.

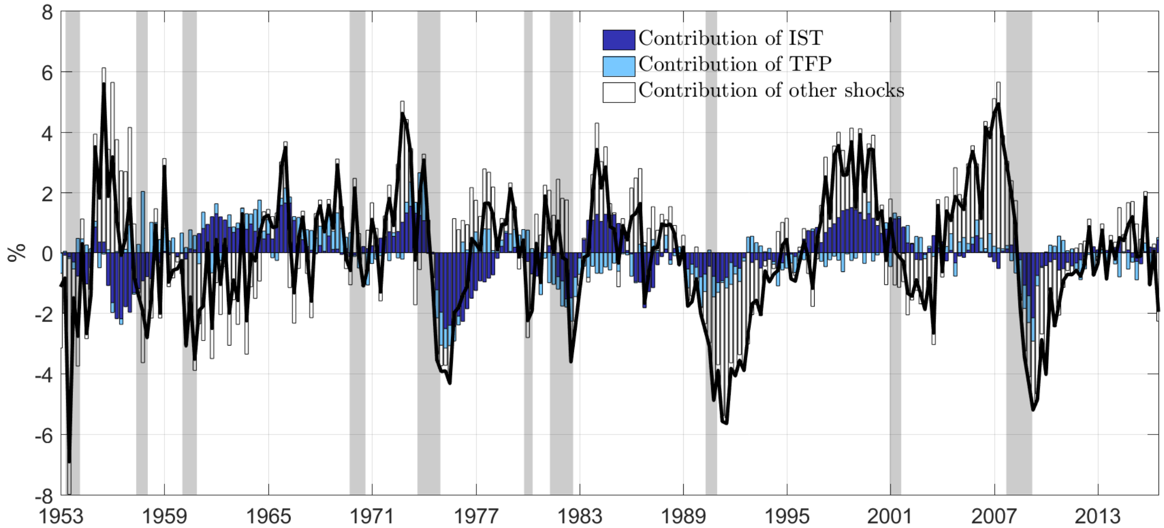
Figure 5: SVAR IRFS TO POSITIVE INVESTMENT SHOCK IDENTIFIED WITH LONG-RUN RESTRICTIONS



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% 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.

constraint should have important effects also on the unconditional dynamics of the macro data. Figure 6 shows the historical decomposition of debt using the long-run identification method. The solid black line plots the actual data of the cyclical component of debt, and the colored bars represent the contribution at each point in time of the different shocks (IST, TFP and other). It can be seen that IST shocks have 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. The boom and bust of the 2000s, on the other hand, was less influenced by IST according to the SVAR model. Appendix E.3 provides the historical decompositions of the remaining variables in the system.

Figure 6: SVAR: HISTORICAL VARIANCE DECOMPOSITION OF FIRM DEBT



Note: The figure shows the historical variance decomposition of firm debt estimated by the SVAR model identified with long-run restrictions. The black line is the percent deviation from trend of debt liabilities (loans and debt securities) of the nonfinancial business sector, taken from the US financial accounts. The bars indicate the contribution of different structural shocks to the variance of debt 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 white bars. Shaded areas indicate NBER recessions. The decomposition is calculated following Kilian and Lütkepohl (2017).

Monte Carlo simulations. To verify the ability of the SVAR methodology to distinguish between different borrowing 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 borrowing constraint specification (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 and run the SVAR identified with long-run restrictions on each of them. The results, shown in Appendix E.4, are reassuring. For example, the negative debt response generated from a collateral constraint model is fully contained in the 68% confidence set across Monte Carlo repetitions.

Robustness checks. I explore robustness of the SVAR results along several dimensions. First, following Fisher (2006), I split the sample in the early 1980's to account for 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, but more hump-shaped rather than settling at a permanent level. Second, I construct the business debt times 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, and even negative for the first three quarters. Third, similar to many papers in the IST literature, 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.[60] The results are very similar to the ones obtained using NIPA data. Finally, as the data on investment deflator dynamics is subject to a few large spikes, I also adjust this data for outliers as a robustness check. The IRFs get smaller in magnitude, but their shapes and statistical significance is preserved.

4.3 Panel projections in firm-level US data

The SVAR results indicate that the earnings-based constraint is relevant for debt fluctuations in the aggregate economy. The responses of aggregate earnings and capital are consistent with the model mechanism. In this subsection, I exploit micro-level information on how firm borrowing is restricted to verify the proposed mechanism more directly. I merge the Dealscan data set used in Section 2 with balance sheet information from the Compustat Quarterly data base to obtain a firm panel that has information on earnings-based covenants and collateral as well as on rich firm characteristics. I regress firm-level borrowing on the macro investment shock obtained from the SVAR. I obtain average IRFs across all firms, as well as heterogeneous IRFs for different borrower types, allowing me to verify whether the suggested mechanism is plausible in generated debt dynamics at the firm level.[61]

4.3.1 Panel setting and assumptions

I estimate the IRF of borrowing of firm i at horizon h to the investment shock by running the linear regression

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

and obtaining estimates of β_h, $h = 0, 1, 2, \ldots, H$. The right hand side variable $\hat{u}_{IST,t}$ denotes the time series of the identified exogenous investment shock from the SVAR model above. $\boldsymbol{X_{i,t}}$ is a vector of controls. t is a linear time trend. This regression is a panel version of the local projection method to estimate IRFs following Jordà (2005). Equation (16) gives an average IRF across *all* firms in the panel. My model predicts the response of debt to the

[60] This series was originally constructed by Bob Gordon and extended by Cummins and Violante (2002). See also DiCecio (2009) for details. Appendix A.3 contains a figure comparing the long-run trends and cyclical dynamics in the two relative investment prices.

[61] I also study the firm-level debt responses to a fall in the relative price of investment goods, using an IV strategy based on investment shocks. A similar approach of estimating firm-level responses to macroeconomic shocks has been taken recently by Bahaj, Foulis, Pinter, and Surico (2018) Cloyne, Ferreira, Froemel, and Surico (2018) who study the heterogeneous firm-level effects of aggregate monetary policy shocks.

investment shock in this regression to be positive under an earnings-based constraint ($\beta_h > 0$) and negative with a collateral constraint ($\beta_h < 0$).

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

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

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 further below. The interactions with these dummy variables allow me to estimate heterogeneous IRFs for four different firm groups. In particular, the IRF of a "earnings only" ("collateral only") borrower at horizon h is given by the sum of the coefficients β_h and β_h^{earn} (β_h and β_h^{coll}). My theoretical mechanism predicts that $\beta_h + \beta_h^{earn} > 0$ and $\beta_h + \beta_h^{coll} < 0$.

An alternative version of (17) based on an IV strategy is provided in Appendix F.2. The idea is to 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. The corresponding results are presented in the same appendix and are discussed below.

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).[62] The final data set I use 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

[62] I am extremely grateful to these authors for publicly providing this link. More details about the construction of the merged data set can be found in Appendix A.2.

credit.[63] Summary statistics for the full data sample and conditional on the first grouping 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 in credible, this shock is a purely exogenous regressor, meaning that there are no endogeneity issues in (16). Clearly, however, the dummy interactions to generate heterogeneous responses in equation (17) are a 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. Specifically, 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. In addition, as is standard in local projections, I add two lags of the exogenous macro shock to "mop up" any serial correlation in the shock. Furthermore, I add a control variable that is intended to capture macroeconomic shocks other than investment shocks, which I construct from the SVAR residuals.[64] I set $H = 12$, and keep the firm composition constant when expanding h, that is, I restrict the analysis to firms where debt information is available for the current and 12 quarters ahead.

It should be emphasized that while Compustat is an actual panel, the loan issuance information from Dealscan is "sparse" in the sense that firms only have an issuance that is captured in this data every other quarter. Many firms appear only a few times during the sample period, while their total debt liabilities are continuously recorded in Compustat. This has two consequences. First, using any Dealscan information at time t means that the sample to estimate (17) is restricted to those firms that have a loan issuance captured by the Dealscan data in period t, which reduces the sample relative to the one I can use to estimate (16). Second, this 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.

4.4 Firm-level results: heterogeneous responses to investment shocks

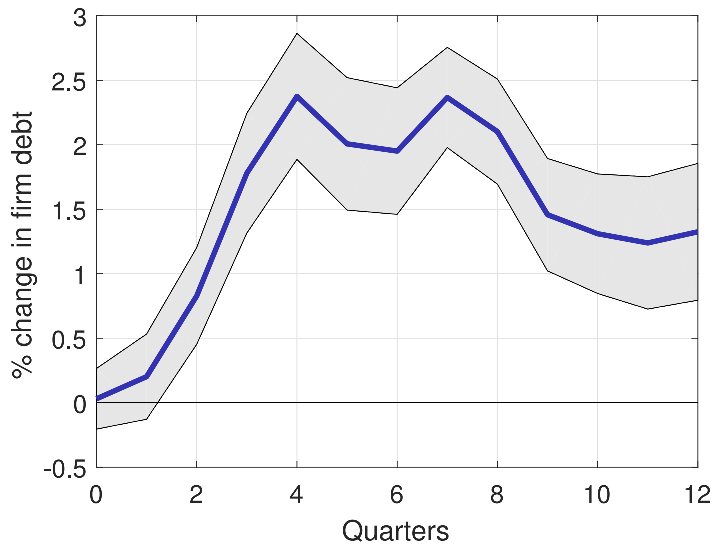
I first present the average debt response across all firm in the panel, that is, the estimates of β_h in (16) across horizons, together with the associated 90% bands. I cluster standard errors at the 3-digit industry level to allow for correlation in the residuals across of firms within the same industry. In this regression I do not add any controls other than lags of

[63] This follows Lian and Ma (2018), who point out that secured "revolvers" are typically asset-based.

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

the left-hand-side variable, a time trend and the exogenous shock itself. Figure 7 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 subset of the total US nonfinancial business sector for which I use data in the SVAR.

Figure 7: EMPIRICAL FIRM-LEVEL IRF OF DEBT TO AN INVESTMENT SHOCK

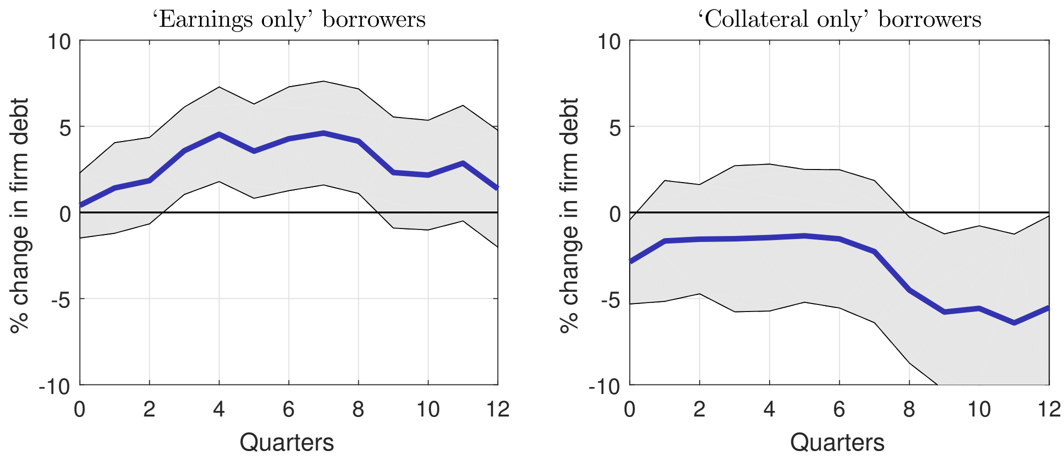


Note: The figure plots the average IRF of firm debt to a macro investment shock across individual firms, estimated using the method of Jordà (2005) in a panel data context, as formulated by equation (16). The macro shock has been identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). The data set used is a merge of Dealscan loan-level information with balance sheet variables from the Compustat quarterly data base. The IRF is shown in percent. 90% bands are calculated using standard errors clustered at the 3-digit industry level. 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.

