Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations∗

Thomas Drechsel¶
University of Maryland

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Abstract

Microeconomic evidence on US corporate credit suggests a direct 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. In a business cycle model, an earnings-based constraint implies that debt expands in response to investment shocks, whereas a collateral constraint implies that credit contracts. The paper verifies the empirical relevance of this differential prediction in macro and micro data. At the aggregate level, firm debt responds positively to investment shocks, which supports the economy-wide relevance of earnings-based constraints. At the micro level, firms that face earnings-based constraints indeed borrow more in response to investment shocks, while firms that pledge collateral borrow less. 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 compared to a model with collateral constraints.

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

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¶Department of Economics, University of Maryland, Tydings Hall, College Park, MD 20742, United States; E-Mail: drechsel@umd.edu; Web: http://econweb.umd.edu/~drechsel.
1 Introduction

Firm credit displays large swings which correlate with fluctuations in output, employment and investment. Research on the drivers of this comovement has focused on the evolution of constraints to credit over the business cycle, and how this feeds back to economic activity. This paper studies the macroeconomic consequences of earnings-based constraints on firm borrowing. The focus on earnings-based credit constraints is in contrast with asset-based collateral constraints, which have become a cornerstone of many business cycle models.\(^1\) It is motivated by direct evidence on the importance of firms’ current earnings flows for their access to debt. Micro data covering more than 50,000 loans to 15,000 US companies reveals the pervasive use of earnings-based loan covenants that make it difficult for firms to borrow when their current earnings are low.\(^2\) I show that incorporating an earnings-based constraint in business cycle analysis is crucial for correctly capturing aggregate and firm-level credit dynamics, and demonstrate that the constraint alters the transmission of fiscal and monetary policy in the macroeconomy.

Earnings-based borrowing constraints imply credit dynamics that differ from the ones generated by collateral constraints. I demonstrate this in a theoretical model in which firm borrowing can be restricted either by a multiple of the firm’s current earnings or by a fraction of its capital.\(^3\) Structural shocks that move earnings and the value of capital in the same direction, such as TFP shocks, have a qualitatively similar impact on borrowing with either type of constraint. Depending on the constraint, however, debt either increases or decreases in response to shocks that move earnings and the value of collateral in opposite directions. This is the case for investment shocks, which improve the ability of firms to turn resources into productive capital.\(^4\) Positive investment shocks cause more investment, stronger economic activity and larger earnings, while they reduce the price of capital relative to other goods. As a consequence, increased earnings allow for more debt under the earnings-based constraint, whereas the lower relative value of capital reduces credit access under the collateral constraint.

I use this opposite model prediction on the borrowing response to investment shocks as a strategy to disentangle empirically which type of credit constraint is more relevant. In both macro and micro data, my findings are consistent with the presence of earnings-based constraints, and not in line with the predictions implied by collateral constraints. At the aggregate level, the results are based on a structural vector autoregression (SVAR). I apply identification schemes in which investment shocks are identified from their low frequency impact on the relative price of equipment.

\(^{1}\)The catalyst for research on collateral constraints was the seminal work by Kiyotaki and Moore (1997).\(^{2}\)My motivating facts build on existing empirical studies on corporate credit constraints, in particular Lian and Ma (2018) who propose earnings-based constraints as a key determinant for firms’ access to debt.\(^{3}\)Specifying the constraint with current rather than expected future earnings is motivated by the empirical evidence. I show that my model predictions also hold if expected future earnings restrict debt, as the main mechanism I focus on persistently moves earnings and the value of collateral in different directions.\(^{4}\)Previous studies have found that these shocks are an important quantitative feature of business cycles, see for example Justiniano, Primiceri, and Tambalotti (2010, 2011). My use of the term investment shock at this stage encompasses different variations, including investment-specific technology shocks and marginal efficiency of investment shocks. I provide details on the differences between these concepts in the text.
investment. This is based on the idea that low-frequency movements of the relative price of investment purely reflect relative technology.\textsuperscript{5} Using two alternative versions of implementing this identifying assumption, by imposing long-run restrictions (following Fisher, 2006), as well as medium-run restrictions (following Francis, Owyang, Roush, and DiCecio, 2014), I find that business sector debt increases in response to a positive investment shock, supporting the economy-wide relevance of earnings-based as opposed to collateral constraints. In line with the model mechanism, earnings rise and the value of the capital stock falls.

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

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 contains a number of additional shocks and frictions, such as price and wage rigidities, alongside a constraint which limits debt by both an earnings-based and a collateral component. The components are linearly weighted by a parameter, which I estimate together with the other structural parameters of the model on US postwar data. The estimation assigns a posterior weight of 0.9 to the earnings-based borrowing component, 0.1 to the collateral component. This means that US macroeconomic data favors the dynamics arising from earnings-based constraints also through the lens of a richer model that encompasses additional transmission channels. Counterfactual exercises in the estimated model indicate that the presence of earnings-based constraints dampens the output response to fiscal shocks, whereas monetary shocks have 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 estimated price rigidity that emerges in the presence of the earnings-based constraint. The estimated model also implies that investment...

\textsuperscript{5}Specifically, the investment shock is identified from its negative impact on new equipment goods. The focus on equipment is consistent with the loan-level data, where equipment is the largest category of collateral for firms, ahead of real estate. I also verify that the shock I identify reduces the price of used (secondary market) equipment goods, since in practice both new and used assets could be pledged as collateral.
shocks account for more than half of the variation in US output. This lends further support to my focus on investment shocks for verifying the relevance of earnings-based credit constraints using the SVAR and firm-level panel projection approaches. 

Relation to the literature. First and foremost, this paper contributes to the literature that studies the role of financial frictions in macroeconomics, which goes back to the seminal work of Bernanke and Gertler (1989), Shleifer and Vishny (1992), and Kiyotaki and Moore (1997). 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 for the purpose of understanding macroeconomic fluctuations.

Second, the motivating evidence I provide builds on existing insights, mostly from the empirical corporate finance literature, on loan covenants and on the relevance of current earnings for credit access more broadly. Important contributions are Chava and Roberts (2008) and Sufi (2009), who emphasize the widespread use of covenants in corporate debt contracts. Based on a comprehensive empirical analysis, Lian and Ma (2018) propose that the key constraint to firm debt are cash flows measured by earnings. These authors focus on causally identifying the extent to which increases in earnings as opposed to assets relax borrowing constraints at the micro level. In a simple model, they also show theoretically that cash-flow based lending may dampen financial accelerator effects. More recently, Greenwald (2019) studies the role of different covenant types in the transmission of monetary policy shocks at the firm-level. My contribution relative to these papers is twofold. I show that focusing on investment shocks provides a way

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6In principle my empirical strategy to distinguish the relevant credit constraint in the SVAR and firm-level projections does not require investment shocks to be important quantitatively, as long as they are correctly identified. In the quantitative model, I also verify that the earnings-based constraint plays a key role in the absence of investment shocks and when no information on investment is used for the estimation.


10An earlier paper that aims to identify the determinants of borrowing constraints at the micro level, but does not focus on earnings constraints, is Chaney, Sraer, and Thesmar (2012). Recent work by Adler (2018) studies the impact of covenants on investment, by focusing more directly on covenant breaches as well as on precautionary motives arising from potential breaches.
to disentangle earnings-based from collateral constraints, and exploit this theoretical insight to verify the relevance of earnings-based constraints in both macro and micro data. Moreover, I build a quantitative model that encompasses additional frictions and transmission channels, in which I study both the relative quantitative contribution of alternative credit constraints, as well as how they differentially affect the transmission of monetary and fiscal shocks.

Third, there are a few existing papers with models in which flow variables rather than assets restrict borrowing, including Kiyotaki (1998). My paper explicitly compares the consequences of different flow-related and collateral constraints on firms. In particular, I provide a detailed theoretical exploration to show that the difference between earnings-based on collateral constraints is not driven by the flow vs. stock distinction, but by the definition of earnings as opposed to other financial flow indicators. In relation to my quantitative model that features both constraint types, Greenwald (2018) proposes a model with both (flow-based) payment-to-income limits and (collateral-based) loan-to-value constraints on household mortgage borrowing. I focus on corporate debt rather than on household mortgages.

Fourth, my paper relates to the literature on investment shocks, which includes theoretical work such as Greenwood, Hercowitz, and Huffman (1988) and Greenwood, Hercowitz, and Krusell (2000), and papers that identify investment shocks in SVARs building on Fisher (2006). Justiniano, Primiceri, and Tambalotti (2010, 2011) investigate the role of investment shocks in US business cycles and find them to be a key force behind output fluctuations. I contribute to this literature by analyzing credit dynamics that arise from investment shocks.

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

**Structure of the paper.** Section 2 presents micro evidence motivating the focus on earnings-based borrowing constraints. Section 3 introduces a business cycle model that features an earnings-based constraint and discusses its implied dynamics in comparison to a collateral constraint. Section 4 verifies the model predictions for investment shocks using both SVAR analysis on aggregate data and panel projections on firm-level data. Section 5 estimates a quantitative New Keynesian model with different credit constraints. Section 6 investigates the role of credit constraints in the transmission of monetary and fiscal shocks. Section 7 concludes.

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12 A related study is Corbae and Quintin (2015). See also the constraint formulation in Kaplan, Mitman, and Violante (2017). Earlier work that studies household mortgages in business cycle models typically focuses on collateral, see for example Iacoviello (2005) and Iacoviello and Neri (2010).

13 See also Schmitt-Grohe and Uribe (2012) for a business cycle model with investment shocks. Papanikolaou (2011) and Kogan and Papanikolaou (2013) provide applications to asset pricing.
2 Motivating evidence on earnings-based corporate borrowing

This section presents motivating microeconomic evidence on corporate borrowing in the US economy. Using information from more than 50,000 loan deals issued to 15,000 firms, I show that earnings are a key indicator that determines the extent to which firms have access to funds. The facts I document echo the analysis carried out by Lian and Ma (2018), who present detailed evidence that US nonfinancial firms primarily borrow based on earnings flows. While I focus on the role of earnings indicators in loan covenants, the importance of current earnings in determining credit access goes beyond their prominence in covenants, which I explain in more detail below.

Data source. I use the Thomson Reuters LPC Dealscan database. For the United States, this data covers around 75% of the total commercial loan market in terms of volumes. The data contain rich information, including the identity of borrower and lender, the amount, maturity, interest rate and, importantly, loan covenants. The unit of observation is a loan deal, which consists of loan facilities. 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. I consider USD denominated originations since 1994 for US nonfinancial corporations. Appendix A contains further information on the data set as well as summary statistics. In Section 4.3, I merge the Dealscan data to the Compustat Quarterly data, which covers accounting information of listed US companies.

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 the right to call back the loan. In practice, a breach can lead to various outcomes, including renegotiations of penalty payments, higher interest rates or other changing conditions in the contract. Importantly, breaches have been shown to occur frequently with large economic effects. Chodorow-Reich and Falato (2017) show for example that one third of US nonfinancial firms breached their covenants during the 2008-09 financial crisis. Roberts and Sufi (2009a) find that net debt issuing activity experiences a large and persistent drop immediately after a covenant violation. These findings

14 In conjunction with laying out a macro model that features this type of borrowing, I discuss theoretical microfoundations for the presence of earnings-based debt contracts in Appendix B.

15 See Chava and Roberts (2008). The data does not include a meaningful share of marketable debt instruments such as corporate bonds. However, commercial loans do remain the most important category of liabilities of US firms: 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. Lian and Ma (2018) provide evidence in line with what I argue in this section based on data that also includes bonds.

16 Ivashina and Scharfstein (2010) study the syndication aspect of corporate borrowing in more detail. For work with a more explicit focus on credit lines see for example Sufi (2009) and Acharya, Almeida, and Campello (2013).

17 Chava and Roberts (2008) find strong effects of breaches on investment and Falato and Liang (2017) strong effects on employment. See also Adler (2018) for a study of covenant breaches and their effects.
indicate that debt access is significantly reduced when the variable specified in the covenant moves above (below) its maximum (minimum) value.

### Table 1: Loan Covenant Types, Values and Frequency of Use

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

Note: The table lists the most pervasive covenant types, sorted by frequency in the Dealscan loan data. Covenant types with a frequency above 10% are included. As there can be more than one covenant per loan, the frequency adds up to more than 100%. EBITDA abbreviates earnings before interest, taxes, depreciation and amortization. As indicated in brackets, a minimum interest coverage covenant 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 consists of loan deals with at least one loan covenant, issued between 1994 and 2015 by US nonfinancial corporations. The mean and frequency are weighted with real loan size. ‘M’ and ‘B’ refer to million and billion of 2009 real USD.

