ONLINE APPENDIX

Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations

by Thomas Drechsel

Contents

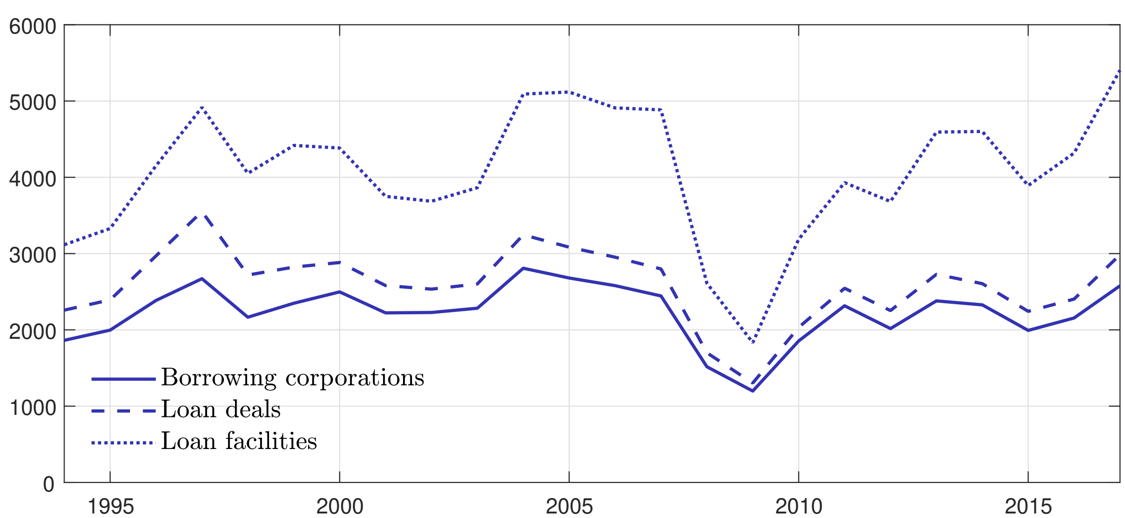
A Details on the data

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

A.1 Thomson Reuters LPC Dealscan data set

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

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



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

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

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

Table A.1: SUMMARY STATISTICS FOR DEALSCAN DATA

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

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

Table A.2: INDUSTRY COVERAGE IN DEALSCAN DATA

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

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

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

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

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

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

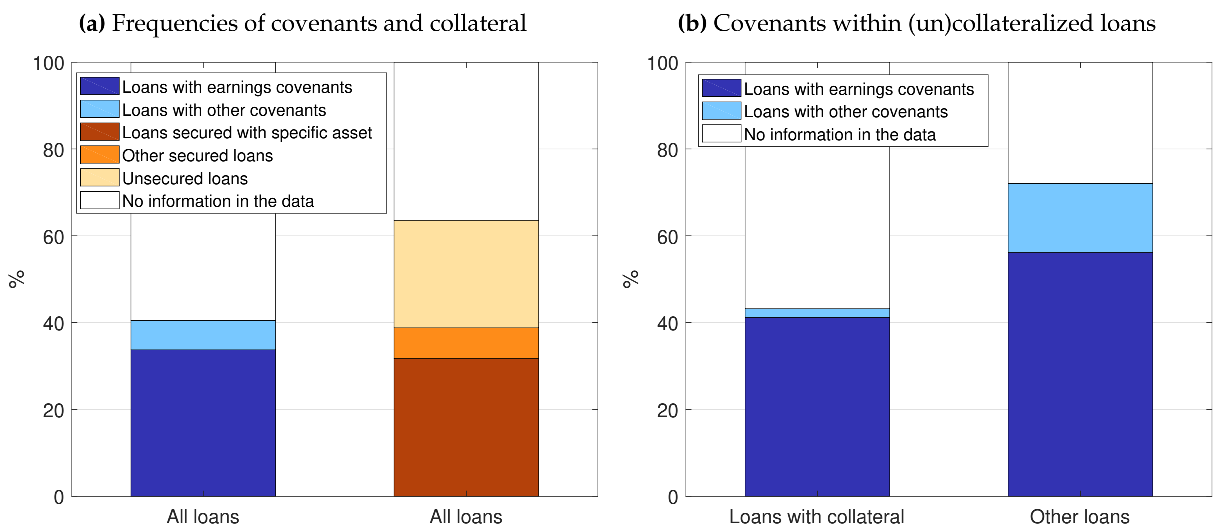
Collateral type	**Number of loan facilities**	**Volume in bn USD**
Property & Equipment	2356	427
Accounts Receivable and Inventory	1879	394
Intangibles	1398	268
Cash and Marketable Securities	1009	365
Real Estate	743	155
Ownership of Options/Warrants	104	20
Patents	81	12
Plant	51	14
Agency Guarantee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

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

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

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

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



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

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

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

A.3 Merged Compustat-Dealscan panel data set

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

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

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

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

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

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

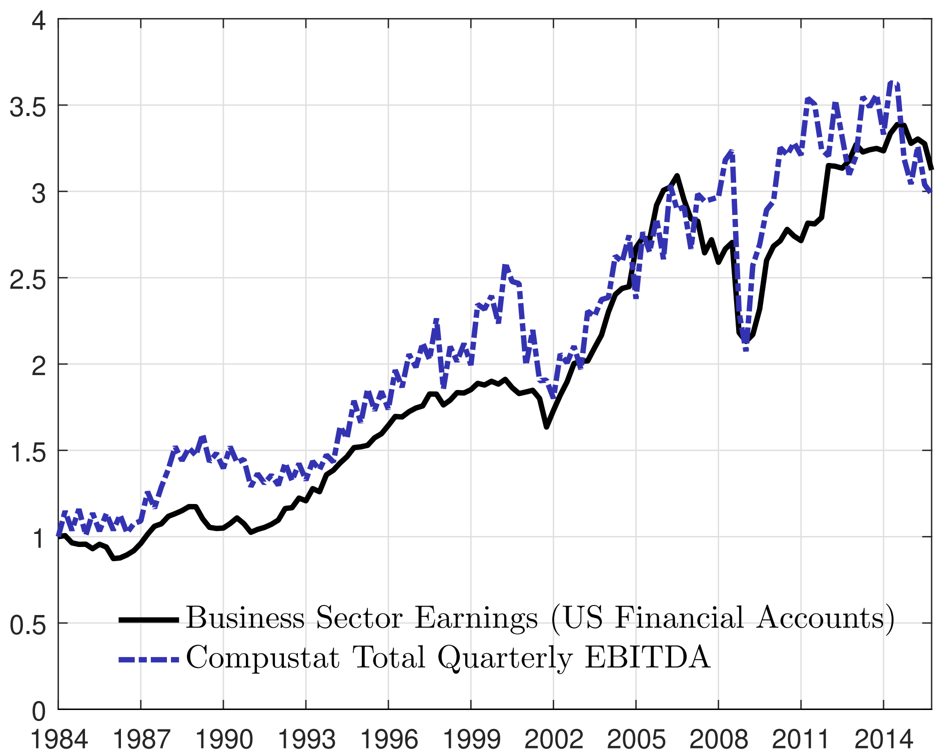
	Firm-qrt obs	Mean	SD	Min	Median	Max
Panel (a): Borrower-quarter observations in which loans have earnings covenants only ($N = 1,844$)						
Real total assets (bn 2009 USD)	53,136	7.5	21.7	0.0	2.1	552.7
Real sales (bn 2009 USD)	53,544	1.5	3.4	0.0	0.5	55.8
Real sales growth (percent)	53,304	3.9	16.3	-30.8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

A.4 Aggregate data used for SVAR and model estimation

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

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

Figure A.3: US FINANCIAL ACCOUNTS VS. COMPUSTAT



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

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

Panel (a): Data used in estimation of SVAR

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

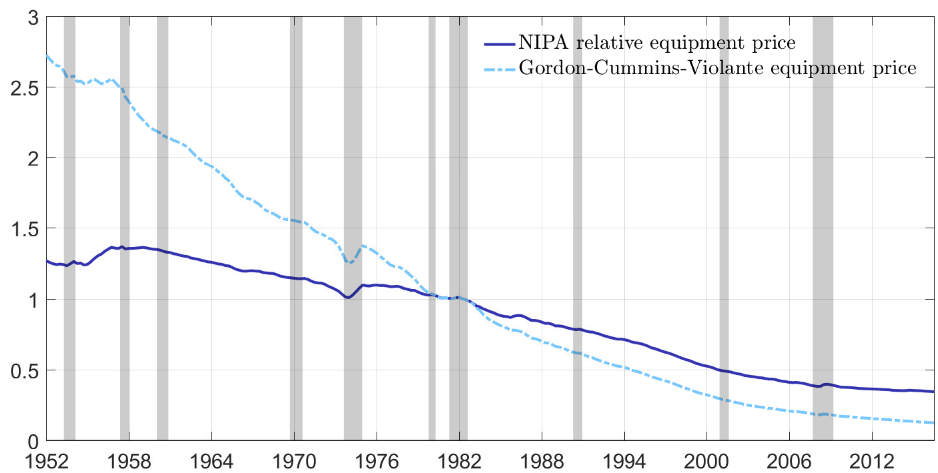
Panel (b): Data used in estimation of New Keynesian model

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

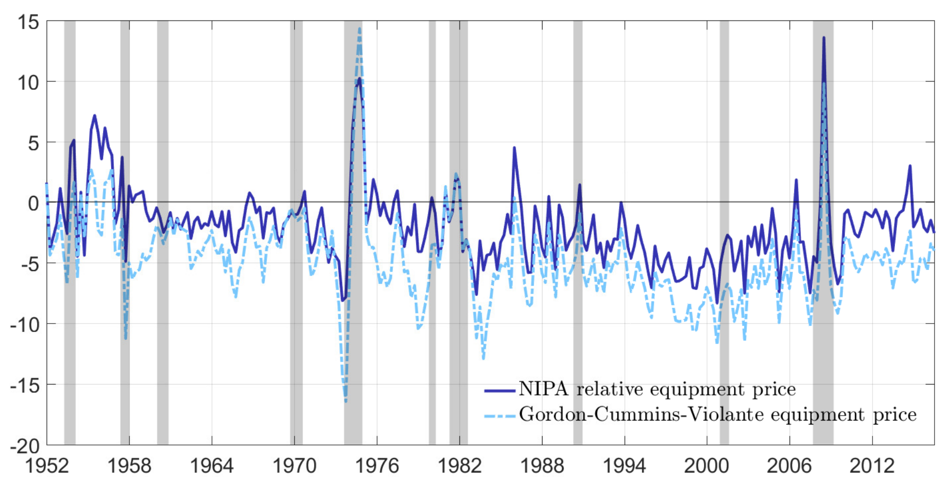
Details on relative equipment prices. Figure A.4 compares the two alternative measures used for the relative price of equipment investment. The first is the one based on NIPA data, constructed as the ratio between the equipment investment deflator and the deflator of consumption on nondurables and services.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

Figure A.4: MEASURES OF THE RELATIVE EQUIPMENT PRICE

(a) Levels (1982:Q3 = 100)



(b) Growth rates (annualized %)



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

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

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

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

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

A.5 Constructing industry-level equipment price sensitivities

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

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

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

$$-\Delta \log p_{k,s,t} = \lambda_s \hat{u}_{IST,t} + \varepsilon_{s,t} \tag{1}$$

I take the negative because I would like to use estimates of λ_s to construct a regressor that enters in the local projections as an "industry-specific investment shock", that is, is a shock that is *inversely* related to the price of equipment in a given industry. I take the log difference, in line with the fact that the SVAR system is set up such that $\hat{u}_{IST,t}$ is defined as a permanent shock to the log difference of the aggregate equipment price. After estimating (1), I construct

$$\hat{u}_{IST,s,t} = \hat{\lambda}_s \hat{u}_{IST,t} \tag{2}$$

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

Note that while the local projection are quarterly, I can only run (1) at annual frequency. Since $\hat{\lambda}_s$ is time-invariant, this should only affect the precision of the estimates but is not a conceptual issue. To estimate (1), I use the same sample as for the SVAR, 1952-2017. The results are very similar when I end the sample for (1) in 1993, prior to the sample start for the local projections in the main text in 1994. In this case the $\hat{\lambda}_s$ coefficient can be interpreted more directly as 'Bartik' weights. My preferred version uses the longer sample as the baseline to increase the precision of the $\hat{\lambda}_s$ estimates at annual frequency.

