Internet Appendix to "Financial Constraints, Sectoral Heterogeneity, and the Cyclicality of Investment"

1 Data Description

1.1 Quarterly Financial Report

The main source of aggregate data is the Quarterly Financial Report for Manufacturing Corporations (QFR). This survey dates back to World War II, when it was administered by the Office of Price Administration. The Census Bureau has been responsible for administering the survey since 1982. These data series are used to construct macroeconomic aggregates such as corporate profits. The QFR sample, which includes approximately 10,000 firms in a given quarter, is chosen based on asset sizes reported in corporate tax returns; any firm with more than \$250,000 in domestic assets is eligible for inclusion, and any firm with more than \$250 million is included in the sample with certainty. Firms who reside between these thresholds are chosen randomly with the goal of obtaining a representative sample and are included for 8 consecutive quarters with one-eighth of the sample replaced each quarter.

Historical data dating back to 1947 are available for download from the Census Bureau's website.[1] At the time of the first draft of this paper in February 2019, publicly available data from before 1987 were only be available in physical publications or microfilm. Using these physical copies, I digitized the data going back to 1966Q1. This process consisted of mostly manual entry and occasional use of optical character recognition (OCR) software when available. To ensure that the data series were digitized correctly, I have checked that aggregating the component series by either size or sector add up to the correct total in each quarter.

Each physical publication includes observations for the current quarter as well as the

[1] https://www.census.gov/econ/qfr/

four preceding quarters. With few exceptions most of the data series were digitized from the publications in Q1 of each year. Using these five level observations, I calculated the four implied quarterly growth rates, giving me a series of growth rates. By using growth rates calculated within each release, I avoid problems from comparing levels before and after methodological changes (including changes in accounting procedures in 1973 and industry reclassifications in 1984 and 2001). I then applied these growth rates to the levels of the most recent releases, effectively taking the original growth paths and shifting them to the most up-to-date level. I deflate the stock of net property, plant, and equipment using the nonresidential fixed investment price index. All other variables are deflated using the GDP price index.

The respondents are aggregated by sector as well as asset size. The data consist of eight nominal asset "buckets": under \$5 million, \$5-10 million, \$10-25 million, \$25-50 million, \$50-100 million, \$100-250 million, \$250-1,000 million, and \$1+ billion. Industries are classified by the Census Bureau based on sources of revenue. As part of its submission, each company in the survey reports a breakdown of gross receipts by source industry. To be in the scope of the QFR manufacturing sample, a firm must have manufacturing as its largest source of gross receipts. Once a corporation is assigned to the manufacturing sector, it is categorized into a subsector based on its largest share of *manufacturing* receipts. For example, if a firm has 40% of its revenue from manufacturing and 30% each from mining and retail trade, then the firm would be classified in the manufacturing sector. If 60% of the firm's manufacturing activity was conducted in the machinery subsector and 40% in the chemicals subsector, then the activities of the entire corporation would be assigned to the machinery subsector. These classifications are reviewed periodically and changed as needed for as long as the corporation remains in the sample.

To demonstrate that the QFR data are in line with other measures of the capital stock, I compare them to fixed asset data from the Bureau of Economic Analysis (BEA). These data provide end-of-year estimates of the value of total fixed assets for both the durable and nondurable manufacturing sectors. Figure A.1 shows the year-over-year changes in the BEA measure compared to the Q4/Q4 changes in the QFR data and suggests that the two data series are capturing the same fundamental investment behavior. The correlations between the BEA and QFR measures are high for the total series (0.87) as well as both the durable (0.83) and nondurable (0.81) subseries, suggesting that the QFR data can be appropriately described as a higher-frequency and more detailed version of the BEA fixed asset data.

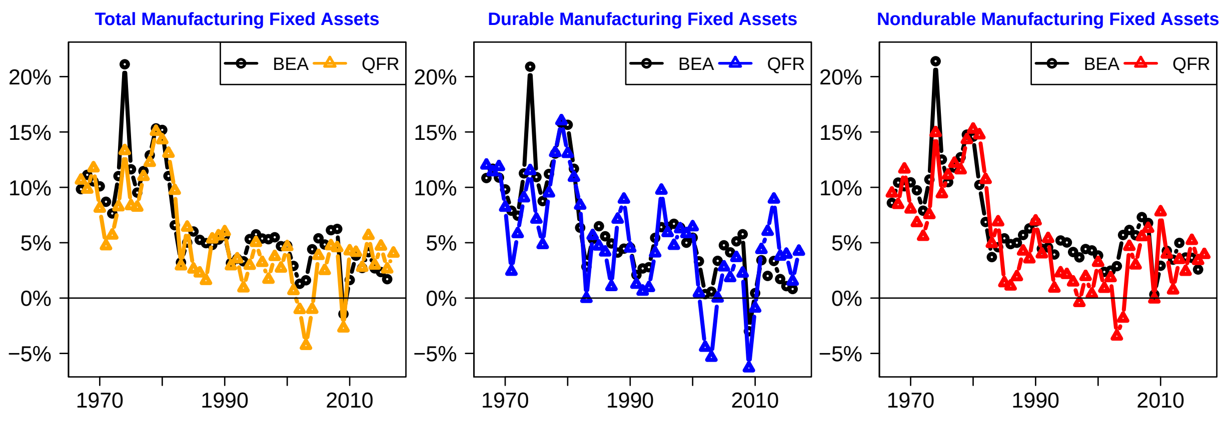

Figure A.1: Y/Y % Changes in BEA and QFR Fixed Asset Measures

Note: This figure compares the yearly percent changes in the BEA and QFR measures of the nominal fixed asset stock for the manufacturing sector. The QFR numbers are shown as the year-over-year change in the fourth quarter of each year for comparison to the BEA data (which are at an annual frequency and recorded at year-end).

1.2 Building Permit Data

This section describes the building permit data used in the paper. Building permits are required when undertaking new construction, and this information is publicly available through local municipalities. Dodge Analytics[2] collects this information, which includes the type of structure and a cost estimate used for tax purposes.

Obtaining accurate cost information is important for local permit issuing authorities because more expensive construction projects are assessed greater permit fees. Section 108.3 of the 2018 International Existing Building Code states:

"The applicant for a permit shall provide an estimated permit value at time of application. Permit valuations shall include total value of work including materials and labor for which the permit is being issued, such as electrical, gas, mechanical, plumbing equipment, and permanent systems. If, in the opinion of the code official, the valuation is underestimated on the application, the permit shall be denied unless the applicant can show detailed estimates to meet the approval of the code official. Final building permit valuation shall be set by the code official."[3]

These are used as guidelines by local municipalities and form the foundation of permit procedures in most cases. They are generally taken at face value by the issuing agencies. In some cases jurisdictions will also include their own terms and requirements. Rather than relying on contractor estimates, many municipalities establish a fixed formula determining the cost per square foot based on the type of construction.[4]

In general, contractors have incentives to underestimate how much projects will cost given that these estimates for the basis for permit fees and certain types of taxes. Some municipalities will require a contractor to submit a signed affidavit showing the final construction costs for tax purposes, and Dodge Analytics will often follow up with contractors

[2] https://www.construction.com/

[3] https://codes.iccsafe.org/content/IEBC2018/CHAPTER-1-SCOPE-AND-ADMINISTRATION?site_type=public

[4] Boulder, Colorado is an example of such a county. Their valuation table can be found here: https://bouldercolorado.gov/links/fetch/23187

to obtain final valuations as part of its data collection process, but it is likely that many of the permits included in their data are ultimately based on the initial estimates provided by contractors before work has started. In practice these institutional features can certainly lead to variation in the valuations of similar projects across municipalities, but they are likely to wash out when aggregating up to the national level and comparing these totals over time.

1.3 Compustat Data

1.3.1 Measuring investment

All of the variable definitions are standard and follow the literature closely, especially Jeenas (2019) and Ottonello and Winberry (2020). I use the nonresidential fixed investment price index to deflate the capital stock and the GDP price index to deflate all other variables. I use data starting in 1985 to avoid changes with sampling composition before that. In line with my analysis of aggregate data, I only consider monetary shocks that occur up to 2004.

- **Manufacturing**: My main analysis focuses on the manufacturing sector. I define a firm to be in the manufacturing sector if it is classified as being in manufacturing according to either the SIC (codes starting with 20-39) or NAICS (codes starting with 31-33). These can be classified into durable or nondurable producers according to the following sectors:

	SIC	**NAICS**
Durable	24-25, 32-40	33, 321, 327
Nondurable	20-23, 26-31	31, 322-326

  To match the definitions used in the QFR data as closely as possible, I classify firms as durable or nondurable according to the following procedure:

  1. Firms are classified as durable producers if they have a durable NAICS code as defined above.

2. If a firm has no NAICS code but has a durable SIC code as defined above, I define it as durable.

3. In rare instances, the NAICS and SIC codes suggest different sectors; this occurs because a small number of industries have been reclassified over time. In these cases I use the NAICS classification.

- **Investment**: This variable denotes the capital stock of each firm at the end of the quarter. As the initial entry I use the firm's first observation of *Property, Plant, and Equipment (Gross)*, which is item 118 and denoted *PPEGTQ* in the Compustat database. From this initial level, I add the quarterly change in *Property, Plant, and Equipment (Net)*, which is item 42 and denoted *PPENTQ*. I use this method because there are many more observations of the net measure than the gross measure of each firm's capital stock. If a firm is missing a single value of *PPENTQ* between two nonmissing values, I linearly impute it using the observations on either side. For instances of two or more consecutive missing values for a firm, no imputation is done. I only consider investment "runs" of least 40 consecutive quarterly observations after imputation in my main analysis.

- **Dropped observations**: To minimize the effects of outliers and reporting errors, I exclude firm-quarter observations with any of the following features:

  1. A ratio of acquisitions ($AQCY$) to assets (ATQ) larger than 5%.
  2. An investment rate (defined as $\frac{k_t - k_{t-1}}{k_{t-1}}$) in the top or bottom 0.5 percent of the distribution.
  3. A leverage ratio greater than 10 or a net current leverage ratio either above 10 or below -10.
  4. Changes in quarterly real sales of more than 100% or less than -100%.

Summary statistics are shown in Table A.1.

Variable	All Manufacturing		Nondurable		Durable	
	Δk_t	Assets	Δk_t	Assets	Δk_t	Assets
Mean	0.012	\$1,766	0.013	\$2,784	0.011	\$1,207
Median	-0.002	\$111	-0.001	\$149	-0.003	\$98
Std. Dev.	0.126	\$8,650	0.134	\$11,979	0.122	\$5,699

Table A.1: Summary Statistics for Manufacturing Firms in Compustat

Note: These statistics cover only manufacturing firms in Compustat from 1985-2008. Assets are deflated using the GDP price index and expressed in millions of 2009 dollars. Δk_t refers to the change in the log level of property, plant, and equipment net of depreciation (NPPE) deflated by the nonresidential fixed investment price index. Statistics for changes in NPPE are calculated across all firm-quarters while the ones for assets are calculated as the time average of the cross sectional value in each quarter.

1.4 Monetary Shocks

I use as a measure of exogenous monetary policy shocks the series generated by Coibion (2012) that extends the original work of Romer and Romer (2004). This methodology uses the FOMC Greenbook forecasts, which are a crucial and high-quality source of information for FOMC participants, to represent the Fed's information set. These forecasts are used as the input for a forward-looking Taylor Rule similar to the one below, and the shocks are taken to be the series of residuals ϵ_t^m.

$$\Delta i_t = \beta i_{t-1} + \sum_k \phi_x^k E_t x_{t+k} + \sum_k \phi_\pi^k E_t \pi_{t+k} + \epsilon_t^m \tag{1}$$

The time series of shocks is shown in Figure A.2 below.

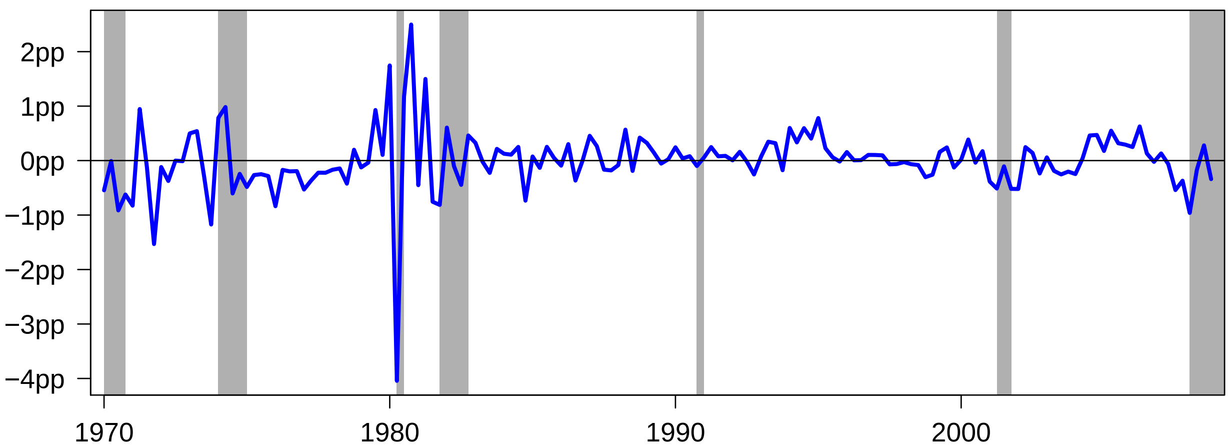

Figure A.2: Time Series of Monetary Shocks

Note: This figure shows the monetary shock series used in my analysis. The shock series I use is developed in Romer and Romer (2004) and extended in Coibion (2012). Positive values correspond to contractionary shocks.

2 Additional empirical results

This section shows a range of additional robustness checks and extensions to my main results. In Section 2.1, I show that my main results are robust to alternative econometric specifications, controls, lag lengths, and time periods, and that the main findings still obtain using a standard recursive VAR instead of a local projection framework. I also provide standard errors for estimates based on BEA investment data and show that the difference between manufacturing investment and that of several other sectors is statistically significant, including for aggregate investment. In Section 2.2, I analyze structures investment for manufacturers, which is the type of investment with the longest useful lifespan and thus should be most sensitive to the user cost channel I describe in the main paper.