**The importance of earnings.** Table 1 lists the most popular covenant types, sorted by their frequency of use. The frequency is calculated for loans that feature at least one covenant and 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. The key take-away from the table is that the three most frequently used covenants are all related to earnings indicators. The specific earnings measure is EBITDA, which measures earnings before interest, taxes, depreciation and amortization. EBITDA is a widely used indicator of a firm’s economic performance. It captures firm profits that come directly from its regular operations and is readily available for scrutiny by lenders as part of standard financial reporting. The most frequent covenant implies that the level of debt cannot exceed this earnings measure by a multiple of 4.6 at any given point in time. In other words, lenders directly write into the contract that earnings should fulfill a given target as a condition of the loan. I interpret this widespread use of earnings-based covenants as suggestive evidence that the flow of current earnings constitutes an important constraint on companies’ access to debt. A key question of this paper is whether credit dynamics support this interpretation, and how it affects conclusions 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 related to earnings. For example, lenders may base their decisions on credit ratings, which are typically constructed with a strong emphasis on EBITDA. 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.
form of internal credit risk models that use earnings as an input, or be based on reference levels in earnings ratios that lenders are accustomed to consider without explicitly using covenants. Accordingly, the model of Section 3 will not be a model of covenants, but will capture the broader interpretation that current firm earnings affect their access to credit.

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

(a) Frequencies of covenants and secured loans

(b) Covenants within (un)covolateralized loans

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-related 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 (darker), other secured loans (medium) and unsecured loans (light). In both bars, loans without the relevant information are represented by the white area. Panel (b) repeats the left column of Panel (a), but breaks down the sample into loans secured with specific assets and other loans. The sample consists of loan deals issued between 1994 and 2015 by US nonfinancial corporations.

**Earnings-based vs. asset-based lending.** Figure 1 analyzes the value-weighted frequency of loan covenants and of collateral, that is, debt that is secured with specific assets. This is an important comparison, as business cycle research has put a strong emphasis on modeling credit frictions via collateral constraints (see literature review in Section 1). Panel (a) compares value-weighted shares of different loan characteristics. The left bar presents the share of loans with at least one earnings-related covenant (dark blue area) and with only other covenant types (light blue area). For the remaining share, the information on covenants is not available (white area). The right bar presents the share of loans that are secured with specific assets, other secured loans, unsecured loans, and loans without information on whether they are secured (dark orange, medium orange, light orange, and white areas, respectively). The left bar indicates that earnings-based covenants, which dominate within covenants overall, feature in around 35%}

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19Since the information on covenants is at the deal-level, while the information on collateral is at the facility-level, I aggregate to the deal level, summing over the relevant facilities within deals.

20According to Lian and Ma (2018), loans secured with “all assets” in Dealscan should be classified as cash-flow based loans, as the value in the case of bankruptcy is calculated based on the cash flows from continuing operations. Therefore, I define loans backed by specific assets as secured loans but assign those that are backed by “all assets” to the category called “Other secured loans”. I thank Yueran Ma and Chen Lian for a helpful discussion.
of loans. This number is a lower bound, as the remainder of loans does not have any information, which does not necessarily mean that covenants are absent. The key insight from the figure is that the share of earnings-based covenants is higher than the share of debt secured by specific assets, shown in the right bar. Finally, a sizable chunk of loans 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 covenants and collateral is systematically related across loans. The panel shows that covenants are more likely to appear in a loan contract when specific collateral is not present, but loans backed by specific assets still have a reasonably high share of covenants. Hence, earnings-based covenants are used both in addition to and instead of collateral.

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

### 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 prototype business cycle model in which the firm issues two debt types, 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 of the type that appears in many existing models. To derive differential predictions, the characterization of the dynamics focuses on a structural shock that moves earnings and the value of collateral in opposite directions: the investment shock. Section 5 extends the model to a quantitative framework and highlights how the earnings-based constraint differentially affects the transmission of other shocks, including monetary and fiscal shocks.

#### 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.

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21 The magnitudes that Lian and Ma (2018) report paint a picture that is even stronger in favor of earnings-based relative to asset-based borrowing. They develop an algorithm that classifies contracts strictly into either one or the other type and conclude that 80% of US corporate debt is earnings-based.
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

$$y_t = z_t k_t^\alpha n_t^{1-\alpha},$$

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

$$\pi_t \equiv y_t - w_t n_t.$$  

This definition of earnings corresponds to EBITDA, that is, sales net of overhead and labor costs, but without subtracting investment, interest payments or taxes. Hence, the model definition in (2) is in line with the evidence provided in Section 2. $\pi_t$ is the measure that will enter the firm’s earnings-based borrowing constraint to be introduced below.

Capital $k_{t-1}$ is predetermined at the beginning of the period and its law of motion is

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

where $\delta$ is the depreciation rate and $v_t$ is a stochastic disturbance. 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 $v_t$ simply as “investment shocks”. The term $\Phi_t \left( \frac{i_t}{i_{t-1}} \right)$ introduces investment adjustment costs. Following Christiano, Eichenbaum, and Evans (2005) 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 operate 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”. In the case of $v_t$, it is important to note that even

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

23 See for example Hayashi (1982) who introduces a similar formulation as in equation (3) and refers to the
in the absence of any adjustment costs, this disturbance will be inversely related to the relative price of $k_t$ in consumption units. To see this, consider the flow of funds constraint of the firm, in units of the consumption good, which reads

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

$\Psi(d_t)$ denotes the dividend (equity payout) function, and the $b$ terms capture debt financing, both of which will be explained 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:

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

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),

$$\Psi(d_t) = d_t + \psi(d_t - \bar{d})^2,$$  \hspace{1cm} (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.\textsuperscript{24} Debt financing can be undertaken in the form of two alternative one-period risk-free bonds, denoted $b_{\pi,t}$ and $b_{k,t}$, where $b_{\pi,t-1}$ and $b_{k,t-1}$ are predetermined at the beginning of period $t$. The effective gross interest rates faced by firms are $R_{\pi,t}$ and $R_{k,t}$, and are both subject to a tax advantage, captured by $\tau_\pi$ and $\tau_k$, of the following form:

$$R_{j,t} = 1 + r_{j,t}(1 - \tau_j), \quad j \in \{\pi, k\}$$  \hspace{1cm} (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).\textsuperscript{25}

\textsuperscript{24} Altinkilic and Hansen (2000) provide evidence of increasing marginal costs in equity underwriting. Discussions of dividend smoothing motives go back to Lintner (1956).

\textsuperscript{25} In effect, the tax advantage makes the firm “less patient” than the market, which discounts at rate $\frac{1}{1 + r_{j,t}}$, and composite term $\left[1 - \Phi_t \left( \frac{m_t}{m_{t-1}} \right) \right] g_t$ as the “installation function”. In his setting, there is no variation in IST.
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

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

The \( \theta \) parameters capture the exogenous tightness of the constraints. I will study calibrations
in which firms borrow up to either one or the other constraint. In the earnings-based borrowing
constraint (8), debt is limited by a multiple \( \theta_{\pi} > 1 \) of current earnings, \( \pi_t \).\(^{26}\) 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).\(^{27}\) In equation (9) debt issued by the firm in \( t \) is limited by a
fraction \( \theta_k < 1 \) of capital net of depreciation next period, valued at price \( p_{k,t+1} \). In the borrowing
constraint, \( p_{k,t+1} \) 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 \( 1/v_t \). In the empirical analysis I use both
new and secondary market investment goods prices as proxies for \( p_k \).

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

\(^{26}\)A constraint on \( b_{j,t} \) rather than \( b_{j,t}/(1 + r_{j,t}) \) would capture a different timing of the interest payment and
would not change the dynamics of the model in a meaningful way. The same is true for a constraint on \( b_{j,t}/R_{j,t} \).

\(^{27}\)Lian and Ma (2018) emphasize the presence of both debt-to-earnings ratios as well interest coverage ratios in
covenants. In a recent paper, Greenwald (2019) investigates the role of coverage ratio covenants in the transmission
of monetary policy.
limitations. In the case of the collateral constraint, a large body of work shows 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 the withdrawal remains an off-equilibrium threat (see for example Hart and Moore, 1994). In the case of the earnings-based borrowing constraint, one interpretation is that the borrower has the ability to divert funds, in which case the lender can seize and operate the firm herself. As the lender cannot perfectly predict the value of the firm when it is taken over, she estimates this contingent firm value as a multiple of current earnings. A second interpretation is that the firm is able to directly pledge its earnings stream rather than an asset in return for obtaining debt access. A third interpretation is based on regulation. Regulatory requirements on lenders require a different risk treatment of loans that feature a low earnings-to-debt ratio. The earnings-based credit constraint could reflect such regulation. In Appendix B, I sketch out a specific formal environment that captures the first of these three potential interpretations. In that appendix, I also discuss the existing literature on the microfoundations of loan covenants, and provide additional details on relevant regulation.

Naturally, the formalization of the constraints ignores some differences between asset-based loans and loans subject to earnings covenants. For example, while collateral is pledged upon origination and may be seized in the case of default, covenants can be exercised at any point during the lifetime of a loan. I abstract from these differences on two grounds. First, the fact that only the specific variable entering the right hand side of the debt limit is different between (8) and (9) allows for transparency in characterizing the differential consequences. Second, the Dealscan data shows that the maturity of corporate debt is relatively short, in particular compared to household debt. This observation also justifies the simplification that both borrowing constraints affect one-period debt, which abstracts from considerations regarding maturity choice.

**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

$$\max E_0 \sum_{t=0}^{\infty} \Lambda_t d_t$$

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

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

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

3.1.2 Household, government and equilibrium

Details on the household problem, the government and the definition of the equilibrium can be found in Appendix C.2. The household consumes the good produced by the firm and supplies labor. It does not receive the tax rebate on debt and therefore becomes the saver in equilibrium. The government runs a balanced budget in every period.

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 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 \( MRS = MPN \) and in which the amplification arising from either constraint is relatively small.\(^{31}\)

| Table 2: MODEL PARAMETERIZATIONS |
|---------------------------|-------------------------------|
| Parameter | Value | Details on parameterization |
| \( (a) \) Structural parameters |
| \( \alpha \) | 0.33 | Capital share of output of 1/3 |
| \( \delta \) | 0.025 | Depreciation rate of 2.5% per quarter |
| \( \phi \) | 4 | Prior of Smets and Wouters (2007) |
| \( \beta \) | 0.9752 | Steady state annualized interest rate of 6.6%* |
| \( \chi \) | 1.87 | Target \( n = 0.3 \) in steady state |
| \( \psi \) | 0.46 | Jermann and Quadrini (2012) |
| \( (b) \) Model with earnings-based constraint only |
| \( \theta_k \) | 0 | Shut off collateralized borrowing |
| \( \tau_k \) | 0 | Shut off collateralized borrowing |
| \( \theta_s \) | 4.6/4 | Average value of debt-to-EBITDA covenants* |
| \( \tau_s \) | 0.35 | Following Hennessy and Whited (2005) |
| \( (c) \) Model with collateral constraint only |
| \( \theta_k \) | 0.0485 | Same steady state debt as Panel (b) |
| \( \tau_k \) | 0.35 | Following Hennessy and Whited (2005) |
| \( \theta_s \) | 0 | Shut off earnings-based borrowing |
| \( \tau_s \) | 0 | Shut off earnings-based borrowing |

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

\(^{31}\)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 stronger responses to shocks. See also Chari, Kehoe, and McGrattan (2007) for a general discussion of the labor wedge in business cycle models. Christiano, Eichenbaum, and Trabandt (2015) emphasize the quantitative role of working capital constraints during the Great Recession.
3.2 Model parameterization and specification

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

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

This specification gives a steady state market value of capital of 1. Furthermore, in steady state, $\Phi''(1) = \bar{\sigma}$. Panel (a) of Table 2 summarizes the values I set for the structural parameters of the model. Most parameter values are standard in business cycle research for the US case or match standard moments in US macroeconomic data. I set $\bar{\sigma} = 4$ in line with Smets and Wouters (2007). To parameterize $\beta$, I calculate the average interest rate faced by firms in the Dealscan database. Panels (b) and (c) of the table show the calibration of the parameters that are related to the alternative borrowing constraints (8) and (9). In this part of the paper, I investigate model dynamics using the simplification that either one or the other constraint is faced by the firm. To do this, I exploit the fact that the model nests special cases 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. I set the tax advantage of debt $\tau_j$ 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 EBITDA and my model is quarterly, I divide by four. I then set the tightness of the collateral component to that value which achieves the exact same steady state debt level, which results in $\theta_k = 0.0485$. The results shown in the stylized model environment of this section are robust to meaningful 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 $\theta$ parameters across a range of values.

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32 For the results 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.
33 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.
34 Throughout my analysis I focus on binding borrowing constraints. This assumes that shocks are small enough in magnitude to keep the Lagrange multiplier on the constraint positive, that is, $\mu_{jt} > 0$, $j \in \{k, \pi\}$, $\forall t$. Modifying my model to feature occasionally binding constraints would be relatively straightforward. This would make it feasible to also study possible switching effects between different types of borrowing constraints over the business cycle, similar to what Greenwald (2018) and Ingholt (2018) emphasize for the case of household mortgages.
3.3 Credit dynamics implied by earnings-based vs. collateral constraints

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

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

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

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

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 4 further below.
responses to this shock thus imply sharply different debt dynamics depending on the relevant borrowing constraint. This directly opposite response will provide the testing ground for my empirical analysis in Section 4.