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

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

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

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

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

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

B Discussion of microfoundation

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

B.1 A formal rationalization of the alternative borrowing constraints

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

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

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

$$s_t^k + \frac{b_t^k}{1+r_t} \geq \theta_k \mathbb{E}_t p_{k,t+1}^k (1-\delta) k_t^k. \tag{3}$$

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 (3), we obtain

$$
\begin{aligned}
s_t^k &\geq 0 && (4)\\
\theta_k \mathbb{E}_t p_{k,t+1}^k (1-\delta) k_t^k - \frac{b_t^k}{1+r_t} &\geq 0, && (5)
\end{aligned}
$$

which can be rearranged to the collateral constraint in the main text.

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

Formally, the lender makes the approximation

$$
\tilde{V}_{d,t}^{end} \approx \theta_\pi \pi_t^\pi. \tag{6}
$$

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

$$
\begin{aligned}
s_t^\pi &\geq 0 && (7)\\
\theta_\pi \pi_t^\pi - \frac{b_t^\pi}{1+r_t} &\geq 0. && (8)
\end{aligned}
$$

The last inequality can be arranged to the earnings-based borrowing constraint introduced in the main 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 the alternative borrowing

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

constraints 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.

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

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

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

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

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

C Details on the model

C.1 Model setup

C.1.1 Firm optimality conditions

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

$$\lambda_{i,t} = \frac{1}{P_t \Psi_{d,i,t}} \tag{9}$$

$$P_t \left[\Upsilon_{2,i,t} + \mathbb{E} m_{t+1} \left(\frac{\Psi_{d,i,t}}{\Psi_{d,i,t+1}} \right) \Upsilon_{1,i,t+1} \right] - \zeta_{i,t} \Psi_{d,i,t} = 0 \tag{10}$$

$$Q_{i,t} v_t \Phi_{2,i,t} + \mathbb{E} m_{t+1} Q_{i,t+1} v_{t+1} \Phi_{1,i,t+1} - \frac{1}{\Psi_{d,i,t}} = 0 \tag{11}$$

$$\frac{\lambda_{i,t}}{R_t} - \frac{\mu_{i,t}}{P_t(1+r_t)} - \mathbb{E} m_{t+1} \lambda_{i,t+1} = 0 \tag{12}$$

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

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

$$\frac{F^k_{n,i,t} - W_t/P_t}{\Psi^k_{d,i,t}} - \zeta^k_{i,t} D^k_{n,i,t} = 0 \tag{13}$$

$$\frac{F^\pi_{n,i,t} - W_t/P_t}{\Psi^\pi_{d,i,t}} - \zeta^\pi_{i,t} D^\pi_{n,i,t} + \mu^\pi_{i,t} \theta_\pi \left(F^\pi_{n,i,t} - W_t/P_t \right) = 0 \tag{14}$$

$$-Q^k_{i,t} + \mu^k_{i,t} \theta_k (1-\delta) \mathbb{E} p^k_{k,t+1} + \mathbb{E} m_{t+1} \left(\frac{F^k_{k,i,t+1}}{\Psi^k_{d,i,t+1}} - \zeta^k_{i,t+1} D^k_{k,i,t+1} + (1-\delta) Q^k_{i,t+1} \right) = 0 \tag{15}$$

$$-Q^\pi_{i,t} + \mathbb{E} m_{t+1} \left(\frac{F^\pi_{k,i,t+1}}{\Psi^\pi_{d,i,t+1}} + \mu^\pi_{i,t+1} \theta_\pi F^\pi_{k,i,t+1} - \zeta^\pi_{i,t+1} D^\pi_{k,i,t+1} + (1-\delta) Q^\pi_{i,t+1} \right) = 0 \tag{16}$$

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

$$p_{i,t} = P_t Y_t^{(\eta_t - 1)/\eta_t} \left[z k^\alpha_{i,t} n^{1-\alpha}_{i,t} \right]^{(1-\eta_t)/\eta_t} \equiv P_t D_{i,t} \tag{17}$$

$$p_{i,t} y_{i,t} = P_t Y_t^{(\eta_t - 1)/\eta_t} \left[z k^\alpha_{i,t} n^{1-\alpha}_{i,t} \right]^{1/\eta_t} \equiv P_t F_{i,t} \tag{18}$$

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

C.1.2 Aggregation

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

$$Y_t = \left(\int_0^1 y_{i,t}^{\frac{1}{\eta}} di\right)^{\eta} = \left((1-\chi)(y^k_t)^{\frac{1}{\eta}} + \chi(y^\pi_t)^{\frac{1}{\eta}}\right)^{\eta} \tag{19}$$

$$P_t = \left(\int_0^1 p_{i,t}^{\frac{1}{1-\eta}} di\right)^{1-\eta} = \left((1-\chi)(p^k_t)^{\frac{1}{1-\eta}} + \chi(p^\pi_t)^{\frac{1}{1-\eta}}\right)^{1-\eta} \tag{20}$$

$$N_t = (1-\chi)n^k_t + \chi n^\pi_t \tag{21}$$

$$I_t = (1-\chi)i^k_t + \chi i^\pi_t \tag{22}$$

$$B_t = (1-\chi)b^k_t + \chi b^\pi_t, \tag{23}$$

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

C.1.3 Household and government sector

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

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}}\right) \tag{24}$$

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

$$C_t + \sum_{j[\chi]} \left\{\frac{b^j_t}{(1+r_t)P_t} + p^j_{f,t}s^j_t\right\} + T_t = w_t N_t + \sum_{j[\chi]} \left\{\frac{b^j_{t-1}}{P_t} + (d^j_t + p^j_{f,t})s^j_{t-1}\right\}, \tag{25}$$

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

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

$$P_t T_t = \sum_{j[\chi]} \left(\frac{b_t^j}{R_t} - \frac{b_t^j}{(1+r_t)} \right), \tag{26}$$

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

The monetary authority follows an interest rate rule specified as

$$\frac{1+r_t}{1+\bar{r}} = \left(\frac{\pi_t^p}{\bar{\pi}^p} \right)^{\nu}, \tag{27}$$

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

C.1.4 Details on model parameterization and specification

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

$$\Phi\left(\frac{i_{i,t}^j}{i_{i,t-1}^j} \right) = \frac{\phi}{2} \left(\frac{i_{i,t}^j}{i_{i,t-1}^j} - 1 \right)^2. \tag{28}$$

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

$$\Upsilon(p_{i,t-1}^j, p_{i,t}^j, Y_t) = \frac{\upsilon}{2} \left(\frac{p_{i,t}^j}{p_{i,t-1}^j} - 1 \right)^2 Y_t \tag{29}$$

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

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

Table C.1: MODEL PARAMETERIZATION

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

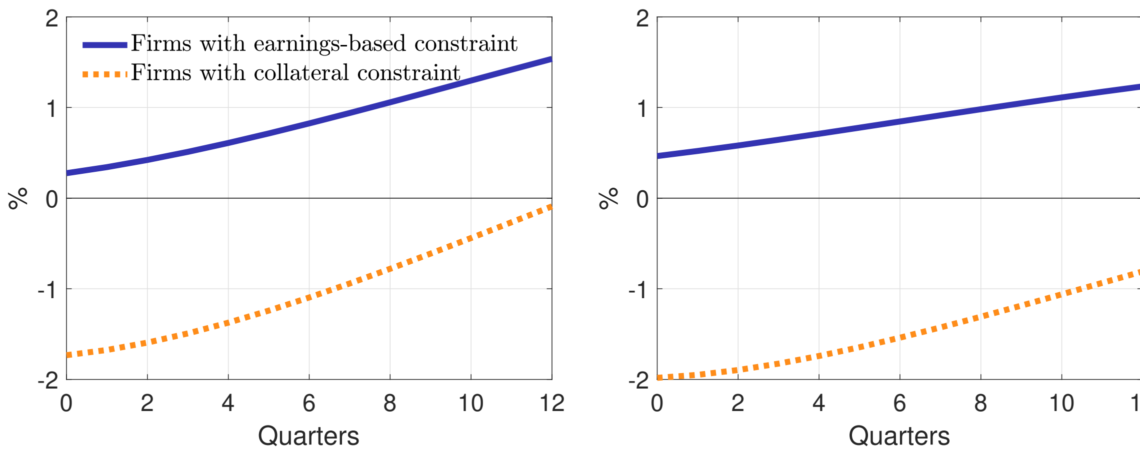
Notes. * indicates parameters that are calculated directly from Dealscan.

C.2 Additional model results

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

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

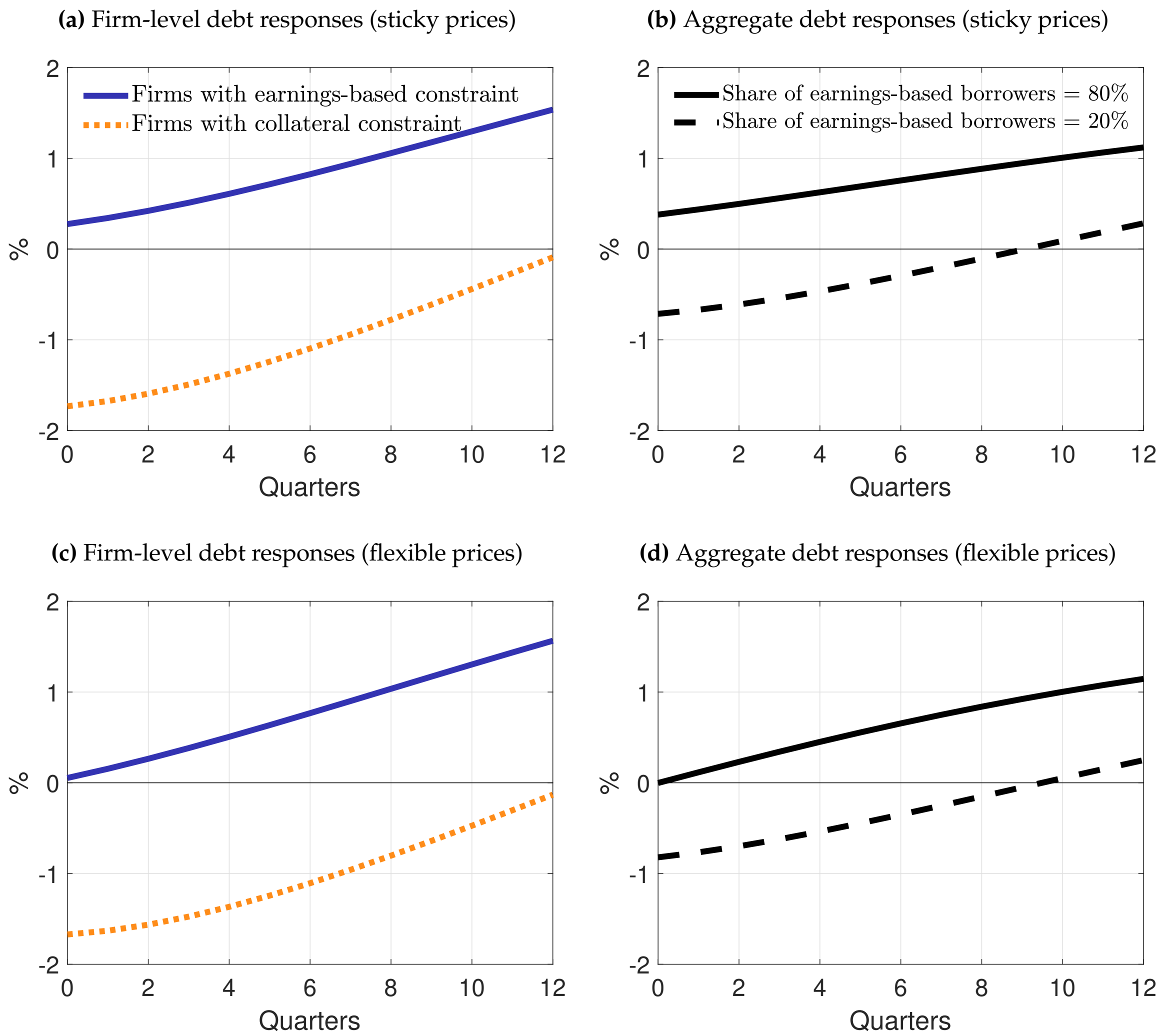
(a) Borrower type-specific investment shock | **(b)** Aggregate investment shock