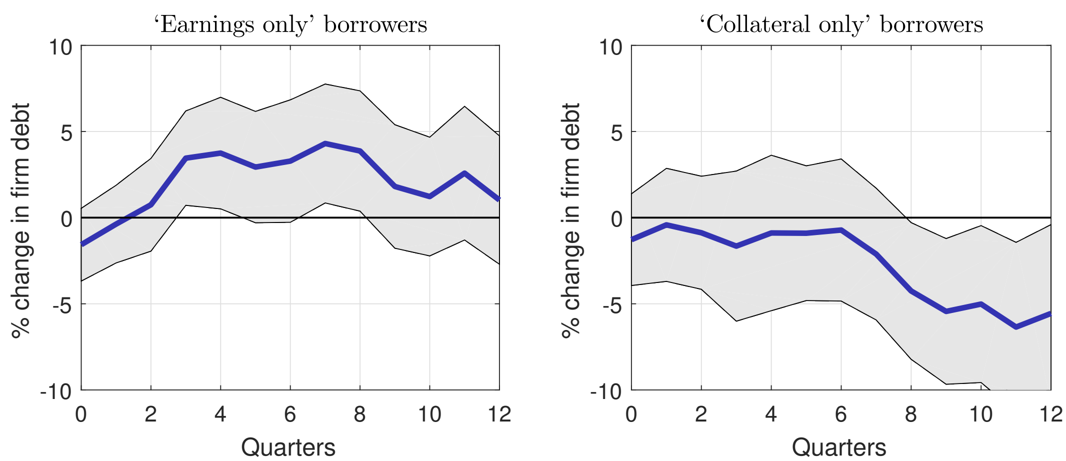
The heterogeneous borrower IRFs based on estimating equation (16) are presented in Figure 8. These results are based on a specification with detailed firm-level controls: 3-digit industry, size as measured by number of employees and growth of real sales. As discussed above, I also control for other macroeconomic shocks. Panel (a) shows the baseline results where 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 alternative classification of asset-based debt based on whether a firm uses secured revolvers (see Lian and Ma, 2018). Again, I plot 90% error bands based on standard errors that are clustered at the 3-digit industry level. Note that the bands across all four figures are wider than in Figure 7 due to the lower number of observations when using $\mathbb{1}_{i,t,earn}$ and $\mathbb{1}_{i,t,coll}$ in

Figure 8: 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). 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, 2018). 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 data base. 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. A formal test rejects the null hypothesis of equal responses across the two firm types for various horizons, as shown in Table F.1 in the Appendix. The results for alternative specifications, as well as the responses for the remaining two borrower types are given in Appendix F.

the regression. Both panels of Figure 8 show that the IRF of debt to an investment shock is positive for firms that are subject to earnings-related loan 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. 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 model counterpart. Similar to the model prediction, the response on impact in Panel (a) is significantly negative. However it then rises and is again significantly negative after around 2 years. This may be due to the fact that the theoretical mechanism I propose equates the dynamics of new and already installed capital prices is not borne out by the data. Empirically, the relative price effect at the heart of my mechanism may not be strong enough to generate a negative effect for collateral borrowers that is as sizable as in the model. Reassuringly, the null hypothesis of an equal response across the two borrower is rejected over several horizons at the 5% level. This is not directly visible in Figure 8, but is formally presented in Table F.1 in the Appendix.

Appendix F presents a host of additional results based on alternative variations of equation (17). First, I show the results for a 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 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 8 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. Taken together, the heterogeneous responses are in line with the model mechanism, where the positive investment shock induces a reduction in debt under the collateral constraint but a rise in debt if the earnings-based constraint binds.

4.5 Take-away: empirical dynamics in line with earnings-based constraint

The proposed model mechanism allows to distinguish between alternative borrowing constraints based on credit dynamics arising from investment shocks. In an economy in which firms are borrowing constrained, a boom driven by an expansionary shock which suppresses capital prices, debt levels rise in the presence of an earnings-based constraint, but not if capital serves as collateral. The empirical responses of debt to investment shocks in macroeconomic data, shown above, indicate that the relevant one for US aggregate corporate debt dynamics is such an earnings-based constraint. Moreover, heterogeneous firm-level responses are 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 in a quantitative macro model

This section extends the model of Section 3 to incorporate features of a New Keynesian quantitative macro model. Specifically, I add a number of shocks and frictions, such as price and wage rigidities to feature alongside borrowing constraints. I estimate the model on US time series to let the data speak about the importance of earnings-based borrowing relative to borrowing against collateral and relative to other frictions in the economy. This analysis goes beyond the focus on the sign of debt responses, which has guided my analysis above.

5.1 Setup of the quantitative model

The model is a New Keynesian DSGE model in the spirit of Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). These models have become the workhorse model in central banks, perhaps due to their appealing philosophy: in order to gauge the overall effect of any macroeconomic policy change, this policy needs to be assessed net of other important forces that operate across parts of the economy.[65] For the purpose of adding borrowing constraints in a New Keynesian structure, I build on a variation of the Smets and Wouters (2007) model suggested by Jermann and Quadrini (2012).[66] The details of the model are provided in Appendix G, in what follows I elaborate mainly on the borrowing constraints.

While in Section 3 I study alternative models in which either the earnings-based or collateral constraint is binding, I now move to a formulation where both constraints are present simultaneously and where the estimation of the model can attribute a different relative importance to either constraint. Specifically, there is a continuum of firms which have access to a nominal risk-free bond that is constrained by a weighting between a earnings-based and a collateral component. The interest rates paid on the debt is subject to a tax advantage of the type in equation (7). The constraint of firm i reads

$$\frac{b_{i,t}}{P_t(1+r_t)} \leq \omega\theta_{\pi,t}\pi_{i,t} + (1-\omega)\theta_{k,t}\mathbb{E}_t p_{kt+1}(1-\delta)k_{i,t}. \tag{18}$$

ω captures the relative weight on the earnings-based component in firm borrowing. I estimate this parameter together with the other structural parameters of the model. The θ parameters are subject to shocks to financial conditions.

[65] For recent discussions, see for example Galí (2018) and Christiano, Eichenbaum, and Trabandt (2018).

[66] The quantitative model of Jermann and Quadrini (2012) differs from Smets and Wouters (2007) in the following ways. Firms rather than households own and accumulate capital. Nominal rigidities arise because 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. The exogenous disturbances do not feature moving average terms. Finally, firms have access to debt and receive a tax advantage on debt. I also add some corrections to the model that were suggested by Pfeifer (2016).

5.2 Data and estimation settings for quantitative model

For the estimation of the model I use the 7 observables suggested by Smets and Wouters (2007) (output, consumption, investment, employment, interest rates, wages and inflation) and add the change in nonfinancial sector debt from the flow of funds, scaled by output, as an eighth observable. My data treatment captures explicitly the variation in the relative prices between consumption and investment goods: I obtain real variables by deflating with the consumption deflator of nondurables and services. This is a similar treatment to the one in Justiniano, Primiceri, and Tambalotti (2011). Details on the data used for estimation are provided in Appendix A.3.

I estimate the model with Bayesian methods, combining the likelihood of the model with prior information on the parameters.[67] I calibrate the means of $\theta_{\pi,t}$ and $\theta_{k,t}$ in the same way as in Section 3. For ω I specify a uniform prior between 0 and 1. For comparability to previous studies, I otherwise estimate the same set of parameters as Jermann and Quadrini (2012) and use identical priors. I obtain 1,000,000 million draws from a Markov Chain Monte Carlo algorithm and discard the first 20% and use the remaining ones to compute posteriors.

5.3 Model estimation results: the quantitative role of earnings-based debt

I analyze the role of earnings-based borrowing constraints in the estimated New Keynesian model from a number of angles. Specifically, I present the posterior estimate of the weight on the earnings-based component in the constraint, characterize the debt responses to investment and other shocks in different model counterfactuals, and study how the constraint affects the transmission of fiscal and monetary shocks.

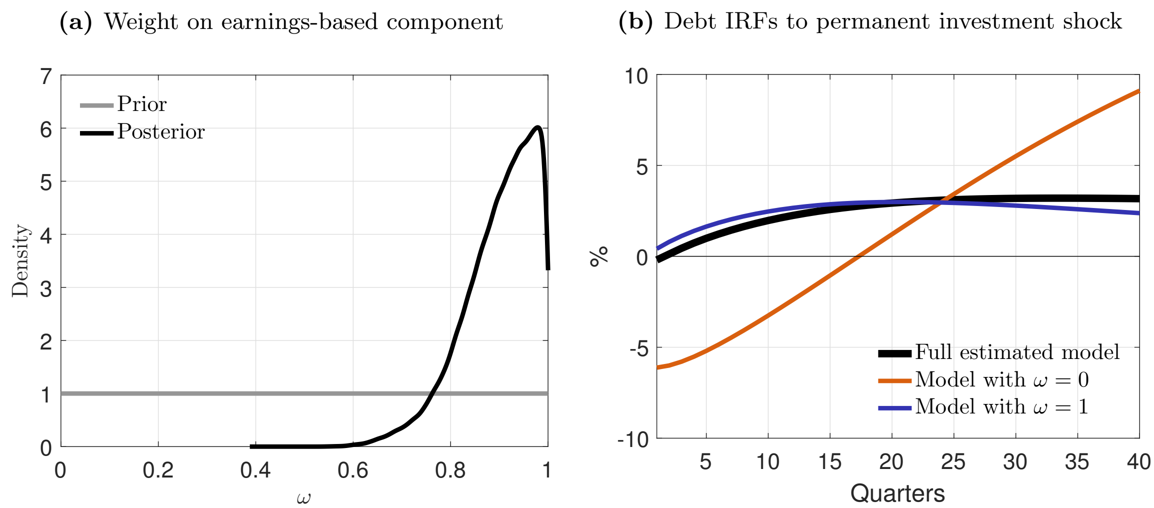
The estimated weight on earnings-based debt. Panel (a) of Figure 9 plots the prior and posterior density of ω. A value of 0 implies a model with only a collateral constraint, while 1 implies the presence of only an earnings-based constraint. The figure shows that while the prior assigns an equal importance to any weight, the posterior density implies a clear tilt towards the earnings constraint with a mean estimate of $\omega = 0.90$. This finding provides additional evidence that the dynamics in US data, now interpreted through the lens of a richer model structure, favor the earnings-based constraint. The results implies that the collateral component remains a feature of the model, although with a much lower weight.[68]

Panel (b) presents the IRFs of real debt liabilities to a permanent positive investment shock, calculated at the posterior means of the estimated model (thick black line). The chart also contains corresponding IRFs in counterfactual models in which the weight of the

[67] An and Schorfheide (2007) provide a survey on Bayesian techniques to estimate DSGE models. For a recent exploration of the sensitivity of these methods to misspecification, see Den Haan and Drechsel (2018).

[68] Table G.1 in the Appendix presents the priors and posterior estimates of all other parameters.

Figure 9: PROPERTIES OF THE ESTIMATED QUANTITATIVE MODEL

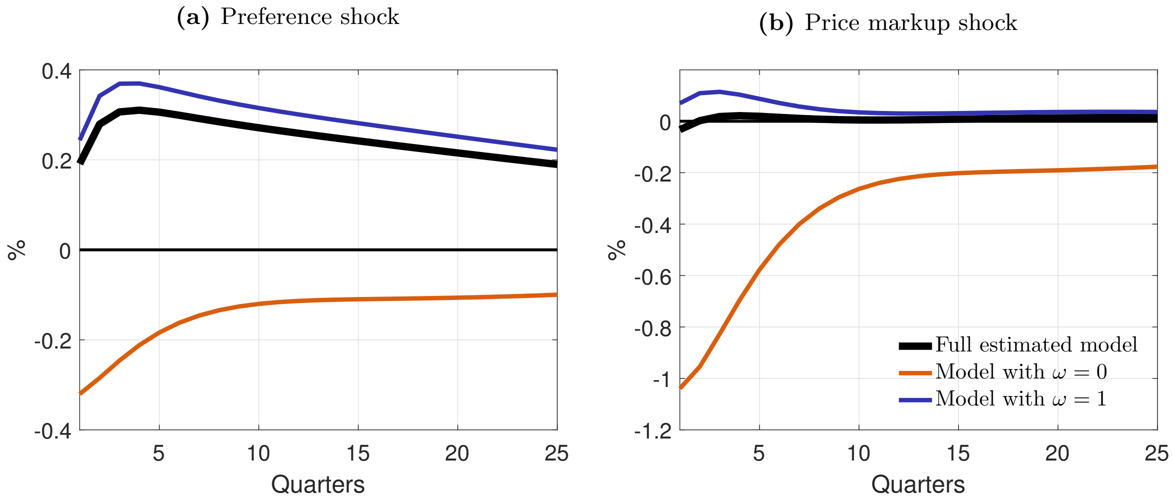


Note: Panel (a) presents the prior and posterior density (grey and black solid lines, respectively) over values of ω, as estimated in the quantitative New Keynesian model on US data. An estimate of 0 implies a model with only a collateral constraint, while an estimate of 1 implies a model with only an earnings-based constraint. See equation (18). Panel (b) shows the IRFs to a permanent investment shock, calculated at the posterior means of the estimated model (thick black line) and for counterfactual models in which the weight of the earnings-based constraint is set to 1 (blue line) and 0 (orange line), but all other parameters are kept at their estimated values. Debt refers to the level of real debt liabilities.

earnings-based constraint is set to 1 (blue line) and 0 (orange line), while the other parameters are kept at their posterior mean estimates. In line with the insights of Section 3, permanent investment shocks lead to a persistent increase in debt, fostered by a rise in earnings. A pure collateral constrained model would predict a fall in debt, due to the lower value of collateral in equilibrium. The mechanism that is at the heart of Sections 3 and 4 thus remains intact also when a variety of other frictions are present alongside the borrowing constraint.

Additional sign differences in debt responses. Figure 10 plots the IRFs of firm debt to other selected shocks in the New Keynesian model. Panel (a) presents the responses to a preference shock (an exogenous increase in the household's discount factor), while Panel (b) shows those for a price markup shock. Again, both charts display the IRF calculated at the posterior means of the estimated model (thick black line) together with corresponding IRFs in counterfactual models in which $\omega = 1$ and $\omega = 0$ (blue and orange lines, respectively). The figure shows that the two borrowing constraints imply counterfactual signs of the responses of debt also for additional shocks in the model. In both cases, the response of the pure earnings-based constraint model lie close to the model in which the weighting between the two components is estimated. This is intuitive, since the posterior estimate of ω is close to, but not equal to, 1.