2.1 Robustness checks

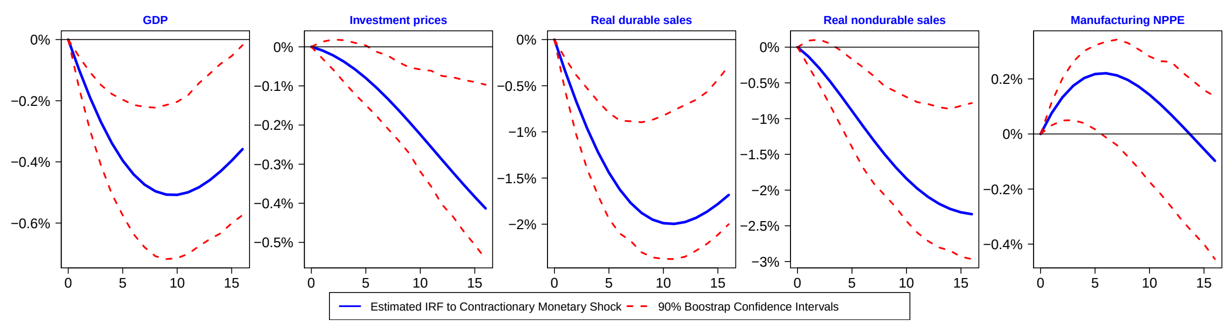

Figure B.1: VAR impulse responses to contractionary MP shock (90% CI)

Note: This figure shows the impulse response to a one standard deviation contractionary FFR shock estimated from a standard recursive SVAR using the following variable ordering: real GDP, the relative price of the nonresidential fixed investment to the GDP deflator, real durable sales, real nondurable sales, the real aggregate capital stock for the manufacturing sector, and the Federal Funds Rate. The FFR is in levels and all other data series are in logs. The data span 1970-2008 to match the baseline specification. Bootstrapped 90% confidence intervals are calculated based on 250 draws.

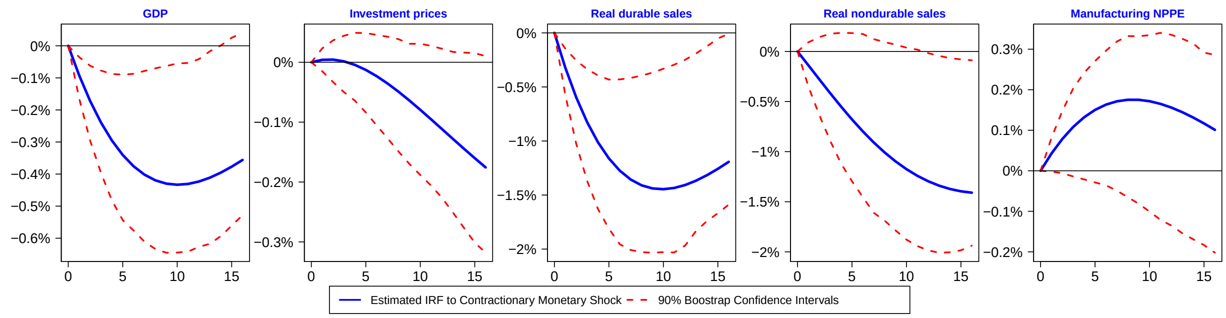

Figure B.2: VAR using data from 1970-2021

Note: This figure shows the impulse response to a one standard deviation contractionary FFR shock estimated from a standard recursive SVAR using the following variable ordering: real GDP, the relative price of the nonresidential fixed investment to the GDP deflator, real durable sales, real nondurable sales, the real aggregate capital stock for the manufacturing sector, and the Shadow Funds Rate (SFR) developed in Wu and Xia (2016). Data cover 1970-2021. The SFR is in levels and all other data series are in logs. Bootstrapped 90% confidence intervals are calculated based on 250 draws.

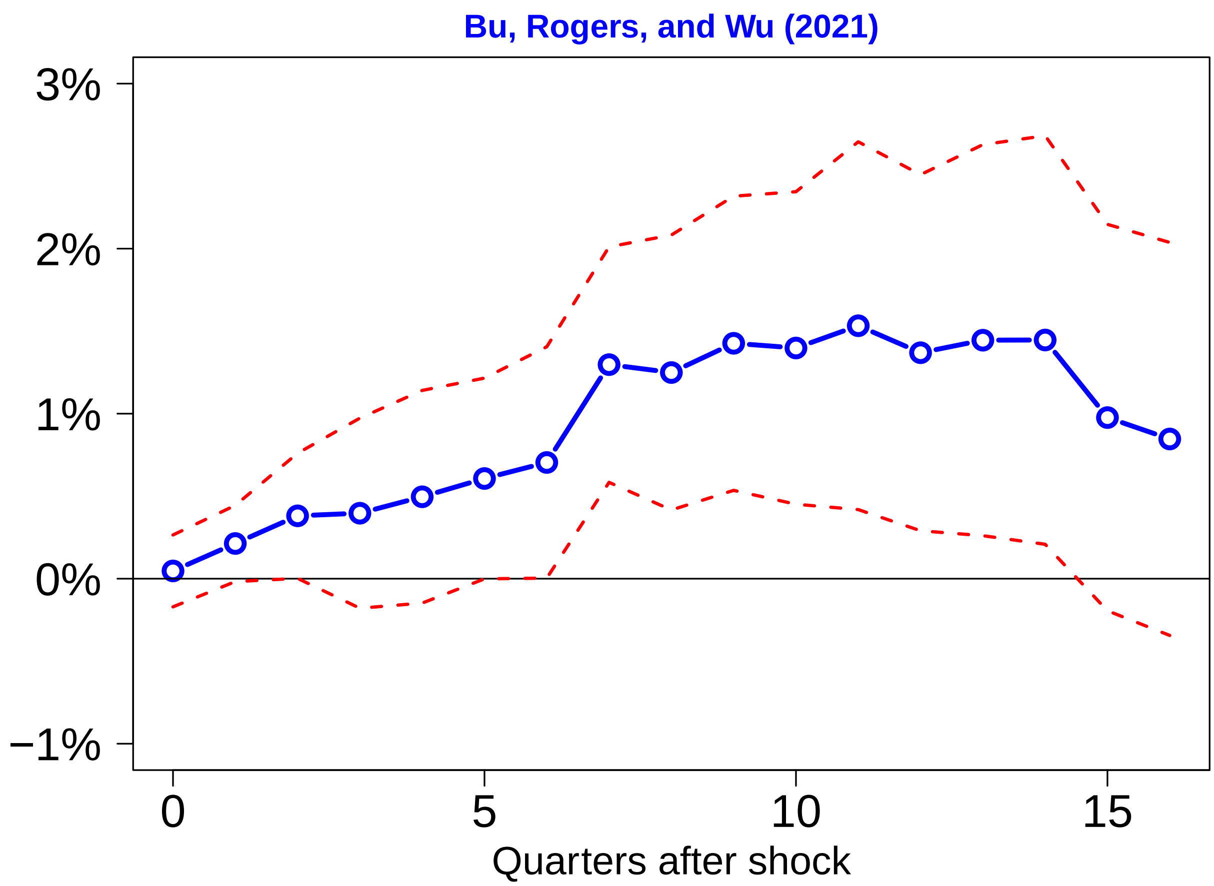

Figure B.3: IRF using data from 1995-2021

Note: This figure shows the response of the aggregate real capital stock for the manufacturing sector from the QFR to a two standard deviation monetary policy shock identified in Bu et al. (2021) including data from 1995-2021. The regression includes a linear time trend and eight lags each of the dependent variable and the shock. Dashed red lines show 90% confidence intervals calculated using Newey-West standard errors.

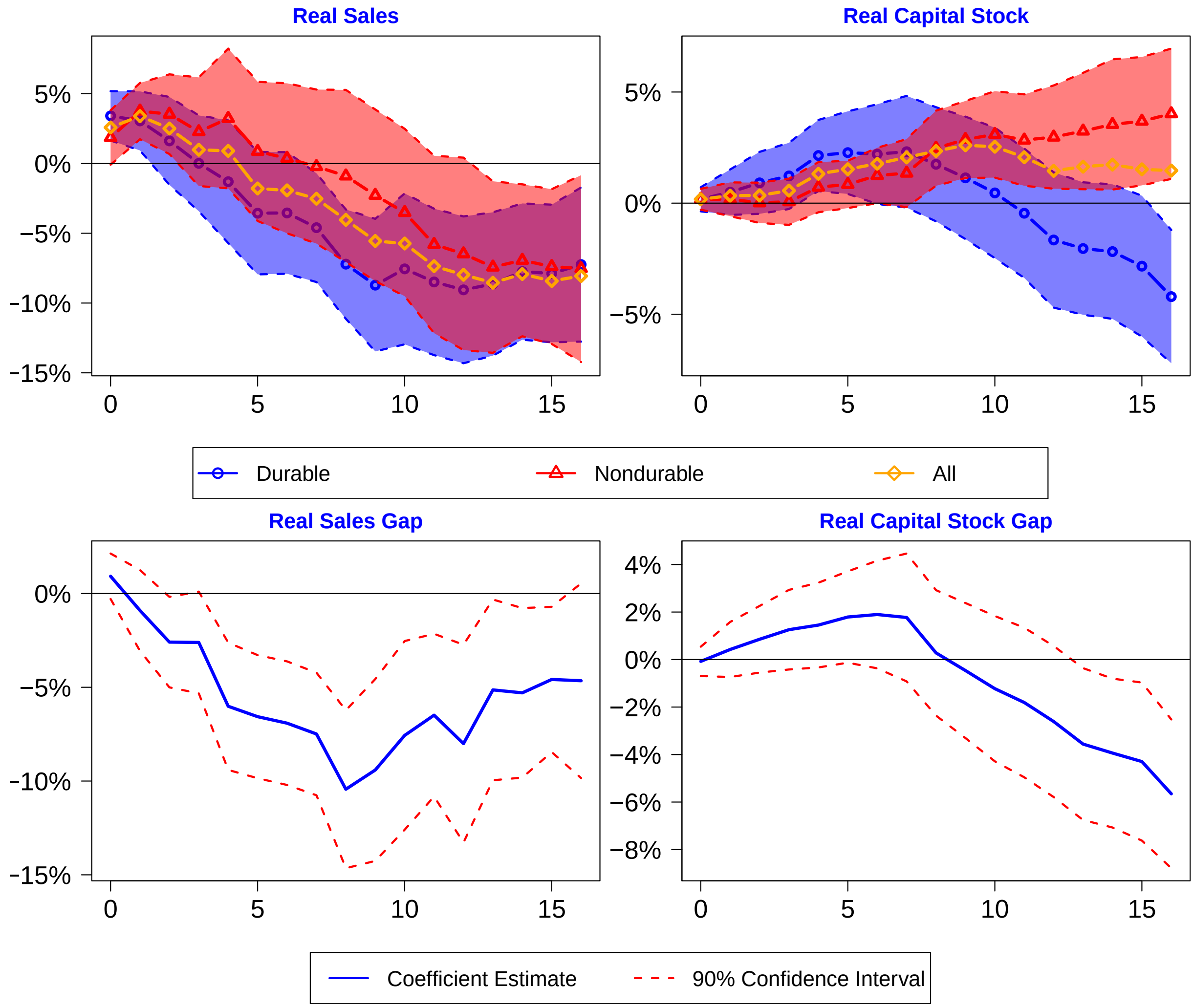

Figure B.4: IRFs using Gertler-Karadi shocks

Note: This figure shows the coefficient estimates γ_h^i from Equation 1 of the main paper using the shocks identified in Gertler and Karadi (2015). I use the identified series of shocks from their VAR and use them as exogenous regressors in my baseline LP approach. The top row shows the responses of NPPE, which is measured by the QFR item "Stock of Property, Plant, and Equipment Net of Depreciation" and deflated using the NIPA nonresidential fixed investment price index, and sales, which is the QFR sales measure deflated by the GDP deflator. The bottom row shows the estimated log difference between each measure: $y_t \equiv \log(X_t^D) - \log(X_t^N)$. 90% confidence intervals are calculated using Newey-West standard errors. Regressions include data from 1975-2008.

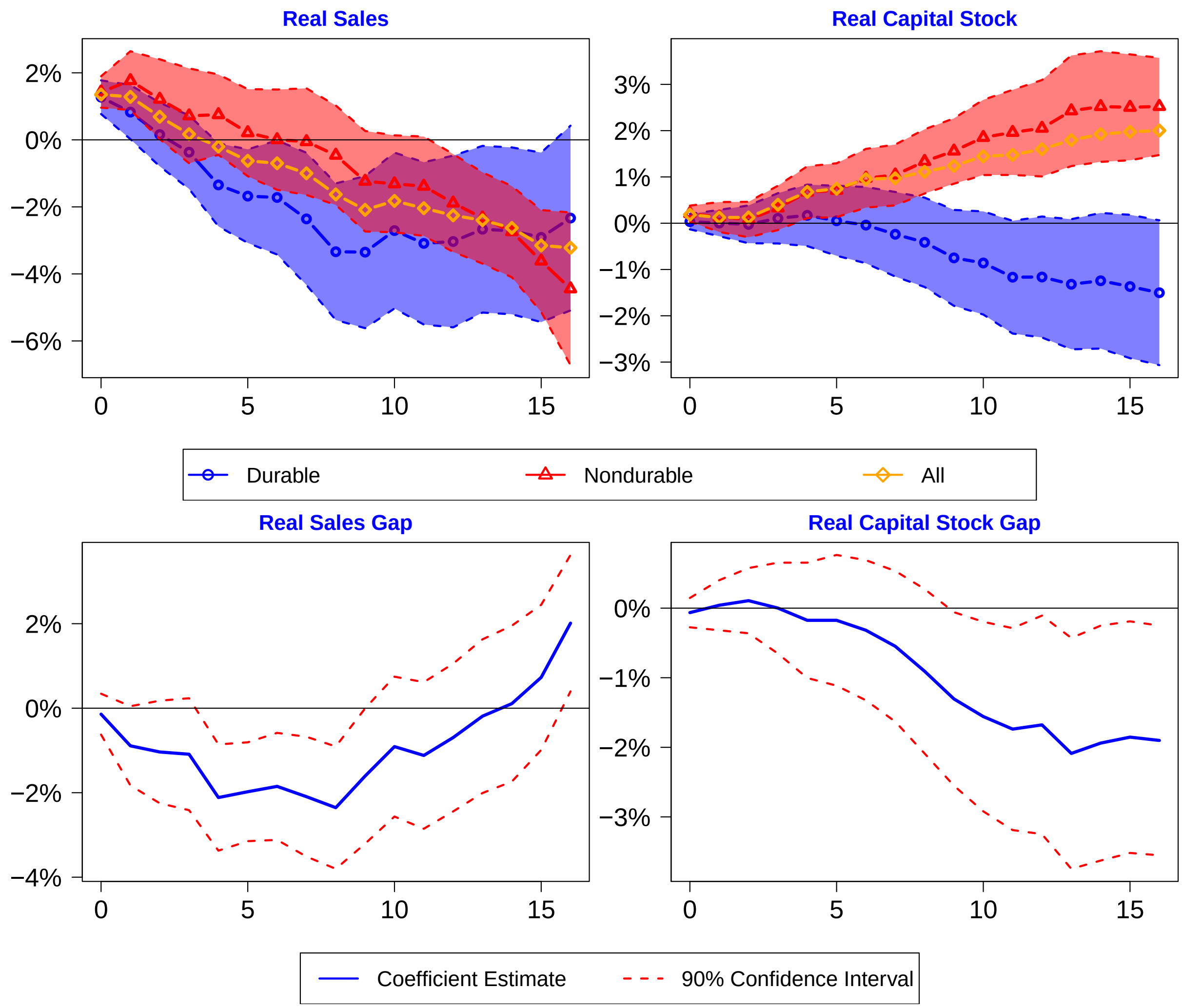

Figure B.5: IRFs using data from 1975-2008

Note: This figure shows the coefficient estimates γ_h^i from Equation **??**, which correspond to the effects of a 100bp contractionary monetary shock. The horizontal axes correspond to quarters after the shock. The top row shows the responses of NPPE, which is measured by the QFR item "Stock of Property, Plant, and Equipment Net of Depreciation" and deflated using the NIPA nonresidential fixed investment price index, and sales, which is the QFR sales measure deflated by GDP price index. The bottom row shows the estimated effects on the log difference between each measure: $y_t \equiv \log(X_t^D) - \log(X_t^N)$. All regressions include a linear time trend and eight lags each of the dependent variable and the shock. 90% confidence intervals are calculated using Newey-West standard errors. Regressions include data from 1975-2008.