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

C.2.2 Sticky vs. flexible prices

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



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

(b) Aggregate debt responses (sticky prices)

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

(d) Aggregate debt responses (flexible prices)

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

C.2.3 Alternative version with long-term debt

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

$$\begin{aligned} P_t\Psi(d_{i,t}) + P_t i_{i,t} + P_t\Upsilon(p_{i,t-1}, p_{i,t}, Y_t) + (c+\gamma)\widetilde{b}_{i,t-1} = \\ (p_{i,t}y_{i,t} - W_t n_{i,t}) + q_t(\widetilde{b}_{i,t} - (1-\gamma)\widetilde{b}_{i,t-1}) \end{aligned} \tag{30}$$

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

$$\bar{q}_t \frac{\widetilde{b}^{\pi}_{i,t}}{P_t} \leq \theta_\pi \pi^{\pi}_{i,t} \tag{31}$$

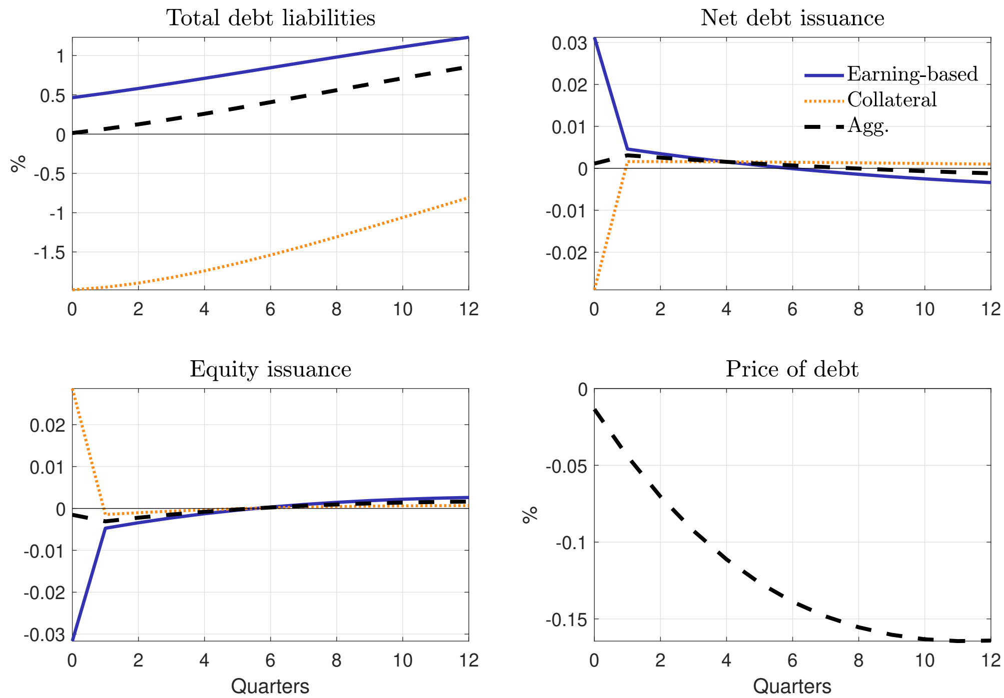
$$\bar{q}_t \frac{\widetilde{b}^{k}_{i,t}}{P_t} \leq \theta_k \mathbb{E}_t p^k_{k,t+1}(1-\delta)k^k_{i,t}, \tag{32}$$

where $\bar{q}_t$ is the bond price paid by the lenders. Equations (31) and (32) capture that the level of total liabilities is constrained by a multiple of earnings and a fraction of capital, respectively. This is in line with the empirical evidence, where covenant indicators, such as the debt-to-earnings ratio, are usually calculated based on *all* liabilities of the firm, including existing liabilities. Chava and Roberts (2008), among others, discuss how covenants are in fact imposed to avoid dilution of existing debt holders.

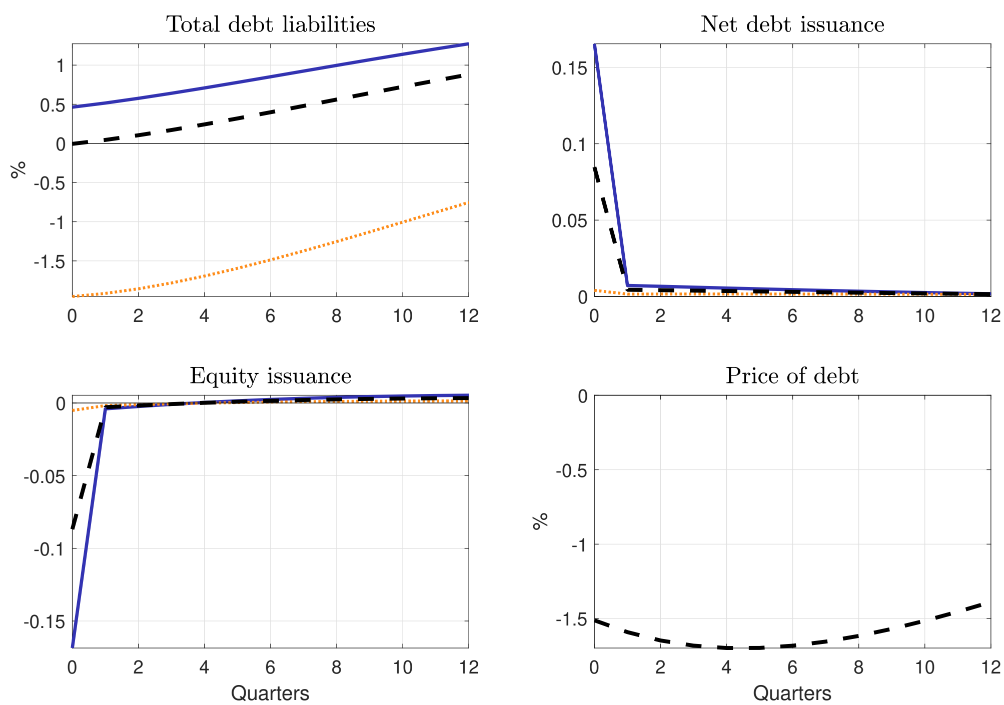
Comparison of investment shock dynamics. I set $\gamma = 0.05$ to match the average debt maturity of 5 years in Dealscan, and β and c to match the average interest rate (in the same way as for the baseline model in the text). Figure C.3 shows the responses of selected variables to an aggregate investment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

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

(a) Selected IRFs with short-term debt specification



(b) Selected IRFs with long-term debt specification



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

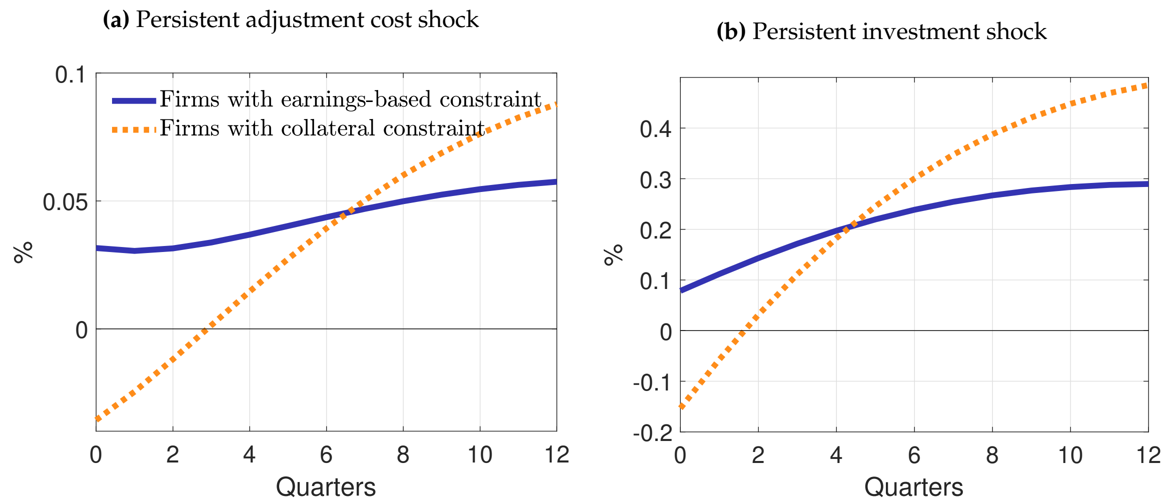
The main difference between the two settings lies in how net debt issuance, the price of debt, and equity issuance adjust to the shock. In Figure C.3, real net debt issuance is computed as $(q_t(\widetilde{b}_{i,t} - (1-\gamma)\widetilde{b}_{i,t-1}) - \gamma\widetilde{b}_{i,t})/P_t$, where for short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

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

C.2.4 Different types of investment shocks

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

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



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

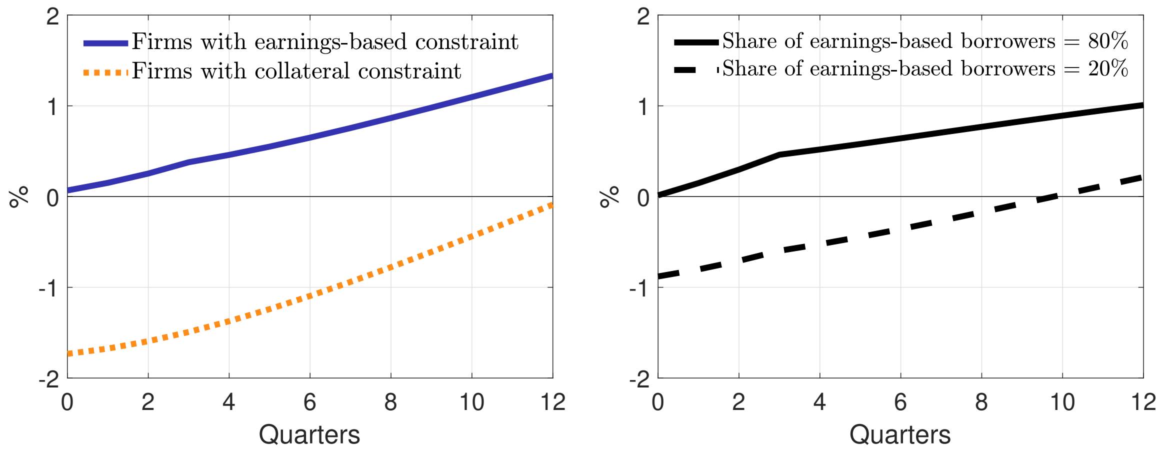
To demonstrate this, Figure C.4 examines IRFs to different shocks that all affect the relative price of investment. In Panel (a), the IRFs to a negative transitory adjustment cost shock across the two borrower types are plotted. To allow for a shock to adjustment costs I make the parameter ϕ time-varying,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

