Financial Constraints, Sectoral Heterogeneity, and the Cyclicality of Investment*

Cooper Howes†

First version: February 2019
This version: May 2021

Abstract

While investment in most sectors declines in response to a contractionary monetary policy shock, investment in the manufacturing sector *increases*. Using manually digitized aggregate income and balance sheet data for the universe of US manufacturing firms, I show this increase is driven by the types of firms which are least likely to be financially constrained. A two-sector New Keynesian model with financial frictions can match these facts; unconstrained firms are able to take advantage of the decline in the user cost of capital caused by the monetary contraction while constrained firms are forced to cut back.

JEL Classification: E22, E32, E52

Keywords: Monetary Policy, Investment, Financial Frictions

*I would like to thank Saroj Bhattarai and Olivier Coibion for their invaluable guidance and support; Gabriel Chodorow-Reich, James Cloyne, Marco Del Negro, Aaron Flaaen, Marc Giannoni, Simon Gilchrist, Kevin Kuruc, Oleg Itskhoki, Victoria Ivashina, Dirk Krueger, Ali Ozdagli, Felipe Schwartzman, Alan Taylor, and Choongryul Yang for useful discussions; seminar participants at the University of Texas at Austin, Federal Reserve Bank of Boston, Federal Reserve Bank of Kansas City, and Society for Economic Dynamics 2019 Annual Meeting for helpful comments and feedback; several anonymous referees for thoughtful comments and suggestions that substantially improved the paper; and Dodge Analytics for generously providing building permit data. The views expressed in this paper are those of the author and do not represent those of the Federal Reserve Bank of Kansas City or the Federal Reserve System.

†FRB of Kansas City, 1 Memorial Drive, Kansas City MO 64108; cooper.howes@kc.frb.org

1 Introduction

Productive capital goods are among the most volatile and interest-sensitive components of GDP and receive significant attention from monetary policymakers. While past work such as Bernanke et al. (1999) and Christiano et al. (2005) has confirmed the conventional wisdom that aggregate investment is strongly procyclical in response to monetary shocks, these findings belie meaningful heterogeneity across sectors; in particular, investment in the manufacturing sector is strongly *countercyclical* conditional on monetary policy shocks. A model with financial constraints that vary across sectors can explain this behavior and suggests that the easing of financial constraints can lead to more strongly countercyclical aggregate investment dynamics in response to monetary policy.

I start by establishing several new stylized facts regarding manufacturing investment in Section 2. The main analysis utilizes manually digitized aggregate data from the Quarterly Financial Report for Manufacturing Corporations (QFR), which contain detailed income and balance sheet information for the entire manufacturing sector dating back to 1966. The aggregate capital stock in the manufacturing sector increases by almost 2% in the years following a 100 basis point contractionary monetary shock. This increase is driven entirely by nondurable producers, as durable producers reduce their investment in response to the shock. The QFR data also show that durable manufacturers display a greater degree of financial constraint across several metrics commonly cited in the finance literature: they rely more on short-term debt, their cash flow is more volatile, and they have consistently lower dividend payout ratios.

Data from the National Income and Product Accounts (NIPA) can be used to further analyze these results. They suggest that structures, which have longer lives and more procyclical costs than other types of capital goods, are particularly important for explaining the investment behavior observed in the QFR. Data on building permits for new manufacturing structures from Dodge Analytics support these findings. While the number of new permits falls in response to contractionary monetary shocks, the total *value* of new permits rises. This suggests, at least for structures, that the increase in the value of the capital stock in manufacturing is driven by fewer, larger projects. This is consistent with the idea that unconstrained manufacturing firms take advantage of lower construction costs caused by monetary contractions by undertaking large projects with long useful lifespans. The capital stock dynamics observed in the QFR can also be found in quarterly data from Compustat. Section 3 shows that Compustat aggregates for firms with predominantly US sales behave in a very similar manner to the QFR aggregates, which only include US firms' domestic operations.