Figure 10: DEBT IRF TO ADDITIONAL SHOCKS ACROSS MODEL COUNTERFACTUALS



Note: The figure shows the IRFs of firm real debt liabilities to a preference shock (Panel a) and a price markup shock (Panel b). In both cases, the IRFs are calculated at the posterior means of the estimated model (thick black line) and for counterfactual models which are the weight of the earnings-based constraint is set to 1 (blue line) and 0 (orange line), but all other parameters are kept at their estimated values.

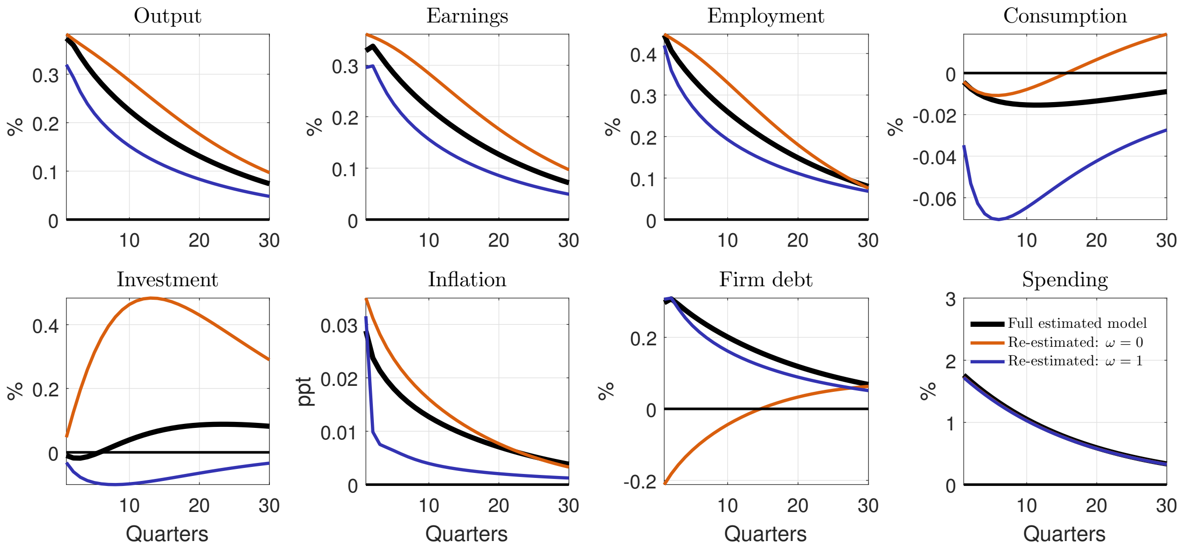
Counterfactual dynamics for policy shocks. So far my analysis has primarily focused on the dynamics of firm debt to distinguish the role of different borrowing constraints. Figure 11 turns to studying the responses of other macroeconomic variables and examine the consequences of the earnings-based constraint for the overall transmission of shocks in the economy. To illustrate the role of the constraints in the quantitative model, I focus on policy shocks. Panel (a) shows the responses to an expansionary fiscal shock, that is, an exogenous increase in government spending. Panel (b) focuses on a contractionary monetary shock, an exogenous increase in the interest rate. In each case I plot the IRFs of the estimated model, calculated at the posterior means as the thick black line, together with IRFs from counterfactual models based on setting $\omega = 1$ (blue line) and $\omega = 0$ (orange line), and re-estimating the other parameters of the model.[69] For studying policy, this is my preferred type of counterfactual, as I want to characterize hypothetical situations in which a policy maker would only have one or the other model at her disposal.

The figure demonstrates that a policy maker would reach different conclusions across estimated models with alternative borrowing constraints. The presence of earnings-based debt alters the transmission of both fiscal and monetary shocks. In the case of fiscal policy, the intuition is as follows. The spending shock gives rise to higher demand for the consumption good produced by the firm, which raises earnings and gives an incentive for bringing resources

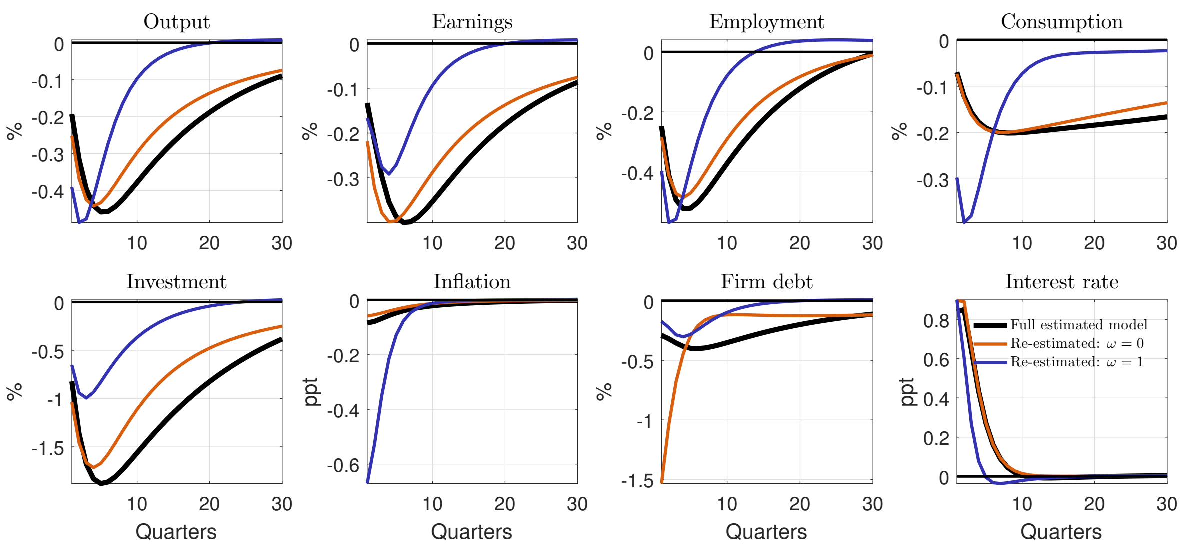
[69] When calculating the IRFs to the fiscal shock, I use the persistence and standard deviations of the disturbances that are implied by the baseline model to ensure comparability. In the case of the monetary shock, I rescale the size of the shock to give the same interest rate response.

Figure 11: POLICY SHOCKS IN COUNTERFACTUAL ESTIMATED MODELS

(a) Selected IRFs to an expansionary government spending shock across models



(b) Selected IRFs to a contractionary monetary policy shock across models



Note: The figure shows the IRFs of selected economic variables to a fiscal policy shock (Panel a) and a monetary policy shock (Panel b). In both panels, the IRFs are calculated at the posterior means of the estimated model (thick black line) and for counterfactual models in which the weight of the earnings-based constraint is set to 1 (blue line) and 0 (orange line), and the other structural parameters are re-estimated. In panel (a), the shock size and persistence to create the IRFs is the same across models. In Panel (b) the size of the shock is adjusted to give the same interest rate response on impact.

to the presence. Under the earnings-based constraint this incentive is strong enough to crowd out investment. As debt access is determined by earnings, firms borrow more. With a collateral constraint, investment has the additional benefit of building collateral, so firms respond but raising investment and the crowding-out effect disappears. This response is not strong enough to offset the tightening constraint from the fall in the value of capital and the firm reduces borrowing. In net terms, the crowding out of investment dampens the overall stimulus from the spending shock with an earnings constraint. Despite the reduced debt space with the collateral constraint, the stimulus is stronger. Most of the IRFs from the model with both components lie between the IRFs of the counterfactual models.

In the case of the monetary shock, the counterfactual estimations show that the earnings-based constraint implies a stronger inflation response and a somewhat stronger but less persistent output response to than the collateral constraint. A comparison of the estimated parameter values of the different models reveals that this is driven by the fact that a model with only an earnings-based constraint implies a relatively low degree of price rigidity relative to the pure collateral model.[70] This finding demonstrates that the specification of the borrowing constraint interacts with other frictions of the model, which highlights that the specification of firm borrowing constraints is crucial for drawing conclusions from a quantitative macro model. Finally, in the case of the monetary shock it is noteworthy that the IRFs of the baseline model, which features both an earnings and collateral component, are generally closer to the ones stemming from the pure collateral constraint model. This is due to the fact that the in the re-estimation of the counterfactual models both the dynamics in response to shocks as well as their relative contribution changes. This means that any individual IRF of the model with both components does not necessarily lie in between the two counterfactual models. In fact, the presence of the earnings-based constraint makes the responses to monetary shocks stronger, but the implied model assigns a lower importance to monetary policy shocks for US business cycles.

Variance decomposition of observables. To conclude the analysis of the quantitative model, Table 3 presents the forecast error variance decomposition of the variables that are used as observables to estimate the model (Table G.3 in the Appendix shows the corresponding decomposition for a model without any borrowing constraints). This decomposition shows the relative importance that the model attributes to different structural shocks in driving a given observable. For example, according to the model markup shocks to prices and wages are an important driver of inflation dynamics, while consumption growth dynamics are importantly affected by shocks to intertemporal preferences. One observation that stands out in the table in the overall importance of investment shocks. Consistent with

[70]Table G.1 in the appendix shows the priors and posterior of the model with both components. This model is estimated with a high degree of price adjustment costs, which is driven by the collateral component.

Table 3: VARIANCE DECOMPOSITION OF OBSERVABLES IN ESTIMATED QUANTITATIVE MODEL (IN %)

	TFP	**Inv**	**Pref**	**Price**	**Wage**	**Gov**	**Mon**	**Fin**
Output growth	4.74	53.47	11.7	5.86	2.49	13.09	6.16	2.48
Consumption growth	5.53	5.02	82.81	1.39	1.21	0.02	4.01	0
Investment growth	2.52	86.81	0.25	2.69	2.61	0	5.09	0.03
Inflation	13.07	13.87	4.97	43.48	18.73	0.83	4.98	0.05
Interest rate	4.11	11.94	3.07	16.47	8.12	0.56	55.72	0.01
Employment growth	29.64	39.72	7.27	1.54	3.73	11.12	5.92	1.06
Wage growth	14.21	2.45	2.02	23.86	57.33	0.02	0.08	0.03
Debt issuance	1.13	4.75	0.74	1.65	0.56	0.69	1.14	89.35

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 G.1 contains details on the model and specification of the structural shocks.

similar findings in the literature, the investment margin appears to be crucial for capturing variation in US macroeconomic data. This lends further support to using this shock in the context of studying which type of corporate borrowing constraints are in line with credit dynamics at the macro and micro level.

6 Conclusion

Capturing the relation between credit and economic activity is crucial for understanding macroeconomic fluctuations. This paper emphasizes the fact that firms' borrowing capacity is tightly connected to their earnings flows, as current earnings are subject to scrutiny by lenders. Grounded on microeconomic evidence on this link, I propose a debt limit that restricts borrowing to a multiple of earnings. The predictions of a business cycle model which features this earnings-based borrowing constraint are in line with both aggregate and cross-sectional credit dynamics in US data. Furthermore, the constraint plays a key role in drawing quantitative conclusions about the transmission of shocks in the economy.

To the extent that debt-to-earnings ratios are targeted in macroprudential regulation, the insights provided in this paper encourage further research to improve policies targeted at firms in credit slumps. Moreover, obtaining a deeper understanding of the cross-sectional heterogeneity that determines the specific conditions under which companies borrow, as well as the potential interaction between different types of credit constraints faced by firms over the business cycle are promising subjects for future research in the field of macro-finance.

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Appendix to

Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations

by Thomas Drechsel (LSE)

Contents

A Details on the data

This appendix provides details on the data sources used across all sections of the paper. First, the Thomson Reuters LPC Dealscan data base. This data set is used for the motivational evidence in Section 2 of the paper, 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. This data is used in Section 4.3 for the local projections of the investment shock in panel data. Third, the times series data used for the estimation of the SVAR in Section 4.1 and the estimation of the quantitative model in Section 5.