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

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

(a) Firm-level debt responses

(b) Aggregate debt responses



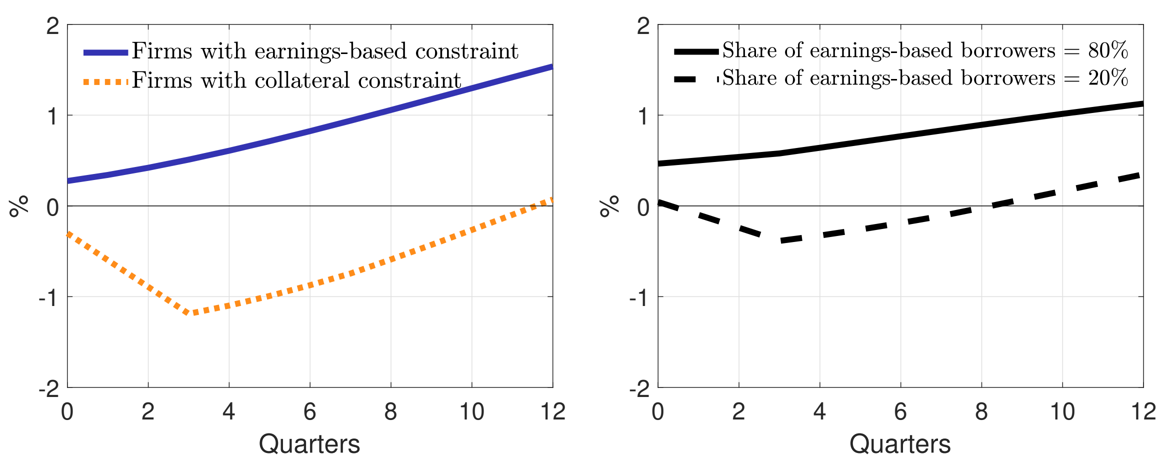
Notes. This figure shows the main model IRFs from the main text for a formulation of the earnings-based constraint in which current and three lags of earnings enter on the right hand side of the constraint. This is based on the idea that covenants may in practice be evaluated based on a 4-quarter trailing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

C.2.6 Collateral constraint with capital evaluated at historical costs

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

(a) Firm-level debt responses

(b) Aggregate debt responses



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

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

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

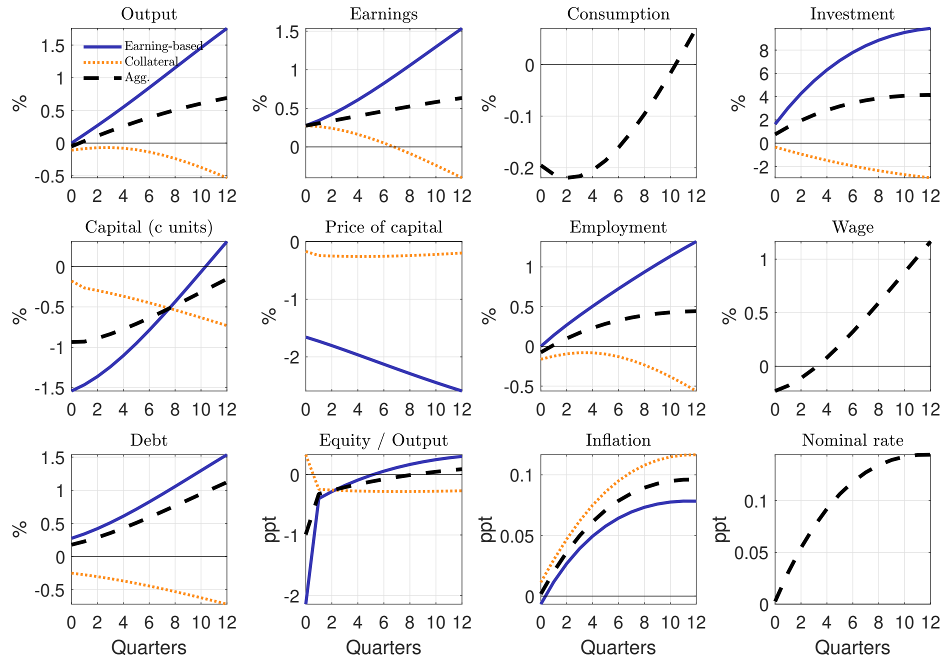


Figure C.8: MODEL IRFS TO INVESTMENT SHOCK TO FIRM TYPE $j = k$ WITH $\chi = 0.5$

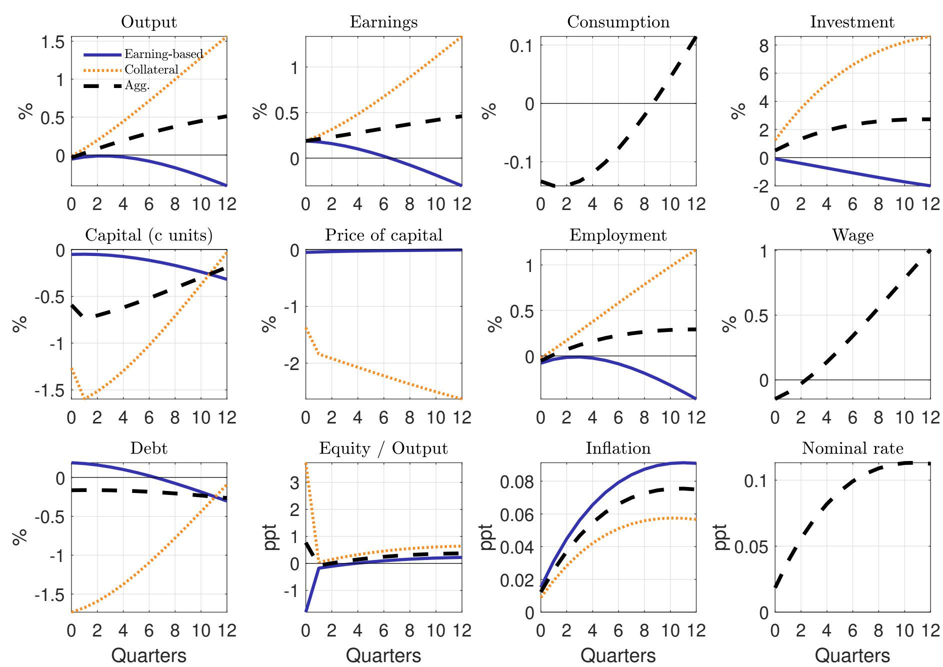


Figure C.9: MODEL IRFS TO AGGREGATE INVESTMENT SHOCK WITH $\chi = 0.2$

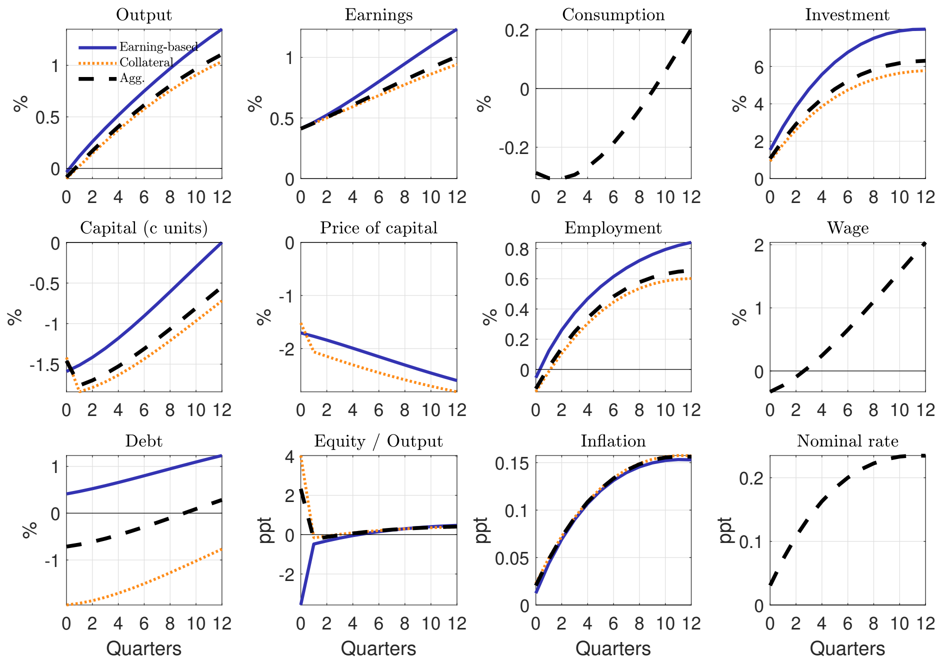
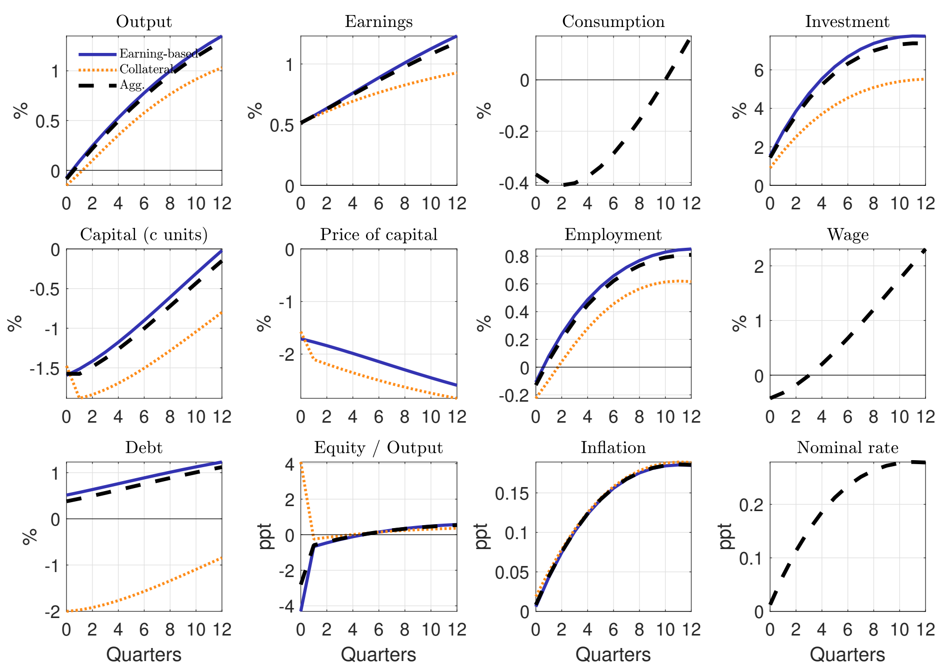