The key feature underlying these countercyclical responses to monetary shocks is the long lifespan of investment goods. Transitory shocks that do not affect relative prices will have a small effect on the demand for investment, because most of its value comes from future service flows after the shock dissipates. In contrast, shocks that affect relative prices can lead to large changes in investment, as getting a discount today is equivalent to locking in a long series of lower marginal costs in the future. Firms that are financially constrained may not be able to take advantage of these buying opportunities, however, as falling investment prices also mean reduced collateral values and therefore reduced borrowing capacity. This means contractionary demand shocks can have a net expansionary effect on investment for unconstrained firms (but not constrained firms) if they sufficiently lower its relative price.

I argue that monetary policy acts as this type of shock. In an economy with only one good, contractionary monetary policy will raise interest rates and lower demand, but there will be no relative price effects, so demand for investment goods will fall. In a multi-sector economy with separately priced investment and non-investment goods, however, monetary policy can also affect relative prices. If the decline in the relative price of investment is sufficiently large it can offset the higher interest rates and make investment more appealing. I test this in the data by calculating measures of manufacturing-specific user costs that incorporate relative prices, interest rates, and depreciation. These user cost measures suggest that the decline in the relative price of investment more than offsets the higher interest rates caused by the monetary contraction. The heterogeneity in responses across sectors can be explained by differing degrees of financial constraint.

To analyze the quantitative role of financial factors in explaining this investment heterogeneity and explore counterfactual exercises that change or eliminate financial constraints, I incorporate them into a model. Section 4 develops an otherwise-standard New Keynesian model in which durable producers—consistent with the stylized facts I document in the QFR—exhibit a greater degree of financial constraint than nondurable producers. The model is able to generate firm investment responses that match the data because it limits the ability of financially constrained agents to respond to changes in monetary policy.

In the model, the relative price of investment goods falls in response to a monetary contraction. This reduces the value of collateral held by the constrained durable producers, who are forced to reduce their durable purchases. Unconstrained nondurable producers are able to take advantage of the lower prices and increase their investment expenditure. Households, a fraction of which are also constrained, are affected by a similar mechanism that leads to declines in aggregate consumption in both the nondurable and durable sectors. By generating on-impact investment and consumption responses consistent with the data, I am also able to resolve the "comovement puzzle" first reported in Barsky et al. (2007), who pointed out that simple New Keynesian models predict large increases in durable purchases in response to contractionary monetary shocks due to their extreme forward-looking nature.

These results complement recent work analyzing how firm characteristics can influence the effects of monetary shocks on investment including Cloyne et al. (2019), Crouzet and Mehrotra (2020), Jeenas (2019), and Ottonello and Winberry (2020), and have two important implications. First, they suggest policymakers should pay particularly close attention to the balance sheets of financially constrained firms when trying to use monetary policy as a tool to stabilize business cycles, as binding financial constraints can actually prevent them from adjusting and instead lead to increased investment in other, less-constrained sectors. Second, to the extent that financial modernization can reduce these financial constraints in other sectors, my model suggests that more firms should be able to take advantage of temporary demand-driven drops in prices when choosing the timing of their capital goods purchases.

2 Evidence of Manufacturing Investment Cyclicality

This section provides evidence from aggregate data that manufacturing investment is countercyclical conditional on monetary shocks and argues that this behavior is consistent with heterogeneity in financial constraints. Manually digitized historical data from the Quarterly Financial Report for Manufacturing Corporations show that the aggregate manufacturing sector capital stock increases in response to a contractionary monetary shock. Building permit data suggest that the responses of structures, which have longer lives and more cyclically sensitive prices relative to other types of investment, are driven by the intensive margin. I argue that changes in investment prices can explain this behavior. Many different empirical estimates of the user cost of capital fall in response to contractionary monetary shocks, suggesting that firms have an opportunity to benefit from short-term fluctuations in the prices of these long-lived investment goods. Firms in the nondurables sector drive the increase in the aggregate manufacturing sector capital stock and these are the types of manufacturers that exhibit fewer signs of financial constraint.

2.1 Data

The main source of data is the Quarterly Financial Report for Manufacturing Corporations (QFR), a comprehensive survey of income and balance sheet information for the US manufacturing sector. A detailed description of the data, which were digitized manually going back to 1966Q1 from physical publications, can be found in the appendix. Relatively few papers have used these data; the most famous example is Gertler and Gilchrist (1994), who used the data to suggest that small firms are more sensitive to monetary policy changes than large firms. Some more recent examples include Crouzet (2017), Kudlyak and Sánchez (2017), and Crouzet and Mehrotra (2020).