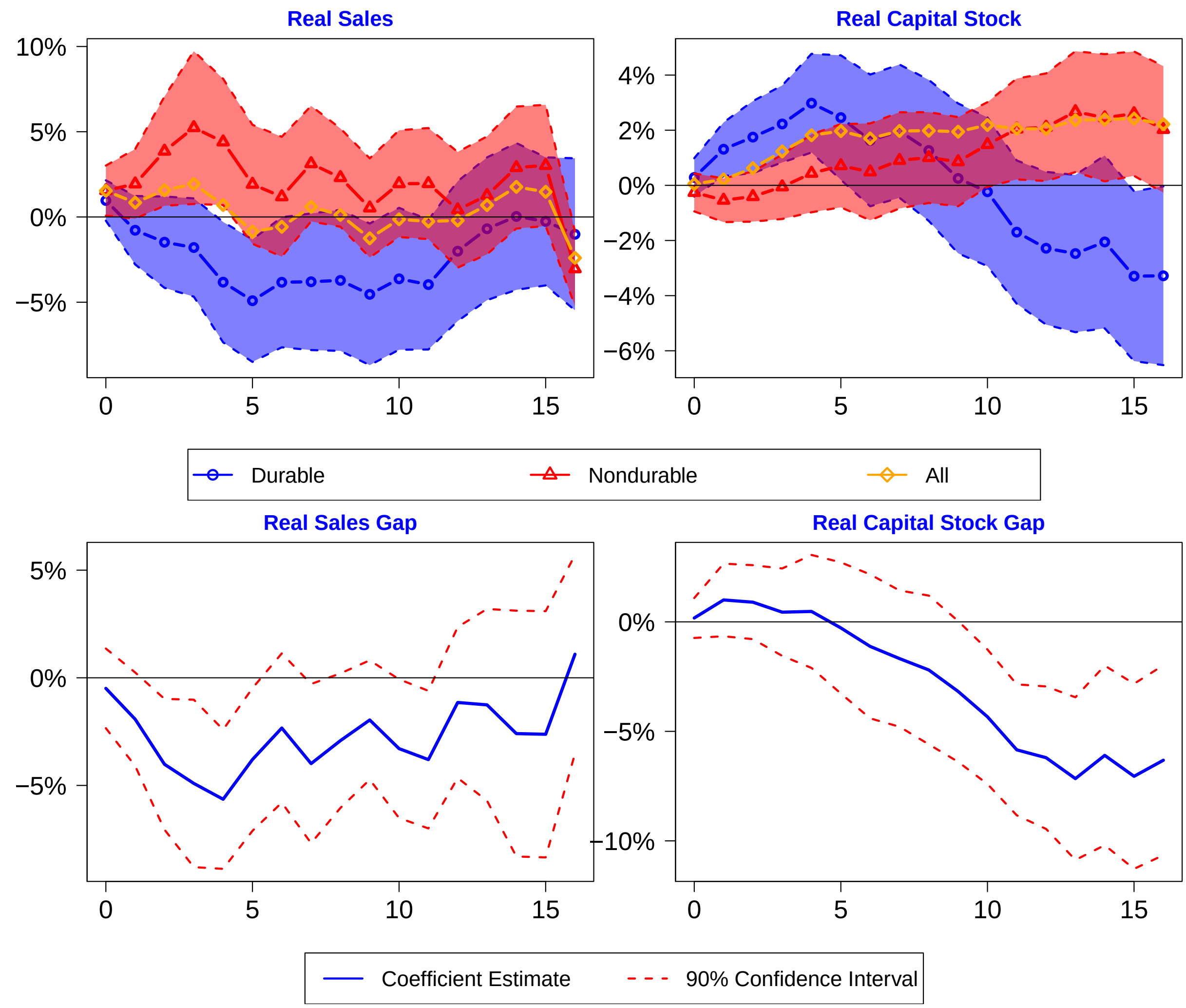

Figure B.6: IRFs using data from 1985-2008

Note: This figure shows the coefficient estimates γ_h^i from Equation **??**, which correspond to the effects of a 100bp contractionary monetary shock. The horizontal axes correspond to quarters after the shock. The top row shows the responses of NPPE, which is measured by the QFR item "Stock of Property, Plant, and Equipment Net of Depreciation" and deflated using the NIPA nonresidential fixed investment price index, and sales, which is the QFR sales measure deflated by GDP price index. The bottom row shows the estimated effects on the log difference between each measure: $y_t \equiv \log(X_t^D) - \log(X_t^N)$. All regressions include a linear time trend and eight lags each of the dependent variable and the shock. 90% confidence intervals are calculated using Newey-West standard errors. Regressions include data from 1975-2008.

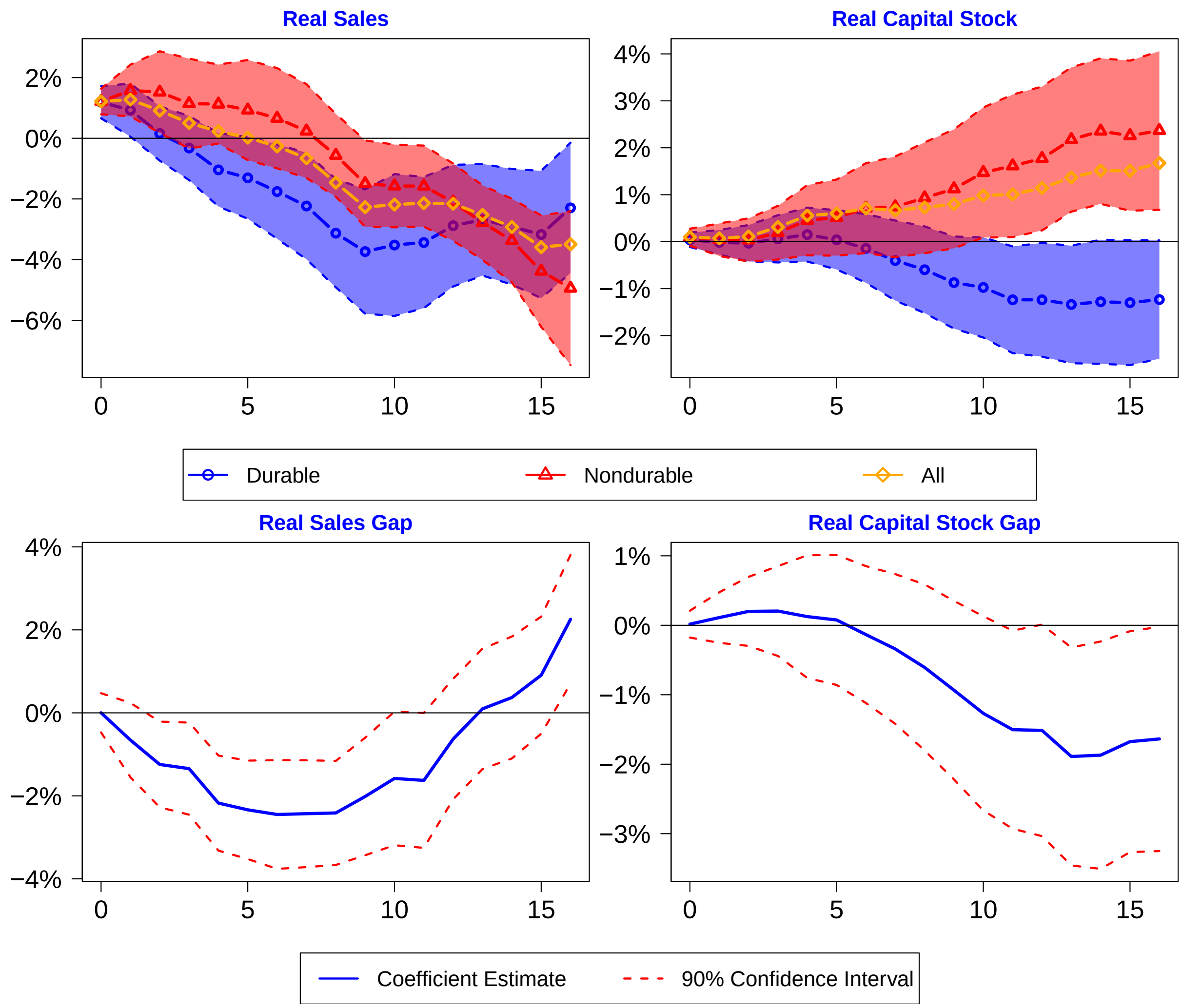

Figure B.7: IRFs using data from 1970-2000

Note: This figure shows the coefficient estimates γ_h^i from Equation **??**, which correspond to the effects of a 100bp contractionary monetary shock. The horizontal axes correspond to quarters after the shock. The top row shows the responses of NPPE, which is measured by the QFR item "Stock of Property, Plant, and Equipment Net of Depreciation" and deflated using the NIPA nonresidential fixed investment price index, and sales, which is the QFR sales measure deflated by GDP price index. The bottom row shows the estimated effects on the log difference between each measure: $y_t \equiv \log(X_t^D) - \log(X_t^N)$. All regressions include a linear time trend and eight lags each of the dependent variable and the shock. 90% confidence intervals are calculated using Newey-West standard errors. Regressions include data from 1970-2000.

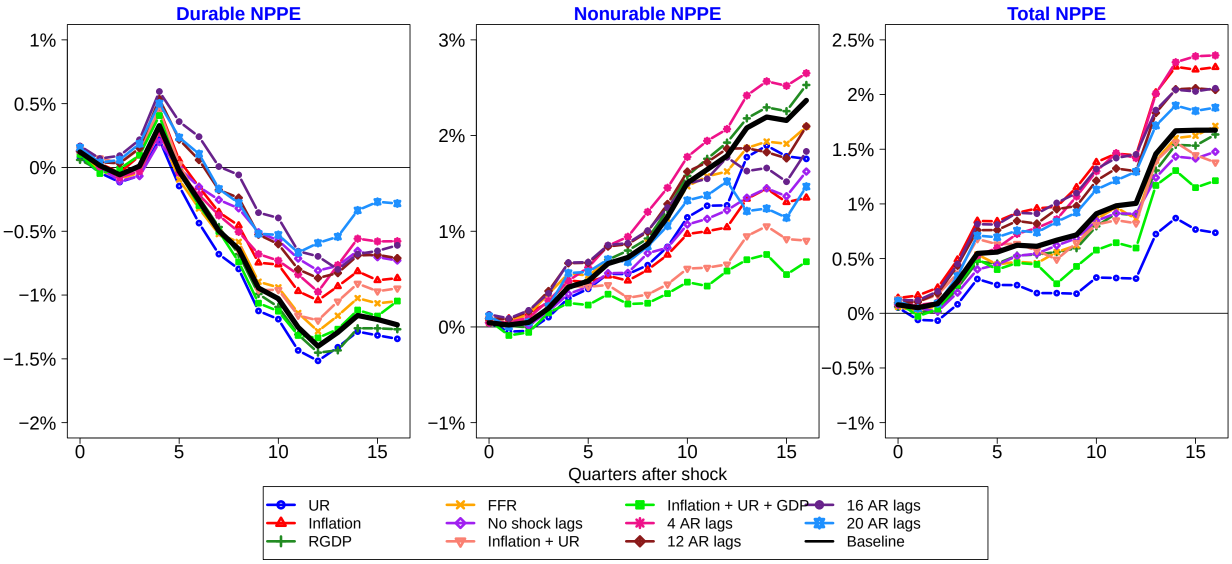

Figure B.8: Robustness of main results to different controls

Note: This figure shows the impulse responses of the capital stocks for the durable, nondurable, and aggregate manufacturing sectors to a 100bp contractionary monetary shock. All regressions use data from 1970-2008. Each line corresponds to a different econometric specification shown in the legend. The "Baseline" specification, shown as the black line, corresponds to my main specification in Section 2. The "UR", "Inflation", "RGDP", and "FFR" specifications adds eight lags each of the unemployment rate, CPI inflation, real GDP growth, and the Federal Funds Rate, respectively, as controls to the baseline specification. The "No shock lags" specification excludes lags of the monetary shock as controls. The "N AR lags" specifications correspond to using $N \in \{4, 12, 16, 20\}$ lags each of the dependent variable and the monetary shock instead of the 8 lags used in my baseline specification.