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

3.4 Discussion: borrowing against flow vs. stock variables

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

In light of these insights, we can see that the earnings-based borrowing constraint (8) and the collateral constraint (9) are *not* equivalent for two reasons. First, they differ in terms of the *flow definition*. The earnings-based constraint features earnings rather than dividends. Second, they differ in terms of the *flow timing*. The earnings-based constraint features a current flow variable rather than the NPV of all current and future flows. In the model, I can check directly which of these two differences drives the results in Figure 2, by comparing the responses of \( d_t, V_{d,t}, \pi_t, V_{\pi,t} \) and \( Q_t k_{t-1} \) to the investment shock. Figure 3 displays these IRFs as a comparison of different

17
variables that could potentially limit borrowing. The figure shows that both current earnings as well as the NPV of earnings rise in response to the shock. With any earnings-related constraint, additional debt could be issued in response to the investment shock and the timing of earnings by itself is not key. In contrast, dividends as well as the NPV of dividends, which equals the firm value and the value of the capital stock under the Hayashi conditions, both decline. This leads to the counterfactual debt response with the collateral constraint. Hence, for the investment shock the difference in the debt response is driven by the flow definition. The main results of the model arise not because debt is constrained by a flow instead of by an asset value per se, but by the specific variable that defines this flow, current earnings.

Figure 3: IRFs of different flow and asset value variables to permanent investment shock

Note: The figure displays model IRFs of selected variables to a permanent investment shock, generated from a version of the model without any debt. This is intended to highlight the relation between alternative flows and asset values which may affect the right hand side of potential borrowing constraints. The unit of the IRFs is in levels of consumption units in the model (earnings and dividend flows are additionally scaled by 10). The net present values (NPVs) are recursively computed in the model using the household’s stochastic discount factor.

3.5 Additional results and robustness

Different types of shocks 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. For the purpose of the empirical verification of the mechanism in Section 4, I will focus on that component of \( v_t \) that captures IST. This allows me to establish a mapping of \( v_t \) to the data. At this stage, in terms of the main message behind the results, the distinction between these refined concepts is not of first order importance. The proposed mechanism has a broad interpretation which carries through to other shocks that affect the economy’s investment margin. To demonstrate this, Figure 4 plots two more sets of IRFs. In Panel (a), the IRFs to a

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36 Under the functional form of investment adjustment costs chosen in (12), the Hayashi conditions are not satisfied in the model (see also Jaimovich and Rebelo, 2009). However in the calibration the numerical difference between NPV of dividends and the market value of capital is very small, as can be seen from the similarity between the dashed line in the left chart and the solid line in the right chart of Figure 3.
negative transitory adjustment cost shock for the two model versions are plotted. It is evident that this shock also results in a different sign of the debt responses 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 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. 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 opposite qualitative predictions under the alternative constraints.

**Figure 4: Model IRFs of Firm Debt: Additional Investment Margin Shocks**

(a) Persistent adjustment cost shock

(b) Persistent investment shock with $\phi = 0$

Note: The figure displays IRFs of firm debt to additional investment margin shocks generated from the model, under the two alternative calibrations in which only the earnings-based constraint (dark blue line) or only the collateral constraint (light orange line) is present. Panel (a) plots the IRFs to a negative adjustment costs shock with $\rho = 0.5, \sigma = 1$. Panel (b) repeats the investment shock IRFs from Figure 2 as a transitory but persistent shock ($\rho_v = 0.5, \sigma_v = 0.05$) without adjustment costs ($\phi = 0$). The different signs across models show that the proposed mechanism is broad enough to carry through to different types of shock to the investment margin.

**Robustness to constraint timing.** In Appendix C.5 I repeat Figures 2 and 4 for a version of the earnings-based constraint in which current and three lags of earnings enter the constraint. This is based on the idea that covenants 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.

**The dynamics of other variables.** 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 C.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.\footnote{Cordoba and Ripoll (2004) provide a detailed
exploration of this insight. I therefore show the responses of other variables only insofar as they
help me to understand the different debt dynamics across parameterizations of the model. In
the quantitative extension of the model in Section 5, I consider the dynamics of a variety typical
macroeconomic variables of interest.}

37

4 Verifying the model predictions for investment shocks

This section uses the differential predictions on the borrowing response to investment shocks
as a strategy to disentangle empirically which type of credit constraint is more relevant. I resort
to both aggregate and firm-level data, using an SVAR (Section 4.1 and 4.2) as well as a panel
regression framework that allows for heterogeneous responses to shocks (Section 4.3 and 4.4).
As explained in Section 3, investment shock can take the form of shocks to investment-specific
technology (IST) as well as to marginal investment efficiency (MEI). The former type is directly
tied to a readily available empirical counterpart, the inverse relative price of investment goods.
Specifically, I use equipment prices to construct this relative price, which is in line with the micro
data.\footnote{Observable time series of this price have been exploited by previous research to identify
IST shocks. I build on this work to study the dynamics of debt conditional investment shocks.
That is, while the interpretation of the model mechanism can be applied to different shocks to the
investment margin, for the purposes of verifying the predictions empirically, I focus on a specific
component of the investment margin, a shock to IST.\footnote{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
turns out that the IST shock I identify is reasonably important in terms of the historical variance decomposition
of debt implied by the SVAR (see Appendix D.3).}}

4.1 SVAR on aggregate data

I specify an SVAR to estimate the impact of IST shocks on the US economy as a whole, using
two identification schemes. First, I identify IST shocks using long-run restrictions building on
the work of Fisher (2006).\footnote{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).} Second, I use medium-run restrictions following Francis, Owyang,

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Roush, and DiCecio (2014). I apply both identification methods to US postwar data. In addition, I set up a Monte Carlo experiment in which I 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. Finally, I also verify that the shock I identify reduces the price of used (secondary market) equipment goods. This is to alleviate the concern that I identify the shock from its negative impact of the price of new equipment, while both new and used capital may be pledged as collateral in practice.

4.1.1 SVAR setting and identifying assumptions

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

$$B_0Y_t = B_1Y_{t-1} + \ldots + B_pY_{t-p} + u_t,$$

(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

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

(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 $B(1)^{-1} = [B_0 - B_1 - \ldots - B_p]^{-1}$. 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. It is important to highlight that these restrictions are satisfied in the theoretical 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.

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41 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 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 is maximized at a specific finite horizon \( h \). These restrictions have been introduced to overcome weaknesses of the long-run identification method, such as their small sample properties (for details see Faust and Leeper, 1997). Based on the ideas of Uhlig (2003), Francis, Owyang, Roush, and DiCecio (2014) identify a technology shock as the shock that maximizes the FEVD share of labor productivity at horizons of 2.5 to 20 years. Barsky and Sims (2011) implement a variant of this method where the shock maximizes the sum of the FEVD up to a specific horizon. I follow the former authors' variant of this identification scheme. Using the same vector of observables \( Y_t \), I identify the IST shock as the shock that maximizes the FEVD share in the relative price of investment at varying horizons \( h \).

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

\[
Y_t = \begin{bmatrix}
\text{dlog}(p_{kt}) & \text{dlog}(y_t/n_t) & \text{log}(n_t) & \text{dlog}(\pi_t) & \text{dlog}(p_{kt}k_t) & \text{dlog}(b_t)
\end{bmatrix}'.
\]

\( p_{kt} \) is the relative price of investment, which corresponds to \( v_t^{-1} \) if \( v_t \) captures IST. This is the system used under both identification schemes.

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. I construct this relative price from NIPA data and use the Gordon-Violante-Cummins (GVC)
Furthermore, I explore the responses of secondary market equipment prices to the IST shock, as in practice both new and used capital could serve as collateral (see Appendix D.6). In principle, one could also proxy the price of capital with stock prices. However, what matters for the mechanism I highlight in this paper is not the firm value (or stock market) response, but the response of the value of assets that serve as collateral. In the data, the value of collateral and the market value of the firm in its entirety are different. I therefore focus on the price of equipment, which is the most important category of collateral in the loan-level data (see Table A.4 in the Appendix). For debt I use the sum of loans and debt securities for the nonfinancial business sector 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. 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 for quarterly US data from 1952 to 2016 for $p = 4$ are shown in Figure 5. The figure presents the IRFs for a positive permanent IST shock identified based on its long-run impact on the relative price of investment. Appendix D.2 presents the analogous IRFs based on the medium-horizon identification scheme with $h = 20$ and $h = 40$, implying that IST is the main driver of the relative price of investment at a 5 and 10 year frequency, respectively. The key insight is that for both identification methods the SVAR estimates a positive response of debt. This is in line with the model predictions for the earnings-based constraint but not for the collateral constraint. Consistent with the mechanics of the earnings-based borrowing constraint, the rise in debt is accompanied by growing earnings and a fall in the value of capital. The dynamics in US data, conditional on identified shocks, thus lend support to the importance of earnings-based borrowing for debt dynamics in US business cycles. In fact, these results shows that the predictions from collateral constraints for investment shocks are at odds with the data.

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45 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 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.

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

47 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.

48 Appendix D.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.
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.

**Historical variance decompositions.** My empirical strategy relies on the sign of the responses, and conceptually it does not require that the shock explains a large fraction of economic fluctuations. However, if the shock is an important driver of macroeconomic dynamics, the relevance of the earnings-based borrowing constraint likely has important effects also on the unconditional dynamics of the data. Appendix D.3 provides the historical decompositions of the six macroeconomic variables in the system. The figures in this appendix show the contribution at each point in time of the different shocks (IST, TFP, other). It is evident that IST shocks played a marked role in different episodes of the postwar US business cycle. For example, consistent with the narrative around the tech boom, the 1990s expansion was strongly driven by IST.

**Monte Carlo simulations.** To verify the ability of the SVAR 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, presented in Appendix D.4, are reassuring. In particular, the negative debt response generated from a collateral constraint model is fully contained in the 68% confidence set across Monte Carlo repetitions.

**The response of used equipment prices.** In practice, borrowers may pledge both new and used capital as collateral. This could be an issue for my empirical strategy, as I identify the investment shock from the price of new equipment. To address this concern, I also demonstrate that the investment shock I identify above reduces the prices of used (secondary market) equipment goods. This means validation of the main mechanism of this paper also holds if secondary prices of capital were to predominantly determine the value of collateral in corporate debt contracts. The results are presented in detail in Appendix D.5.

**Additional robustness checks.** I explore robustness of the SVAR results along a variety of dimensions. First, following Fisher (2006), I split the sample in the early 1980’s to account for the change in the trend exhibited by the relative price of investment. In the first part of the sample the shapes of the IRFs are preserved, while the bands get wider. In the second part, the debt response to IST is again positive and significant, just more hump-shaped rather than settling at a permanent level. Second, I construct the business debt time series separately for loans and debt securities. This split reveals that the debt IRF in Figure 5 is mainly driven by loan dynamics, while the response for debt securities is noisy, 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. 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 resulting IRFs are somewhat smaller in magnitude, but their shapes and statistical significance is preserved.

### 4.3 Panel projections in firm-level data

In this subsection, I exploit micro-level information on firms’ debt contracts to provide direct evidence on the proposed mechanism. I merge the Dealscan data set used in Section 2 with balance sheet information from Compustat. This gives me a firm panel with information on

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49 I use data on used aircrafts from Lanteri (2018), as well as the prices of used vehicles provided by the BLS.

50 The fact that secondary market prices fall in response to an investment shock is plausible from a theoretical point of view. In a model with different (complementary) vintages of capital, one would expect that no-arbitrage restrictions between the different asset types ensure that prices qualitatively move in the same direction if an exogenous shock reduces the price of one of the vintages.
earnings-based covenants and collateral as well as on rich firm characteristics. I regress firm-level borrowing on the investment shock obtained from the SVAR.\footnote{Related studies on firm-level responses to macro shocks are Ottonello and Winberry (2018), Jeenas (2018), Bahaj, Foulis, Pinter, and Surico (2018) and Cloyne, Ferreira, Froemel, and Surico (2018), who all focus on monetary policy rather than investment shocks.} I obtain average IRFs across all firms, as well as separate IRFs for different borrower types, allowing me to verify whether my suggested mechanism is plausible in generating debt dynamics at the firm level. Furthermore, I study the firm-level debt responses to a fall in the relative price of investment goods, using an IV strategy. I also extend the analysis to study the response of firm-level investment.

4.3.1 Panel local projection setting and assumptions

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

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

and obtaining estimates of $\beta_h$, $h = 0, 1, 2, \ldots, H$. The right hand side variable $\hat{u}_{IST,t}$ denotes the time series of the identified exogenous investment shock from the SVAR model above. $X_{i,t}$ is a vector of rich firm-level and industry-level 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. Recall that my model predicts the response of debt to the investment shock in this regression to be positive with earnings-based constraints ($\beta_h > 0$) and negative with collateral constraints ($\beta_h < 0$).