The QFR data are well suited for answering this question. First and foremost, they are representative of the entire manufacturing sector, including small and non-public firms. This is important because a large body of empirical evidence, including recent work such as Hadlock and Pierce (2010), finds small and non-public firms are more likely to be financially constrained. The data offer detailed balance sheet information at the quarterly frequency, which makes them better suited to analyze the responses of short-term fluctuations in monetary policy than annual BEA or Census data. And unlike the US Financial Accounts data, which aggregate balance sheet information across nonfinancial corporate businesses of all sectors and sizes, the QFR data provide sector-specific measures of financial ratios as well as capital stocks. While the QFR data do not have any firm-level detail, I show in Section 3 that the results from the QFR align well with estimates obtained using aggregated firm-level data from Compustat and complement the findings from other work that uses the QFR microdata.

2.2 Empirical Responses to Monetary Shocks

To analyze the empirical responses of consumption and investment to monetary policy shocks, I use a local projection specification based on Jordà (2005). The estimating equation, which is similar to the one used in Ramey (2016), is shown in Equation 1. In this setup y^i_{t+h} represents the h-period ahead realization of the log of the outcome variable y for sector i at time t, ϵ_t represents the monetary policy shock at time t, and $\nu^i_{t,h}$ is an error term.

$$y^i_{t+h} = c^i_h + q^i_h + Trend + \sum_j \beta^i_{j,h} X^i_{t-j} + \sum_k \Omega^i_{k,h} Z_{t-k} + \gamma^i_h \epsilon_t + \nu^i_{t,h} \tag{1}$$

Sales and capital stocks are the primary outcomes of interest.[1] I use the series developed by Romer and Romer (2004) (R&R) and extended by Coibion (2012) as my measure of monetary policy shocks ϵ_t. X^i includes sector-specific controls (6 lags of the dependent variable y^i_t) and Z includes aggregate controls (1 lag each of real GDP growth and ϵ_t). The regression also includes a linear time trend and calendar quarter fixed effects q^i_h to deal with seasonality. In line with R&R, the sample starts in 1970 and includes shocks through 2004. Outcomes beyond 2008 are not considered to avoid concerns surrounding the zero lower

[1] Unlike measures of investment or capital expenditure, capital stocks are directly recorded in the QFR.

bound on nominal interest rates and the financial crisis. Appendix B describes the selection of controls and shows that my main results are robust to alternative start dates, aggregate controls, investment price indices, and choice of autoregressive lag length. I also show that my findings do not depend on a particular shock identification strategy. Using monetary shocks identified by Gertler and Karadi (2015) instead leads to very similar results, as does a standard recursive VAR.

The coefficient γ_h^i represents the percent change in the h-period ahead forecast in variable y for sector i. Newey-West standard errors are used to account for the serial correlation in residuals that arises from successively lagging the dependent variable. The top panels of Figure 1 show the responses of sales and the capital stock.