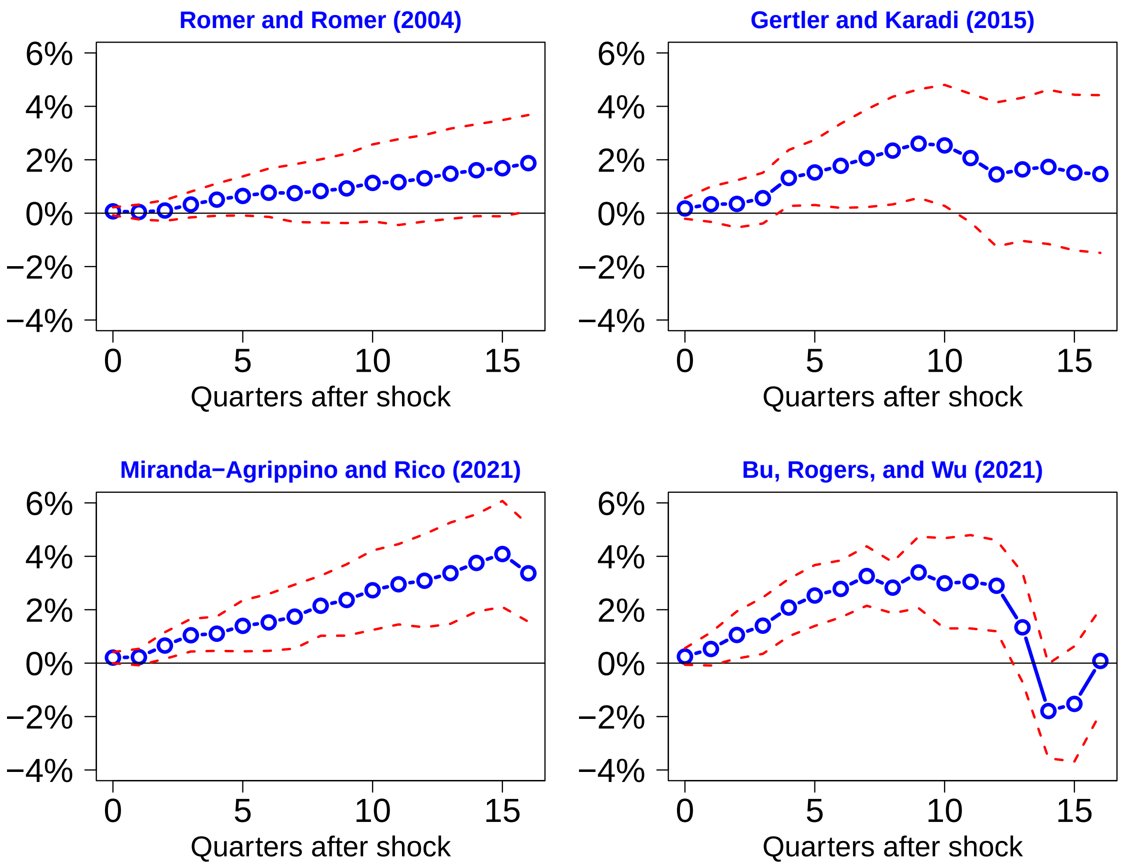

Figure B.9: IRFs excluding linear time trend

Note: This figure shows the response of the aggregate real capital stock for the manufacturing sector from the QFR to a variety of monetary policy shocks. The top left panel shows the response to a 100bp contractionary shock identified using the approach of Romer and Romer (2004) including data from 1970-2008 (I use the extended version of the shocks developed by Coibion (2012)). The upper right panel shows the response to a 100bp contractionary shock identified in Gertler and Karadi (2015) including data from 1975-2008. The lower left panel shows responses to a two standard deviation shock identified in Miranda-Agrippino and Ricco (2021) including data from 1991-2008. The lower right panel shows the response to a two standard deviation shock identified in Bu et al. (2021) including data from 1995-2008. All regressions include eight lags each of the dependent variable and the shock, but not a linear time trend. Dashed red lines show 90% confidence intervals calculated using Newey-West standard errors.

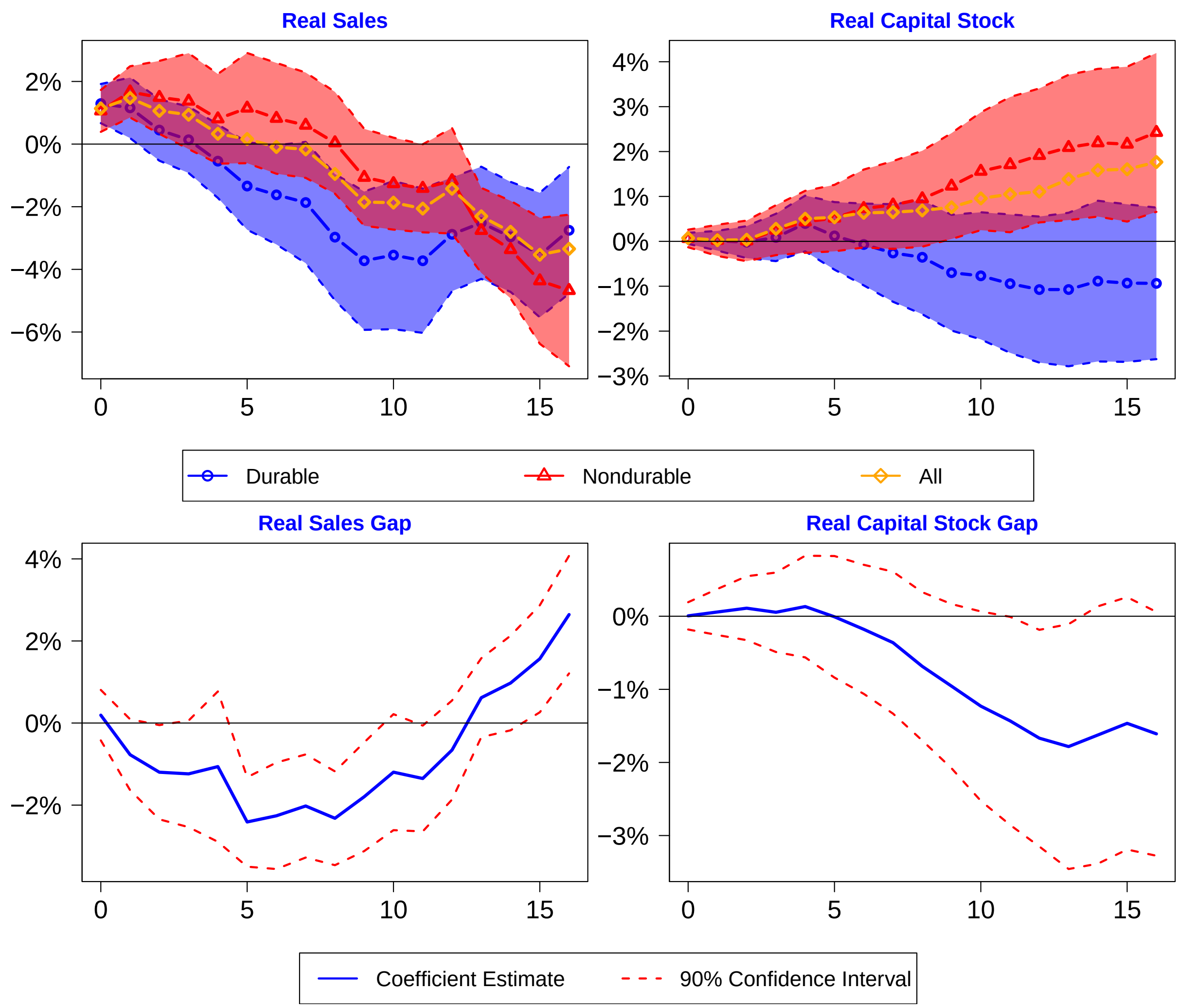

Figure B.10: IRFs excluding linear time trend

Note: This figure shows the effects of a 100bp contractionary monetary shock using a modified version of my baseline regression specification which replaces the linear time trend with eight lags of log real GDP. The horizontal axes correspond to quarters after the shock. The top row shows the responses of NPPE, which is measured by the QFR item "Stock of Property, Plant, and Equipment Net of Depreciation" and deflated using the NIPA nonresidential fixed investment price index, and sales, which is the QFR sales measure deflated by the NIPA manufacturing output price index for each sector. The bottom row shows the estimated effects on the log difference between each measure: $y_t \equiv \log(X_t^D) - \log(X_t^N)$. 90% confidence intervals are calculated using Newey-West standard errors. Regressions include data from 1970 through 2008.

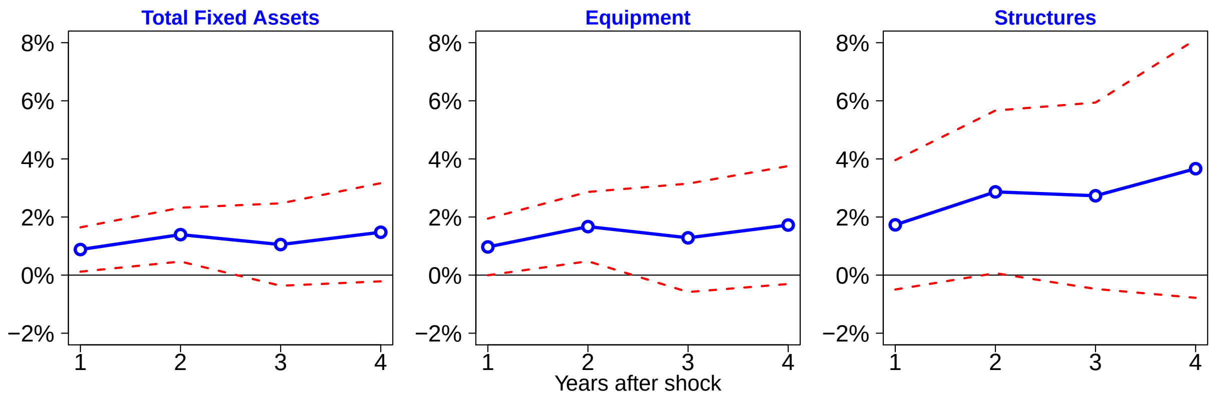

Figure B.11: Investment responses to monetary shocks using BEA fixed asset data (90% CI)

Note: This figure shows the same impulse responses of investment in total fixed assets, equipment, and structures for the manufacturing sector to a 100bp contractionary monetary shock as shown in Figure 4 of the main paper with the addition of 90% confidence intervals calculated using Newey-West standard errors. I add up the quarterly monetary shock series in each year to obtain an annual series to facilitate analysis of the BEA data (which is at the annual frequency). Regressions use a local projection specification that includes a linear time trend and four lags of the dependent variable as controls.

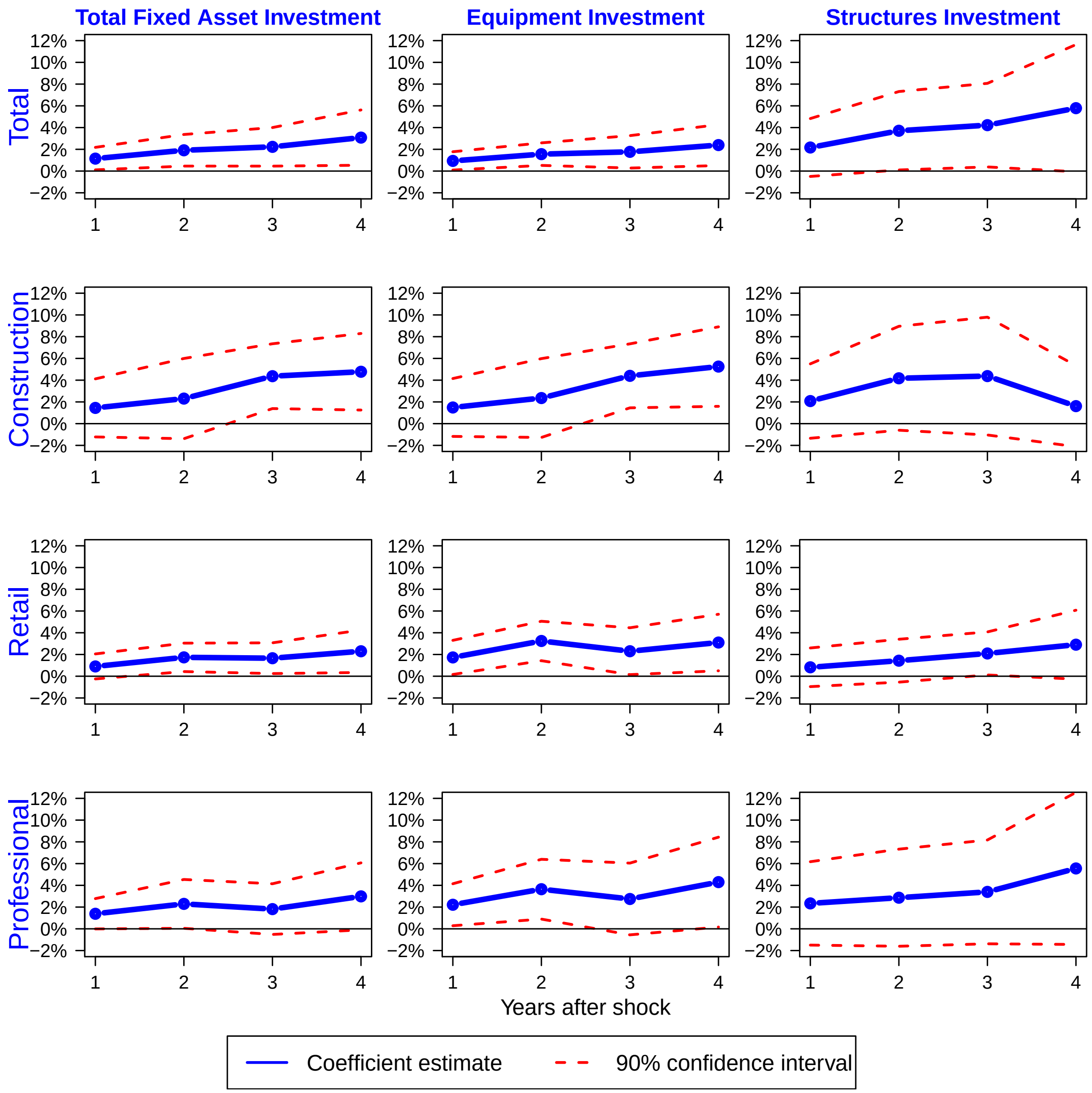

Figure B.12: Investment responses to monetary shocks using BEA fixed asset data (90% CI)

Note: This figure shows the impulse responses of the log difference between investment in the manufacturing sector and investment for the total economy as well as the construction, retail trade, and professional service sectors. I add up the quarterly monetary shock series in each year to obtain an annual series to facilitate analysis of the BEA data (which is at the annual frequency). Each row corresponds to the sector shown to the left, and each column corresponds to the asset category shown at the top. Regressions use a local projection specification that includes a linear time trend and four lags of the dependent variable as controls. 90% confidence intervals calculated using Newey-West standard errors.

2.2 Structures analysis

Structures, which according to the BEA's fixed asset data accounts represent about 80% of the capital stock across the entire economy and 35% of the capital stock for the manufacturing sector, provide detailed evidence that the cost of new investment falls in response to contractionary monetary shocks and that financially unconstrained firms take advantage of these lower prices. Buildings have much longer lifespans than most other types of capital goods, meaning that they should be particularly sensitive to price changes. The cost of new construction (including materials and wages) is strongly correlated with the residential housing market, which is known to deteriorate sharply following a monetary contraction (see for example Leamer (2015)). This reduced demand lowers building costs and leads to large estimated increases in manufacturing construction. Detailed commercial building permit data show that this investment response is driven by the intensive margin: the *number* of new manufacturing structures falls while the total *value* of new structures rises.

The inverse relationship between manufacturing and residential construction activity growth can be seen in the responses to monetary shocks in the top row of Figure B.13. While residential investment falls by almost 8% before returning to its baseline level, there is a much more muted effect in nonresidential structures investment. This is driven in part by manufacturing structures investment, which increases by up to 7.3%. Residential investment averaged about 58% of total structures investment from 1970-2008, meaning construction costs such as wages and building materials are driven to a large degree by activity in the housing market. This can be seen in the bottom row of Figure B.13, which shows the responses of construction employment, real building costs[5], and the NIPA real manufacturing structures price deflated by the GDP price index. These measures show that the relative cost of construction falls significantly in the wake of contractionary monetary shocks and can help explain why manufacturing firms increase their investment expenditure in response.

[5]This measure is the Engineering News-Record's Building Cost Index, which is calculated based on a variety of wages and materials in the construction industry and deflated using the GDP price index.