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

$$\log(b_{i,t+h}) = \alpha_h + \beta_h \hat{u}_{IST,t} + \gamma X_{i,t} + \beta_{h,earn} \mathbb{I}_{i,t,earn} \times \hat{u}_{IST,t} + \alpha_{h,earn} \mathbb{I}_{i,t,earn} + \beta_{h,coll} \mathbb{I}_{i,t,coll} \times \hat{u}_{IST,t} + \alpha_{h,coll} \mathbb{I}_{i,t,coll} + \delta t + \eta_{i,t+h},$$

where $\mathbb{I}_{i,t,earn}$ and $\mathbb{I}_{i,t,coll}$ 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 an “earnings only” (“collateral only”) borrower at horizon $h$ is given by the sum of the coefficients $\beta_h$ and $\beta_{h,earn}$ ($\beta_h$ and $\beta_{h,coll}$). My theoretical mechanism predicts that $\beta_h + \beta_{h,earn} > 0$ and $\beta_h + \beta_{h,coll} < 0$. I discuss below how I address the endogenous selection into borrower types.

An alternative version of (17) is based on an IV strategy. The idea is to study the responses to 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 discussed below and presented in detail in Appendix E.2. Finally, I also study the response of firm-level investment by replacing $b_{i,t+h}$ in equation (17) with $inv_{i,t+h}$ (real capital expenditures from Compustat). The results are discussed below, with details provided in Appendix E.5.

4.3.2 Data and specification used for panel regressions

The Dealscan-Compustat merge is enabled by a link file connecting the identifiers in the two data sets, which has been created by Michael Roberts and collaborators (see Chava and Roberts, 2008). The resulting data set covers around 150,000 firm-quarter observations for more than 4,000 distinct firms from 1994 to 2015. $b_{i,t}$ is the quarterly level of debt liabilities from Compustat (calculated as the sum of the items ‘dltq’ and ‘dlccq’). Consistent with the data treatment in the SVAR, I obtain a real series by deflating with the consumption deflator for nondurable goods and services. The firm-level classification into “earnings borrowers” and “collateral borrowers” based on the information in Dealscan is consistent with the aggregate shares I present in Figure 1. $1_{i,t,earn}$ is equal to 1 if a given firm issues a loan with at least one earnings covenant. $1_{i,t,coll}$ 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 $1_{i,t,coll}$ based on whether the firm uses a secured revolving line of credit. This follows Lian and Ma (2018), who point out that secured “revolvers” are typically asset-based. Summary statistics for the full data sample and conditional on the grouping by borrower type are provided in Appendix A.2.

I focus on the version of $\hat{u}_{IST,t}$ estimated using long-run restrictions in Section 4.1. To the extent that my identification in the SVAR is credible, this shock is a purely exogenous regressor, meaning that there are no endogeneity issues with respect to this variable in (16). Clearly, however, the dummy interactions to generate heterogeneous responses in equation (17) are a cause for concern. There may be omitted variables that affect both the left hand side and the endogenous selection of borrowers into a particular type. I address this problem by controlling for omitted characteristics that may simultaneously be driving debt responses to investment shocks and selection into borrower types. Concretely, I use a specification with 3-digit industry-level fixed effects and firm size, as well as firm-level real sales growth to control for firm-specific cyclical conditions. In an alternative specification, I also introduce firm-level fixed effects. In all versions of (16) and (17) that I estimate, I include one lag of the left hand side variable and a linear time trend to the regression. Furthermore, I add a control variable that is intended to capture macroeconomic shocks other than investment shocks, which I construct from the SVAR residuals.\textsuperscript{52} I set $H = 12$, and keep the firm composition constant when expanding $h$.

While Compustat is a panel and debt liabilities are continuously recorded, 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. This has two consequences. First, using any Dealscan

\textsuperscript{52}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.
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. While this potentially introduces an upward bias in the estimates for (17), I focus on the sign and relative size of $\beta_{\text{earn}}^h$ and $\beta_{\text{coll}}^h$.

4.4 Firm-level results: heterogeneous responses to investment shocks

Average debt responses. I first present the debt response for all firm in the panel, that is, the estimates of $\beta^h$ in (16), together with the associated 90% bands based on two-way clustered standard errors by firm and quarter.\footnote{In the relatively conservative choice of computing two-way clustered standard errors I follow the papers that apply similar techniques, e.g., Ottonello and Winberry (2018), Jeenas (2018) and Cloyne, Ferreira, Froemel, and Surico (2018). I also tried clustering standard errors at the 3-digit industry, which gives very similar results.} In this regression I do not add any controls other than lags of the left-hand-side variable, a time trend and the exogenous shock itself. Figure 6 shows that the dynamic response of firm debt to an investment shock is positive, in line with the aggregate debt response in the SVAR, and consistent with the model in which the earnings-based constraint is the relevant debt limit. It matches the SVAR responses also in terms of the magnitude and persistence. This is reassuring, since Compustat-Dealscan firms are a specific but quantitatively meaningful subset of the total nonfinancial business sector for which I use data in the SVAR.

Debt responses by borrower types. The heterogeneous IRFs based on estimating equation (16) are presented in Figure 7. These results are based on a specification with 3-digit industry fixed effects, size as measured by number of employees and growth of real sales. As described above, I also control for other macroeconomic shocks using the orthogonalized SVAR innovations. Panel (a) shows the results based on the classification of collateralized debt is based on whether a given firm’s borrowing is secured with specific assets (see Section 2 for details). Panel (b) shows the results using the 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 constructed from standard errors that are clustered by firm and quarter. The bands across all four figures are wider than in Figure 6 due to the lower number of observations when using $\mathbb{1}_{i,t,\text{earn}}$ and $\mathbb{1}_{i,t,\text{coll}}$ in the regression. Both panels of Figure 7 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. 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 7, but is formally presented in Table E.1 in the Appendix. Interestingly, while the shape of the IRF for earnings-borrowers is similar to the model prediction – small on impact and then increasing
Figure 6: EMPIRICAL FIRM-LEVEL IRF OF DEBT TO AN INVESTMENT SHOCK

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

Persistently – the IRF of collateral borrowers differs from its model counterpart. Similar to the model prediction, the response on impact in Panel (a) is negative. However it displays its most significant reduction only after around 2 years. A possible interpretation of this delayed response is the fact that one aspect of the model in Section 3 – the dynamics of new and already installed capital prices are the same – is not borne out by the data. Empirically, the relative price effect at the heart of my mechanism may therefore not generate a negative effect for collateral borrowers that is as sizable and immediate as in the model. Interestingly, the responses of used (secondary market) equipment prices that I investigate in Appendix D.5 also show a negative but sluggish response, providing some additional evidence for this interpretation.

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

(a) Using collateral classification based on specific assets

(b) Using collateral classification based on secured revolvers

Note: The figure displays average IRFs of firm borrowing within different firm groups, estimated using the method of Jordà (2005) in a panel context, as formulated by equation (17). In both panels, the debt IRF for borrowers with earnings covenants and no collateral (left) and borrowers without earnings covenants but with collateral (right) are plotted. The results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks). 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 database. 90% bands are calculated using two-way clustered standard errors by firm and quarter. The IRFs shown in the figure are consistent with the model’s prediction of a positive debt response under an earnings-based constraint and a negative one under a collateral constraint. A formal test rejects the null hypothesis of equal responses across the two firm types for various horizons, as shown in Table E.1 in the Appendix. The results for alternative specifications, as well as the responses for the remaining two borrower types are given in Appendix E.
The response of firm-level investment. To explore firm-level outcomes other than the response of borrowing, I extend the analysis to study the response of firm-level investment (capital expenditures) to the same shock. This is an outcome variable that is naturally of interest, and is also the focus in recent papers that study firm-level responses to monetary shocks. The results, presented in Appendix E.5, line up directly with the dynamics of debt. ‘Earnings borrowers’ significantly increase their investment in response to the shock, while ‘collateral borrowers’ reduce investment. In line with the broad contours of the debt response, the negative response of firms that borrow against collateral is relatively sluggish. While capital expenditures are more lumpy and volatile at the firm level, and the IRFs look therefore much less smooth than for debt, a formal test again rejects the null hypothesis that the responses are the same across borrower types.

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

The proposed model mechanism allows to distinguish between alternative borrowing constraints by conditioning on investment shocks. In an expansion driven by a shock that 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 aggregate debt dynamics is such an earnings-based constraint. Moreover, the heterogeneous firm-level responses are directly in line with the mechanism: earnings-based borrowers increase their debt liabilities in response to an aggregate investment shock, firms subject to collateral constraints do not.

5 Earnings-based borrowing in a quantitative macro model

This section extends the model of Section 3 to incorporate features of a New Keynesian macro model. Specifically, I add a number of shocks and frictions, such as price and wage rigidities, to operate alongside borrowing constraints. I estimate the model on US time series to investigate the importance of earnings-based borrowing relative to borrowing against collateral, and the importance of borrowing constraints relative to other frictions in the economy.

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). The philosophy behind these models is that in order to gauge the overall effect of any macroeconomic policy change, this policy should be assessed net of other important forces that operate across the economy. For the purpose of adding borrowing constraints, I build on a variation of the Smets and Wouters (2007) model suggested by Jermann and Quadrini (2012). The details of the model are provided in Appendix F, in what follows I elaborate mainly on the borrowing constraints.

54The 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
While in Section 3 I study alternative model calibrations in which either the earnings-based or the collateral constraint is binding, I now move to a formulation in which both constraints are present simultaneously and based on which 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 (in real terms) by a weighting between an 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

$$\frac{b_{i,t}}{P_t(1+r_t)} \leq \omega\theta_{\pi,t}\pi_{i,t} + (1-\omega)\theta_{k,t}\pi_{i,t} + (1-\delta)k_{i,t}. \quad (18)$$

The parameter $\omega$ 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 and let the data speak about the importance of the alternative constraint formulations. The $\theta$ terms are subject to shocks to financial conditions, with their mean calibrated based on the micro data. I choose the formulation of (18) as a reduced form way to capture that, in the aggregate, either constraint type may contribute to macroeconomic dynamics to a certain degree. Using such a weighting is appealing for two reasons. First, it has the advantage that the relative contribution of two variations of the credit friction can be represented directly by one single parameter, without requiring additional modifications of an otherwise standard New Keynesian structure. Second, the formulation allows me to conveniently carry out counterfactual exercises in which I set $\omega$ to 0 and 1 and study the corresponding model properties.

5.2 Data and estimation settings for quantitative model

For the estimation of the model I retrieve quarterly data for the 7 observables used by Smets and Wouters (2007) (output, consumption, investment, employment, interest rates, wages and inflation) and add the change in nonfinancial sector debt from the Flow of Funds, scaled by output, as an eighth observable. Consistent with the previous sections of this paper, 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). Following the same authors, the sample period for the baseline estimation is 1954:Q3 - 2009:Q1. 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. I calibrate the means of $\theta_{\pi,t}$ and $\theta_{k,t}$ in the same way as in Section 3. For $\omega$ I specify a uniform prior between 0 and 1. For comparability to previous studies, I

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price adjustment costs rather than Calvo pricing. The monetary policy maker targets output deviations from steady state rather than from the natural level. The disturbances do not feature moving average terms. Finally, firms receive a tax advantage on debt. I also add some corrections to the model that were suggested by Pfeifer (2016).

While there is available prior information on the shares of earnings-based borrowing and debt secured with specific assets – including the evidence shown in Section 2 – I impose the uniform prior in order to use the New Keynesian structure.
otherwise estimate the same set of parameters as Jermann and Quadrini (2012) and use identical priors. I obtain 1,000,000 draws from a Markov Chain Monte Carlo algorithm, 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 shocks in different model counterfactuals, and analyze to what degree the different shocks in the model contribute to the variation in the data. In Section 6 I turn to studying policy based on counterfactual model estimations.

Figure 8: Properties of the estimated quantitative model

(a) Weight on earnings-based component

(b) Debt IRFs to permanent investment shock

Note: Panel (a) presents the prior and posterior density (grey and black solid lines, respectively) over values of $\omega$, 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 (dotted black line) and for counterfactual models in which the weight of the earnings-based constraint is set to 1 (dark blue line) and 0 (light orange line), but all other parameters are kept at their estimated values. Debt refers to the level of real debt liabilities.

The estimated weight on earnings-based debt. Panel (a) of Figure 8 plots the prior and posterior density of $\omega$. 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-based 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 Keynesian DSGE model as a separate device to study the relative importance of the constraints based on the information purely contained in macroeconomic data.
earnings-based constraint. The results also highlight that the collateral component does remain a feature of the model, although with a much lower weight. Table F.1 in the Appendix presents the priors and posterior estimates of all structural parameters.