A.1 Thomson Reuters LPC Dealscan data set

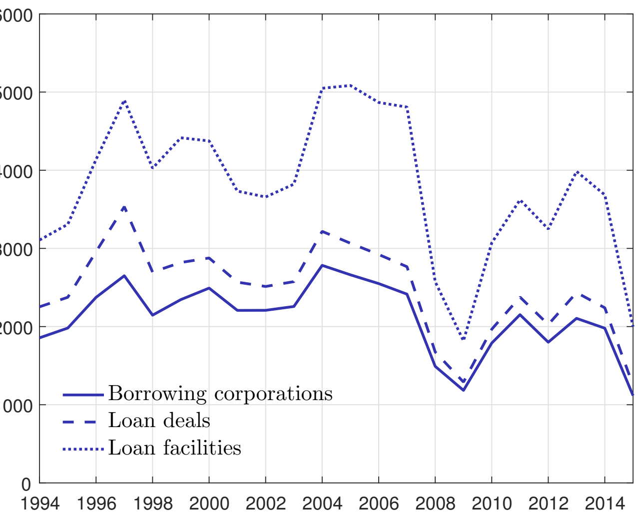
LPC Dealscan is a detailed loan-level data base provided by Thomson Reuters. The data was retrieved in March 2017 through the LSE Library Services and consists of a full cut of the entire data base provided by Thomson Reuters as of October 2015. The data covers around 75% of the total US commercial loan 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. Note that 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 (2018), 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-Compustata 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). 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 deseasonalise 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). Note that 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

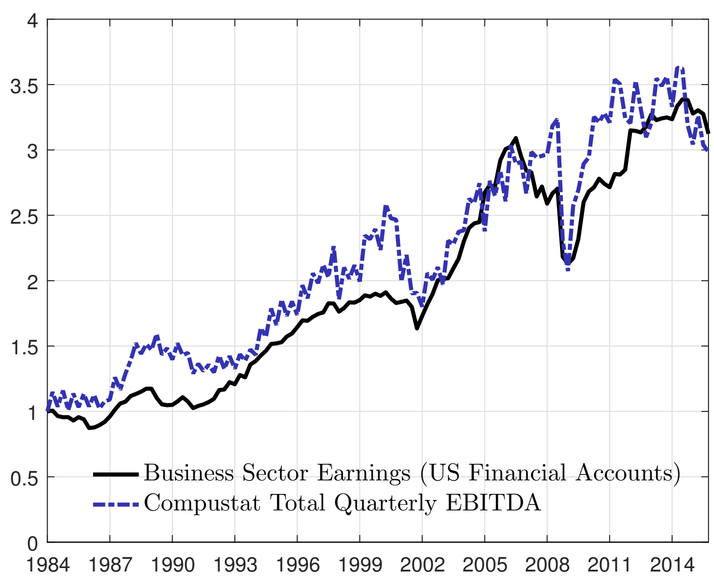
	Firm-qrt obs	Mean	SD	Min	Median	Max
Borrowers taking at least one loan with earnings covenants only ($N = 1,721$)						
Real total assets (bn 2009 USD)	46,680	5.4	17.2	0.0	1.6	455.6
Real sales (bn 2009 USD)	46,680	1.1	2.7	0.0	0.4	55.0
Real sales growth (percent)	46,044	4.9	16.3	-27.6	2.8	43.3
Employment (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 US aggregate time series data

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 the same as 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: FA146110005.Q) and corporate profits before tax excluding IVA and CCAdj (USFA: FA146110005.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

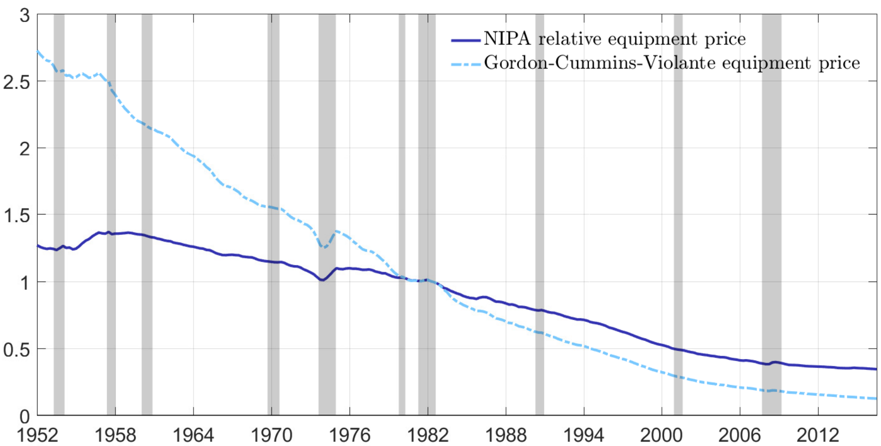
Panel (b): Data used in estimation of New Keynesian model

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
Debt issuance / output	Change in level of business sector debt (sum of USFA: FA104122005.Q and FA144123005.Q), divided by real output (see above)	none

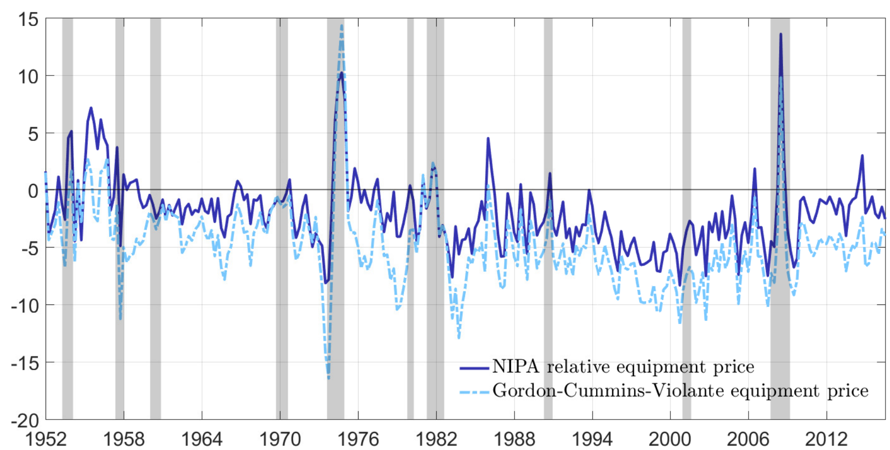
Details on relative equipment prices. Figure A.3 compares the two alternative measures used for the relative price of equipment investment. The first is the one based on NIPA data, constructed as the ratio between the equipment investment deflator and the deflator of consumption on nondurables and services.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

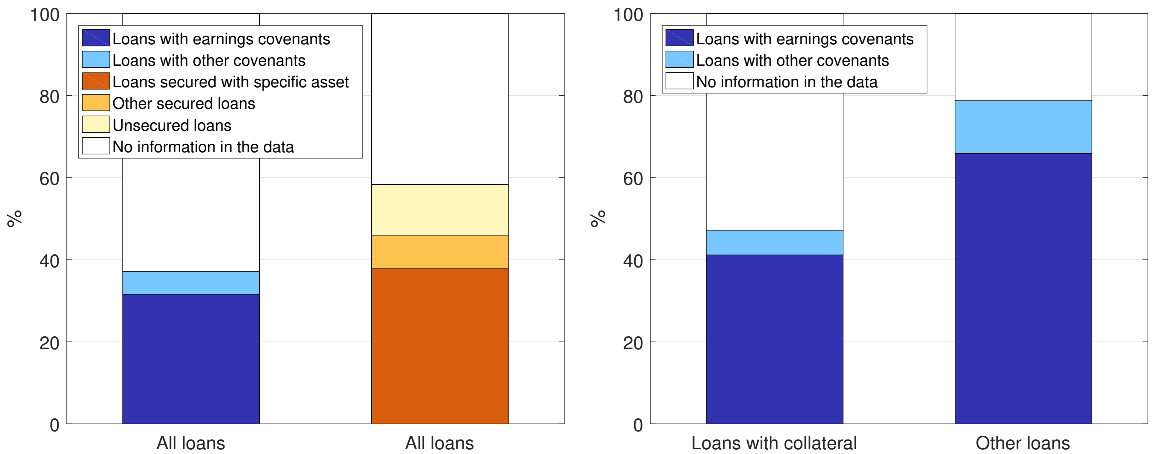
	Test statistic	**5% critical value**	**Reject?**
NIPA levels	-3.34	-3.43	No
NIPA first differences	-5.40	-3.43	Yes
GVC levels	-0.15	-3.43	No
GVC first differences	-6.99	-3.43	Yes

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 Additional evidence

Figure B.1: THE IMPORTANCE OF EARNINGS-BASED AND ASSET-BASED DEBT (EQUAL-WEIGHTED SHARES)

(a) Frequencies of covenants and secured loans **(b)** Covenants within (un)collateralized loans



Note: The figure repeats Figure 1 of the main text for equal-weighted rather than value-weighted shares. Panel (a) displays the 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 (with any information on secured/unsecured). The sample used for both panels consists of loan deals issued between 1994 and 2015 by US nonfinancial corporations.

C 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.

C.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

$$s_{k,t} + \frac{b_{k,t}}{1 + r_{k,t}} \geq \theta_k \mathbb{E}_t p_{k,t+1}(1 - \delta)k_t. \tag{19}$$

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 (19), we obtain

$$s_{k,t} \geq 0 \quad (20)$$

$$\theta_k \mathbb{E}_t p_{k,t+1}(1-\delta)k_t - \frac{b_{k,t}}{1+r_{k,t}} \geq 0, \quad (21)$$

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.[71] Specifically, she evaluates firm ownership after default by using fixed multiple of the last available realization of a fundamental profitability indicator, EBIDTA. Formally,

$$\tilde{V}_{d,t}^{end} \approx \theta_\pi \pi_t. \quad (22)$$

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

$$s_{\pi,t} \geq 0 \quad (23)$$

$$\theta_\pi \pi_t - \frac{b_{k,t}}{1+r_{k,t}} \geq 0. \quad (24)$$

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

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

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.

C.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).

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-EBIDTA ratio of borrowers.[72] Whether transactions are defined in this way in turn affects risk-weights and hedging requirements for lenders.

In the case of mortgages, regulatory requirements on income flows have been highlighted by Greenwald (2017), 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-EBIDTA 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.

[72]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 can be found in EU regulations.

D Details on the model of Section 3

D.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:

$$F_{n,t} = w_t \tag{25}$$

$$R_{k,t}\mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}\right\} + \mu_{k,t}\frac{R_{k,t}}{1+r_{k,t}} = 1, \tag{26}$$

$$R_{\pi,t}\mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}\right\} + \mu_{\pi,t}\frac{R_{\pi,t}}{1+r_{\pi,t}} = 1, \tag{27}$$

$$Q_t = \mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}\left[(1-\delta)Q_{t+1} + F_{k,t+1} + \mu_{\pi,t+1}\theta_\pi F_{k,t+1}\right] + \mu_{k,t}\theta_k(1-\delta)p_{k,t+1}\right\} \tag{28}$$

$$Q_t v_t[(1-\Phi_t) - \Phi_{1,t}i_t] + \mathbb{E}_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}Q_{t+1}v_{t+1}\Phi_{-1,t+1}i_{t+1}\right\} = 1 \tag{29}$$

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 (29). 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 text.

D.2 Household, government, and definition of equilibrium

D.2.1 Household problem

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

$$\mathbb{E}_0\sum_{t=0}^{\infty}\beta^t u(c_t, n_t), \tag{30}$$

subject to the budget constraint

$$c_t + \frac{b_{\pi,t}}{1+r_{\pi,t}} + \frac{b_{k,t}}{1+r_{k,t}} + p_t s_t + T_t = w_t n_t + b_{\pi,t-1} + b_{k,t-1} + s_{t-1}(d_t + p_t). \tag{31}$$

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

$$u(c_t, n_t) = log(c_t) + \chi \, log(1 - n_t), \tag{32}$$

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

$$u_{c_t} w_t + u_{n_t} = 0 \tag{33}$$

$$u_{c_t} = \beta(1 + r_{k,t})\mathbb{E}_t u_{c_{t+1}} \tag{34}$$

$$u_{c_t} = \beta(1 + r_{\pi,t})\mathbb{E}_t u_{c_{t+1}} \tag{35}$$

$$u_{c_t} p_t = \beta \mathbb{E}_t (d_{t+1} + p_{t+1}) u_{c_{t+1}}, \tag{36}$$

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

D.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

$$T_t = \frac{b_{k,t}}{R_{k,t}} - \frac{b_{k,t}}{(1 + r_{k,t})} + \frac{b_{\pi,t}}{R_{\pi,t}} - \frac{b_{\pi,t}}{(1 + r_{\pi,t})}. \tag{37}$$

D.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 D.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.

D.3 Specification of stochastic processes

The stochastic processes underlying the exogenous disturbances are defined as

$$log(z_t) = (1-\rho_z)log(\overline{z}) + \rho_z log(z_{t-1}) + u_{z,t} \quad (38)$$

$$log(v_t) = (1-\rho_v)log(\overline{v}) + \rho_v log(v_{t-1}) + u_{v,t} \quad (39)$$

$$log(\phi_t) = (1-\rho_\phi)log(\overline{\phi}) + \rho_\phi log(\phi_{t-1}) + u_{\phi,t} \quad (40)$$

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 $\{\sigma_z, \sigma_v, \sigma_\phi\}$.

D.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 (26), (27), (34) and (35).

3. Steady state must fulfill $Q = 1$

4. Solve (28) for the steady state capital-labor ratio as a function of model primitives.

5. Calculate steady state wage rate w from (25) using steady state capital-labor ratio.

6. Combine the capital-labor ratio, the wage rate, (33) 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.

Note that to allow for adjustment cost shocks I introduce a small alteration to the model in which steady adjustment are non-zero. In particular I define

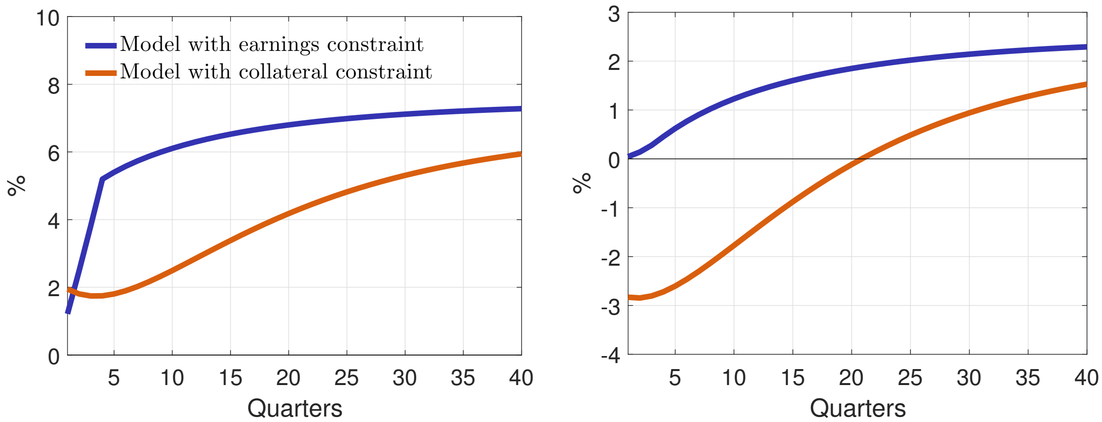
$$\Phi_t \left(\frac{i_t}{i_{t-1}} \right) = \frac{\phi_t}{2} \left(\frac{i_t}{i_{t-1}} - \iota \right)^2,$$

and set ι to 0.999.