Figure B.14 shows the price indices for each component of total investment and highlights the fact that the decline in prices is not unique to manufacturing structures. While manufacturing-specific investment deflators are not available in the NIPA data, this exercise suggests that structures play an outsized role in driving the response of manufacturing investment to monetary shocks. The BEA fixed asset data do have manufacturing-specific investment price indices, and the responses of these are shown in Figure B.15. Because these data are only available at the annual level, the coefficient estimates are much noisier. Nonetheless, they are consistent with the idea that contractionary monetary policy has a persistently more negative effect on manufacturing structures prices relative to other types of investment.

Building permit data allow for more detailed analysis of structures investment at the "project" level. Dodge Analytics is a consulting firm that collects commercial building permits based on county-level filings. They generously shared aggregate data on commercial building permits dating back to 1967 for the total number and value of new (defined as those with a planned start date within 60 days) building permits split by type of structure. Details and definitions of the data can be found in Appendix A. These data are useful because they can distinguish between the extensive (more/fewer projects) and intensive (more/less costly projects) margins when analyzing changes in construction activity.

The results for manufacturing structures are shown in Figure B.16. The leftmost panel shows that the number of new permits drops following the shock before returning to its pre-shock level over four years. The total value of the projects, shown in the middle panel, closely matches the shape of the response of the NIPA measure of manufacturing construction value by increasing for about two years. The right panel shows that the increase in total value is driven by an increase in the average permit value. To the extent that larger and less financially constrained manufacturing firms undertake more valuable construction projects, these results are consistent with the idea that it is the subset of financially unconstrained firms which take advantage of declining construction costs and increase their investment.

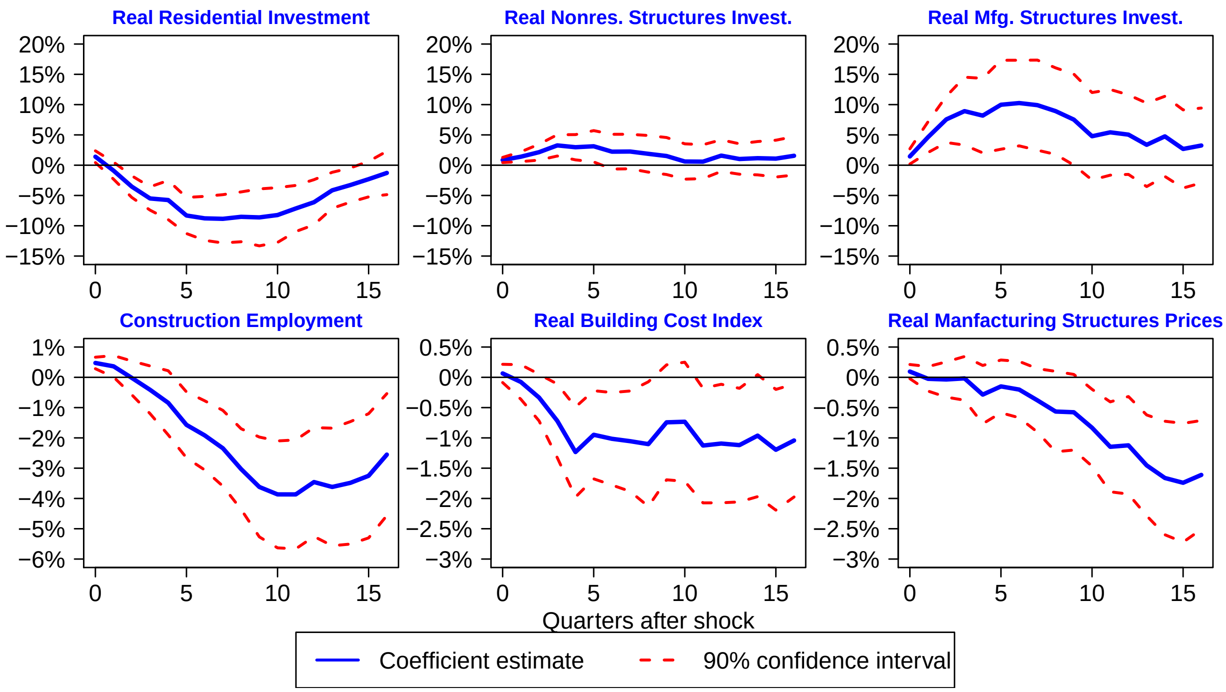

Figure B.13: Empirical Responses to 100bp Contractionary MP Shock (90% CI)

Note: Real residential investment, real nonresidential structures investment, and real manufacturing structures investment data come from the NIPA. Construction employment data are from the BLS establishment survey (CES). The Real Building Cost Index is calculated by dividing the nominal building cost index calculated by the Engineering News-Record, which is based on measures of material and labor costs, by the GDP price index. Real manufacturing structures prices are calculated by dividing the NIPA price index for manufacturing structures investment by the GDP price index. Regressions use the same specification as my baseline results (Equation 1 of the main paper), but without calendar quarter fixed effects since the data are already seasonally adjusted, and they include data from 1970-2008.

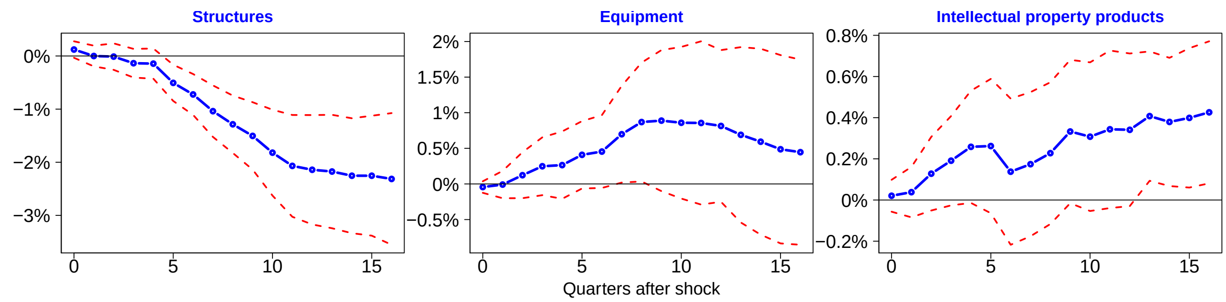

Figure B.14: Relative investment price response to monetary shocks (90% CI)

Note: This figure shows the estimated impulse response to a 100bp contractionary monetary shock for each component of the nonresidential fixed investment price index relative to the GDP price index. Data are quarterly and come from the National Income and Product Accounts. Regressions use the same specification as my baseline results (Equation 1 of the main paper), but without calendar quarter fixed effects since the data are already seasonally adjusted, and they include data from 1970-2008. Dashed red lines correspond to 90% confidence intervals calculated using Newey-West standard errors.

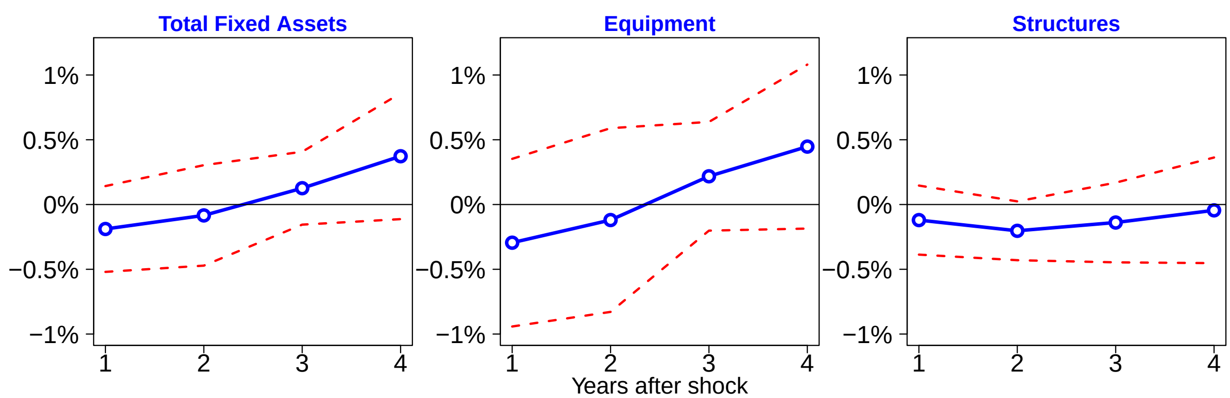

Figure B.15: Relative investment price response to monetary shocks (90% CI)

Note: This figure shows the impulse responses of investment price indices for total fixed assets, equipment, and structures for the manufacturing sector to a 100bp contractionary monetary shock. I add up the quarterly monetary shock series in each year to obtain an annual series to facilitate analysis of the BEA data (which is at the annual frequency). Regressions use a local projection specification that includes a linear time trend and four lags of the dependent variable as controls. Dashed lines represent 90% confidence intervals calculated using Newey-West standard errors.

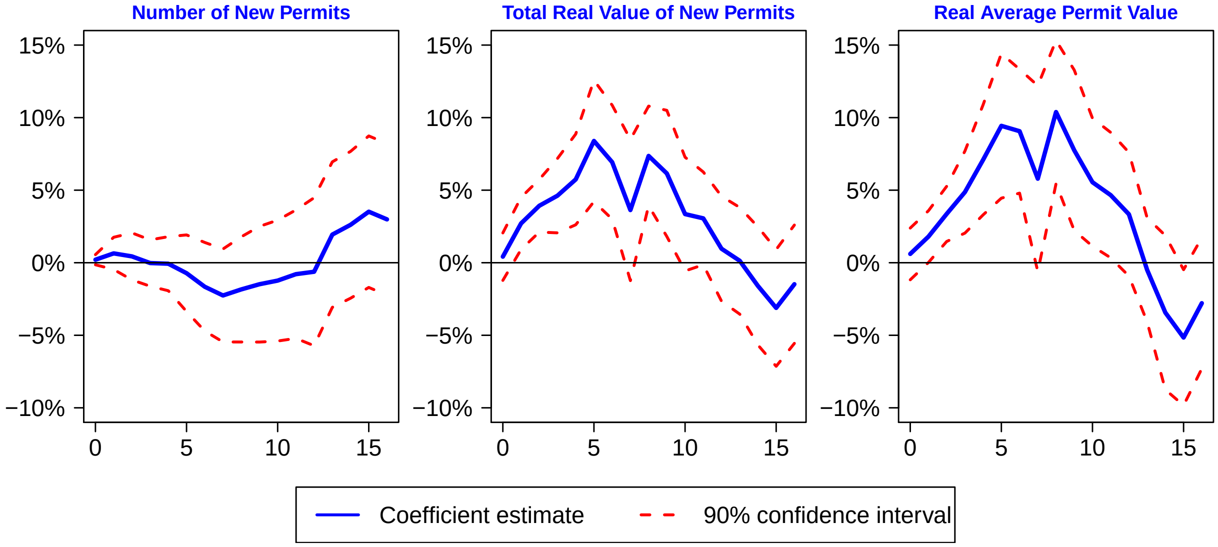

Figure B.16: Empirical Responses to 100bp Contractionary MP Shock (90% CI)

Note: This figure shows impulse responses of the number and value of new manufacturing building permits to a 100bp contractionary monetary policy shock. Building permit data were generously provided by Dodge Analytics and are smoothed using a four-quarter moving average. New permits are defined as those with a planned start date of within 60 days. Only permits for manufacturing structures are included. The real value of all permits is obtained by deflating the nominal value by the manufacturing structures investment price index. The real average permit value is obtained by dividing the real value of new permits by the number of new permits. The specification is the same as my baseline (shown as Equation 1 of the main paper). Regressions include data from 1970-2008.

3 Compustat results

My main results showed that contractionary monetary policy shocks led to increases in investment driven by firms in the nondurable sector. This section shows that my results can also be seen using both aggregated and firm-level data from Compustat. Throughout this section, I construct capital stocks using the procedure outlined in Ottonello and Winberry (2020). This methodology takes as an initial value the earliest observation of the value of each firm's gross stock of property, plant, and equipment and then adds to this series the change in the *net* stock of property, plant, and equipment in each quarter. The process used to construct the data is described in detail in Appendix A.

3.1 Aggregate results

While firms in Compustat report capital stock measures that include international operations, firms in the QFR are specifically asked to restrict their responses to include only US operations. Thus to facilitate more accurate comparison, I use the geographical segment data in Compustat to restrict analysis to firms which are more likely to align with the QFR sample.

I create a set of "domestic" firms by dropping those that explicitly report a significant share of sales outside the US. Of US firms which report both total and foreign sales, a firm is classified as having foreign operations if the average share of foreign sales to total sales is greater than 20% over the quarters in which the company reports both. After dropping these firms with substantial foreign operations, the remaining group of domestic firms represents approximately 95% of the capital stock of the manufacturing sector in Compustat in the 1980s, though this share drops to just above 50% by 2012. The results of this approach are shown in Figure C.1. Nondurable manufacturers are estimated to increase their capital stock while durable producers show a decline, particularly toward the end of the response horizon. These results suggest that the primarily domestic firms in Compustat show very similar capital stock behavior to the patterns observed in the QFR.

These patterns are robust to alternative operational classification. This can be seen in Figure C.2 below, which shows several different approaches to classifying firms. The blue line shows results for firms which explicitly report making a majority of their sales in the US. Firms in the Compustat segments file report both country and a domestic indicator variable for each segment (so that the US operations of a foreign company will be classified as foreign while the US operations of a US company will be classified as domestic). Of firms who report both US domestic sales and total sales, a firm is classified as being "predominantly US" if the average share of US domestic sales to total sales is greater than 80% over the quarters in which the company reports both. The red line, which corresponds to the approach used in Figure C.1, excludes firms with an average share of foreign sales to total sales greater than 20% over the quarters in which a company reported both. These specifications are different conceptually in that not all firms report segment information in Compustat; as a result, the group that excludes explicitly foreign firms is much larger than the group that includes only explicitly US-focused firms. Finally, the orange line shows the results including all manufacturing firms in Compustat, regardless of the existence or scale of their international operations. These results are generally similar across specifications, particularly for durable producers, suggesting that the aggregate Compustat results are not sensitive to my choice of geographic classification.