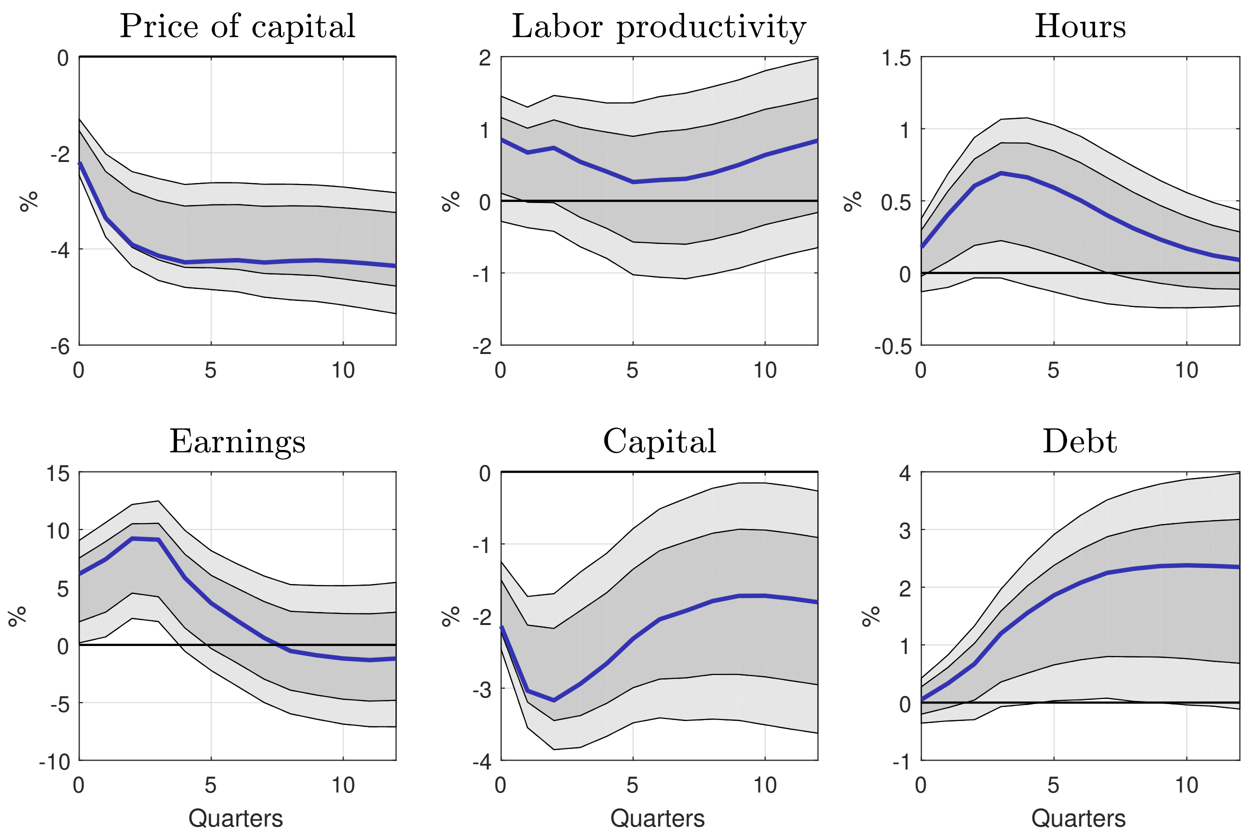
Figure C.10: MODEL IRFS TO AGGREGATE INVESTMENT SHOCK WITH $\chi = 0.8$



D Additional results for SVAR

D.1 SVAR IRFs of all variables to IST shock

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

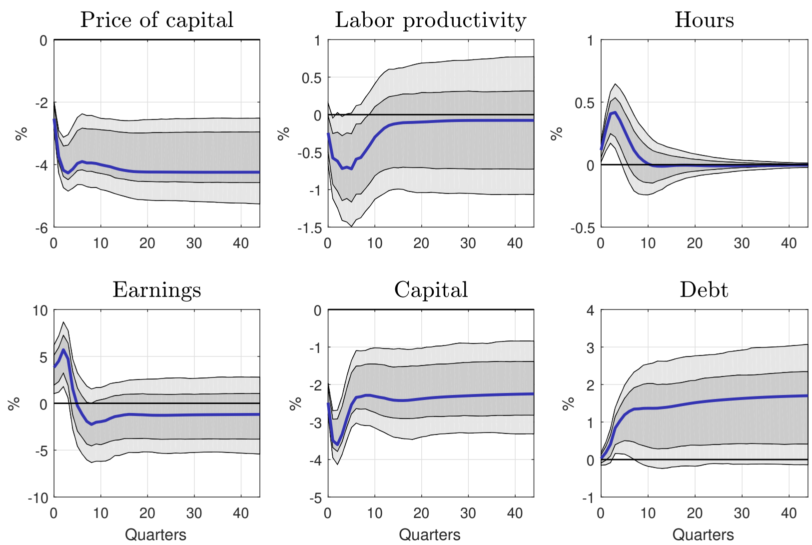


Notes. The figure displays the IRFs to a investment-specific shock identified from an estimated SVAR model using US data. The identification scheme relies on long-run restrictions following Fisher (2006). The responses are shown for all six variables included in the system, in percent. The unit of the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

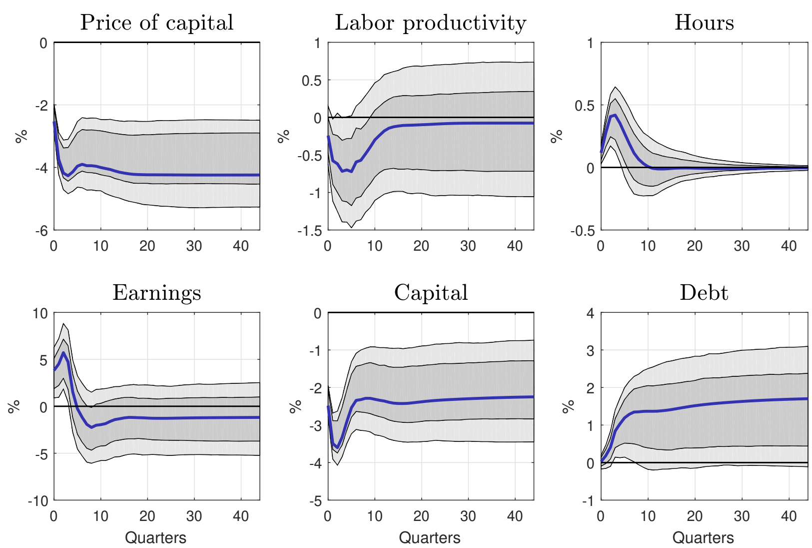
D.2 SVAR IRFs using medium-term restrictions

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

(a) Identification based on 5-year horizon



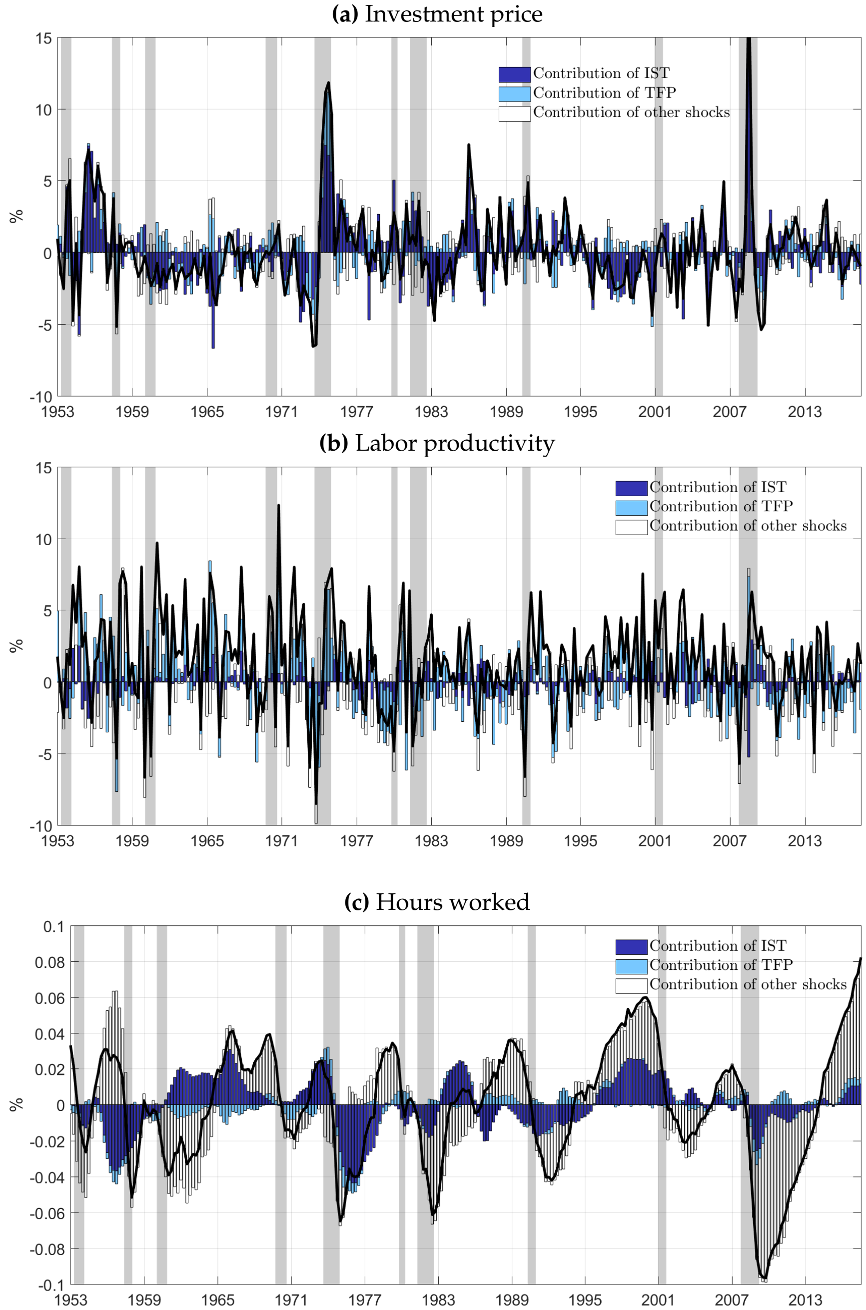
(b) Identification based on 10-year horizon