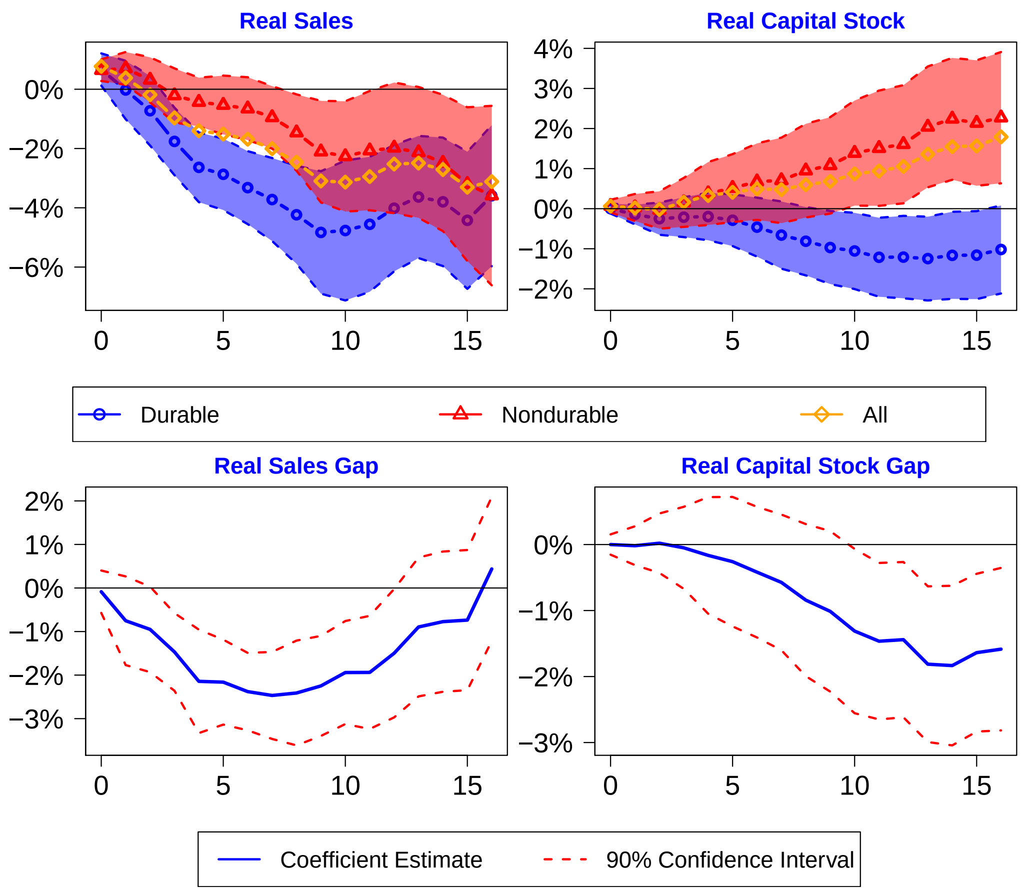

Figure 1: Empirical Responses to 100bp Contractionary MP Shock (90% CI)

Note: This figure shows the coefficient estimates γ_h^i from Equation 1, 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 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 shocks from 1970-2004 and outcomes through 2008.

Following a 100 basis point contractionary monetary shock, sales of manufacturing firms decline significantly, remaining 3-4% below their pre-shock levels between three and four years after the shock. As in Erceg and Levin (2006), the drop is even larger for durable producers, who experience sales declines of up to 5%. Despite the drop in sales the capital stock of all manufacturers rises by about 1.8%. This is driven by a large and statistically significant increase of 2.3% on the part of nondurable producers. The capital stock of durable producers, on the other hand, declines by up to 1.2%.

The persistence of these responses is consistent with Ramey (2016), who does not directly estimate the responses of investment to monetary policy shocks but finds the largest effects on industrial production at the 2-4 year horizon across a variety of specifications. These findings are also in line with Jeenas (2019), who analyzes the response of investment to monetary policy shocks in Compustat and finds the largest investment effects occur between 1-3 years after the shock, and can be accounted for by mechanisms such as those in Zorn (2018) and Arredondo (2020).

These estimates are obtained from separate regressions for each sector. An alternative approach is to directly estimate the differential responses between the durable and non-durable sectors in the same equation. The bottom panels of Figure 1 show the coefficient estimates from Equation 1 with the dependent variable replaced with "gaps" measuring the differential effect between sectors instead of estimating the effects on each sector separately. The gaps are defined as the log difference between the durable and nondurable sectors: $y_t \equiv \log(X_t^D) - \log(X_t^N)$, where X is the variable of interest. The capital stock gap falls slowly to around 2% before stabilizing around two and a half years after the shock. This provides further evidence for the different behavior of the capital stocks in each sector.

This countercyclical response of investment to a monetary shock in the manufacturing sector stands in contrast to most other sectors. Establishing this fact requires moving beyond the QFR, which has historically focused on manufacturing.[2] The BEA fixed asset accounts provide an alternative measure of sector-specific capital stocks. There are two important conceptual differences between the series. First, the QFR measures are calculated based on assets' current book value, whereas BEA capital stock measures are calculated as the sum of depreciated flows of past purchases. Despite this difference, Appendix A shows that the patterns in the BEA and QFR data have consistently reflected similar underlying trends. The second difference is that the BEA measures are only available at an annual frequency. As a result, for the results using BEA fixed asset I only estimate responses in one-year intervals starting one year after the shock. While noisy, the point estimates provide evidence

[2]The QFR began coverage of mining, wholesale trade, and retail trade in 1974 and was expanded to include a selection of service industries in 2010.

of manufacturing investment behavior consistent with the QFR results.