**The response to investment shocks.** Panel (b) presents the IRFs of real debt to a permanent investment shock, calculated at the posterior means of the estimated model (dotted black line). The chart also contains corresponding IRFs for models in which the weight of the earnings-based constraint is set to 1 (dark blue line) and 0 (light orange line), while the other parameters are kept at their posterior mean. 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. Appendix F.3 presents results on the debt responses to other shocks in the model. These results show that the firm credit response to other shocks can also flip sign depending on the relevant borrowing constraint.

**Table 3: Variance decomposition of observables in estimated quantitative model (in %)**

<table>
<thead>
<tr>
<th></th>
<th>TFP</th>
<th>Inv</th>
<th>Pref</th>
<th>Price</th>
<th>Wage</th>
<th>Gov</th>
<th>Mon</th>
<th>Fin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output growth</td>
<td>4.74</td>
<td>53.47</td>
<td>11.7</td>
<td>5.86</td>
<td>2.49</td>
<td>13.09</td>
<td>6.16</td>
<td>2.48</td>
</tr>
<tr>
<td>Consumption growth</td>
<td>5.53</td>
<td>5.02</td>
<td>82.81</td>
<td>1.39</td>
<td>1.21</td>
<td>0.02</td>
<td>4.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Investment growth</td>
<td>2.52</td>
<td>86.81</td>
<td>0.25</td>
<td>2.69</td>
<td>2.61</td>
<td>0.00</td>
<td>5.09</td>
<td>0.03</td>
</tr>
<tr>
<td>Inflation</td>
<td>13.07</td>
<td>13.87</td>
<td>4.97</td>
<td>43.48</td>
<td>18.73</td>
<td>0.83</td>
<td>4.98</td>
<td>0.05</td>
</tr>
<tr>
<td>Interest rate</td>
<td>4.11</td>
<td>11.94</td>
<td>3.07</td>
<td>16.47</td>
<td>8.12</td>
<td>0.56</td>
<td>55.72</td>
<td>0.01</td>
</tr>
<tr>
<td>Employment growth</td>
<td>29.64</td>
<td>39.72</td>
<td>7.27</td>
<td>1.54</td>
<td>3.73</td>
<td>11.12</td>
<td>5.92</td>
<td>1.06</td>
</tr>
<tr>
<td>Wage growth</td>
<td>14.21</td>
<td>2.45</td>
<td>2.02</td>
<td>23.86</td>
<td>57.33</td>
<td>0.02</td>
<td>0.08</td>
<td>0.03</td>
</tr>
<tr>
<td>Debt issuance</td>
<td>1.13</td>
<td>4.75</td>
<td>0.74</td>
<td>1.65</td>
<td>0.56</td>
<td>0.69</td>
<td>1.14</td>
<td>89.35</td>
</tr>
</tbody>
</table>

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

**Variance decomposition of observables.** Table 3 presents the forecast error variance decomposition of the variables that are used to estimate the model. This reveals the relative importance that the model attributes to different structural shocks in driving a given observable. For comparison, Table F.3 in the Appendix shows the corresponding decomposition for a model without credit constraints. One observation that stands out in the table is the overall importance of investment shocks. Consistent with similar findings in the literature, the investment margin appears to be crucial for capturing variation in US macroeconomic data (see in particular Justiniano, Primiceri, and Tambalotti, 2010, 2011). This lends further support to my approach of using this type shock in the context of studying which type of corporate borrowing constraints are
in line with credit dynamics at the macro and micro level. To ensure the quantitative results of this section do not only rely on investment shocks, I also verified that the earnings-based constraint plays a key role in the absence of investment shocks and when no information on investment is used for the estimation (see Appendix F.3).

6 Consequences for fiscal and monetary shocks

This section examines the consequences of earnings-based credit constraints, in comparison to traditional collateral constraints, for the transmission of macroeconomic policy. Figure 9 shows the responses to an expansionary fiscal shock, that is, an exogenous increase in government spending, as well as the dynamics following a contractionary monetary shock, an exogenous increase in the interest rate. In each case, the figure displays the IRFs of the estimated model as the dotted black line, together with IRFs from model version in which $\omega = 1$ (dark blue line) and $\omega = 0$ (light orange line), and the other structural parameters are re-estimated. For studying policy, re-estimation of the other parameters is my preferred type of counterfactual, as I aim to characterize hypothetical situations in which a policy maker would only have one or the other model at her disposal. As I outline below, the presence of earnings-based debt alters the transmission of both fiscal and monetary shocks in economically meaningful ways. The analysis demonstrates that a policy maker would reach substantially different conclusions across estimated models with alternative borrowing constraints faced by firms.

The transmission of fiscal shocks. The model IRFs to the fiscal policy shock, shown in Panel (a) of Figure 9, reveal that the output response to the shock is larger and more persistent in the collateral constraint model than in the one that features earnings-based constraints. The full model, in which $\omega$ is estimated, lies in between the other two. The stronger output stimulus with collateral constraints is also reflected in more elevated responses of employment, earnings and inflation. What stands out is the marked differences in the responses of consumption, investment and debt. Interpreting these differences provides some useful insights on the mechanics of the alternative credit constraints. The economic intuition is as follows. A government spending shock generally gives rise to a temporarily higher demand for the good produced by the firm, which puts upwards pressure on earnings and prices, and provides an incentive for shifting resources to the presence (because overall demand for the good will move back to steady state as the shock dies off). In most standard models, this is accompanied by a “crowding-out” effect on consumption and investment. Under the earnings-based constraint this is indeed the case. Both consumption and investment fall, similar to what happens in a model that does not feature any credit frictions (see for example Smets and Wouters, 2007). As debt access is determined by earnings, and earnings rise, firms will be able to borrow more, but the additional debt space does not overturn the direct crowding-out pressures coming from the spending shock. Under the collateral constraint, on the other hand, investment in capital has the additional benefit of building collateral, captured by
Figure 9: 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 (dotted black line) and for counterfactual models in which the weight of the earnings-based constraint is set to 1 (dark blue line) and 0 (light 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.
a different return term in the investment Euler equation. This difference is strong enough to overturn the crowding-out effect on investment. Firms invest more, which strengthens the overall macroeconomic stimulus of the spending shock. While firms increase investment, the price of capital falls (not displayed in the figure), so the debt space of the firm is reduced. It turns out that this effect on reduced borrowing is not strong enough to hinder the firm from investing, as the firm is also able to use current period income to invest.\footnote{The conclusions for the fiscal shock would likely be very different if the government purchases investment goods rather than final output. This would be an interesting additional experiment in light of how the credit constraint differ. For comparability to other studies, in this paper I focus on the most standard fiscal shock formulation.}

**The transmission of monetary shocks.** In the case of the monetary policy shock, presented in Panel (a) of Figure 9, the IRFs display the same sign for all variables across alternative models. In terms of magnitudes, it is noteworthy that the earnings-based constraint implies a much stronger inflation response than the corresponding response in the model with collateral constraints. The strongly negative inflation response is accompanied by a somewhat stronger but less persistent decline in output.\footnote{It is also visible that for the monetary shock the IRFs of the baseline model are generally closer to the ones of the pure collateral constraint model. Given that the estimated weight on the collateral constraint in the baseline is low, this appears counterintuitive. The explanation is that in the re-estimation of the model both the dynamics as well as the relative contribution of shocks change. For shocks that are not quantitatively important, the responses can therefore be very different from the baseline. In fact, the presence of the earnings-based constraint assigns a lower quantitative contribution to monetary policy shocks for US business cycles overall.} In comparison to the fiscal shock, these differences are more challenging to interpret, and a careful analysis of the different parameter values underlying the IRFs is required: the variation in the estimated structural parameters resulting from the change in $\omega$ show that the differences appear to be driven by the fact that the model with only an earnings-based constraint implies a relatively low degree of price rigidity relative to the pure collateral model (while wage rigidities are similar across models). The explanation is that in New Keynesian models high price rigidities imply countercyclical profits (markups). In the presence of an earnings-based constraint, when profits determine debt access, strong price rigidities therefore appear to be at odds with the strong procyclicality in debt. As debt is used as an observable to estimate the model, the earnings-based constraint implies lower estimated price stickiness. The interaction between credit constraints and the strength of other frictions thus gives rise to a quantitatively different conclusions about monetary policy and its pass-through to prices.

**Understanding credit constraints to draw policy conclusions.** The way in which firm credit constraints are captured in a quantitative macro model changes the conclusions that are drawn about the transmission of policy. Earnings-based constraints imply a weaker output response to fiscal shocks, explained by crowding-out effects on investment that are not present with a collateral constraint. The findings on the transmission of monetary policy show that inflation is more reactive to interest rate shocks with the earnings-based constraint. The reason is the interaction of the credit limit with the implied degree of price rigidity.
7 Conclusion

Capturing the relation between credit and economic activity is crucial for understanding macroeconomic fluctuations. This paper emphasizes a channel by which firms’ borrowing capacity is directly connected to their earnings flows. Grounded on microeconomic evidence on the specification of loan contracts, I propose a debt limit that restricts borrowing to a multiple of earnings. The theoretical predictions of a business cycle model which features this earnings-based borrowing constraint are in line with both aggregate and firm-level 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 may be subject 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.
References


45
Appendix (for Online Publication) to
Earnings-Based Borrowing Constraints
and Macroeconomic Fluctuations
by Thomas Drechsel

Contents

A Details on the data 3
A.1 Thomson Reuters LPC Dealscan data set 3
A.2 Merged Dealscan-Compustata panel data set 7
A.3 US aggregate time series data 9

B Discussion of microfoundation 13
B.1 A formal rationalization of the alternative borrowing constraints 13
B.2 Further discussion of the earnings-based constraint 15

C Details on the model of Section 3 17
C.1 Firm optimality conditions 17
C.2 Household, government, and definition of equilibrium 17
C.2.1 Household problem 17
C.2.2 Government 18
C.2.3 Equilibrium 18
C.3 Specification of stochastic processes 19
C.4 Sketch of analytical calculation of the steady state 19
C.5 IRF comparison with moving average earnings-based constraint 20
C.6 Model IRFs of additional variables 21

D Additional results for SVAR 22
D.1 SVAR IRFs to TFP shock 22
D.2 SVAR IRFs using medium-term restrictions 23
D.3 SVAR historical decompositions 24
D.4 SVAR IRFs using simulated data 26
D.5 SVAR IRFs of used equipment prices 28

E Additional results for firm-level projections 30
E.1 Significance of the difference between heterogeneous debt IRFs 31
E.2 IV strategy 32
E.3 Results for specification with firm fixed effects 34
E.4 Results for all four firm groups 35
E.5 The response of firm-level investment ........................................... 37

F Details on the quantitative model of Section 5 ............................... 40
  F.1 Model setup ............................................................................. 40
    F.1.1 Final good firm ................................................................. 40
    F.1.2 Intermediate goods firms ............................................... 40
    F.1.3 Households ................................................................. 42
    F.1.4 Government ............................................................... 42
    F.1.5 Monetary policy .......................................................... 43
    F.1.6 Stochastic processes ...................................................... 43
  F.2 Additional results from estimated quantitative model ............... 44
    F.2.1 Parameter estimates .......................................................... 44
    F.2.2 Additional sign differences in debt responses ..................... 46
  F.3 Results from alternative versions of the quantitative model ...... 47
    F.3.1 Variance decomposition for model without borrowing constraints .. 47
    F.3.2 Estimated weight on constraints in model without investment shocks .. 47
A Details on the data

This appendix provides details on the data sources used across all sections of the paper. First, Section A.1 describes the Thomson Reuters LPC Dealscan database and presents summary statistics. This data set is used for the motivational evidence in Section 2 of the main text, as well as some of the model calibrations in Section 3. Second, the merged data set consisting of the Dealscan data, together with quarterly balance sheet information from Compustat is explained in Section A.2. This data is used in Section 4.3 of the main paper, for the local projections of the investment shock in panel data. Third, the construction of the time series data used for the estimation of the SVAR in Section 4.1 and the estimation of the quantitative model in Section 5 is laid out in Section A.3.

A.1 Thomson Reuters LPC Dealscan data set

LPC Dealscan is a detailed loan-level database provided by Thomson Reuters. The data was retrieved in March 2017 through the LSE Library Services and consists of a full cut of the entire database provided by Thomson Reuters as of October 2015. The data covers around 75% of the total US commercial loan market (see Chava and Roberts, 2008). The unit of observation is a loan deal, sometimes called loan package, which can consist of several loan facilities. As explained in the main text, rich information is provided both and the deal and facility level. The information is collected at the time of origination but is then not followed over time, so that the data can be thought of as a large cross section with different origination dates.

Data coverage. The raw data set retrieved contains 214,203 deals with 307,660 facilities for 78,646 unique borrowers globally. For the main sample considered in the text I choose loan packages in which the lender is a US nonfinancial Corporation (excluding SIC codes 6000-6999) and the debt is US Dollar denominated. Following Chava and Roberts (2008), I start the sample with loans originated in 1994. These choices result in a sample of 54,400 packages, 83,290 facilities and 15,358 unique borrowing corporations. The number of deals per borrower ranges from 1 to 41, with on average 7.35 deals per borrower. Figure A.1 summarizes the number of deals, facilities and borrowers split up by origination time.