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

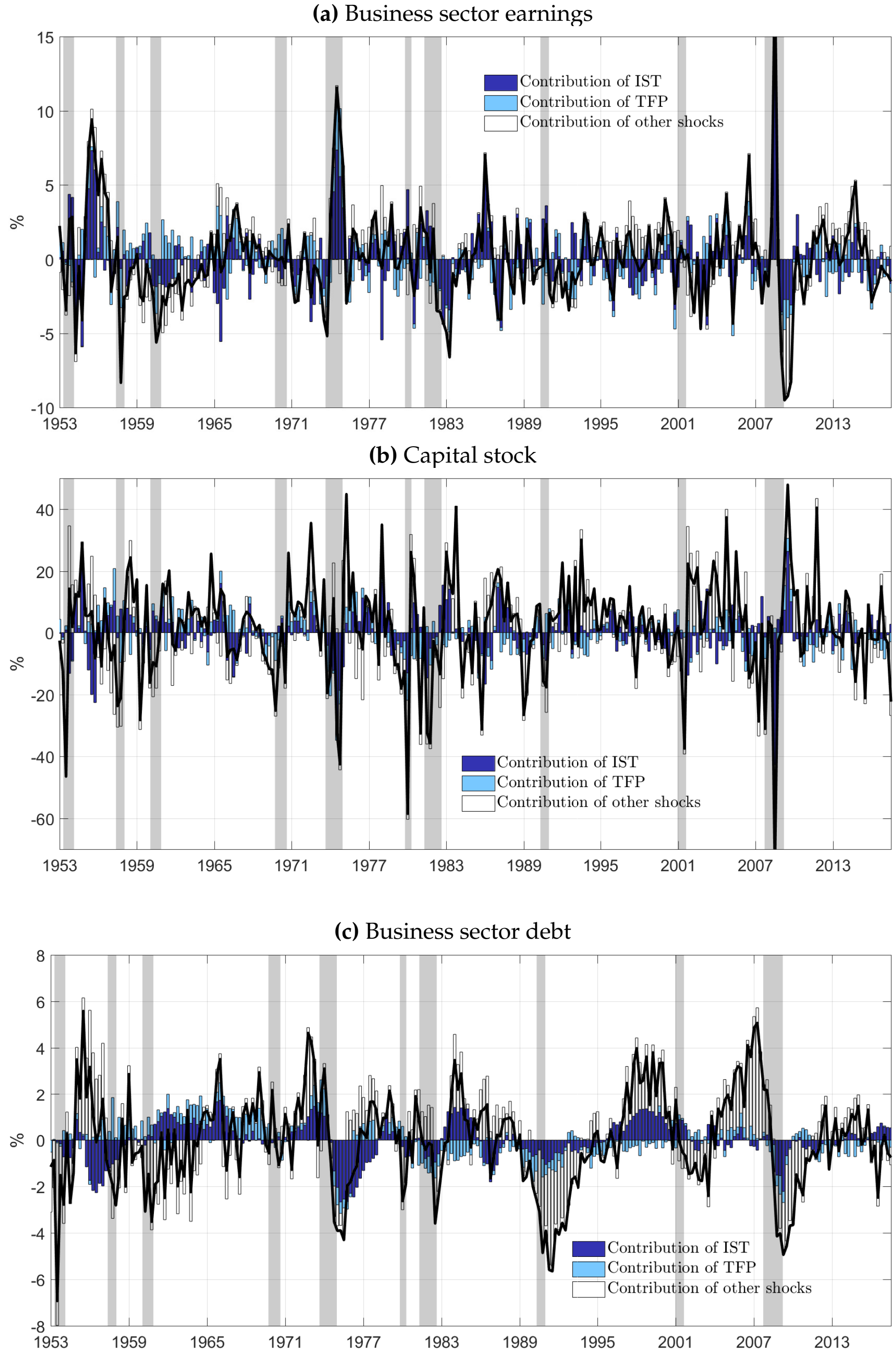
D.3 SVAR historical decompositions

Figure D.3: SVAR: HISTORICAL VARIANCE DECOMPOSITIONS



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

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

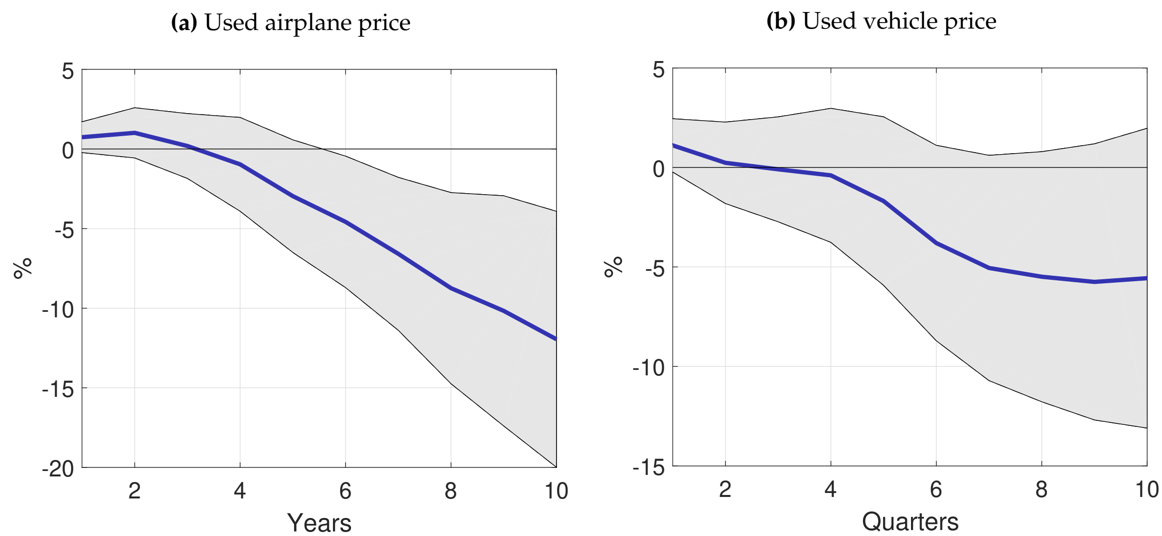


Notes. Historical variance decomposition of variables as estimated by the SVAR model identified with long-run restrictions. The black line is the actual (detrended) data series. The bars indicate the contribution of different structural shocks to the variance of the respective observable as estimated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

D.4 SVAR IRFs of used equipment prices

The investment shock that is the focus of the main text is identified from its negative impact on the price of *new* investment goods. In the prototype business cycle model of the paper, 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 the paper also reduces the prices of *used* equipment goods. This means that the validation of the main mechanism of this paper also holds if secondary prices of capital were to predominantly determine the value of collateral in corporate debt contracts.

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



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

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

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

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

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

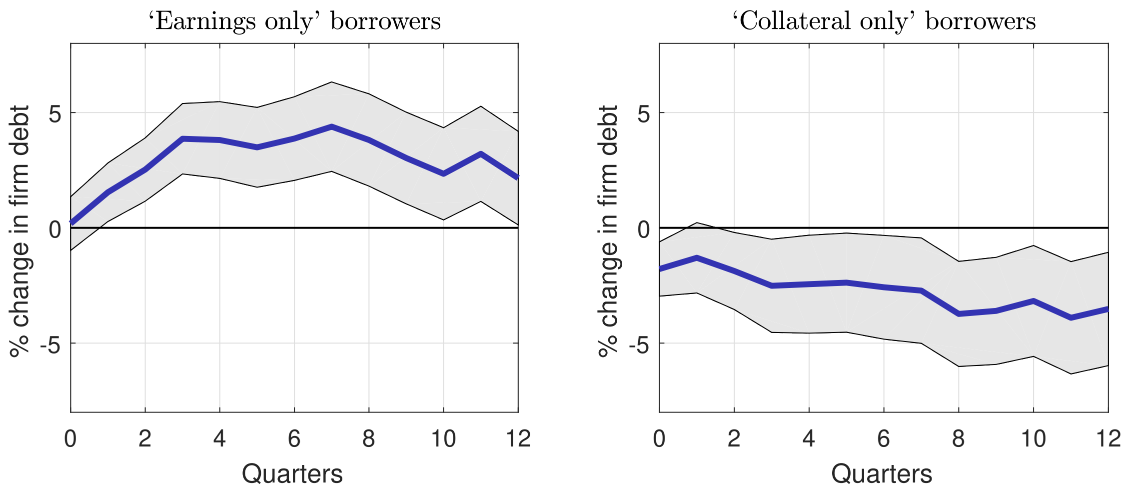
E Additional results for firm-level projections

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

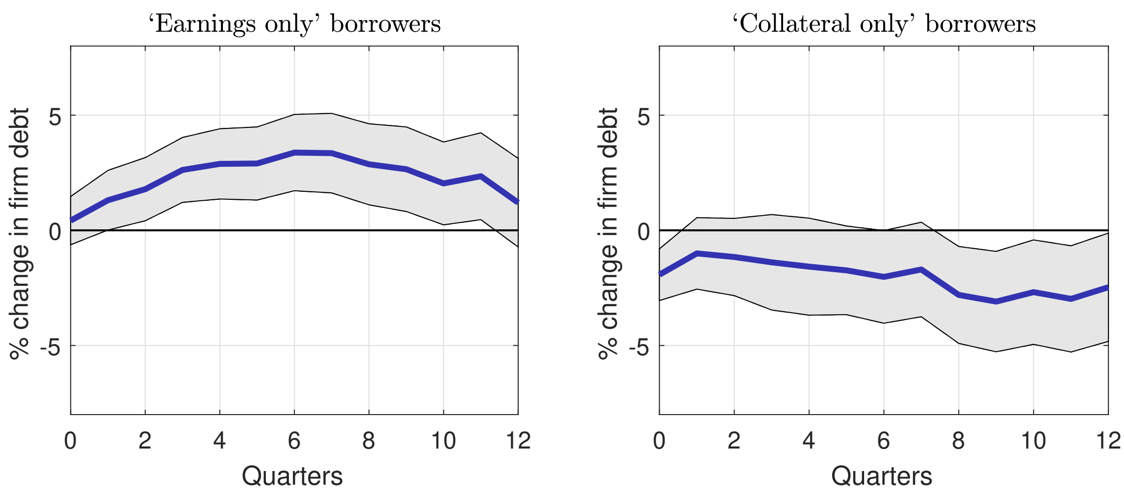
E.1 Alternative definitions of collateral borrowers

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

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



(b) Using alternative collateral classification based on specific assets



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

E.2 Significance of the difference between heterogeneous debt IRFs

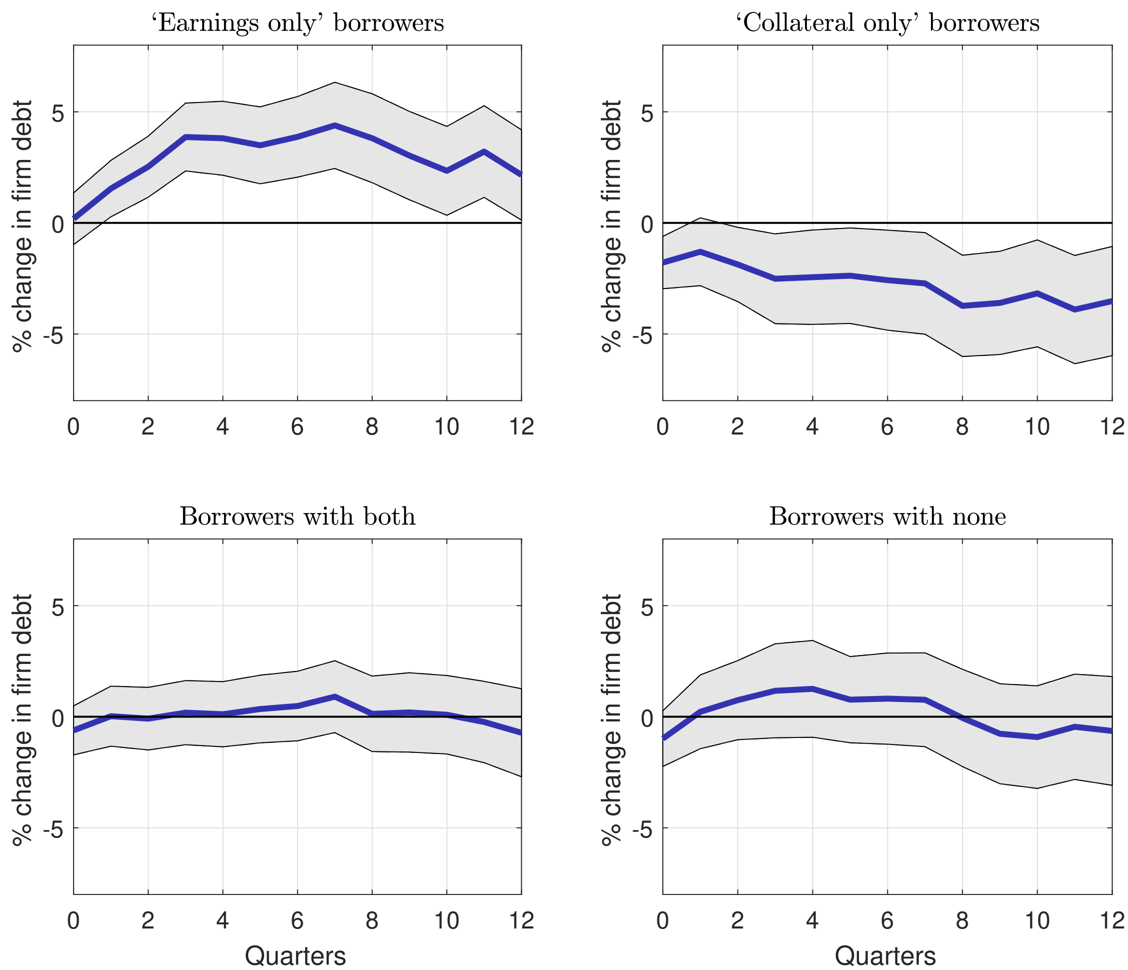
Table E.1: ESTIMATES OF THE DIFFERENCE BETWEEN IRF COEFFICIENTS