The top left panel of Figure 2 shows the responses of the total fixed asset stock for a wide variety of sectors and shows several striking features. The first is that, as in the QFR data, the capital stock of the manufacturing sector increases in response to a contractionary monetary shock. The second is that the capital stocks of most other industries (including the aggregate, which is shown as the solid black line) decline. The top right panel shows the response of equipment, which represents about 15% of the total capital stock for all industries. While the dispersion of responses is a bit higher than total fixed assets the pattern is quite similar. As in the total fixed asset case, manufacturing is clearly an outlier in terms of its countercyclical response. The stock of structures in manufacturing has a more modest increase and the stocks of several other industries climb in response to the shock as well. The rightmost panel shows that these increases in manufacturing investment occur despite a drop in sales that is larger than in most other industries. These results are also consistent with estimates using BEA investment flows rather than capital stocks, which are shown in Figure 3.

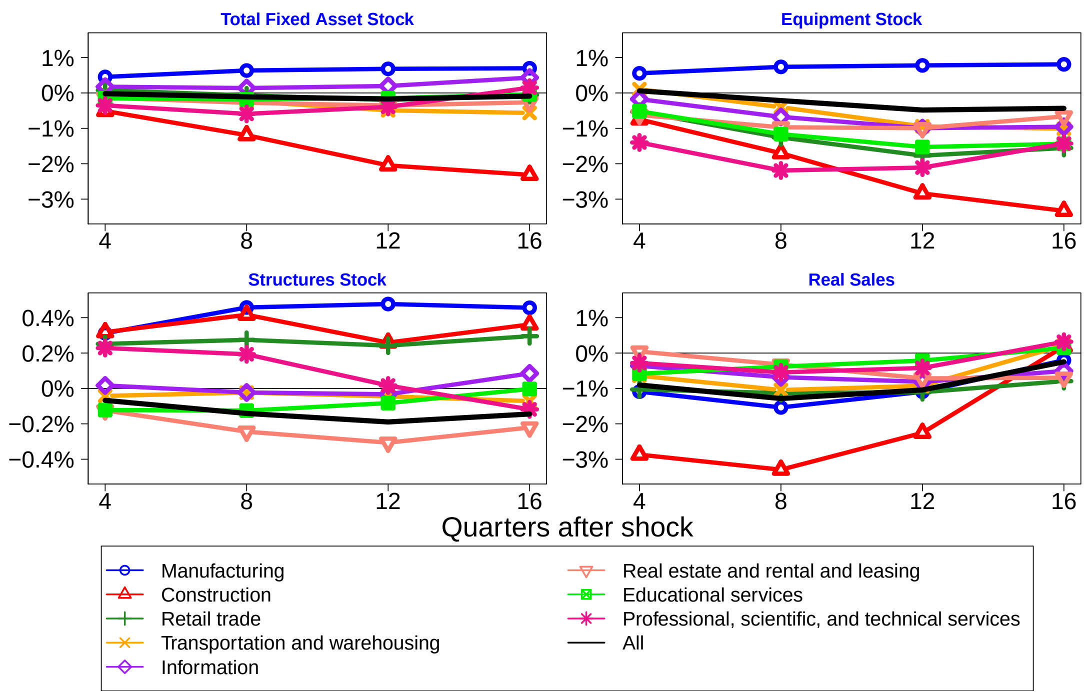

Figure 2: Empirical Responses of Asset Stocks to 100bp Contractionary MP Shock

Note: This figure shows the responses of investment to a 100bp monetary shock using Equation 1. Because the BEA data are only available at an annual frequency, I estimate responses in four-quarter intervals starting one year after the shock. The horizontal axes correspond to quarters after the shock. Regressions include shocks from 1970-2004 and outcomes through 2008.