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

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

Note: The figure plots the number of loan deals (or packages), loan facilities and borrowing corporations for the
sample used in the main analysis of the paper, broken down by origination date since 1994. The sample covers
USD denominated debt for US nonfinancial corporations.
Table A.1: SUMMARY STATISTICS FOR DEALSCAN DATA

<table>
<thead>
<tr>
<th></th>
<th>Deal amount (mio 2009 USD)</th>
<th>Facility amount (mio 2009 USD)</th>
<th>Facility maturity (months)</th>
<th>Interest rate (drawn spread)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>418.2</td>
<td>273.2</td>
<td>52</td>
<td>259</td>
</tr>
<tr>
<td>Std. deviation</td>
<td>1002.1</td>
<td>683.1</td>
<td>27</td>
<td>166</td>
</tr>
<tr>
<td>1st percentile</td>
<td>2.5</td>
<td>1.3</td>
<td>5</td>
<td>20</td>
</tr>
<tr>
<td>10th percentile</td>
<td>23.7</td>
<td>10.4</td>
<td>12</td>
<td>65</td>
</tr>
<tr>
<td>25th percentile</td>
<td>60.0</td>
<td>29.9</td>
<td>36</td>
<td>150</td>
</tr>
<tr>
<td>Median</td>
<td>151.2</td>
<td>92.2</td>
<td>60</td>
<td>250</td>
</tr>
<tr>
<td>75th percentile</td>
<td>395.8</td>
<td>257.4</td>
<td>60</td>
<td>330</td>
</tr>
<tr>
<td>90th percentile</td>
<td>951.1</td>
<td>619.4</td>
<td>84</td>
<td>450</td>
</tr>
<tr>
<td>99th percentile</td>
<td>4144.2</td>
<td>2750.0</td>
<td>120</td>
<td>830</td>
</tr>
<tr>
<td>Observations</td>
<td>54,397</td>
<td>83,288</td>
<td>76,205</td>
<td>70,282</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Industry</th>
<th>No of firms</th>
<th>No of loan deals</th>
<th>Amount borrowed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer Nondurables</td>
<td>1,120</td>
<td>4,420</td>
<td>1.83</td>
</tr>
<tr>
<td>Consumer Durables</td>
<td>424</td>
<td>1,738</td>
<td>0.80</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>1,741</td>
<td>7,036</td>
<td>2.52</td>
</tr>
<tr>
<td>Oil, Gas, and Coal</td>
<td>805</td>
<td>3,479</td>
<td>1.78</td>
</tr>
<tr>
<td>Chemicals</td>
<td>382</td>
<td>1,699</td>
<td>0.91</td>
</tr>
<tr>
<td>Business Equipment</td>
<td>1,503</td>
<td>4,718</td>
<td>1.76</td>
</tr>
<tr>
<td>Telephone and TV</td>
<td>795</td>
<td>2,755</td>
<td>2.21</td>
</tr>
<tr>
<td>Utilities</td>
<td>767</td>
<td>3,964</td>
<td>2.27</td>
</tr>
<tr>
<td>Wholesale, Retail</td>
<td>2,216</td>
<td>8,579</td>
<td>2.83</td>
</tr>
<tr>
<td>Healthcare</td>
<td>1,003</td>
<td>3,469</td>
<td>1.65</td>
</tr>
<tr>
<td>Other</td>
<td>3,311</td>
<td>10,982</td>
<td>3.93</td>
</tr>
<tr>
<td>No SIC code available</td>
<td>1,290</td>
<td>1,560</td>
<td>0.25</td>
</tr>
</tbody>
</table>

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

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

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

<table>
<thead>
<tr>
<th>Collateral type</th>
<th>Number of loan facilities</th>
<th>Volume in bn USD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Property &amp; Equipment</td>
<td>2292</td>
<td>353</td>
</tr>
<tr>
<td>Accounts Receivable and Inventory</td>
<td>1801</td>
<td>332</td>
</tr>
<tr>
<td>Intangibles</td>
<td>1367</td>
<td>238</td>
</tr>
<tr>
<td>Cash and Marketable Securities</td>
<td>989</td>
<td>328</td>
</tr>
<tr>
<td>Real Estate</td>
<td>737</td>
<td>142</td>
</tr>
<tr>
<td>Ownership of Options/Warrants</td>
<td>104</td>
<td>19</td>
</tr>
<tr>
<td>Patents</td>
<td>84</td>
<td>12</td>
</tr>
<tr>
<td>Plant</td>
<td>50</td>
<td>12</td>
</tr>
<tr>
<td>Agency Guarantee</td>
<td>25</td>
<td>6</td>
</tr>
</tbody>
</table>

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-Compustat panel data set

Compustat Northamerica Quarterly. This data set provides accounting data for publicly held companies in the US and Canada at quarterly frequency starting in 1960. The data was accessed through the Upenn Wharton Research Data Services (WRDS) in September 2016. I keep firms incorporated in the United States with positive assets and sales and exclude Financials (SIC codes 6000-6999). In addition, I generally exclude the sector of 'unclassifiable' firms (SIC codes starting with 99), since this sector contains very few large holding firms, which are typically financial firms (e.g. Berkshire Hathaway). Finally I drop firms that are present less than 5 years. These sample restrictions are typically made in papers that focus on nonfinancial Compustat firms (see for example Bates et al., 2009).

Merge of Dealscan with Compustat. As described in the text, I use Michael Roberts’ identifier link, which is available on Michael Roberts’ personal website and which is infrequently updated. See also Chava and Roberts (2008). I am extremely grateful to these authors for publicly providing this link. The version of the link file which I retrieved is the April 2018 version. I drop firms from Compustat that do not appear at least once in the Dealscan data and restrict the sample to the period covered by the link file. I 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). 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

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

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Series sources and construction</th>
<th>Transform</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative price of investment</td>
<td>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)</td>
<td>log diff</td>
</tr>
<tr>
<td>Relative price of investment</td>
<td>See DiCecio (2009) for details (FRED: PERIC)</td>
<td>log diff</td>
</tr>
<tr>
<td>(alternative measure)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor productivity</td>
<td>Nominal business sector value added (FRED: A195RC1Q027SBEA), deflated with consumption deflator (see above), divided by hours worked (see below)</td>
<td>logdiff</td>
</tr>
<tr>
<td>Hours worked</td>
<td>Hours of all persons in the nonfarm business sector (FRED: HOANBS)</td>
<td>log</td>
</tr>
<tr>
<td>Business sector earnings</td>
<td>Sum of nominal income before taxes in the nonfinancial noncorporate sector (USFA: FA116110005.Q) and corporate profits before tax excluding IVA and CCAdj (USFA: FA106600005.Q), deflated with consumption deflator (see above)</td>
<td>logdiff</td>
</tr>
<tr>
<td>Level of the capital stock</td>
<td>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)</td>
<td>logdiff</td>
</tr>
<tr>
<td>Business sector debt</td>
<td>Level of debt securities and loans in the nonfinancial business sector (constructed from USFA: FA104122005.Q and FA144123005.Q), deflated with consumption deflator (see above)</td>
<td>logdiff</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Series sources and construction</th>
<th>Transform</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>Nominal GDP (FRED: GDP), divided by population (FRED: B230RC0Q173SBEA), deflated with consumption deflator (see above)</td>
<td>logdiff</td>
</tr>
<tr>
<td>Consumption</td>
<td>Real consumption expenditures of nondurable goods and services (FRED: PCNDGC96 and PCESVC96), divided by population (see above)</td>
<td>logdiff</td>
</tr>
<tr>
<td>Investment</td>
<td>Sum of nominal gross private domestic investment expenditures (FRED: GPDI) and nominal private consumption expenditures on durable goods (FRED: PCDG), divided by population (see above), deflated with consumption deflator (see above)</td>
<td>logdiff</td>
</tr>
<tr>
<td>Hours worked</td>
<td>See above</td>
<td>logdiff</td>
</tr>
<tr>
<td>Real wage</td>
<td>Nominal compensation per hour in the nonfarm business sector (FRED: COMPNFB), deflated with consumption deflator (see above)</td>
<td>logdiff</td>
</tr>
<tr>
<td>Inflation</td>
<td>Percentage change in consumption deflator (see above)</td>
<td>none</td>
</tr>
<tr>
<td>Interest rate</td>
<td>Nominal effective Federal Funds Rate (FRED: FEDFUNDS)</td>
<td>none</td>
</tr>
<tr>
<td>Debt issuance / output</td>
<td>Change in level of business sector debt (sum of USFA: FA104122005.Q and FA144123005.Q), divided by real output (see above)</td>
<td>none</td>
</tr>
</tbody>
</table>
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>
<thead>
<tr>
<th>Test statistic</th>
<th>5% critical value</th>
<th>Reject?</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIPA levels</td>
<td>-3.34</td>
<td>-3.43</td>
</tr>
<tr>
<td>NIPA first differences</td>
<td>-5.40</td>
<td>-3.43</td>
</tr>
<tr>
<td>GVC levels</td>
<td>-0.15</td>
<td>-3.43</td>
</tr>
<tr>
<td>GVC first differences</td>
<td>-6.99</td>
<td>-3.43</td>
</tr>
</tbody>
</table>

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

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

B.1 A formal rationalization of the alternative borrowing constraints

**Collateral constraint.** I begin with this constraint, as it is more familiar in the literature. Consider the firm 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 \( b_{k,t} \). 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 \( b_{k,t} \) 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

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

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
\[ s_{k,t} \geq 0 \quad \text{(20)} \]
\[ \theta_k E_t p_{k,t+1} (1 - \delta) k_t - \frac{b_{k,t}}{1 + r_{k,t}} \geq 0, \quad \text{(21)} \]

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 \( \hat{V}^{\text{end}}_{d,t} \) the end-of-period value of the firm after ownership rights have been transferred to the lender. In order to determine this uncertain value, the lender uses the common practice of valuation by multiples.\(^1\) Specifically, she evaluates firm ownership after default by using fixed multiple of the last available realization of a fundamental profitability indicator, EBITDA. Formally,

\[ \hat{V}^{\text{end}}_{d,t} \approx \theta_{\pi} \pi_t. \quad \text{(22)} \]

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

\[ s_{\pi,t} \geq 0 \quad \text{(23)} \]
\[ \theta_{\pi} \pi_t - \frac{b_{k,t}}{1 + r_{k,t}} \geq 0. \quad \text{(24)} \]

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 rights have been transferred. In the case of collateral, there is a rational prediction of the resale value, but a transaction cost needs to be incurred.

\(^1\)For a textbook treatment, see Damodaran (2012).
B.2 Further discussion of the earnings-based constraint

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

The literature on loan covenants can broadly be distinguished between two strands. The first are empirical papers that investigate covenants and their economic effects in firm-level data. This includes the papers that I have cited in Section 2 of the text. Key references are for example Chava and Roberts (2008), Roberts and Sufi (2009a) and Bradley and Roberts (2015). These papers do not provide a fully fledged theoretical rationalization of why loans contain covenants, but mostly take them as a given empirical phenomenon and test their effects in the data. Nevertheless these papers typically do provide some remarks on the rationale for covenants to guide their analysis. The second strand is theoretical work in the (incomplete) contracts literature that directly addresses the microfoundation of covenants. This literature builds on seminal work of Aghion and Bolton (1992) and goes back at least to Jensen and Meckling (1976). One example that directly studies the contractual design of covenants is Garleanu and Zwiebel (2009). See also Diamond, Hu, and Rajan (2017) who lay out a theory of firm financing in which control rights both over asset sales and over cash flows have varying importance over time.

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

Regulation. As mentioned in the main text, an alternative way to think about the earnings-based constraint is the presence of regulation that lenders, in particular banks, are subject to. For example, regulators in the US define “leveraged transactions”, among other criteria, based on the debt-to-EBITDA ratio of borrowers.\footnote{See e.g. the US Interagency Guidance on Leveraged Lending (2013), available at https://www.federalreserve.gov/supervisionreg/srletters/sr1303a1.pdf. Similar definitions can be found in} Whether transactions are defined in this way in turn
affects risk-weights and hedging requirements for lenders.