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

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

E.3 Results for all four firm groups

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

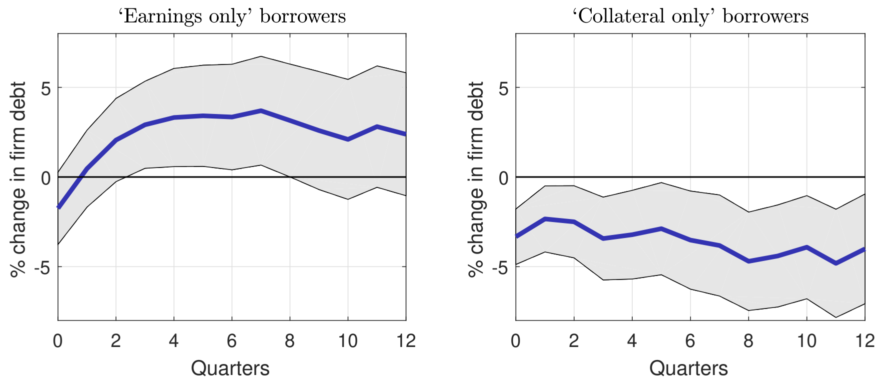


Notes. This figure repeats the IRFs from the main text, and additionally plots the IRFs of the remaining two firm groups: borrowers with both earnings covenants and collateral, and borrowers with neither. The results are based on a specification with detailed firm-level controls (3-digit industry fixed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

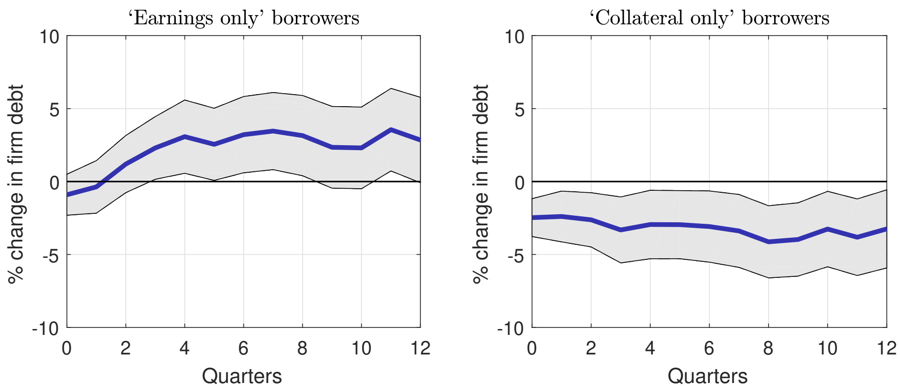
E.4 Results with several simultaneous interactions with the shock

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

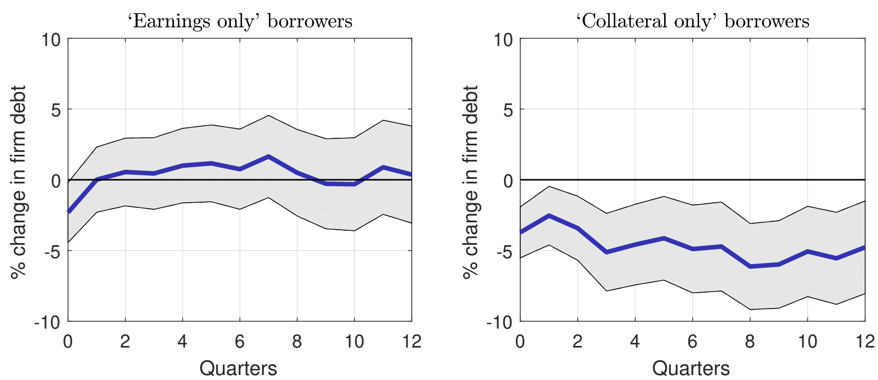
(a) Adding large vs. small interaction on top of borrower type interaction



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



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



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

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

F.1 Model setup

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

F.1.1 Firms

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

$$y_{i,t} = z_t(u_{i,t}k_{i,t-1})^{\alpha} n_{i,t}^{1-\alpha}, \tag{33}$$

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

$$\Xi(u_t) = \bar{\xi}(u_t^{1+\xi} - 1)/(1+\xi) \tag{34}$$

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

F.1.2 Households

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

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \gamma_t \beta^t \left(\frac{(c_{\ell,t} - hc_{\ell,t-1})^{1-\sigma}}{1-\sigma} - \chi_n \frac{n_{\ell,t}^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} \right) \tag{35}$$

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

$$c_{\ell,t}+\sum_{j[\chi]}\left\{\frac{b^j_{\ell,t}}{(1+r_t)P_t}+p^j_{f,t}s^j_{\ell,t}\right\}+T_{\ell,t}+\int q^{\omega}_{\ell,t+1}a_{j,t+1}dw_{\ell,t}=w_{\ell,t}n_{\ell,t}+\sum_{j[\chi]}\left\{\frac{b^j_{\ell,t-1}}{P_t}+(d^j_{\ell,t}+p^j_{f,t})s^j_{\ell,t-1}\right\}, \tag{36}$$

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

$$N_t=\left(\int_0^1 n_{\ell,t}^{\frac{1}{\vartheta_t}}\,dj\right)^{\vartheta_t} \tag{37}$$

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

$$n_{\ell,t}=\left(\frac{w_{\ell,t}}{W_t}\right)^{-\frac{\vartheta_t}{\vartheta_t-1}}N_t, \tag{38}$$

where W_t and N_t are the aggregate wage and employment level, respectively. (38) is taken as given by the household when choosing $n_{\ell,t}$ and $w_{\ell,t}$. Households face wage rigidities. A given household can only change their offered wage with probability $(1-\omega)$. From the optimization problem I derive a log-linear optimal wage equation. Given that all households make the same choices, this implies a sluggish low of motion for the aggregate wage rate W_t. For details, see Jermann and Quadrini (2012).

Household's optimality condition for bonds implies an Euler equation in which the real return $(1+r_t)\left(\frac{P_t}{P_{t+1}}\right)$ is priced with the stochastic discount factor $SDF_{t,t+1}\equiv\frac{\Lambda_{t+1}}{\Lambda_t}=\frac{\beta\gamma_{t+1}u_{c_{t+1}}}{\gamma_t u_{c_t}}$, where $u(\cdot)$ denotes the period utility function in (35).

F.1.3 Government

The government's budget constraint, in nominal terms, is similar to the simpler verion of the model,

$$T_t=\sum_{j[\chi]}\left(\frac{b^j_t}{R_t}-\frac{b^j_t}{(1+r_t)}\right)+P_t g_t, \tag{39}$$

with the addition of real government spending shocks to g_t.

F.1.4 Monetary policy

There is a Taylor rule specified as

$$\frac{1+r_t}{1+\bar{r}}=\left[\frac{1+r_{t-1}}{1+\bar{r}}\right]^{\rho_R}\left[\left(\frac{\pi^p_t}{\bar{\pi}^p}\right)^{\nu_1}\left(\frac{Y_t}{Y_{t-1}}\right)^{\nu_2}\right]^{1-\rho_R}\left[\frac{Y_t/Y^*_t}{Y_{t-1}/Y^*_{t-1}}\right]^{\nu_3}\varsigma_t, \tag{40}$$

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

F.1.5 Stochastic processes

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

$$\log(z_t) = (1-\rho_z)\log(\overline{z}) + \rho_z \log(z_{t-1}) + u_{z,t} \tag{41}$$

$$\log(v_t) = (1-\rho_v)\log(\overline{v}) + \rho_v \log(v_{t-1}) + u_{v,t} \tag{42}$$

$$\log(\gamma_t) = (1-\rho_\gamma)\log(\overline{\gamma}) + \rho_\gamma \log(\gamma_{t-1}) + u_{\gamma,t} \tag{43}$$

$$\log(\eta_t) = (1-\rho_\eta)\log(\overline{\eta}) + \rho_\eta \log(\eta_{t-1}) + u_{\eta,t} - \mu_p u_{\eta,t-1} \tag{44}$$

$$\log(\vartheta_t) = (1-\rho_\vartheta)\log(\overline{\vartheta}) + \rho_\vartheta \log(\vartheta_{t-1}) + u_{\vartheta,t} - \mu_w u_{\vartheta,t-1} \tag{45}$$

$$\log(g_t) = (1-\rho_g)\log(\overline{g}) + \rho_g \log(g_{t-1}) + \rho_{gz}\log(z_t) + u_{g,t} \tag{46}$$

$$\log(\varsigma_t) = (1-\rho_\varsigma)\log(\overline{\varsigma}) + \rho_\varsigma \log(\varsigma_{t-1}) + u_{\varsigma,t} \tag{47}$$

$$\log(\theta_{j,t}) = (1-\rho_\theta)\log(\overline{\theta_j}) + \rho_\theta \log(\theta_{j,t-1}) + u_{\theta,t} \quad j = \{\pi, k\} \tag{48}$$

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

F.1.6 Calibrated parameters

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

F.2 Additional results for estimated quantitative model

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

F.2.1 Parameter estimates

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

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

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

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

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

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

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

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

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

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

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

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

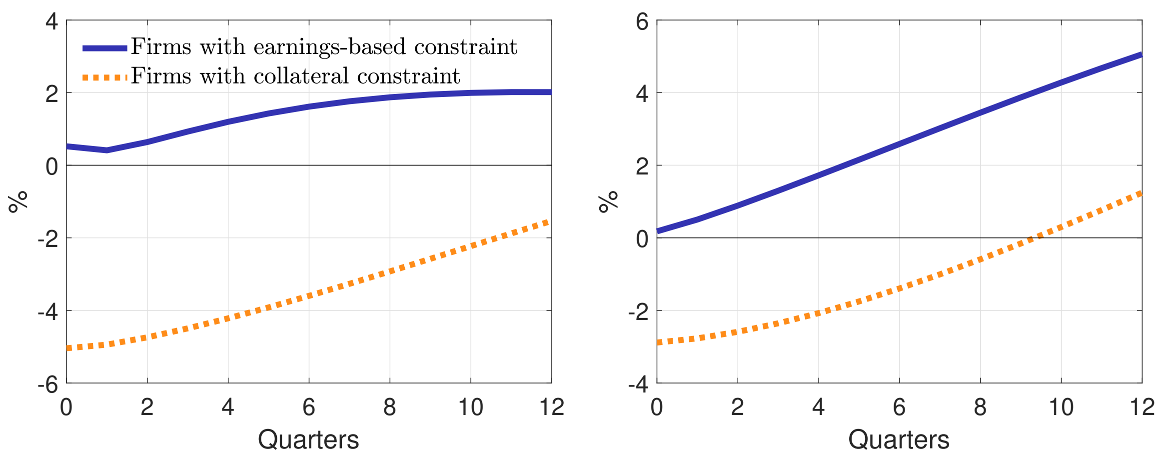
Overall this analysis shows that the main results in the quantitative version of the model are driven both directly by the presence of different types of borrowing constraints, as well as by the different parameters estimates that result from having one or the other constraint in the estimation. Quantitatively,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