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

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

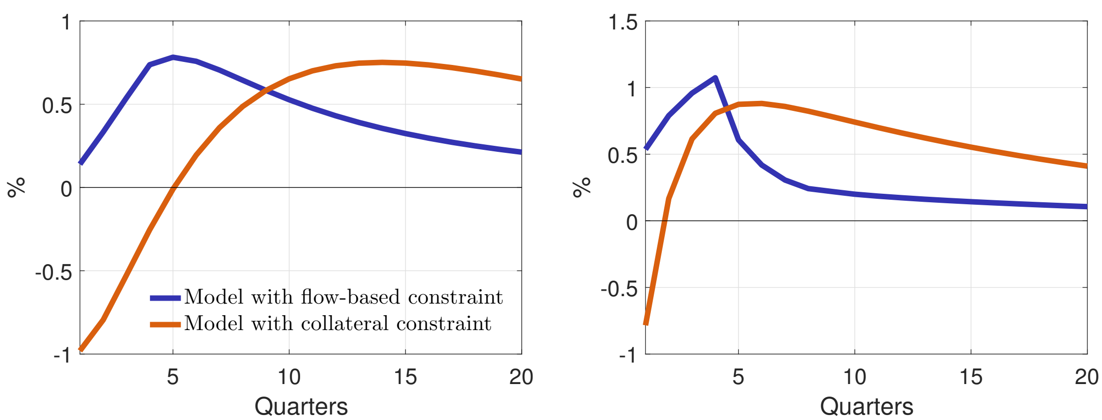
(a) Permanent TFP shock **(b)** Permanent investment shock



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 (blue line) or only the collateral constraint (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 $\sigma_z = \sigma_v = 0.05$.

Figure D.2: MODEL IRFS TO INVESTMENT MARGIN SHOCKS: MODIFIED EARNINGS-BASED CONSTRAINT

(a) Persistent adjustment cost shock **(b)** Persistent investment shock with $\overline{\phi} = 0$



Note: This figure repeats Figure 3 for a formulation of the earnings-based constraint in which current and three lags of earnings enter in equation (8). It displays 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 (blue line) or only the collateral constraint (orange line) is present. Panel (a) plots the IRFs to an adjustment costs shock with $\rho_\phi = 0.5$ and $\sigma_\phi = 0.5$. Panel (b) repeats the investment shock IRFs from Figure 2 without the presence of investment adjustment costs ($\overline{\phi} = 0$).

D.6 Model IRFs of additional variables

Figure D.3: IRFS TO PERMANENT TFP SHOCK

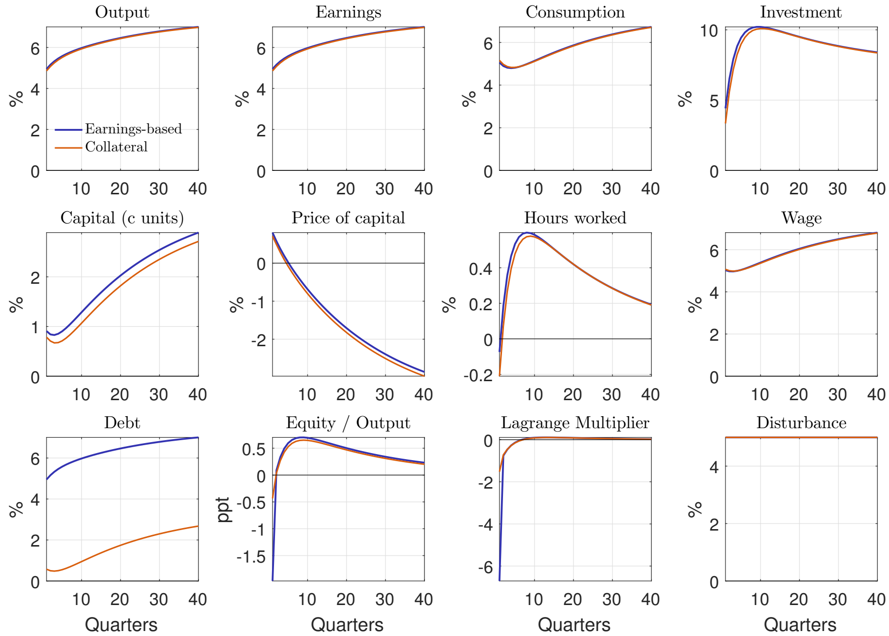
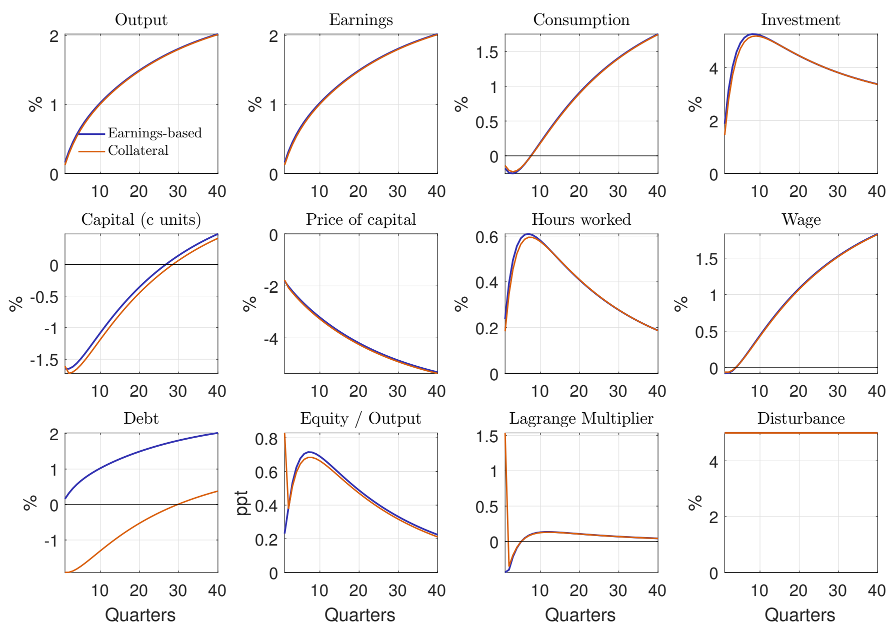


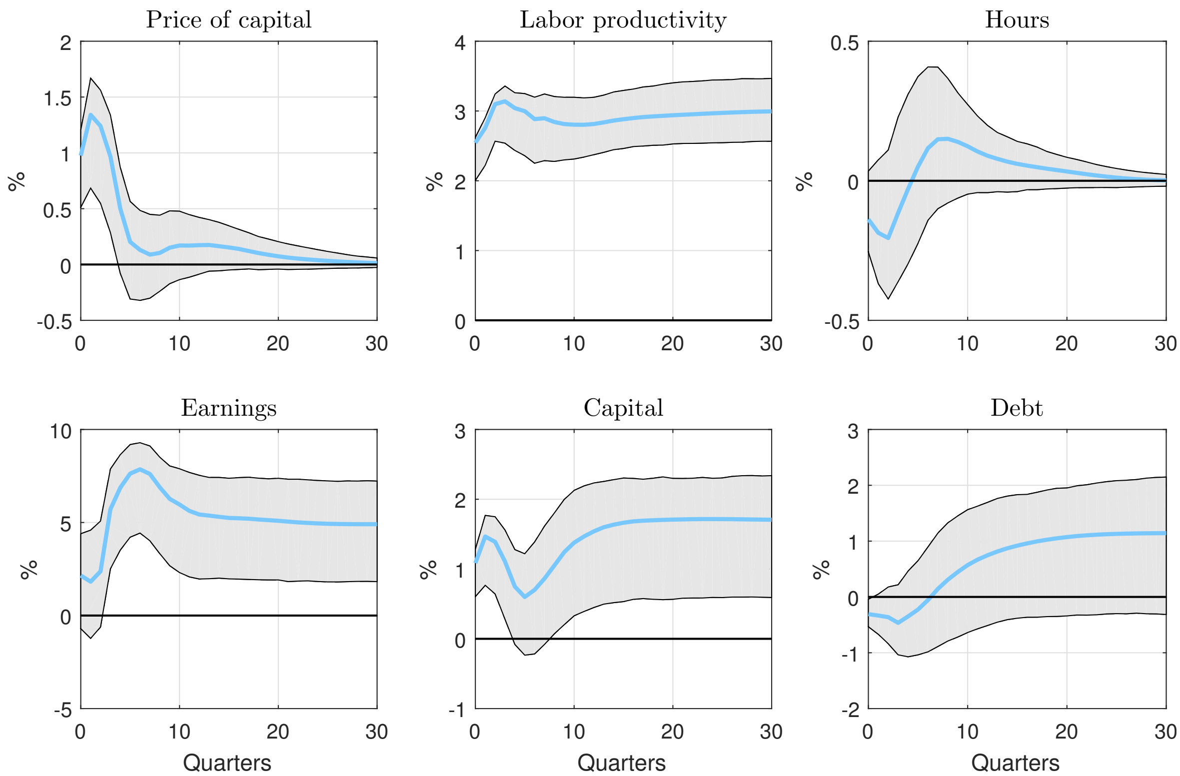
Figure D.4: IRFS TO PERMANENT INVESTMENT SHOCK



E Additional results for SVAR

E.1 SVAR IRFs to TFP shock

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

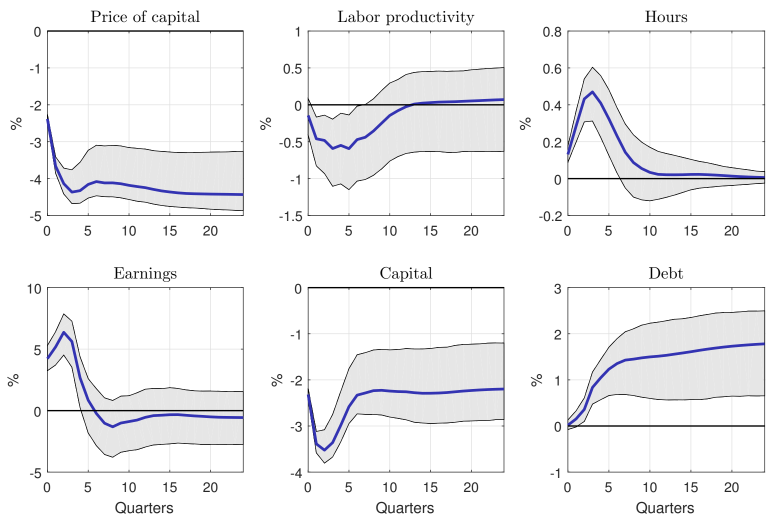


Note: The figure displays the IRFs to a TFP shock identified from an estimated SVAR model using US data. The identification scheme relies on long-run restrictions following Fisher (2006). The responses are shown for all six variables included in the system, in percent. The unit of the shock is one standard deviation. The sample period used for estimation is 1952:Q2 to 2016:Q4. 68% 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.

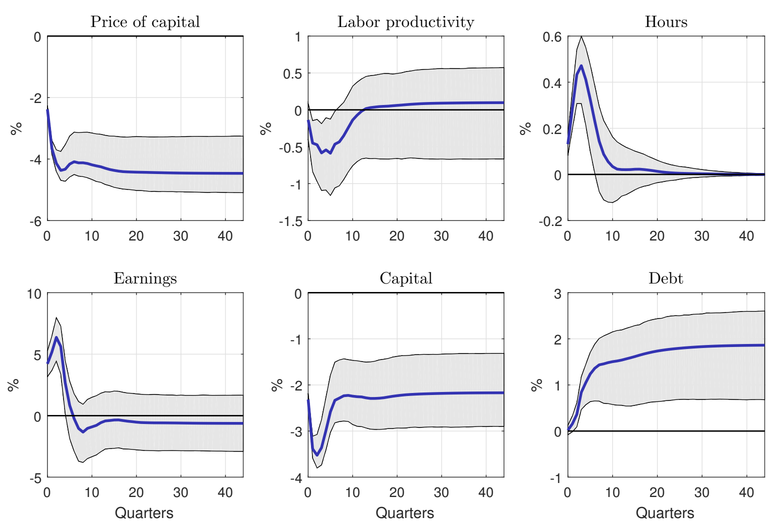
E.2 SVAR IRFs using medium-term restrictions

Figure E.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

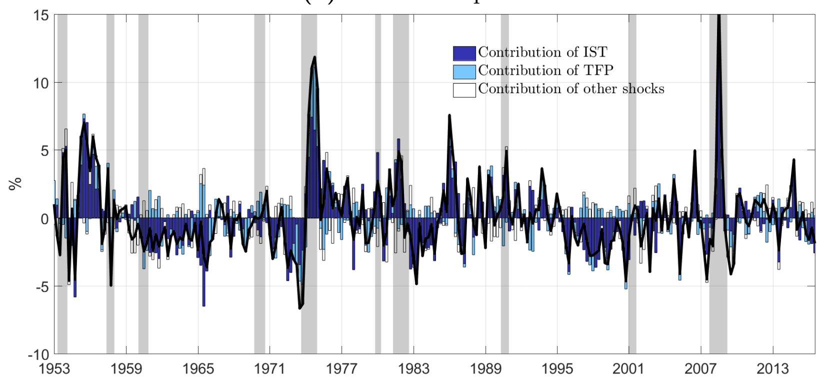


Note: The figure has the same scope as Figure 5 in the main text but uses a different identification scheme. This scheme is based on the method suggested by Barsky and Sims (2012). Panel (a) shows the results for a 5-year horizon ($h = 20$) and Panel (b) for a 10-year horizon ($h = 40$). In both cases, 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% 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.