In the case of mortgages, regulatory requirements on income flows have been highlighted by Greenwald (2018), who also studies collateral (loan-to-value) and flow-related (payment-to-income) constraints. He imposes the two borrowing constraints household debt and refers to them as “institutional rules that are not the outcome of any formal optimization problem”. Given that both collateral and the debt-to-EBITDA ratio also feature in the regulation of lenders that provide fund to nonfinancial firms, an alternative way to think about equations (8) and (9) is that they are the outcome regulation rather than an underlying contracting frictions that lender and borrowing need to overcome.
C Details on the model of Section 3

C.1 Firm optimality conditions

The firm’s optimality conditions with respect to $n_t$, $b_{k,t}$, $b_{\pi,t}$ and $k_t$ and $i_t$ are derived as follows\(^3\)

\[
F_{n,t} = w_t
\]  
\[
R_{k,t} \mathbb{E}_t \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} \right\} + \frac{R_{k,t}}{1 + r_{k,t}} = 1,
\]
\[
R_{\pi,t} \mathbb{E}_t \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} \right\} + \frac{R_{\pi,t}}{1 + r_{\pi,t}} = 1,
\]
\[
Q_t = \mathbb{E}_t \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} \left[ (1 - \delta)Q_{t+1} + F_{k,t+1} + \mu_{\pi,t+1} \sigma \pi F_{k,t+1} + \mu_{k,t} \sigma_k (1 - \delta)p_{k,t+1} \right] \right\}
\]
\[
Q_t v_t \left[ (1 - \Phi_1 - \Phi_{1,t+1}) + \mathbb{E}_t \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} Q_{t+1} v_{t+1} \Phi_{-1,t+1} \right\} = 1 \right.
\]

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 $\Phi_t \left( \frac{i_t}{n_{t-1}} \right)$ and $\Phi_{t+1} \left( \frac{i_{t+1}}{n_t} \right)$ to $i_t$, respectively. The capital price $p_{k,t}$ that is relevant in the collateral constraint is given by (10) in the main text.

C.2 Household, government, and definition of equilibrium

C.2.1 Household problem

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

\[
\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t, n_t),
\]

subject to the budget constraint

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

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

\[
u(c_t, n_t) = \log(c_t) + \chi \log(1 - n_t),
\]

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

\[
uc_t w_t + un_t = 0 \tag{33}
\]

\[
uc_t = \beta (1 + r_{k,t}) E_t u_{ct+1} \tag{34}
\]

\[
uc_t = \beta (1 + r_{\pi,t}) E_t u_{ct+1} \tag{35}
\]

\[
u_{ct} p_t = \beta E_t (d_{t+1} + p_{t+1}) u_{ct+1}, \tag{36}
\]

where $u_{ct}$ and $u_{nt}$ denote marginal utility of consumption and labor, respectively.

**C.2.2 Government**

The lump sum tax $T_t$ is required to finance the tax advantage of debt that is given to the firm, which amounts to the difference between debt issued (valued at $R_j^{-1}$) and debt received (valued at $(1 + r_j)^{-1}$) 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

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

**C.2.3 Equilibrium**

I collect the exogenous states of the model in the vector $x_t = (z_t, v_t, \phi_t)'$. These variables are assumed to follow a stochastic process of the form $x_{t+1} = Ax_t + u_t$, 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: $\Lambda_t = \beta^t u_{ct}$ and $s_t = 1$
4. The government’s budget constraint holds
5. The exogenous disturbances follow $x_{t+1} = Ax_t + u_t$
6. Markets clear

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

C.3 Specification of stochastic processes

The stochastic processes underlying the exogenous disturbances are defined as

\[ \log(z_t) = (1 - \rho_z) \log(z_{t-1}) + u_{z,t} \]
\[ \log(v_t) = (1 - \rho_v) \log(v_{t-1}) + u_{v,t} \]
\[ \log(\phi_t) = (1 - \rho_\phi) \log(\phi_{t-1}) + u_{\phi,t} \]

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

C.4 Sketch of analytical calculation of the steady state

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

1. Drop time subscripts, obtain a system in steady state variables.
2. Steady state must fulfill \(r_j = (1 - \beta)/\beta\), \(R_j = 1 + r(1 - \tau_j)\) and \(\mu_j = (1 + r_f)(1/R_j - \beta)\)
   from bond Euler equations for firm and household, that is, equations (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.

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

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

and set \(\iota\) to 0.999.
C.5 IRF comparison with moving average earnings-based constraint

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

(a) Permanent TFP shock

(b) Permanent investment shock

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

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

(a) Persistent adjustment cost shock

(b) Persistent investment shock with $\Phi = 0$

Note: This figure repeats Figure 4 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 (dark blue line) or only the collateral constraint (light 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 ($\Phi = 0$).
C.6 Model IRFs of additional variables

**Figure C.3:** IRFS TO PERMANENT TFP SHOCK

**Figure C.4:** IRFS TO PERMANENT INVESTMENT SHOCK
D  Additional results for SVAR

D.1  SVAR IRFs to TFP shock

Figure D.1: SVAR IRFs to Positive TFP Shock Identified with Long-Run Restrictions

Note: The figure displays the IRFs to a TFP shock identified from an estimated SVAR model using US data. The identification scheme relies on long-run restrictions following Fisher (2006). The responses are shown for all six variables included in the system, in percent. The unit of the shock is one standard deviation. The sample period used for estimation is 1952:Q2 to 2016:Q4. 68% error bands are calculated using bootstrap techniques. This shock is identified using the same estimation procedure and identification scheme as the investment shock in the main text, but is not used to verify predictions from the theoretical macro model.
D.2 SVAR IRFs using medium-term restrictions

Figure D.2: SVAR IRFs to investment shock identified with medium-horizon restrictions

(a) Identification based on 5-year horizon

(b) Identification based on 10-year horizon

Note: The figure has the same scope as Figure 5 in the main text but uses a different identification scheme. This scheme is based on the method suggested by Francis, Owyang, Roush, and DiCecio (2014). Panel (a) shows the results for a 5-year horizon \((h = 20)\) and Panel (b) for a 10-year horizon \((h = 40)\). In both cases, the responses are shown for all six variables included in the system, in percent. The unit of the shock is one standard deviation. The sample period used for estimation is 1952:Q2 to 2016:Q4. 68% 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.
D.3 SVAR historical decompositions

**Figure D.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 identified with long-run restrictions. The black line is the actual (detrended) data series. The bars indicate the contribution of different structural shocks to the variance of the respective observable as estimated by the SVAR model. The dark blue bars represent investment shocks, the light blue ones TFP shocks, and the contribution of shocks that remain unidentified are shown by the white bars. Shaded areas indicate NBER recessions.
Figure D.4: SVAR: HISTORICAL VARIANCE DECOMPOSITIONS (CONTINUED)

Note: Historical variance decomposition of variables as estimated by the SVAR model identified with long-run restrictions. The black line is the actual (detrended) data series. The bars indicate the contribution of different structural shocks to the variance of the respective observable as estimated by the SVAR model. The dark blue bars represent investment shocks, the light blue ones TFP shocks, and the contribution of shocks that remain unidentified are shown by the white bars. Shaded areas indicate NBER recessions.
D.4 SVAR IRFs using simulated data

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

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

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

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

Note: The figure plots IRFs from an SVAR model estimated on data that is repeatedly simulated from the model in Section 3. Panel (a) uses the data generated with an earnings-based constraint, Panel (b) with a collateral constraint. In both cases, the data is generated from TFP shocks, investment shocks, an additional stationary demand shock. Normal iid measurement error is added to all series. 68% significance sets and means across 10,000 Monte Carlo repetitions are shown.
D.5 SVAR IRFs of used equipment prices

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

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

(a) Used airplane price

(b) Used vehicle price

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

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

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5I thank Andrea Lanteri for kindly sharing this airplane price series.
5I essentially follow Ramey (2016) in constructing the local projection. See also Jordà (2005), as well as Section 4.3 of the main text for additional remarks on local projection methods.
The resulting IRFs are shown in Figure D.6. Both price series show little movement on impact but a negative dynamic response to the investment shock. While the price of used airplanes is reduced significantly after around 5 years, the response of the used vehicle series is generally noisy and not significantly different from zero. In comparison to the IRF of new equipment prices shown in Figure 5 of the main text, both series display a delayed response. Interestingly, this dynamic profile is consistent with the sluggish negative response of debt for collateral borrowers at the micro level in Section 4.3. This suggests that secondary market prices may play a relevant role in the Compustat-Dealscan data used for verification of the mechanism in micro data.
Additional results for firm-level projections

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

**Table E.1: Estimates of the difference between debt IRF coefficients**

<table>
<thead>
<tr>
<th></th>
<th>Classification based on specific assets</th>
<th>Classification based on secured revolvers</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{\text{earn}} - \beta_{\text{coll}}^0$</td>
<td>0.0328</td>
<td>-0.0029</td>
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<tr>
<td></td>
<td>(0.0206)</td>
<td>(0.0241)</td>
</tr>
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<td>$\beta_{\text{earn}} - \beta_{\text{coll}}^1$</td>
<td>0.0308</td>
<td>0.0004</td>
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<td></td>
<td>(0.0268)</td>
<td>(0.0294)</td>
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<td>0.0162</td>
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<tr>
<td></td>
<td>(0.0287)</td>
<td>(0.0319)</td>
</tr>
<tr>
<td>$\beta_{\text{earn}} - \beta_{\text{coll}}^3$</td>
<td>0.0511</td>
<td>0.0511</td>
</tr>
<tr>
<td></td>
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<td>(0.0384)</td>
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<tr>
<td>$\beta_{\text{earn}} - \beta_{\text{coll}}^4$</td>
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<td>0.0464</td>
</tr>
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</tr>
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<td></td>
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<td>(0.0413)</td>
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<td>0.0813*</td>
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<td>(0.0421)</td>
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<tr>
<td></td>
<td>(0.0412)</td>
<td>(0.0453)</td>
</tr>
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</table>

Note: The table shows estimates of the difference between the debt IRFs to investment shocks of earnings borrowers and collateral borrowers as estimated by equation (17) in the main text. The left column shows these estimates for the specification corresponding to Panel (a) of Figure 7 and the right column for Panel (b). Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table shows that the null hypothesis of equal responses across borrower types is rejected at various horizons and for both alternative specifications.
E.2 IV strategy

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

\[
\log(b_{i,t+h}) = \alpha_h + \beta_h p_{k,t} + \gamma X_{i,t} \\
+ \beta_{h,\text{earn}} f_{i,t,\text{earn}} \times p_{k,t} + \alpha_{h,\text{earn}} f_{i,t,\text{earn}} \\
+ \beta_{h,\text{coll}} f_{i,t,\text{coll}} \times p_{k,t} + \alpha_{h,\text{coll}} f_{i,t,\text{coll}} + \gamma t + \eta_{i,t+h},
\]

(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 7, are shown in Figure E.1 below. They paint a very similar picture to the results in the main text. The responses are smaller in magnitude, and standard errors are lower relative to when the shock is used as a regressor directly.
Figure E.1: FIRM-LEVEL IRFS TO FALL IN INVESTMENT PRICE, INSTRUMENTED WITH IST SHOCK

(a) Using collateral classification based on specific assets

(b) Using collateral classification based on secured revolvers

Note: This figure repeats Figure 7 from the text but instead plots the IRFs to a fall in the relative price of investment, instrumented with the investment shock, see equation (E.1) above. In both panels of the figure, the debt IRF for borrowers with earnings covenants and no collateral (left) and borrowers without earnings covenants but with collateral (right) are plotted. The results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks). 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 database. 90% bands are calculated using two-way clustered standard errors by firm and quarter. The IRFs shown in the figure are consistent with the model’s prediction of a positive debt response under an earnings-based constraint and a negative one under a collateral constraint.
### E.3 Results for specification with firm fixed effects

**Figure E.2:** FIRM-LEVEL IRF S INvestment Shock: Firm Fixed Effects Specification

(a) Using collateral classification based on specific assets

(b) Using collateral classification based on secured revolvers

Note: This figure repeats Figure 7 from the text for a regression specification with firm-fixed effects. The figure displays average IRFs of firm borrowing for different firm groups, estimated using the method of Jordà (2005) in a panel data context, see equation (17). In both panels of the figure, the debt IRF for borrowers with earnings covenants and no collateral (left) and borrowers without earnings covenants but with collateral (right) are plotted. Panel (a) uses the collateral classification based on whether a loan is backed by specific assets or not (see details in Section 2). Panel (b) uses an alternative grouping where secured revolvers are categorized as collateralized debt (see Lian and Ma, 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 database. 90% bands are calculated using standard errors clustered at the 3-digit industry level. The IRFs shown in the figure are consistent with the model’s prediction of a positive debt response under an earnings-based constraint and a negative one under a collateral constraint.
E.4 Results for all four firm groups

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

Note: This figure repeats Panel (a) of Figure 7 in the main text, and additionally plots the IRFs of the remaining two firm groups: borrowers with both earnings covenants and collateral, and borrowers with neither. The results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks). The investment shock is identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). The data set used is a merge of Dealscan loan-level information, with balance sheet variables from the Compustat quarterly database. 90% bands are calculated using two-way clustered standard errors by firm and quarter.
Figure E.4: IRFS FOR ALL FOUR CATEGORIES: COLLATERAL CLASSIFICATION BASED ON SECURED REVIDERS