F.2.3 Permanent investment shocks in the estimated model

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

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

(a) Estimated model with $\chi = 0.8$ **(b)** Estimated model with $\chi = 0.2$



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

F.2.4 Local projections using simulated model data

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

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

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

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

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

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

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

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

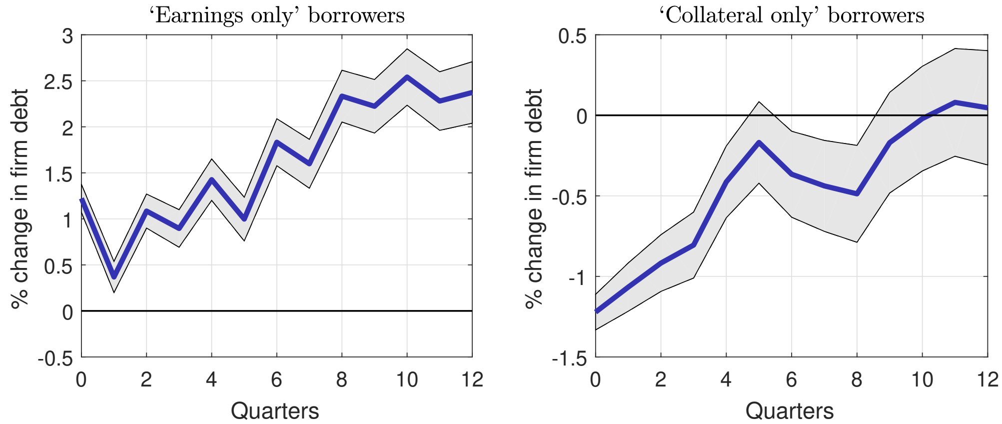
Panels (b) and (c) of Figure F.2 vary κ_f and κ_{mp} in turn. Here I hand pick values that are high enough to illustrate at which point visible challenges for the estimation procedure start occurring. In Panel (b), κ_f is increased to 20 while $\kappa_{mp} = 10$ as in Panel (a). In other words, this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

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

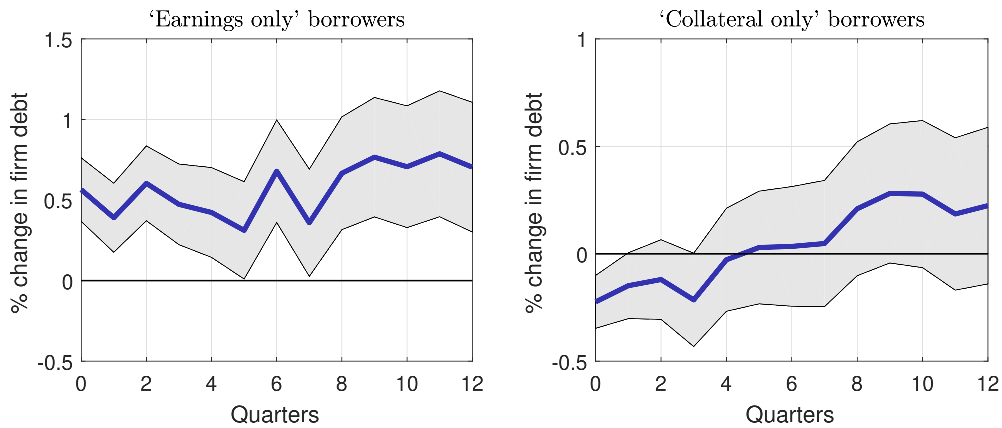
[10] Since there are permanent shocks, the debt data for individual firms can drift to negative values. I set any negative value to missing, mimicking an environment in which firms drop out of (and come back into) the panel. Similar to my empirical application where there is likely nonrandom selection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

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

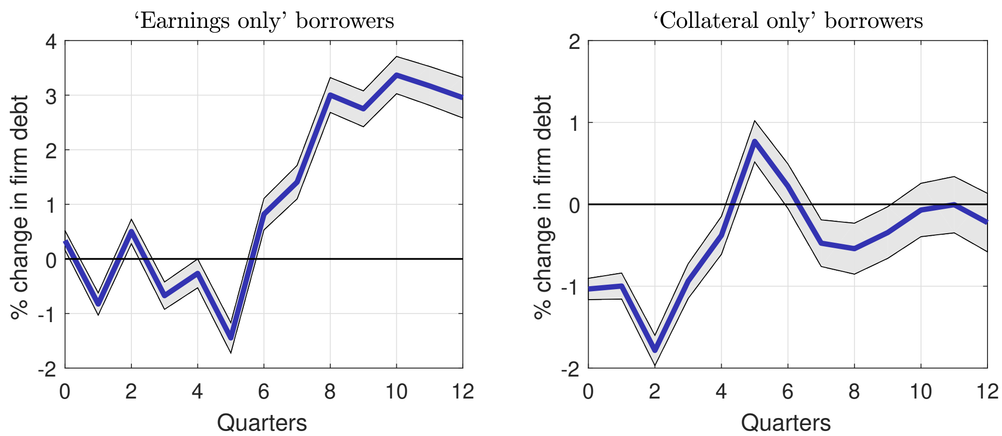
(a) Baseline simulation settings ($\kappa_f = 5$, $\kappa_{mp} = 10$)



(b) Larger firm-specific shocks ($\kappa_f = 20$, $\kappa_{mp} = 10$)



(c) Larger confounding aggregate shocks ($\kappa_f = 5$, $\kappa_{mp} = 50$)



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

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

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

F.2.5 Full variance decompositions

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

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

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

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

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

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

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

G Appendix bibliography

References

AGHION, P. AND P. BOLTON (1992): "An incomplete contracts approach to financial contracting," *The review of economic Studies*, 59, 473–494.

BATES, T. W., K. M. KAHLE, AND R. M. STULZ (2009): "Why Do U.S. Firms Hold So Much More Cash than They Used To?" *The Journal of Finance*, 64, 1985–2021.

BRADLEY, M. AND M. R. ROBERTS (2015): "The Structure and Pricing of Corporate Debt Covenants," *Quarterly Journal of Finance*, 05, 1550001.

CARLING, K., T. JACOBSON, J. LINDE, AND K. ROSZBACH (2007): "Corporate credit risk modeling and the macroeconomy," *Journal of Banking & Finance*, 31, 845–868.

CHAVA, S. AND M. R. ROBERTS (2008): "How Does Financing Impact Investment? The Role of Debt Covenants," *The Journal of Finance*, 63, 2085–2121.

CHODOROW-REICH, G. AND A. FALATO (2021): "The Loan Covenant Channel: How Bank Health Transmits to the Real Economy," *Journal of Finance*.

CHRISTIANO, L. J., M. EICHENBAUM, AND C. L. EVANS (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113, 1–45.

CUMMINS, J. G. AND G. L. VIOLANTE (2002): "Investment-Specific Technical Change in the United States (1947–2000): Measurement and Macroeconomic Consequences," *Review of Economic Dynamics*, 5, 243 – 284.

DAMODARAN, A. (2012): *Investment valuation: Tools and techniques for determining the value of any asset*, vol. 666, John Wiley & Sons.

DIAMOND, D. W., Y. HU, AND R. G. RAJAN (2020): "Pledgeability, Industry Liquidity, and Financing Cycles," *The Journal of Finance*, 75, 419–461.

DICECIO, R. (2009): "Sticky wages and sectoral labor comovement," *Journal of Economic Dynamics and Control*, 33, 538 – 553.

DICHEV, I. D. AND D. J. SKINNER (2002): "Large–Sample Evidence on the Debt Covenant Hypothesis," *Journal of Accounting Research*, 40, 1091–1123.

FISHER, J. D. (2006): "The Dynamic Effects of Neutral and Investment-Specific Technology Shocks," *Journal of Political Economy*, 114, 413–451.

FRANCIS, N., M. T. OWYANG, J. E. ROUSH, AND R. DICECIO (2014): "A Flexible Finite-Horizon Alternative to Long-Run Restrictions with an Application to Technology Shocks," *The Review of Economics and Statistics*, 96, 638–647.

GALI, J. (1996): "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations," Working Paper 5721, National Bureau of Economic Research.

GARLEANU, N. AND J. ZWIEBEL (2009): "Design and Renegotiation of Debt Covenants," *The Review of Financial Studies*, 22, 749–781.

GOMES, J., U. JERMANN, AND L. SCHMID (2016): "Sticky leverage," *American Economic Review*, 106, 3800–3828.

GREENWALD, D. (2018): "The mortgage credit channel of macroeconomic transmission," *Working Paper*.

HENNESSY, C. A. AND T. M. WHITED (2005): "Debt dynamics," *The Journal of Finance*, 60, 1129–1165.

IRELAND, P. N. (2001): "Sticky-price models of the business cycle: Specification and stability," *Journal of Monetary Economics*, 47, 3–18.

JENSEN, M. C. AND W. H. MECKLING (1976): "Theory of the firm: Managerial behavior, agency costs and ownership structure," *Journal of financial economics*, 3, 305–360.

JERMANN, U. AND V. QUADRINI (2012): "Macroeconomic Effects of Financial Shocks," *American Economic Review*, 102, 238–71.

JORDÀ, O. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182.

JUNGHERR, J. AND I. SCHOTT (2021): "Slow debt, deep recessions," *American Economic Journal: Macroeconomics (Forthcoming)*.

JUSTINIANO, A., G. E. PRIMICERI, AND A. TAMBALOTTI (2011): "Investment shocks and the relative price of investment," *Review of Economic Dynamics*, 14, 102 – 121, special issue: Sources of Business Cycles.

LANTERI, A. (2018): "The Market for Used Capital: Endogenous Irreversibility and Reallocation over the Business Cycle," *American Economic Review*, 108, 2383–2419.

LELAND, H. (1994): "Bond Prices, Yield Spreads, and Optimal Capital Structure with Default Risk," *Working Paper*, 41.

LIAN, C. AND Y. MA (2021): "Anatomy of Corporate Borrowing Constraints," *The Quarterly Journal of Economics*, 136, 229–291.

OTTONELLO, P. AND T. WINBERRY (2020): "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Econometrica*, 88, 2473–2502.

PFEIFER, J. (2016): "Macroeconomic Effects of Financial Shocks: Comment," Dynare Working Papers 50, CEPREMAP.

RAMEY, V. (2016): "Chapter 2 - Macroeconomic Shocks and Their Propagation," Elsevier, vol. 2 of *Handbook of Macroeconomics*, 71 – 162.

ROBERTS, M. R. AND A. SUFI (2009): "Control rights and capital structure: An empirical investigation," *The Journal of Finance*, 64, 1657–1695.

SMETS, F. AND R. WOUTERS (2007): "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, 97, 586–606.

STANDARD & POOR'S GLOBAL RATINGS (2013): "General: Corporate Methodology: Ratios And Adjustments," *Available at https://www.maalot.co.il/Publications/MT20190402140633.PDF*.

VOM LEHN, C. AND T. WINBERRY (2021): "The investment network, sectoral comovement, and the changing US business cycle," *The Quarterly Journal of Economics*.