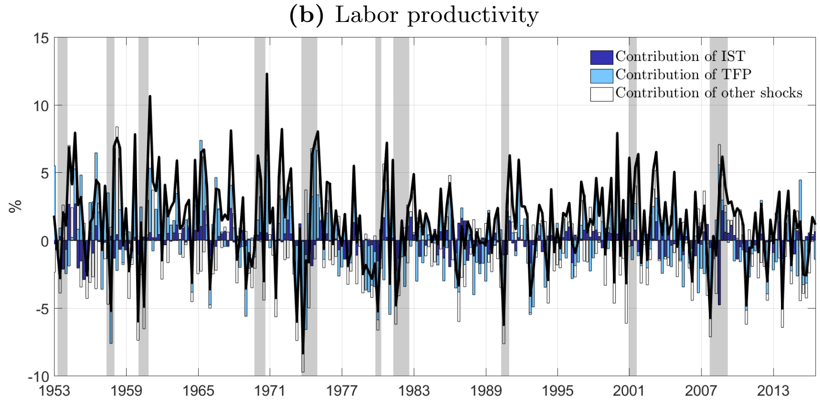
E.3 SVAR historical decompositions for other variables

Figure E.3: SVAR: HISTORICAL VARIANCE DECOMPOSITIONS

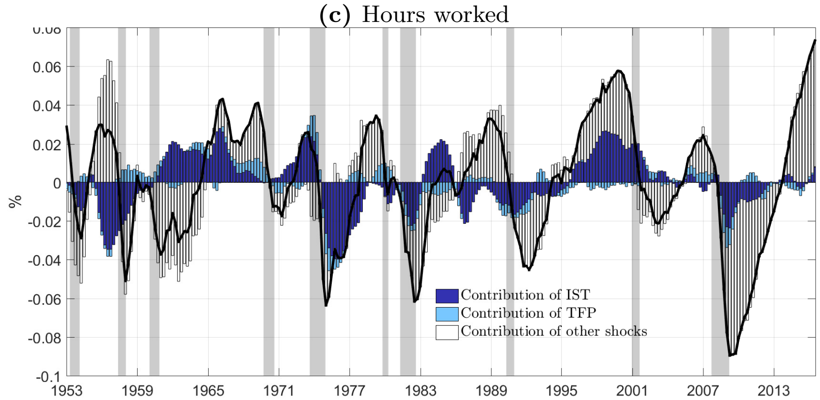
(a) Investment price



(b) Labor productivity



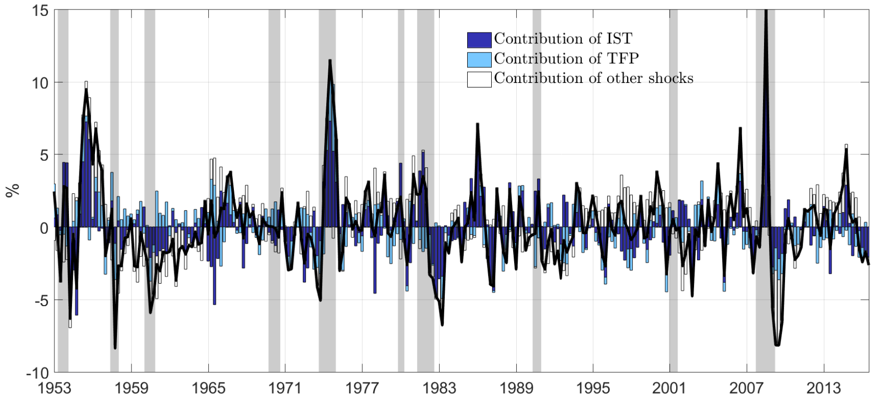
(c) Hours worked



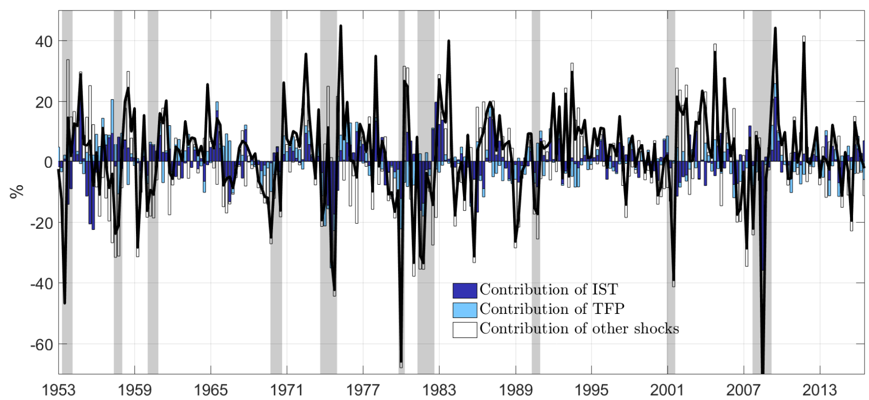
Note: Historical variance decomposition of variables as estimated by the SVAR model. The black line is the actual (detrended) data series. The bars indicate the contribution of different structural shocks to the variance of the respective observable as estimated by the SVAR model. The dark blue bars 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 E.4: SVAR: HISTORICAL VARIANCE DECOMPOSITIONS

(a) Business earnings



(b) Capital stock



Note: Historical variance decomposition of variables as estimated by the SVAR model. 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.

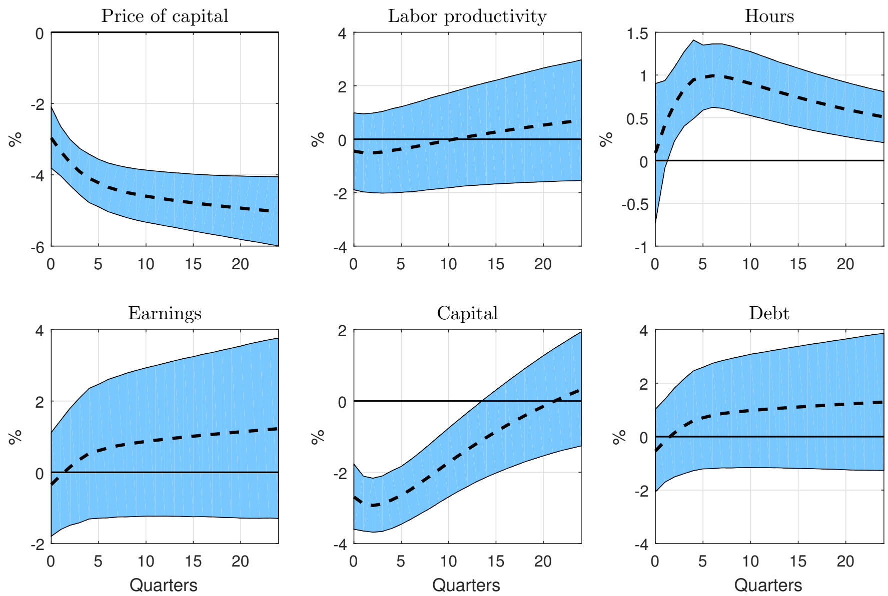
E.4 SVAR IRFs using simulated data

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.

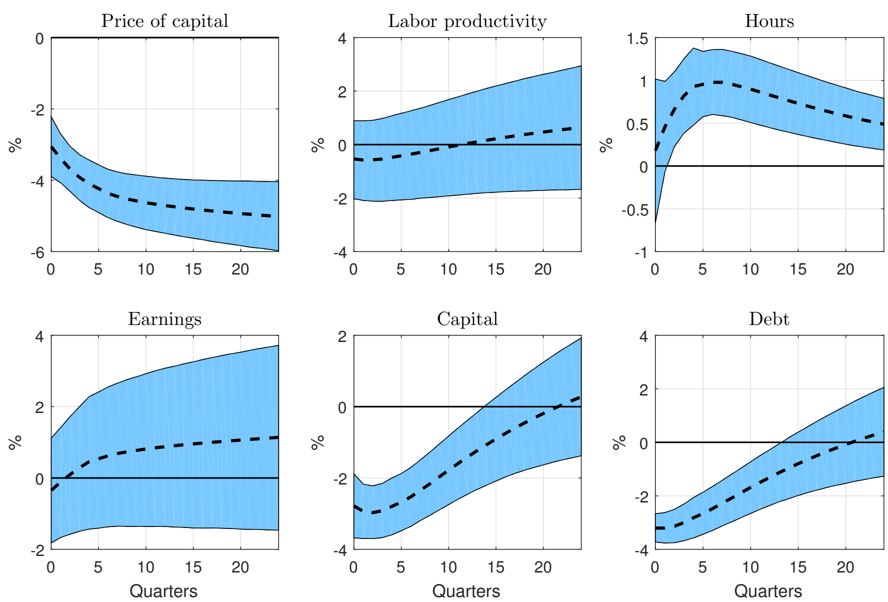
The results of this exercise are shown in Figure E.5. Panel (a) plots the IRFs from estimations on samples generated with the earnings-based constraint, Panel (b) the equivalent with the collateral constraint. Each subpanel shows the mean (dashed line) and and 68% confidence sets (light blue area) across 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 E.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% significance sets and means across 10,000 Monte Carlo repetitions are shown.

F Additional results for firm-level projections

This appendix presents additional results on the estimation of equation (17) in Section 4.3 of the main text. Section F.1 of the appendix reports the coefficient estimates of the difference between earnings and collateral borrowers' debt IRFs, which serves as a formal test of the difference between the IRFs shown in Figure 8. Section F.2 shows the results of Figure 8 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 F.3 contains the results for a firm fixed effects regression specification. In Section F.4, the main results displayed in Figure 8 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.

F.1 Significance of the difference between heterogeneous IRFs

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

	Classification based on specific assets	**Classification based on secured revolvers**
$\beta_0^{earn} - \beta_0^{coll}$	0.0328	-0.0029
	(0.0213)	(0.0248)
$\beta_1^{earn} - \beta_1^{coll}$	0.0308	0.0004
	(0.0318)	(0.0285)
$\beta_2^{earn} - \beta_2^{coll}$	0.0340	0.0162
	(0.0282)	(0.0307)
$\beta_3^{earn} - \beta_3^{coll}$	0.0511	0.0511
	(0.0334)	(0.0365)
$\beta_4^{earn} - \beta_4^{coll}$	0.0600*	0.0464
	(0.0345)	(0.0404)
$\beta_5^{earn} - \beta_5^{coll}$	0.0491	0.0384
	(0.0331)	(0.0370)
$\beta_6^{earn} - \beta_6^{coll}$	0.0581*	0.0400
	(0.0351)	(0.0395)
$\beta_7^{earn} - \beta_7^{coll}$	0.0688*	0.0642*
	(0.0353)	(0.0356)
$\beta_8^{earn} - \beta_8^{coll}$	0.0865**	0.0813**
	(0.0355)	(0.0358)
$\beta_9^{earn} - \beta_9^{coll}$	0.0810**	0.0725*
	(0.0389)	(0.0386)
$\beta_{10}^{earn} - \beta_{10}^{coll}$	0.0773*	0.0624
	(0.0406)	(0.0403)
$\beta_{11}^{earn} - \beta_{11}^{coll}$	0.0927**	0.0893**
	(0.0420)	(0.0432)
$\beta_{12}^{earn} - \beta_{12}^{coll}$	0.0690	0.0658
	(0.0433)	(0.0442)

Note: The table shows estimates of the difference between the IRF 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 8 and the right column for Panel (b). Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

F.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.