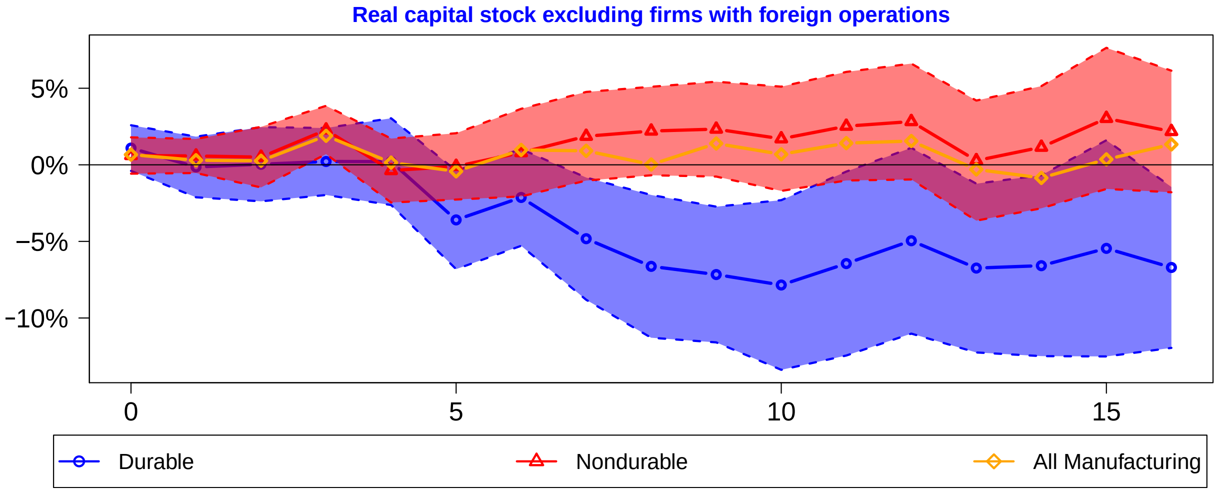

Figure C.1: IRFs for Aggregated Compustat Data, Excluding Foreign Operations (90% CI)

Note: This figure shows impulse responses to a 100bp contractionary monetary shock. The dependent variable is the four-quarter moving average of the aggregate capital stock across Compustat firms deflated by the NIPA nonresidential fixed investment price index. The "Nonforeign" set of firms excludes all firms with an average share of foreign sales to total sales greater than 20% over the quarters in which the company reports both. 90% confidence intervals are calculated using Newey-West standard errors. Regressions use the same specification as my baseline results (shown in Equation 1 of the main paper) and include data from 1987-2008.

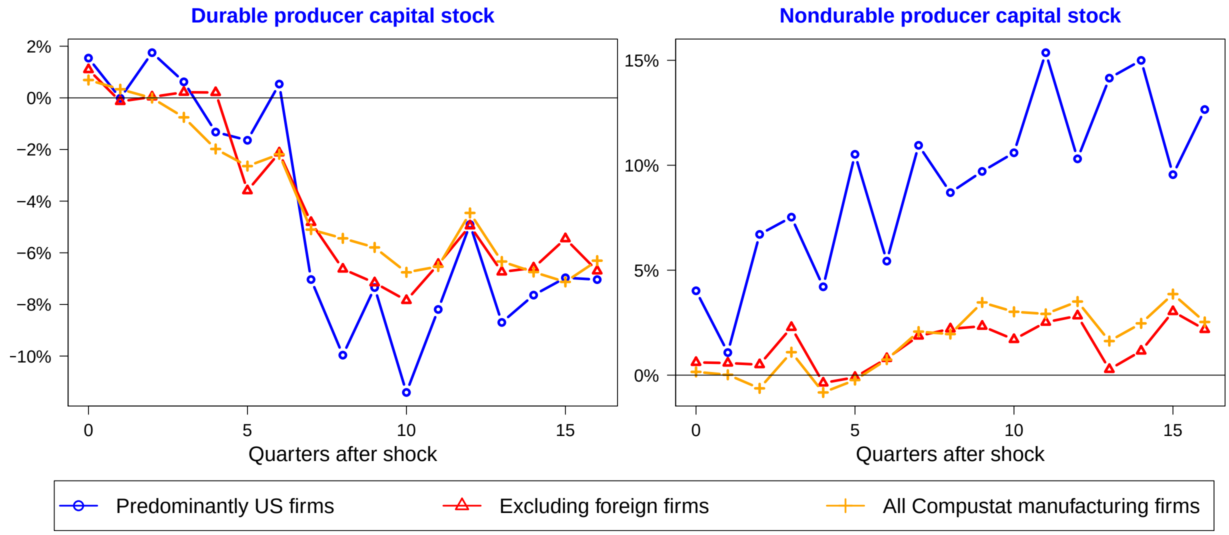

Figure C.2: Empirical responses to 100bp contractionary monetary shock

Note: This figure shows impulse responses to a 100bp contractionary monetary shock. The dependent variable is the four-quarter moving average of the aggregate capital stock across different groups Compustat firms deflated by the NIPA nonresidential fixed investment price index. The "Predominantly US" set of firms includes only those who report both US domestic and foreign sales and which have an average share of US domestic sales to total sales greater than 80% over the quarters in which companies reports both. The "Excluding foreign" group excludes all firms with an average share of foreign sales to total sales greater than 20% over the quarters in which the company reports both. Regressions use the same specification as my baseline results (shown in Equation 1 of the main paper) and include data from 1987-2008.

3.2 Firm-level results

In this section I use firm-level data from Compustat to analyze how firm financial constraints impact the investment response to monetary policy. I estimate the following panel specification:

$$\Delta k_{j,t+h} = \alpha_{j,h} + \delta_{t,h} + \sum_{k=1}^{4} \sigma_h Z_{j,t-k} + \Omega_h Lev_{j,t-1} + \sum_{i \in \{High, Low\}} \gamma_h^i \times Lev_{j,t-1}^i \times \epsilon_t^m + \nu_{j,t+h} \quad (2)$$

$\Delta k_{j,t+h}$ is the cumulative change in the log of the real capital stock between time $t-1$ and time $t+h$ so that $h = 0$ corresponds to the same quarter at which the shock hits and $h = 16$ corresponds to four years after. $\alpha_{j,h}$ is a firm fixed effect, $\delta_{t,h}$ is a time fixed effect, and Z_{t-1} is a vector of lagged firm-level controls including normalized leverage, log assets, sales growth, and the current share of assets. $Lev_{j,t}^i$ represents a set of indicator variables representing whether a firm was in the top ($High$) or bottom (Low) third of leverage ratios across all firms at time $t-1$. Finally ϵ_t^m is the same R&R-style monetary policy shock used in Section 2; because the shock is the same for all firms at each time, the average effect of the monetary shock across firms will be absorbed in the time fixed effects $\delta_{t,h}$. The main coefficient of interest is γ_h^i, which shows the differential effect of a monetary policy shock for a firm with high or low leverage relative to a firm in the middle of the leverage distribution. The estimates of γ_h^{High} and γ_h^{Low} for all horizons up to $h = 16$ are shown in Figure C.3 below.

The left panel shows that firms with low leverage do in fact increase their capital stock following the contractionary monetary policy shock relative to the average firm, with the effect peaking at around 4% about two years after the shock. The right panel shows that firms with high leverage decrease their investment relative to the average firm by up to around 2%. Both of these magnitudes are similar to those shown in my baseline aggregate results, which provides supporting evidence that financial constraints are important for understanding the differences in investment responses to monetary shocks across different sectors.

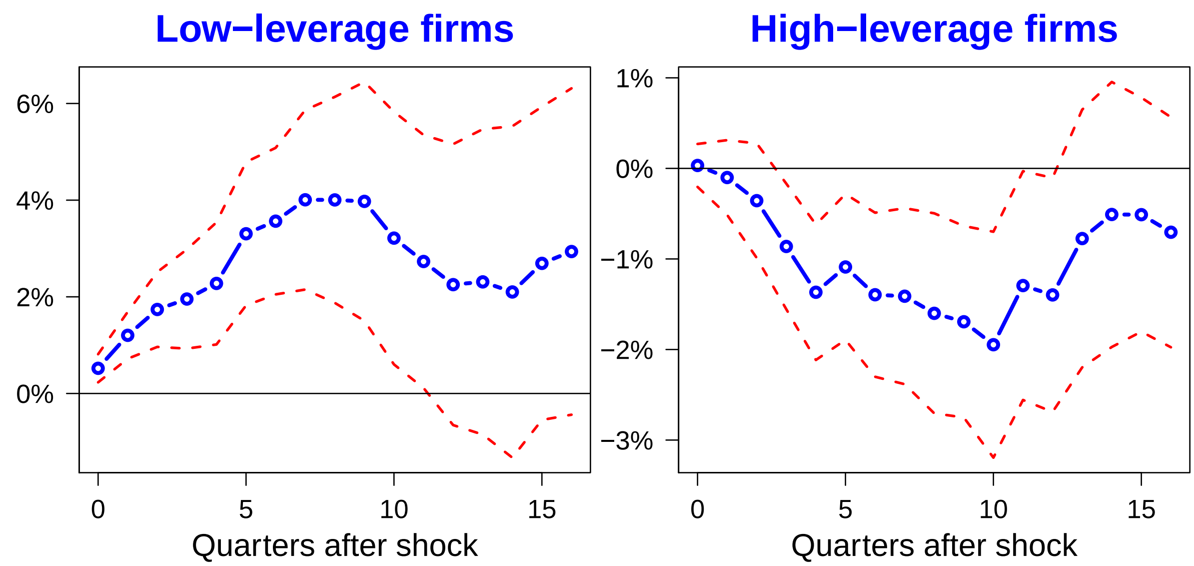

Figure C.3: Firm-level capital stock responses to contractionary monetary shocks (90% CI)

Note: This figure shows the estimated impulse response of the real stock of net property, plant, and equipment (NPPE) for firms in Compustat to a 100bp contractionary monetary shock using the regression specification described in Equation 2. The left panel shows the interaction coefficient between the monetary shock used in my baseline estimates and a dummy variable indicating whether a firm's leverage ratio was in the bottom third across all firms in the quarter prior to the shock. The right panel shows the interaction coefficient between the same shock and a dummy variable indicating whether a firm's leverage ratio was in the top third across all firms in the quarter prior to the shock. The dashed red lines show 90% confidence intervals calculated using Driscoll-Kraay standard errors.

3.3 Comparison to Existing Literature

In this section I compare my results to several recent papers which analyze the cyclical properties of investment. The first is Crouzet and Mehrotra (2020). While my results rely on the publicly available aggregate QFR data and Compustat, they use the QFR microdata. Their paper argues that the industry scope of a firm—that is, the number of industries in which a firm operates—can explain the difference in cyclical sensitivity between small and large firms. They use panel regressions to estimate the response of average firms in the top 1% and bottom 99% of the QFR firm size distribution to monetary policy shocks identified in a similar manner to those used in my paper. In their paper both types of firms decrease their investment in response to contractionary monetary shocks, but they use interactions between durable/nondurable industry dummies and monetary shocks in their specification. To the extent that my results are driven by the distinction between durable and nondurable producers, these interaction terms can reconcile these seemingly contradictory results. Even with this specification, they note that firm-level investment in the QFR microdata increases in response to monetary contractions starting in the 1990s.

The key mechanism in my paper is that investment increases for unconstrained firms in response to falling relative prices, even in the presence of reduced demand. To the extent that the relative price of investment goods also moves in response to other drivers of business cycles, several other findings in their paper provide further support the mechanism at the heart of my paper. Crouzet and Mehrotra (2020) show that while the average marginal effect of GDP growth on fixed investment is positive, the conditional average marginal effect for the largest 0.5% of QFR firms is negative and statistically significant. Furthermore, they find that dividend-paying firms increase their investment during the three years following the onset of a recession; in contrast, investment falls for firms which do not pay dividends. While these empirical results are based on business cycles caused by both monetary and non-monetary shocks, they are consistent with the idea that periods of reduced demand can be attractive times to invest for unconstrained firms.

Several other recent papers also analyze firm-level investment patterns in response to monetary shocks using panel regressions. These include Jeenas (2019), Ottonello and Winberry (2020), and Greenwald et al. (2021). While these papers do not focus explicitly on the heterogeneity of firm responses across sectors, they are both consistent with my findings that it is the *least* financially constrained firms which are most responsive to monetary policy. In addition, Guo (2022), who focuses on financial rather than monetary shocks, provides evidence from Compustat that the firms which are least financially constrained demonstrate countercyclical investment patterns, which dampens the aggregate response to economic shocks through general equilibrium effects.

4 Model

This section shows the parameter values used in the model and the entire set of equilibrium conditions along with several robustness checks and extensions. I show that the main results are robust to forcing durable producers to borrow at the risk-free rate instead of at zero net interest and that the model is still able to generate qualitatively similar results even in the case of equally sticky prices in both sectors. Finally, a simple corporate finance model is used to provide theoretical justification for the fact that durable producers are more financially constrained, and I show that the solution to this model is an "investment multiplier" that takes on the same functional form as the one used in the paper's New Keynesian model.

4.1 Full Set of Equilibrium Conditions

This section shows the set of equations which fully characterize the solution to the model. After plugging in the household's demand curve, the full Lagrangian can be formulated as below. ξ^N is set sufficiently high such that the borrowing constraint does not bind for nondurable producers and thus $\mu_t^N = 0$; as a result, the sector-specific superscripts are omitted in the body of the paper.

$$
\begin{aligned}
\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta_S^t \frac{\lambda_{S,t}}{\lambda_{S,0}} \Bigg\{ & p_t^j(i) \left(\frac{p_t^j(i)}{P_t^j} \right)^{-\epsilon_j} Y_t^j - w_t N_t^j - p_t^D I_t^j - \frac{\phi_j}{2} \left(\Pi_t^j(i) - 1 \right)^2 Y_t^j(i) \\
& + mk_t^j \left[I_t^j \left(1 - \frac{\theta_j}{2} \left(\frac{I_t^j}{I_{t-1}^j} - 1 \right)^2 \right) + (1-\delta_j) K_t^j - K_{t+1}^j \right] + \mu_t^j \left[\xi^j p_t^D K_t^j - w_t N_t^j - p_t^D I_t^j \right] \\
& + mc_t^j \left[A_t (K_t^j)^{\alpha_j} (N_t^j)^{1-\alpha_j} - Y_t^j(i) \right] \Bigg\}
\end{aligned} \tag{3}
$$