Note: This figure repeats Panel (b) of Figure 7 in the main text, and additionally plots the IRFs of the remaining two firm groups: borrowers with both earnings covenants and collateral, and borrowers with neither. The results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks). The investment shock is identified using the SVAR model in the previous section, based on long-run restrictions following Fisher (2006). The data set used is a merge of Dealscan loan-level information, with balance sheet variables from the Compustat quarterly database. 90% bands are calculated using two-way clustered standard errors by firm and quarter.
E.5 The response of firm-level investment

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

\[
\log(\text{inv}_{i,t+h}) = \alpha_h + \hat{\beta}_h u_{IST,t} + \gamma X_{i,t} + \tilde{\beta}_{\text{earn}} h_{i,t,\text{earn}} \times u_{IST,t} + \alpha_{\text{earn}} h_{i,t,\text{earn}} + \tilde{\beta}_{\text{coll}} h_{i,t,coll} \times u_{IST,t} + \alpha_{\text{coll}} h_{i,t,coll} + \delta_t + \eta_{i,t+h},
\]

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

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

Table E.2 presents the coefficient estimates of the difference between earnings and collateral borrowers’ debt IRFs \((\tilde{\beta}_{\text{earn}} - \tilde{\beta}_{\text{coll}})\), and the related standard errors horizon by horizon. This serves as a formal test of the difference between the IRFs shown in Figure E.5. These results show, similar to the results for debt in Table E.1, that the null hypothesis of equal responses across borrower types is rejected at various horizons and for both alternative ways of constructing the collateral borrower dummy.
Figure E.5: FIRM-LEVEL IRFS OF INVESTMENT TO INVESTMENT SHOCK FOR DIFFERENT BORROWER TYPES

(a) Using collateral classification based on specific assets

(b) Using collateral classification based on secured revolvers

Note: The figure displays average IRFs of firm investment (capital expenditures) within different firm groups, estimated using the method of Jordà (2005) in a panel context. In both panels, the investment IRF for borrowers with earnings covenants and no collateral (left) and borrowers without earnings covenants but with collateral (right) are plotted. The results are based on a specification with detailed firm-level controls (3-digit industry fixed effects, size as measured by number of employees, growth of real sales and other macroeconomic shocks). 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 database. 90% bands are calculated using two-way clustered standard errors by firm and quarter. The IRFs shown in the figure are consistent with the model’s prediction of a positive debt response under an earnings-based constraint and a negative one under a collateral constraint. A formal test rejects the null hypothesis of equal responses across the two firm types for various horizons, as shown in Table E.2 below.
## Table E.2: Estimates of the Difference between Investment IRF Coefficients

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<td>0.0484</td>
</tr>
<tr>
<td></td>
<td>(0.0321)</td>
<td>(0.0370)</td>
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<tr>
<td>$\beta_{earn}^4 - \beta_{coll}^4$</td>
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<tr>
<td></td>
<td>(0.0374)</td>
<td>(0.0430)</td>
</tr>
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</table>

Note: The table shows estimates of the difference between the IRFs of firm-level capital expenditures to investment shocks of earnings borrowers and collateral borrowers as estimated by equation (17) in the main text. The left column shows these estimates for the specification corresponding to Panel (a) of Figure 7 and the right column for Panel (b). Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table shows that the null hypothesis of equal responses across borrower types is rejected at various horizons and for both alternative specifications.
F Details on the quantitative model of Section 5

F.1 Model setup

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

F.1.1 Final good firm

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

$$ Y_t = \left( \int_0^1 y_{i,t}^{\frac{1}{\eta_t}} \; di \right)^{\eta_t} . \tag{43} $$

$\eta_t$ 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

$$ p_{i,t} = P_t Y_t^{\frac{\eta_t - 1}{\eta_t}} \frac{1 - \eta_t}{y_{i,t}^{\eta_t}} \tag{44} $$

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

F.1.2 Intermediate goods firms

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

$$ y_{i,t} = z_t (u_{i,t} k_{i,t-1})^{\alpha} n_{i,t}^{1 - \alpha} , \tag{45} $$

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:

$$ n_{i,t} = \left( \int_0^1 \frac{1}{n_{j,i,t}} \; dj \right)^{\varphi_t} , \tag{46} $$
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

$$\pi_{i,t} \equiv y_{i,t} - w_{i,t} n_{i,t}. \quad (47)$$

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

$$k_{i,t} = (1 - \delta) k_{i,t-1} + v_t \left[ 1 - \frac{\phi}{2} \left( \frac{i_{i,t}}{i_{i,t-1}} \right)^2 \right] i_{i,t}. \quad (48)$$

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

Firms take (44) 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

$$p_{i,t} = P_t Y_t^{\frac{1-\alpha}{\eta_t}} \left( z_t (u_{i,t} k_{i,t-1})^{\alpha} n_{i,t}^{1-\alpha} \right)^{\frac{1-\alpha}{\eta_t}}. \quad (49)$$

The capital utilization cost is specified as

$$\Xi(u_t) = \xi_1 (u_t^{1+\xi_2} - 1)/(1 - \xi_2) \quad (50)$$

The parameter $\xi_1$ 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

$$\tilde{\Phi}(p_{i,t-1}, p_{i,t}, Y_t) = \frac{\tilde{\varphi}}{2} \left( \frac{p_{i,t}}{p_{i,t-1}} - 1 \right)^2 Y_t. \quad (51)$$

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 (48) and the demand function given by (44). They now also choose their price $p_{i,t}$ and utilization rate $u_{i,t}$, in addition to $d_{i,t}, n_{i,t}, i_{i,t},$.
k_{i,t}, and b_{i,t}.

F.1.3 Households

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

\[
E_0 \sum_{t=0}^{\infty} \gamma_t \beta^t \left( \frac{(c_{j,t} - h c_{j,t-1})^{1-\sigma}}{1 - \sigma} - \frac{\chi n_{j,t}^{1+\frac{1}{\sigma}}}{1 + \frac{1}{\sigma}} \right)
\]

where \( \gamma_t \) is a preference disturbance and \( h \) captures external consumption habits. The parameter \( \epsilon \) 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

\[
c_{j,t} + \frac{b_{j,t}}{1 + r_t} + p_t s_{j,t} + T_{j,t} + \int \bar{q}_{j,t+1} a_{j,t+1} d\omega_{j,t} = w_{j,t} n_{j,t} + b_{j,t-1} + P_t d_{j,t} + p_t s_{j,t-1}.
\]

\( a_{j,t+1} \) are holdings of state-contingent claims with which households can insure against wage shocks. They are traded at price \( q_{j,t+1} \). The notation in (53) is otherwise similar as in the stylized mode of Section 3.

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

\[
n_{j,t} = \left( \frac{w_{j,t}}{W_t} \right)^{-\frac{\theta_t}{\theta_t-1}} n_t,
\]

where \( W_t \) and \( n_t \) are the aggregate wage and employment level, respectively. (54) is taken as given by the household when choosing \( n_{j,t} \) and \( w_{j,t} \).

Households face wage rigidities, which arise, in the spirit of Calvo, from the fact that a given firm can only change their wage with probability \( (1 - \bar{\omega}) \). From the optimization problem I derive a log-linear optimal wage equation. Given that all households make the same choices, this implies a sluggish low of motion for the aggregate wage rate \( W_t \) (for details, see Jermann and Quadrini, 2012).

Household’s optimality condition for bonds implies an Euler equation in which the real return \( (1 + r_t) \left( \frac{P_t}{P_{t+1}} \right) \) is priced with the stochastic discount factor \( SDF_{t,t+1} = \frac{\Lambda_{t+1}}{\Lambda_t} = \frac{\beta \gamma_{t+1} u_{ct+1}}{\gamma_t u_{ct}} \), where \( u(\cdot) \) denotes the period utility function in (52).

F.1.4 Government

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

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

### F.1.5 Monetary policy

There is a Taylor rule specified as

\[
1 + r_t = \left[ 1 + r_{t-1} \right]^{\rho_R} \left[ \left( \frac{\pi_t^P}{\pi_t} \right)^{\nu_1} \left( \frac{Y_t}{Y_{t-1}} \right)^{\nu_2} \frac{1}{1 + \bar{r}} \right]^{1 - \rho_R} \left[ \frac{Y_t/Y^*_t}{Y_{t-1}/Y^*_t} \right]^{\nu_3} \varsigma_t, \tag{56}
\]

such that interest rates react to deviations of inflation from steady state, output growth, and output growth in deviations from it steady state.\(^6\) Beware that I denote inflation by \( \pi_t^P \), not to be confused with firm profits \( \pi_{i,t} \). \( \rho_R > 0 \) captures interest rate smoothing. \( \varsigma_t \) is a stochastic disturbance that captures monetary policy shocks.

### F.1.6 Stochastic processes

The model features eight structural disturbances, capturing shocks to TFP, investment, preferences, price markups, wage markups, fiscal policy, monetary policy and financial conditions. The follow autoregressive processes of order one:

\[
\begin{align*}
\log(z_t) &= (1 - \rho_z) \log(\bar{z}) + \rho_z \log(z_{t-1}) + u_{z,t} \tag{57} \\
\log(v_t) &= (1 - \rho_v) \log(\bar{v}) + \rho_v \log(v_{t-1}) + u_{v,t} \tag{58} \\
\log(\gamma_t) &= (1 - \rho_\gamma) \log(\bar{\gamma}) + \rho_\gamma \log(\gamma_{t-1}) + u_{\gamma,t} \tag{59} \\
\log(\eta_t) &= (1 - \rho_\eta) \log(\bar{\eta}) + \rho_\eta \log(\eta_{t-1}) + u_{\eta,t} \tag{60} \\
\log(\theta_t) &= (1 - \rho_\theta) \log(\bar{\theta}) + \rho_\theta \log(\theta_{t-1}) + u_{\theta,t} \tag{61} \\
\log(g_t) &= (1 - \rho_g) \log(\bar{g}) + \rho_g \log(g_{t-1}) + u_{g,t} \tag{62} \\
\log(\varsigma_t) &= (1 - \rho_\varsigma) \log(\bar{\varsigma}) + \rho_\varsigma \log(\varsigma_{t-1}) + u_{\varsigma,t} \tag{63} \\
\log(\xi_t) &= (1 - \rho_\xi) \log(\bar{\xi}) + \rho_\xi \log(\xi_{t-1}) + u_{\xi,t} \tag{64}
\end{align*}
\]

The error terms follow standard deviations \( \{\sigma_z, \sigma_v, \sigma_\gamma, \sigma_\eta, \sigma_\theta, \sigma_G, \sigma_\varsigma, \sigma_\xi\} \). 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 \( \bar{\theta} \).

---

\(^6\) See Jermann and Quadrini (2012) for more details.
### F.2 Additional results from estimated quantitative model

#### F.2.1 Parameter estimates

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<th>Prior shape</th>
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<th>Prior Std</th>
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F.2.2 Additional sign differences in debt responses.

Figure F.1 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 marginal utility), 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 $\omega = 0$ (dark blue and light orange lines, respectively). The figure shows that the two alternative borrowing constraints imply opposite signs of the responses of debt also for additional shocks in the model. This is because, similar to the investment shock, both shocks raise earnings but suppress the value of capital. The intuition for the preference shock is that the relative marginal utility between today and tomorrow is raised by the shock. Firms, acting on behalf of the household, cut back on investment, shift resources to the present and pay out dividends. Earnings rise and the capital stock next period is reduced. The intuition for the markup shock is that it allows firms to cut back on production inputs, reducing capital, but simultaneously realize higher profits due to the higher markup. 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 $\omega$ is close to, but not equal to, 1.

Figure F.1: Debt IRF to additional shocks across model counterfactuals

(a) Preference shock

(b) Price markup shock

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 (dotted black line) and for counterfactual models which are the weight of the earnings-based constraint is set to 1 (dark blue line) and 0 (light orange line), but all other parameters are kept at their estimated values.
F.3 Results from alternative versions of the quantitative model

F.3.1 Variance decomposition for model without borrowing constraints

Table F.3: Variance decomposition of observables without borrowing constraints (in %)

<table>
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<tr>
<th></th>
<th>TFP</th>
<th>Inv</th>
<th>Pref</th>
<th>Price</th>
<th>Wage</th>
<th>Gov</th>
<th>Mon</th>
<th>Fin</th>
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<td>1.5</td>
<td>11.7</td>
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<td>14.7</td>
<td>7.6</td>
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<td>7.7</td>
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<td>12.1</td>
<td>34.2</td>
<td>17.5</td>
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<td>13.7</td>
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<td>8.2</td>
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<td>33.0</td>
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<td>0.52</td>
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</table>

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.

F.3.2 Estimated weight on constraints in model without investment shocks

Figure F.2: Weight on earnings-based component in model without investment shocks

Note: The figure presents the prior and posterior density (grey and black solid lines, respectively) over values of $\omega$, as estimated in an alternative version of the quantitative New Keynesian model from Section 5. This model does not feature investment shocks and investment growth is not used as an observable in the estimation. 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).