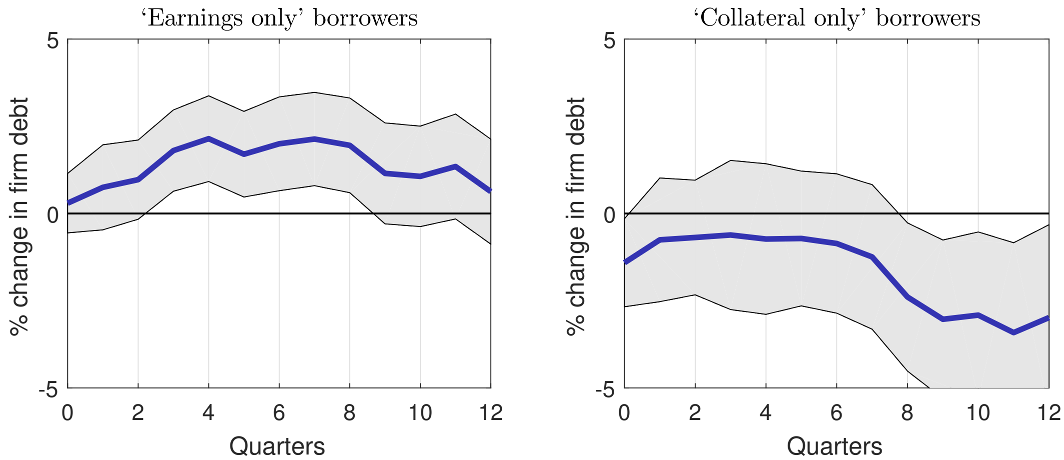
To this end, equation (17) from the main text is modified to

$$\begin{aligned} log(b_{i,t+h}) &= \alpha_h + \beta_h p_{k,t} + \boldsymbol{\gamma X_{i,t}} \\ &+ \beta_h^{earn} \mathbb{1}_{i,t,earn} \times p_{k,t} + \alpha_h^{earn} \mathbb{1}_{i,t,earn} \\ &+ \beta_h^{coll} \mathbb{1}_{i,t,coll} \times p_{k,t} + \alpha_h^{coll} \mathbb{1}_{i,t,coll} + \gamma t + \eta_{i,t+h}, \end{aligned} \tag{41}$$

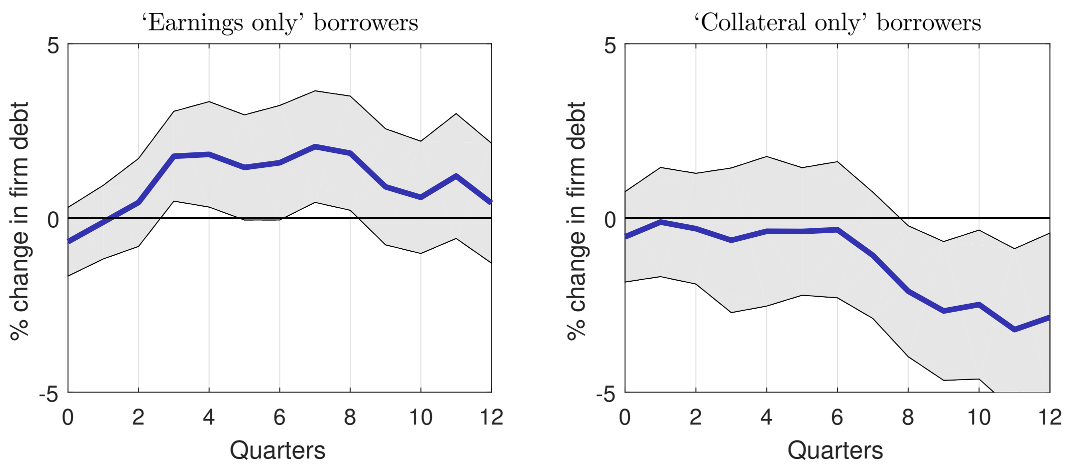
where $p_{k,t}$ is defined as in Section 4.1.2. Equation (41) is then estimated by using $\hat{u}_{IST,t}$ as an IV for $p_{k,t}$. The results for this specification, presented analogous to Figure 8, are shown in Figure F.1 below. They paint a very similar picture to the results in the main text. The responses are smaller in magnitude, and standard errors are lower relative to when the shock is used as a regressor directly.

Figure F.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

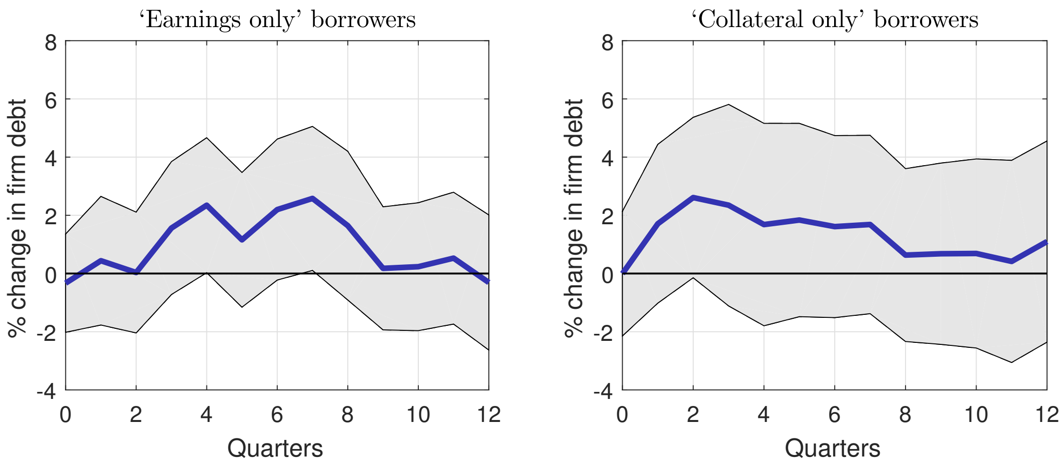


Note: This figure repeats Figure 8 from the text but instead plots the IRFs to a fall in the relative price of investment, instrumented with the investment shock, see equation (F.1) above. In both panels of the figure, the debt IRF for borrowers with earnings covenants and no collateral (left) and borrowers 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). 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, 2018). 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 data base. 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.

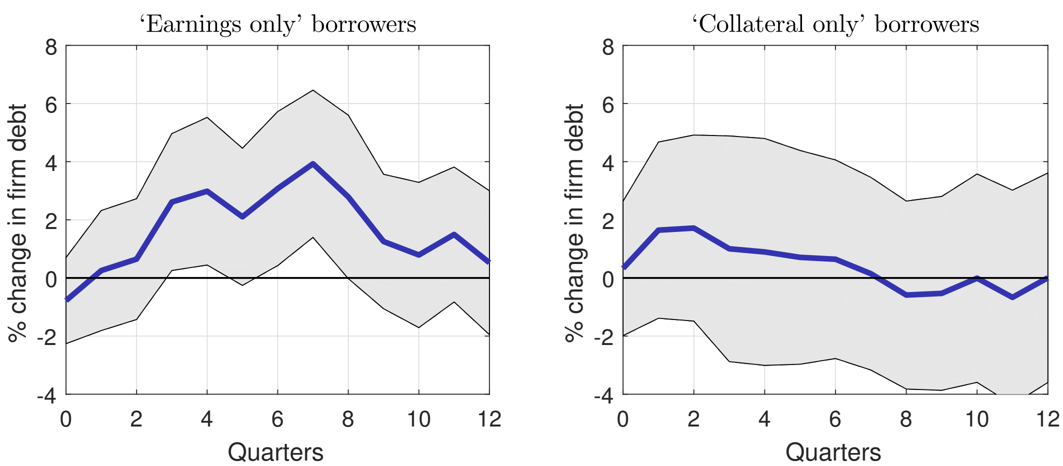
F.3 Results for specification with firm fixed effects

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

(a) Using collateral classification based on specific assets



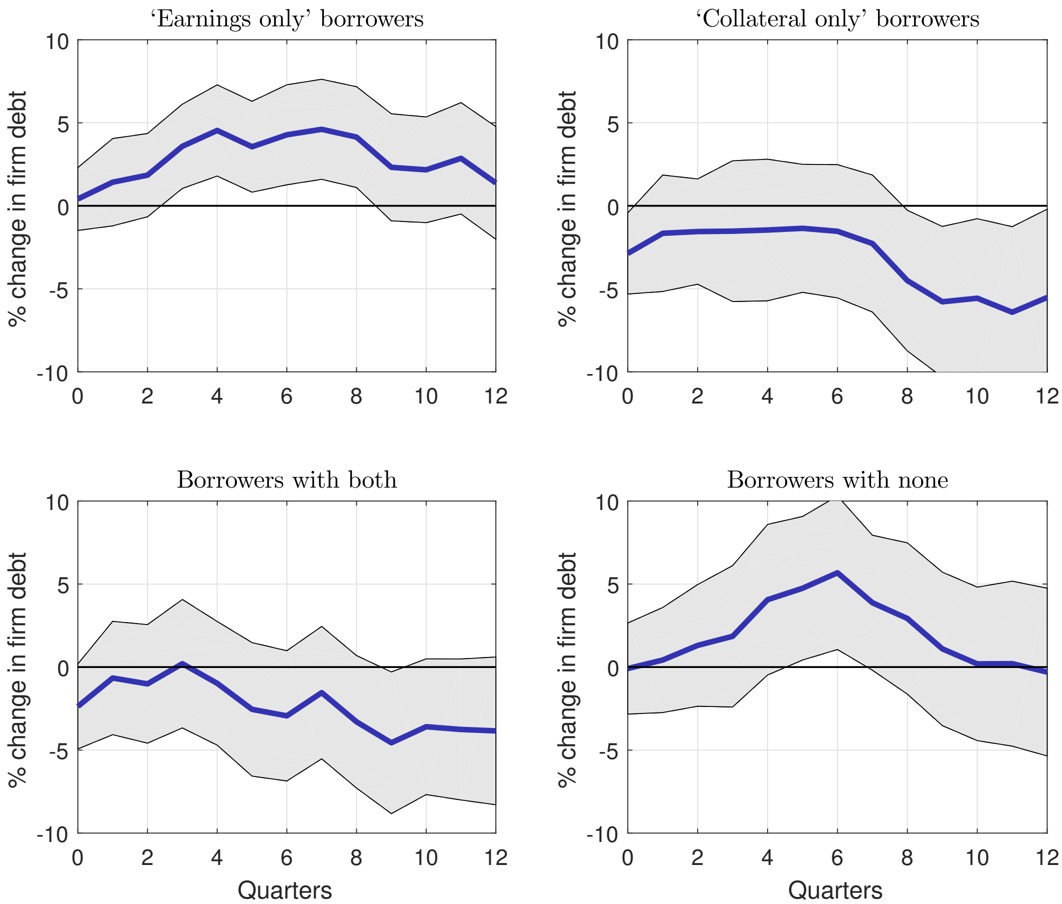
(b) Using collateral classification based on secured revolvers



Note: This figure repeats Figure 8 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, 2018). 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 data base. 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.

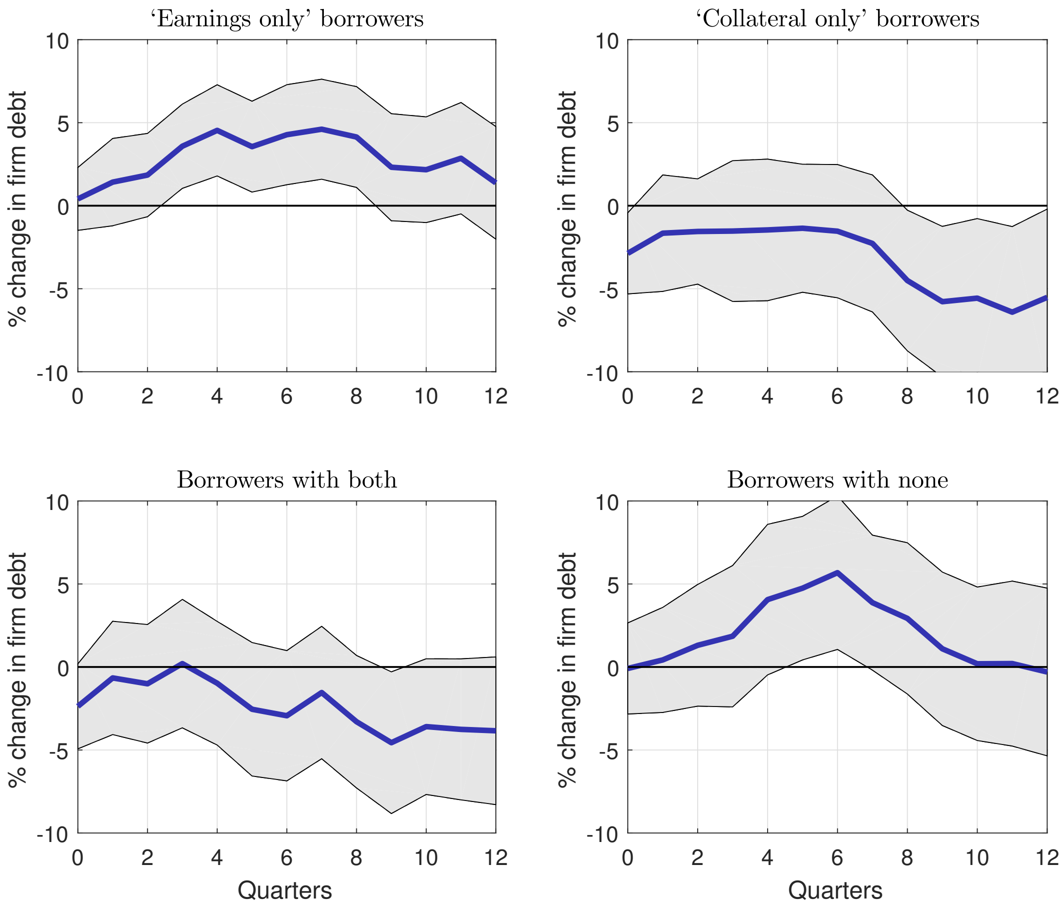
F.4 Results for all four firm groups

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



Note: This figure repeats Panel (a) of Figure 8 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). 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 data base. 90% bands are calculated using standard errors clustered at the 3-digit industry level.