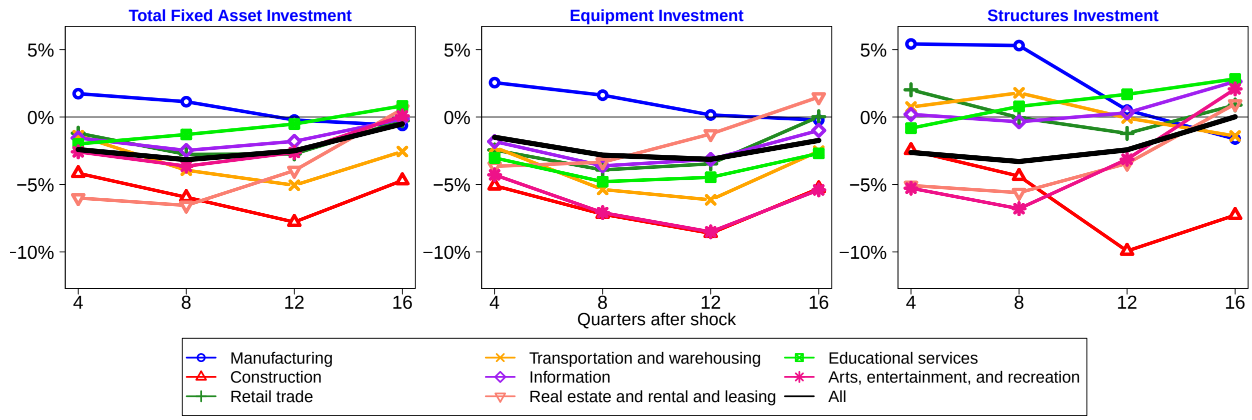

Figure 3: Empirical Responses of Investment to 100bp Contractionary MP Shock

Note: This figure shows the responses of investment to a 100bp monetary shock using Equation 1. Because the BEA data are only available at an annual frequency, I estimate responses in four-quarter intervals starting one year after the shock. The horizontal axes correspond to quarters after the shock. Regressions include shocks from 1970-2004 and outcomes through 2008.

Why does the manufacturing sector display such starkly different investment responses compared to other sectors in the economy? Financial constraints provide one possible explanation. Based on the mechanism proposed in this paper, less financially constrained industries should show smaller reductions (or increases) in investment relative to more financially constrained industries in response to contractionary monetary shocks. While there are few sources of balance sheet information that include small and non-public firms at the industry level outside of the QFR, data from the Census Bureau's Business Dynamics Statistics (BDS) include sector-specific information on firm size and age, both of which have been cited by Hadlock and Pierce (2010) and others as being useful indicators of constraint.

The left panel of Figure 4 shows the share of firms aged 16 years or older using the same industry splits as Figures 2 and 3. Across all sectors, this share is around 30% and has been increasing since the mid-1990s.[3] This share is much higher for manufacturing firms and has increased to more than 50% in recent years. The right panel shows the share of firms in an industry with at least 10 employees. In aggregate, this share has been stable at around 20% for the past several decades. For manufacturing firms, however, this share is more than 40%, and was even briefly above 50% in the early 1980s. The fact that manufacturing firms are much larger and older on average than firms in other industries is consistent with the sector being less financially constrained and can help explain why the investment response of manufacturing firms looks different from that of other sectors.[4]

[3] Regardless of when a firm was first established, the definition of firm age used in the BDS is relative to the beginning of the sample in 1977, so 1993 is the first year that firms could be recorded as having an age of at least 16 years.

[4] Buera et al. (2011) also point out that manufacturing establishments generally operate at a larger scale