The full set of equilibrium conditions are as follows:

$$\eta \left(\frac{1}{C_{B,t}^N - hC_{B,t-1}^N} - h\beta_B E_t \left[\frac{1}{C_{B,t+1}^N - hC_{B,t}^N} \right] \right) = \lambda_{B,t} p_t^N \tag{4}$$

$$w_t = \left(\frac{\nu H_{B,t}^{\chi}}{\lambda_{B,t}} (1+\mu^w) \right)^{1-\rho_w} \left(\frac{w_{t-1}}{\Pi_t} \right)^{\rho_w} \tag{5}$$

$$\lambda_{B,t} p_t^D = \frac{(1-\eta)}{D_{B,t}} + m\psi_t p_t^D \lambda_{B,t} + \beta_B E_t \left[\lambda_{B,t+1} p_{t+1}^D (1-\delta_D) \right] \tag{6}$$

$$(1+i_t)\psi_t = 1 - \beta_B E_t \left[\frac{\lambda_{B,t+1}(1+i_t)}{\lambda_{B,t}\Pi_{t+1}} \right] \tag{7}$$

$$D_{B,t} = C_{B,t}^D + (1-\delta_D) D_{B,t-1} \tag{8}$$

$$(1+i_t) B_{B,t} = m p_t^D D_{B,t} \tag{9}$$

$$p_t^N C_{B,t}^N + p_t^D C_{B,t}^D + \frac{(1+i_{t-1}) B_{B,t-1}}{\Pi_t} = B_{B,t} + w_t H_{B,t}^D + w_t H_{B,t}^N \tag{10}$$

$$\eta \left(\frac{1}{C_{S,t}^N - hC_{S,t-1}^N} - h\beta_S E_t \left[\frac{1}{C_{S,t+1}^N - hC_{S,t}^N} \right] \right) = \lambda_{S,t} p_t^N \tag{11}$$

$$w_t = \left(\frac{\nu H_{S,t}^{\chi}}{\lambda_{S,t}} (1+\mu^w) \right)^{1-\rho_w} \left(\frac{w_{t-1}}{\Pi_t} \right)^{\rho_w} \tag{12}$$

$$\lambda_{S,t} p_t^D = \frac{(1-\eta)}{D_{S,t}} + \beta_S E_t \left[\lambda_{S,t+1} p_{t+1}^D (1-\delta_D) \right] \tag{13}$$

$$D_{S,t} = C_{S,t}^D + (1-\delta^D) D_{S,t-1} \tag{14}$$

$$\lambda_{S,t} = \beta_S E_t \left[\frac{\lambda_{S,t+1}(1+i_t)}{\Pi_{t+1}} \right] \tag{15}$$

$$w_t(1+\mu_t) = (1-\alpha^D) mc_t^D A_t (K_t^D)^{\alpha_D} (H_t^D)^{-\alpha_D} \tag{16}$$

$$w_t = (1-\alpha^N) mc_t^N A_t (K_t^N)^{\alpha_N} (H_t^N)^{-\alpha_N} \tag{17}$$

$$\begin{aligned} (1+\mu_t) p_t^D = mk_t^D & \left[1 - \frac{\theta_D}{2} \left(\frac{I_t^D}{I_{t-1}^D} - 1 \right)^2 - \theta_D \left(\frac{I_t^D}{I_{t-1}^D} - 1 \right) \left(\frac{I_t^D}{I_{t-1}^D} \right) \right] \\ & + \beta_S E_t \left[\left(\frac{\lambda_{S,t+1}}{\lambda_S} \right) mk_{t+1}^D \theta_D \left(\frac{I_{t+1}^D}{I_t^D} - 1 \right) \left(\frac{I_{t+1}^D}{I_t^D} \right)^2 \right] \end{aligned} \tag{18}$$

$$\begin{aligned} p_t^D = mk_t^N & \left[1 - \frac{\theta_N}{2} \left(\frac{I_t^N}{I_{t-1}^N} - 1 \right)^2 - \theta_N \left(\frac{I_t^N}{I_{t-1}^N} - 1 \right) \left(\frac{I_t^N}{I_{t-1}^N} \right) \right] \\ & + \beta_S E_t \left[\left(\frac{\lambda_{S,t+1}}{\lambda_S} \right) mk_{t+1}^N \theta_N \left(\frac{I_{t+1}^N}{I_t^N} - 1 \right) \left(\frac{I_{t+1}^N}{I_t^N} \right)^2 \right] \end{aligned} \tag{19}$$

$$mk_t^D = \beta_S E_t \left[\left(\frac{\lambda_{S,t+1}}{\lambda_S} \right) \left(A_{t+1} \alpha_N {K_{t+1}^D}^{\alpha_D - 1} {H_{t+1}^D}^{1-\alpha_D} mc_{t+1}^D + mk_{t+1}^D (1-\delta_K) + \xi p_{t+1}^D \mu_{t+1} \right) \right] \tag{20}$$

$$mk_t^N = \beta_S E_t \left[\left(\frac{\lambda_{S,t+1}}{\lambda_S} \right) \left(A_{t+1} \alpha_N {K_{t+1}^N}^{\alpha_N - 1} {H_{t+1}^N}^{1-\alpha_N} mc_{t+1}^N + mk_{t+1}^N (1-\delta_K) \right) \right] \tag{21}$$

$$w_t H_t^D + p_t^D I_t^D = \xi p_t^D K_t^D \tag{22}$$

$$\left[(1-\epsilon_D)p_t^D+\epsilon_D mc_t^D\right]-\phi_D\left(\Pi_t^D-1\right)\Pi_t^D+\beta_S\phi_D E_t\left[\left(\frac{\lambda_{S,t+1}}{\lambda_{S,t}}\right)\left(\Pi_{t+1}^D-1\right)\Pi_{t+1}^D\left(\frac{Y_{t+1}^D}{Y_t^D}\right)\right]=0 \tag{23}$$

$$\left[(1-\epsilon_N)p_t^N+\epsilon_N mc_t^N\right]-\phi^N\left(\Pi_t^N-1\right)\Pi_t^N+\beta_S\phi_N E_t\left[\left(\frac{\lambda_{S,t+1}}{\lambda_{S,t}}\right)\left(\Pi_{t+1}^N-1\right)\Pi_{t+1}^N\left(\frac{Y_{t+1}^N}{Y_t^N}\right)\right]=0 \tag{24}$$

$$Y_t^D=A_t\left(K_t^D\right)^{\alpha_D}\left(H_t^D\right)^{1-\alpha_D} \tag{25}$$

$$Y_t^N=A_t\left(K_t^N\right)^{\alpha_N}\left(H_t^N\right)^{1-\alpha_N} \tag{26}$$

$$K_{t+1}^D=(1-\delta_K)K_t^D+I_t^D\left[1-\frac{\theta_D}{2}\left(\frac{I_t^D}{I_{t-1}^D}-1\right)^2\right] \tag{27}$$

$$K_{t+1}^N=(1-\delta_K)K_t^N+I_t^N\left[1-\frac{\theta_N}{2}\left(\frac{I_t^N}{I_{t-1}^N}-1\right)^2\right] \tag{28}$$

$$\omega H_{S,t}^D+(1-\omega)H_{B,t}^D=H_t^D \tag{29}$$

$$\omega H_{S,t}^N+(1-\omega)H_{B,t}^N=H_t^N \tag{30}$$

$$\omega C_{S,t}^D+(1-\omega)C_{B,t}^D=C_t^D \tag{31}$$

$$\omega C_{S,t}^N+(1-\omega)C_{B,t}^N=C_t^N \tag{32}$$

$$\omega D_{S,t}+(1-\omega)D_{B,t}=D_t \tag{33}$$

$$\omega B_{S,t} + (1-\omega) B_{B,t} = 0 \tag{34}$$

$$K_t^D + K_t^N = K_t \tag{35}$$

$$C_t^D + I_t^D + I_t^N + \frac{\phi_D}{2}\left(\Pi^D - 1\right)^2 Y_t^D = Y_t^D \tag{36}$$

$$C_t^N + \frac{\phi_N}{2}\left(\Pi^N - 1\right)^2 Y_t^N = Y_t^N \tag{37}$$

$$A_t = A_{t-1}^{\rho^A} \exp\left(e_t^A\right) \tag{38}$$

$$\beta_S(i + i_t) = (\beta_S(1 + i_{t-1}))^{\rho} \left(\Pi_t^{\phi_\Pi}\right)^{1-\rho} \exp(e_t^M) \tag{39}$$

$$\Pi_t^D = \frac{p_t^D}{p_{t-1}^D} \Pi_t \tag{40}$$

$$\Pi_t^N = \frac{p_t^N}{p_{t-1}^N} \Pi_t \tag{41}$$

$$1 = (p_t^N)^{\eta} (p_t^D)^{1-\eta} \tag{42}$$

4.2 Model extensions

This section considers several extensions to my baseline model. First, I show the results are robust to using sticky prices in both sectors. Even though the assumption that durable prices are more flexible is supported by existing empirical work, my results do not depend on it. Calibrations which use the baseline nondurable price stickiness for both sectors ($\phi_D = \phi_N = 58.25$) lead to an increase in investment in both sectors in response to the contractionary shock, but this depends on the calibration of the other parameters. Even with this higher degree of price stickiness, the model is able to generate the appropriate responses of investment in the case of tighter financial constraints (setting $\xi = 0.04$ instead of its baseline value of 0.1). The IRFs are shown in the left panel of Figure D.1. This suggests that imposing equal degrees of price stickiness will not automatically lead to behavior inconsistent with the main mechanisms described in my paper.

Next, I consider how the model results change if I assume that financially constrained firms borrow intertemporally at the risk-free rate instead of intratemporally without paying interest. In this alternate setup, the equilibrium conditions for households and nondurable producers are unchanged; the only difference is that durable producers now have to pay interest (at the risk-free rate) on the funds they borrow to purchase capital and labor. The modified equations are:

$$w_t(1+\mu_t)(1+i_t) = (1-\alpha^D)mc_t^D A_t (K_t^D)^{\alpha^D}(H_t^D)^{-\alpha^D} \tag{43}$$

$$\begin{aligned}(1+\mu_t)p_t^D(1+i_t) = mk_{D,t}&\left[1-\frac{\theta_D}{2}\left(\frac{I_{D,t}}{I_{D,t-1}}-1\right)^2-\theta_D\left(\frac{I_{D,t}}{I_{D,t-1}}-1\right)\left(\frac{I_{D,t}}{I_{D,t-1}}\right)\right]\\ &+\beta_S E_t\left[mk_{t+1}^D\theta_D\left(\frac{I_{D,t+1}}{I_{D,t}}-1\right)\left(\frac{I_{D,t+1}}{I_{D,t}}\right)\right]\end{aligned} \tag{44}$$

$$(1+i_t)\left(w_t H_t^D + p_t^D I_t^D\right) = \xi p_t^D K_t^D \tag{45}$$

The impulse responses incorporating these modifications are shown in the middle panel of Figure D.1 and are virtually indistinguishable from the baseline results because, as in the data, interest rates are relatively small drivers of user cost compared to the relative price of investment.

The third panel shows model results using an alternative approach to adjusting investment. My baseline model uses the "second-order" adjustment cost approach of Christiano et al. (2005), in which adjustment costs are based on changes in the rate of investment:

$$K_{t+1} = (1-\delta)K_t + I_t \left[1 - \frac{\theta}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2\right] \tag{46}$$

An alternative approach would be to instead use adjustment costs that apply to the capital stock:

$$K_{t+1} = (1-\delta)K_t + I_t - \frac{\theta}{2}\left(\frac{I_t}{K_t} - \delta\right)^2 K_t \tag{47}$$

The results of this alternative adjustment cost formulation are shown in the right panel of Figure D.1. This specification uses the same investment adjustment cost paramters θ^i as in the baseline specification, and all other equations and parameters are unchanged. As in my baseline results, a contractionary monetary shock leads to a gradual decline in the capital stock for durable producers and an increase for nondurable producers. While the model with first-order adjustment costs shows a jump in investment on impact, has peak effects that are larger in magnitude and occurs a bit earlier, and exhibits a more rapid return toward steady state, the shape of the responses are qualitatively similar for the vast majority of the response horizon.

I also show that the assumption of a homogenous durable good that functions both as productive capital and as a consumption good for the household is not crucial to the model's main results. To show this, I modify the baseline model to include two durable sectors: one that produces capital, and another that produces household goods. Both durable sectors have the same production and price setting parameters. They also face the same financial constraints as the durable producers in the baseline model, which restrict their total input expenditure to a fraction of the value of their productive capital stock. The impulse responses for the capital stocks in each sector, as well as the aggregate, are shown in Figure D.2. The durable sector in this figure combines producers of household durable goods and capital goods to make it comparable to the baseline model. These figures show that the main three facts from my baseline model still hold. In response to a contractionary monetary shock: 1) investment declines for durable producers (after a small and short-lived and increase in the version with separate pricing), 2) investment increases for nondurable producers, and 3) on balance, the total combined capital stock of the manufacturing sector increases.

Finally, I show that the outsized responses of output and inflation in my baseline model are the result of choosing parameters to match the investment responses, rather than a fundamental feature of the model. This can be seen in Figure D.3 below, which changes the persistence parameter in the Taylor Rule ρ to be 0.5, instead of its baseline value of 0.9. This change is sufficient to generate responses of inflation and output that are far closer to the data. However, while this specification is able to get the direction of the responses for investment in each sector correct, their magnitudes become much smaller than what we see in the data. Thus, the inability of the baseline model to quantitatively match aggregate output and inflation responses is the result of different objectives when choosing parameters, rather than a fundamental shortcoming of the model's structure. This finding suggests that the large model response of output and inflation under its baseline formulation does not invalidate its conclusion that eliminating financial constraints reduces volatility.

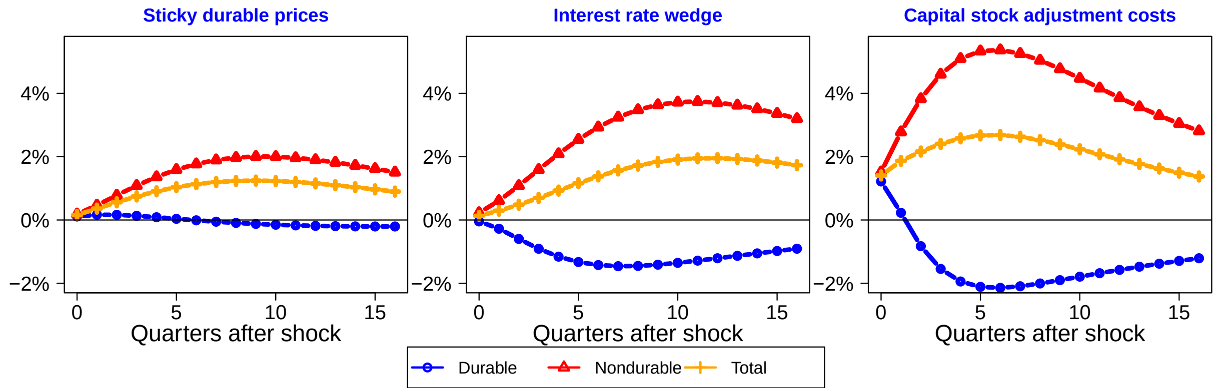

Figure D.1: Capital stock responses under alternative modeling assumptions

Note: This figure shows the impulse responses of the model capital stocks in each sector to a 100bp contractionary monetary shock under several alternative modeling assumptions. The left panel shows results when the price stickiness of both sectors is set to be $\phi_N = \phi_D = 58.25$ and the financial constraint parameter is set to $\eta = 0.04$ while all other parameters remain the same as in Table **??**. The middle panel shows results when durable producers must pay the risk-free rate on their loans. The right panel replaces the "second-order" investment adjustment costs from Christiano et al. (2005) with capital stock adjustment costs using the same parameters.