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



Note: This figure repeats Panel (b) of Figure 8 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). 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 data base. 90% bands are calculated using standard errors clustered at the 3-digit industry level.

G Details on the quantitative model of Section 5

G.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). The core of the model is that of Section 3 but a variety of additional frictions are added.

G.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

$$Y_t = \left(\int_0^1 y_{i,t}^{\frac{1}{\eta_t}} \, di \right)^{\eta_t}. \tag{42}$$

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

$$p_{i,t} = P_t Y_t^{\frac{\eta_t - 1}{\eta_t}} y_{i,t}^{\frac{1-\eta_t}{\eta_t}} \tag{43}$$

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

G.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

$$y_{i,t} = z_t (u_{i,t} k_{i,t-1})^{\alpha} n_{i,t}^{1-\alpha}, \tag{44}$$

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:

$$n_{i,t} = \left(\int_0^1 n_{j,i,t}^{\frac{1}{\vartheta_t}} \, dj \right)^{\vartheta_t}, \tag{45}$$

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

$$\pi_{i,t} \equiv y_{i,t} - w_{i,t} n_{i,t}. \tag{46}$$

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

$$k_{i,t} = (1-\delta)k_{i,t-1} + v_t \left[1 - \frac{\phi}{2}\left(\frac{i_{i,t}}{i_{i,t-1}}\right)^2\right] i_{i,t}. \tag{47}$$

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

Firms take (43) 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

$$p_{i,t} = P_t Y_t^{\frac{\eta_t - 1}{\eta_t}} \left(z_t (u_{i,t} k_{i,t-1})^\alpha n_{i,t}^{1-\alpha}\right)^{\frac{1-\eta_t}{\eta_t}}. \tag{48}$$

The capital utilization cost is specified as

$$\Xi(u_t) = \xi_1 (u_t^{1+\xi_2} - 1)/(1 - \xi_2) \tag{49}$$

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

The firm sets 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 adjustment costs

$$\tilde{\Phi}(p_{i,t-1}, p_{i,t}, Y_t) = \frac{\tilde{\phi}}{2}\left(\frac{p_{i,t}}{p_{i,t-1}} - 1\right)^2 Y_t. \tag{50}$$

The firm has 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 equation (18).

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 (18), the law of motion of capital (47) and the demand function given by (43). 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 $b_{i,t}$.

G.1.3 Households

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

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \gamma_t \beta^t \left(\frac{(c_{j,t} - hc_{j,t-1})^{1-\sigma}}{1-\sigma} - \chi \frac{n_{j,t}^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} \right) \tag{51}$$

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

$$c_{j,t} + \frac{b_{j,t}}{1+r_t} + p_t^f s_{j,t} + T_{j,t} + \int q_{j,t+1}^{\bar{\omega}} a_{j,t+1} dw_{j,t} = w_{j,t} n_{j,t} + b_{j,t-1} + P_t d_{j,t} + p_t^f s_{j,t-1}. \tag{52}$$

$a_{j,t+1}$ are holdings of state-contingent claims with which households can insure against wage shocks. They are traded at price $q_{j,t+1}^w$. The notation in (52) is otherwise similar as in the stylized mode of Section 3.

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

$$n_{j,t} = \left(\frac{w_{j,t}}{W_t} \right)^{-\frac{\vartheta_t}{\vartheta_t - 1}} n_t, \tag{53}$$

where W_t and n_t are the aggregate wage and employment level, respectively. (53) 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 euqation 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 (51).

G.1.4 Government

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

$$T_t = \frac{b_t}{R_t} - \frac{b_t}{(1+r_t)} + P_t G_t, \tag{54}$$

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.

G.1.5 Monetary policy

There is a Taylor rule specified as

$$\frac{1+r_t}{1+\bar{r}} = \left[\frac{1+r_{t-1}}{1+\bar{r}}\right]^{\rho_R} \left[\left(\frac{\pi_t^p}{\bar{\pi}^p}\right)^{\nu_1} \left(\frac{Y_t}{Y_{t-1}}\right)^{\nu_2}\right]^{1-\rho_R} \left[\frac{Y_t/Y_t^*}{Y_{t-1}/Y_{t-1}^*}\right]^{\nu_3} \varsigma_t, \tag{55}$$

such that interest rates react to deviations of inflation from steady state, output growth, and output growth in deviations from it steady state.[73] Note 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.

G.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 follow autoregressive processes of order one:

$$\begin{aligned}
log(z_t) &= (1-\rho_z)log(\overline{z}) + \rho_z log(z_{t-1}) + u_{z,t} && (56)\\
log(v_t) &= (1-\rho_v)log(\overline{v}) + \rho_v log(v_{t-1}) + u_{v,t} && (57)\\
log(\gamma_t) &= (1-\rho_\gamma)log(\overline{\gamma}) + \rho_\gamma log(\gamma_{t-1}) + u_{\gamma,t} && (58)\\
log(\eta_t) &= (1-\rho_\eta)log(\overline{\eta}) + \rho_\eta log(\eta_{t-1}) + u_{\eta,t} && (59)\\
log(\vartheta_t) &= (1-\rho_\vartheta)log(\overline{\vartheta}) + \rho_\vartheta log(\vartheta_{t-1}) + u_{\vartheta,t} && (60)\\
log(g_t) &= (1-\rho_g)log(\overline{g}) + \rho_g log(g_{t-1}) + u_{g,t} && (61)\\
log(\varsigma_t) &= (1-\rho_\varsigma)log(\overline{\varsigma}) + \rho_\varsigma log(\varsigma_{t-1}) + u_{\varsigma,t} && (62)\\
log(\xi_t) &= (1-\rho_\xi)log(\overline{\xi}) + \rho_\xi log(\xi_{t-1}) + u_{\xi,t} && (63)
\end{aligned}$$

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 $\bar{\vartheta}$.

[73] See Jermann and Quadrini (2012) for more details.

G.2 Additional estimation results

Table G.1: PRIORS AND POSTERIORS FROM BAYESIAN ESTIMATION

	Prior shape	Prior Mean	Prior Std	Post. mean	90% HPD interval	
ω	Uniform	0.5	$\sqrt{12}$	0.8992	0.7968	1
$\tilde{\phi}$	Inv-Gamma	0.1	0.3	23.433	19.7002	26.9731
σ	Normal	1.5	0.37	1.6721	1.1921	2.1902
ϵ	Normal	2	0.75	1.6229	0.6464	2.5399
h	Beta	0.5	0.15	0.9709	0.9615	0.981
$\bar{\omega}$	Beta	0.5	0.15	0.843	0.7718	0.9049
ϕ	Inv-Gamma	0.1	0.3	5.7251	4.2177	7.4163
ψ	Beta	0.5	0.15	0.4556	0.2548	0.658
κ	Inv-Gamma	0.2	0.1	0.3395	0.2072	0.4685
ρ_R	Beta	0.75	0.1	0.6434	0.5823	0.703
ν_1	Normal	1.5	0.25	2.3287	1.9708	2.6836
ν_2	Normal	0.12	0.05	-0.0487	-0.0862	-0.0117
ν_3	Normal	0.12	0.05	0.2181	0.1536	0.2865
$\bar{\eta}$	Beta	1.2	0.1	1.459	1.3817	1.5376
$\bar{\vartheta}$	Beta	1.2	0.1	1.1519	1.0229	1.2823
ρ_z	Beta	0.5	0.2	0.9903	0.9844	0.9967
ρ_{gz}	Beta	0.5	0.2	0.9328	0.8756	0.9908
ρ_v	Beta	0.5	0.2	0.754	0.6814	0.8303
ρ_γ	Beta	0.5	0.2	0.3669	0.2594	0.4754
ρ_η	Beta	0.5	0.2	0.8893	0.8407	0.9364
ρ_ϑ	Beta	0.5	0.2	0.3034	0.2215	0.3831
ρ_G	Beta	0.5	0.2	0.9442	0.9084	0.9813
ρ_ς	Beta	0.5	0.2	0.4173	0.3167	0.5171
ρ_ξ	Beta	0.5	0.2	0.9893	0.9821	0.9967
σ_z	Inv-Gamma	0.001	0.05	0.0073	0.0067	0.0079
σ_v	Inv-Gamma	0.001	0.05	0.1343	0.0933	0.1754
σ_γ	Inv-Gamma	0.001	0.05	0.247	0.1786	0.3092
σ_η	Inv-Gamma	0.001	0.05	0.0162	0.0133	0.0191
σ_ϑ	Inv-Gamma	0.001	0.05	1.3028	0.9642	1.5692
σ_G	Inv-Gamma	0.001	0.05	0.0176	0.0161	0.019
σ_ς	Inv-Gamma	0.001	0.05	0.0094	0.0086	0.0102
σ_ξ	Inv-Gamma	0.001	0.05	0.0395	0.0356	0.0434

Table G.2: PRIORS AND POSTERIORS FOR MODEL WITHOUT BORROWING CONSTRAINT

	Prior shape	**Prior Mean**	**Prior Std**	**Post. mean**	**90% HPD interval**	
$\tilde{\phi}$	Inv-Gamma	0.1	7.083	6.26	7.9168	0.3
σ	Normal	1.5	2.0603	1.7621	2.3992	0.37
ϵ	Normal	2	0.7779	0.6112	0.9231	0.75
h	Beta	0.5	0.8091	0.7676	0.8505	0.15
$\bar{\omega}$	Beta	0.5	0.2911	0.199	0.424	0.15
ϕ	Inv-Gamma	0.1	5.8699	5.0646	6.4816	0.3
ψ	Beta	0.5	0.7283	0.625	0.8244	0.15
κ	Inv-Gamma	0.2	0.8349	0.6237	1.0961	0.1
ρ_R	Beta	0.75	0.654	0.6256	0.6834	0.1
ν_1	Normal	1.5	3.0458	2.9881	3.0903	0.25
ν_2	Normal	0.12	-0.0166	-0.0539	0.0156	0.05
ν_3	Normal	0.12	0.1713	0.1063	0.2213	0.05
$\bar{\eta}$	Beta	1.2	1.4217	1.3582	1.4741	0.1
$\bar{\vartheta}$	Beta	1.2	1.0774	1.0462	1.1093	0.1
ρ_z	Beta	0.5	0.983	0.9749	0.9911	0.2
ρ_{gz}	Beta	0.5	0.9509	0.9113	0.9928	0.2
ρ_v	Beta	0.5	0.7128	0.6586	0.7668	0.2
ρ_γ	Beta	0.5	0.8122	0.7699	0.8559	0.2
ρ_η	Beta	0.5	0.9775	0.9606	0.9957	0.2
ρ_ϑ	Beta	0.5	0.9848	0.9734	0.9965	0.2
ρ_G	Beta	0.5	0.9781	0.9612	0.996	0.2
ρ_ς	Beta	0.5	0.1896	0.1158	0.2653	0.2
σ_z	Inv-Gamma	0.001	0.0072	0.0067	0.0077	0.05
σ_v	Inv-Gamma	0.001	0.1865	0.1709	0.2027	0.05
σ_γ	Inv-Gamma	0.001	0.0585	0.0505	0.0663	0.05
σ_η	Inv-Gamma	0.001	0.0113	0.01	0.0124	0.05
σ_ϑ	Inv-Gamma	0.001	0.0628	0.0521	0.0727	0.05
σ_G	Inv-Gamma	0.001	0.0177	0.0162	0.0191	0.05
σ_ς	Inv-Gamma	0.001	0.0097	0.0088	0.0106	0.05

Table G.3: VARIANCE DECOMPOSITION OF OBSERVABLES WITHOUT BORROWING CONSTRAINTS (IN %)

	TFP	**Inv**	**Pref**	**Price**	**Wage**	**Gov**	**Mon**	**Fin**
Output growth	11.9	27.4	1.5	11.7	33.1	10.2	4.2	-
Consumption growth	11.1	6.6	14.7	7.6	52.7	0.9	6.3	-
Investment growth	1.7	82.1	7.7	1.5	6.8	0.0	0.3	-
Inflation	12.4	12.1	34.2	17.5	9.8	0.3	13.7	-
Interest rate	6.0	18.2	38.9	8.2	6.9	0.5	21.3	-
Employment growth	25.7	25.3	0.6	3.4	33.0	9.3	2.8	-
Wage growth	27.4	3.2	5.4	55.3	6.2	0.1	2.4	-
Debt issuance	0.37	0.29	28.66	4.44	65.26	0.52	0.46	-

Note: Repeats Table 3 from the text, but for a version of the model that is re-estimated without any borrowing constraints. In this model, debt is in zero net supply so debt issuance cannot be used as an observable, so the financial shock is dropped. The table shows the infinite horizon forecast error variance decomposition of the observables used for this model version. 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.