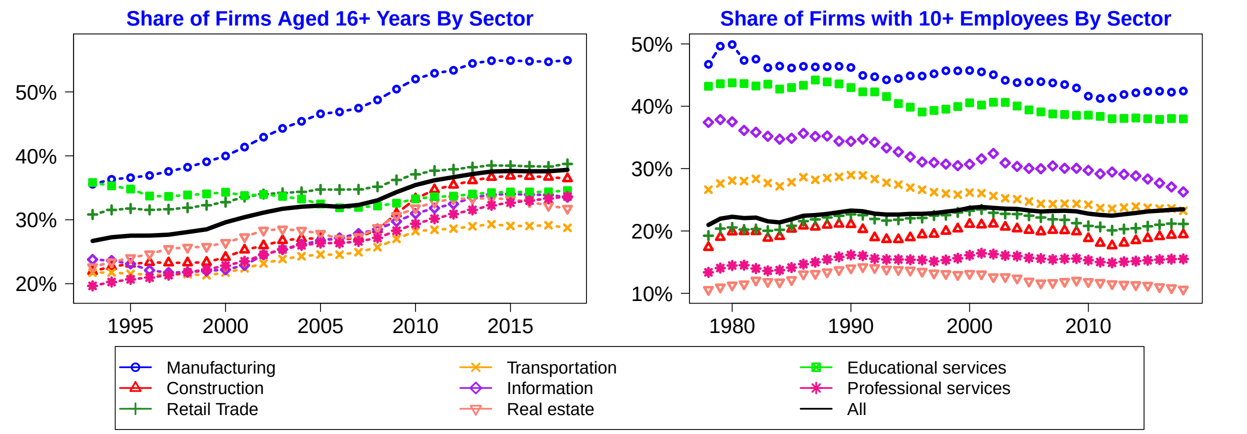

Figure 4: Firm Age and Size Measures by Industry

Note: This figure shows firm age and size detail calculated from the Census Bureau's Business Dynamics Statistics (BDS) using the same industry splits as Figures 2 and 3. The left panel shows the share of firms aged 16 or more years by sector. The series starts in 1993 because the BDS data calculate firm age based on when a firm entered the sample, so all firms were age 0 in 1977 when data collection began and 1993 is the first year in which a firm could be counted as being at least 16 years old. The right panel shows the share of firms in each sector with at least 10 employees starting in 1978 when the data are first reported.

Further evidence that manufacturing firms are less financially constrained relative to firms in other industries can be found in Greenwald et al. (2020), who analyze the degree to which firms drew down credit lines in response to COVID-19 during the first quarter of 2020. They find that the vast majority of new credit during the first half of 2020 flowed to large and publicly traded firms, which are the types of firms least likely to be constrained. When they analyze their results by industry, the show that the manufacturing sector accounted for the largest share of the aggregate change in actual utilized credit, suggesting that these firms were able to take advantage of their borrowing capacity during downturns. This ability to borrow more than firms in other sectors following a negative shock allows manufacturing firms to take advantage of lower investment prices in response to monetary contractions and can help explain why investment in the manufacturing sector displays a cyclical sensitivity that is fundamentally different than that of firms in other sectors. While this evidence focuses on the manufacturing sector as a whole, in Section 2.5 I provide more detail that durable producers display more evidence of financial constraint than nondurable producers and that these differences can help explain the patterns observed in the data.

due to fixed costs that require financing. Thus while the manufacturing sector is more constrained *ex ante*, firms in this sector should on average be less financially constrained than their non-manufacturing counterparts *conditional on operating*.

2.3 Structures Investment Detail

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 5. 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 5, 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.

Building permit data allow for 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 6. The leftmost panel

[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.