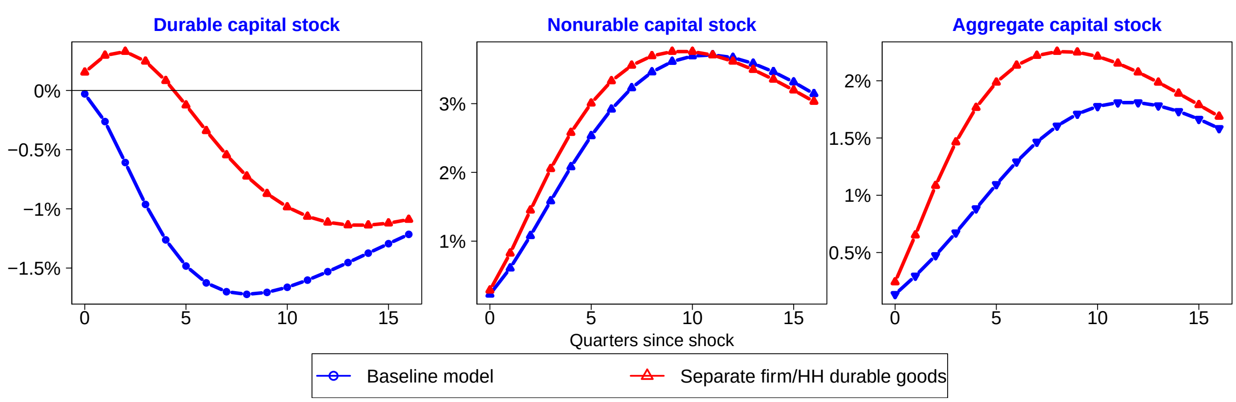

Figure D.2: Model IRFs with distinct household durables and capital goods

Note: This figure shows impulse responses for capital stocks to a 100bp monetary contraction for two different versions of the model. The blue lines correspond to the baseline model. The red lines correspond to a modified version of the model that includes two durable sectors: one that produces capital, and another that produces household goods. Both durable sectors have the same production and price setting parameters. They also face the same financial constraints as the durable producers in the baseline model, which restrict their total input expenditure to a fraction of the value of their productive capital stock.

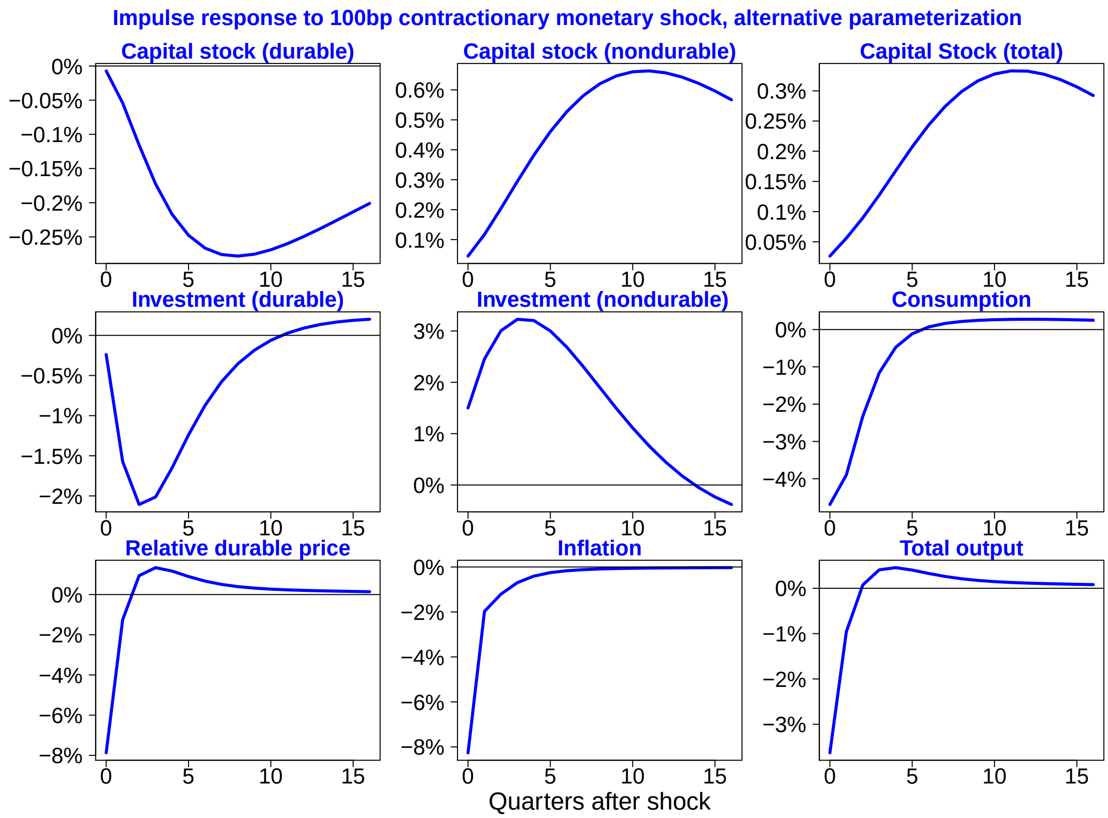

Figure D.3: Estimated impulse responses to 100bp contractionary monetary shock

Note: This figure replicates Figure 8 of the main paper with a modified Taylor Rule persistence parameter ($\rho = 0.5$, compared to an original value of 0.9).

4.3 Theoretical Basis for Lending Frictions

The New Keynesian model used in the paper treated durable goods producers as exogenously subject to financing constraints. This section outlines a plausible theoretical mechanism that would endogenously lead to such frictions: the fact that durable producers face more volatile demand for their product due to its longevity.

I use the workhorse model developed in in Tirole (2010) to analyze this mechanism for several reasons. First, the model is simple, tractable, and allows for analytic results. Second, the model is flexible enough to easily incorporate a stylized type of demand volatility. Finally, the solution to the model is an "investment multiplier" which says that the amount of funds that a firm is able to raise is a linear function of the value of its assets, which is the same functional form as the one found in the paper's more elaborate New Keynesian model. While not all of the parameters which determine the investment multiplier in this simplified context have direct counterparts in the larger model, this section provides justification for my choice of working capital constraint and allows for some insightful comparative static exercises.

4.3.1 The Simple Model

There is a risk-neutral entrepreneur with sole access to the technology to produce their good. The production of the project is a function of the investment X and effort $e \in \{l, h\}$ put into it. The entrepreneur has net worth A that can be invested in the project; if he wishes to invest $X > A$, he must borrow $L = X - A$ from the banking sector, which is perfectly competitive and risk neutral.

The financing of the projects is non-trivial due to the presence of a moral hazard problem. If the entrepreneur exerts high effort e_h, the project succeeds with probability p_h and produces according to the linear "production" function RX where R is the productivity or return of the project and $X \in [0, \infty)$. If the entrepreneur exerts low effort, the project succeeds with probabilty $p_l < p_h$ and the entrepreneur receives private benefits proportional to the level of investment BX. I assume that $p_h R > 1 > p_l R + B$, which tells us that the project is only NPV positive on a per-unit basis in the case of high effort, and $p_h R < 1 + \frac{p_h B}{\Delta p}$, which leads to a bounded quantity of investment.

Because effort is not observable the contract cannot directly reward the entrepreneur for working hard, so it must be set up in an incentive-compatible manner to prevent them from running away with the money. This means that the entrepreneur must have enough "skin in the game" such that their private benefit from working hard exceeds their gains from shirking. The contracting problem will have individual rationality (IR) constraints for both the borrower and lender and an incentive compatibility (IC) constraint for the borrower.

Formally, their problem will be to split the investment X and total expected successful return R into separate pieces for both the lenders and borrowers. Incentive compatibility will require that the expected gain for the producer exceeds the private benefit of shirking:

$$R_b(e_h)X \geq R_b(e_l)X \implies p_h R_b X \geq p_l R_b X + BX \implies R_b X \geq \frac{BX}{\Delta p} \tag{48}$$

Here I've defined $\Delta p \equiv (p_h - p_l)$ to be the improvement in success probability that results from hard work. Because the per-unit net return of the project $(p_h R - 1)$ is greater than 1, the constrained investors will always have incentives to invest more in the project and they will only be limited by the set of contracts agreeable to the bank. Thus, their IC constraint will bind ($R_b X = \frac{BX}{\Delta p}$) and their IR constraint will be slack. The positive net return will result in constrained investors optimally pledging their full wealth A to the project so that $L = X - A$.

I now write the IR constraint for the bank knowing that the optimal contract will induce high effort on the part of the firm and that shirking will not be observed in equilibrium. I also allow for an outside option of investing their funds to earn a risk-free gross interest rate of $(1 + i)$:

$$(1+i)L \geq p_h R_l X \implies (1+i)(X - A) \geq p_h \left[RX - R_b X\right] \tag{49}$$

The second inequality holds because the lender's return can be written as the total return minus the portion promised to the borrower. Because the entrepreneurs have market power in this setup, the IR constraint will bind for the bank and they will receive expected net returns of zero in equilibrium. Thus, combining Equations 48 and 49 leads to following condition:

$$(1+i)(X-A) = p_h\left[RX - R_b X\right] \implies (1+i)(X-A) = p_h\left[RX - \frac{BX}{\Delta p}\right]$$

$$\implies X\left[1 - \frac{p_h}{1+i}\left(R - \frac{B}{\Delta p}\right)\right] = A \implies X = \left(\frac{1}{1-\frac{p_h}{1+i}\left[R-\frac{B}{\Delta p}\right]}\right)A \tag{50}$$

Re-write the utility function as a linear function of X and then plug in the investment multiplier derived above to write the borrower's net utility as follows:

$$U^B = (p_h R - 1)X = \left(\frac{p_h R - 1}{1-\frac{p_h}{1+i}\left[R-\frac{B}{\Delta p}\right]}\right)A \tag{51}$$

Because all firms have constant returns to scale and the project has positive NPV, they will always want to invest as much as possible. The model solution will be an "investment multiplier" k that reflects the return of the project, the outside interest rate, the project's probaiblity of success, and the severity of the moral hazard problem. In this setup, because R is known by both parties before the investment is sunk, the contract can be interpreted as either debt or equity.

4.3.2 Implications of Demand Volatility

A simple way to extend the model to allow for durable goods to have more volatile demand is to treat the parameter R as a random variable that is realized after financing is obtained but prior to effort being exerted. In this setup the per-unit returns to investment can be thought of as the price of the good being sold; in this context, durable producers face more volatile returns because their good is longer-lived, and this longevity makes intertemporal substitution easier and leads to a more volatile price. In this section I show that the combination of volatile returns and equity contracts will cause the investment multiplier to decrease in the case of a mean-preserving spread in the return.

The simplest illustration of how demand volatility can influence terms of equity is in the discrete case. Instead of being deterministic as in the previous section, the return $\tilde{R}$ is now a random variable that is realized after investment has been sunk but before effort has been exerted. It takes on a value of R_0 with probability θ and R_1 with probability $1 - \theta$. Define the expected return $\bar{R} \equiv \theta R_0 + (1 - \theta) R_1$. In expectation the investment project is NPV positive in the case of high effort: $p_h \bar{R} > 1 > p_l \bar{R} + B$. As a result, the entrepreneur will want to exert effort when the high return R_h is realized. If R_0 is realized, there is no surplus to be gained from exerting effort since $p_l R_0 + B > p_l R_0$, so the entrepreneur will slack.[6]

If the borrower could credibly commit to working hard regardless of the realization of $\tilde{R}$, then they would be able to promise a higher return to the lender and receive more financing. However, because the bank knows that the entrepreneur will not exert effort if R_0 is realized, they will internalize this outcome when making their lending decision and subsequently reduce the available quantity of funds. In this sense it is the bank who bears the downside risk to bad realizations of $\tilde{R}$ while the entrepreneur captures the upside. It is this fundamental asymmetry that allows volatility to exacerbate financial constraints even when all agents are risk neutral.

The optimal equity contract will involve the borrower receiving a share γ of the proceeds of the project regardless of outcome. If R_0 is realized, the borrower will find it optimal not to exert effort, and the gross expected return will be $p_l R_0$. If R_1 is realized, the borrower will find it optimal to exert effort, and the gross return will be $p_h R_1$. The incentive compatibility

[6] Once financed, the funds can only be allocated toward the project. This prevents the entrepreneur from simply "running away with the money" and earning a net return of 1 if R_0 is realized, which would be higher than the expected value of shirking on the project.

condition requires $\gamma p_h R_1 \geq \gamma p_l R_1 + B \implies \gamma = \frac{B}{R_1 \Delta p}$.

The lender will receive a per-unit share of $1-\gamma$ of the per-unit return of the project, which can be written $\hat{R} \equiv \theta p_l R_0 + (1-\theta) p_h R_1$. Their IR constraint requires that they receive in expectation enough to keep them indifferent between investing and earning the risk-free rate: $(1+i)(X-A) = X(1-\gamma)\hat{R}$. Plugging in the borrower's IC constraint yields the model's solution:

$$(1+i)(X-A) = X\left(1 - \frac{B}{\Delta p R_1}\right)\hat{R} \implies X = \left[\frac{1}{1 - \left(\frac{1-\frac{B}{\Delta p R_1}}{(1+i)}\hat{R}\right)}\right] A \tag{52}$$

If $\theta = 0$, then $\hat{R} = p_h R_1$, and the solution collapses to that of the previous section. In this deterministic case, the borrowers would expect to receive $(1-\gamma)p_h\bar{R}$. In the presence of moral hazard, however, the fact that the borrowers will not exert effort if R_0 is realized prevents the lender from earning this return. Instead, they earn $(1-\gamma)\hat{R}$. This difference can be written:

$$p_h\bar{R} - \hat{R} = p_h\left(\theta R_0 + (1-\theta)R_1\right) - \left(\theta p_l R_0 + (1-\theta)p_h R_1\right) = \theta \Delta p R_0 \tag{53}$$

As long as $R_0 > 0$, this difference will be positive, which means that the investment multiplier will be larger in the deterministic case even when the expected returns are the same. The fact that the benefits of shirking only accrue to the borrower and not the lender lead to a lower investment multiplier for more volatile projects.

4.3.3 Relationship to DSGE Model

In these models the solution is an investment multiplier of the form $X = \xi A$ where X was the amount of funds obtained by the entrepreneur and invested in the project, A is the value of the entrepreneur's assets pledged toward the project, and ξ is the multiplier that links the two. If $\xi_i > \xi_j$, then firm i is able to obtain a greater amount of financing for the same initial level of assets, and thus firm i can be interpreted as less financially constrained than firm j. The previous section showed that $\xi_{baseline} > \xi_{volatile}$, showing that firms facing a mean-preserving spread in the volatility of their expected returns would be able to obtain a smaller financing multiplier:

$$\left(\frac{1}{1-\frac{p_h}{1+i}\left[\bar{R}-\frac{B}{\Delta p}\right]}\right) > \left(\frac{1}{1-\left(\frac{1-\frac{B}{\Delta p R_1}}{(1+i)}\hat{R}\right)}\right) \tag{54}$$

The conceptual link between this simple model and the more complex DSGE model in the body of the paper is quite clear. In that model, the main borrowing constraint for durable producers was:

$$w_t H_t^D + p_t^D I_t^D = \xi p_t^D K_t^D \tag{55}$$

The total amount invested in the "project" each period—which in this case corresponds to the production of durable goods—is simply the total expenditure on labor and capital, so $X = w_t H_t^D + p_t^D I_t^D$. The total amount of assets available to the producer each period is simply the value of their capital stock, so $A = p_t^D k_t^D$. Putting these together, this becomes $X = \xi A$, which is precisely the same functional form as in the baseline model.

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