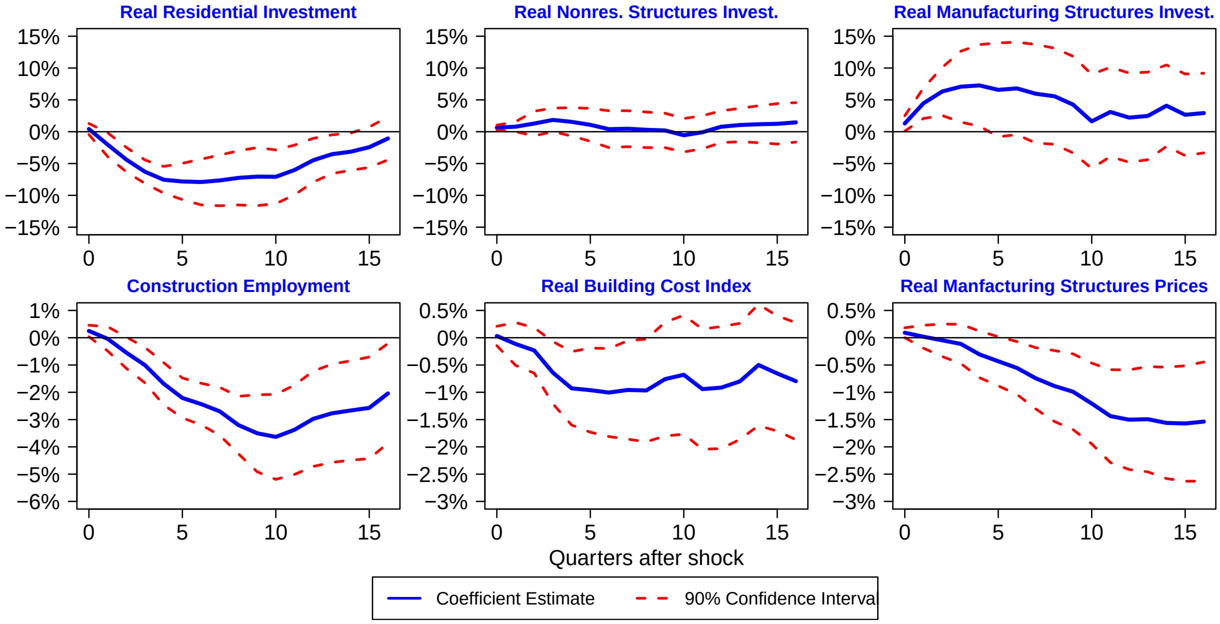

Figure 5: Empirical Responses to 100bp Contractionary MP Shock (90% CI)

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. The estimating equation is Equation 1 but does not include calendar quarter fixed effects as the data are already seasonally adjusted. Regressions include shocks from 1970-2004 and outcomes through 2008.

shows that the number of new permits is strongly procyclical, declining by about 4% 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 confirms that the average project size is strongly countercyclical. While these results are consistent with the idea that it is the subset of financially unconstrained firms which are able to respond to the decline in construction costs and increase the total value of manufacturing structures put in place, the next section shows that the procyclical movement in the cost of investment is not limited to structures.

2.4 User Costs and Monetary Policy

Investment decisions take into consideration not just relative prices but also other factors such as depreciation, adjustment costs, financial frictions, and expected price dynamics. Deriving an empirical estimate of the comprehensive cost of investment (known as the user cost of capital) is the driving question behind a large literature which dates back to Hall and

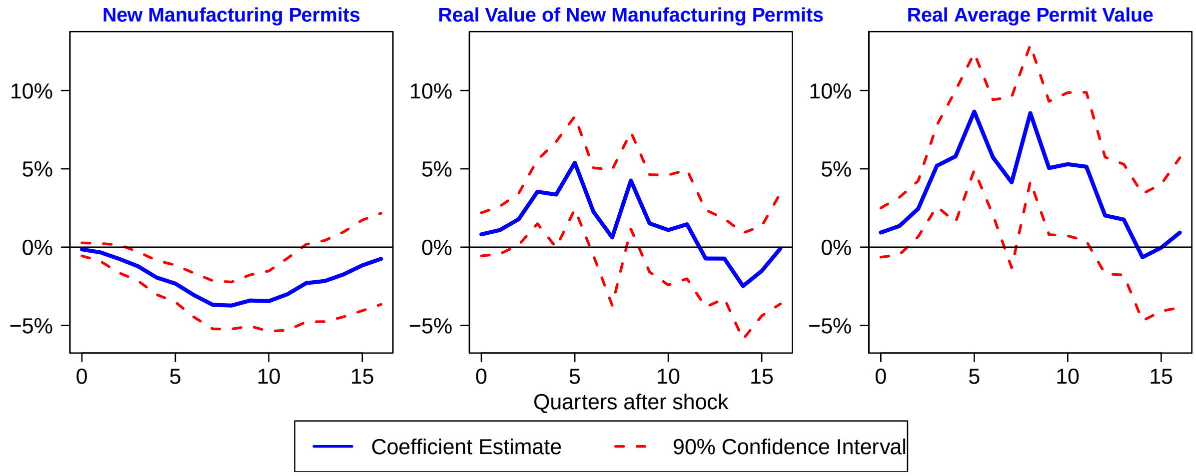

Figure 6: Empirical Responses to 100bp Contractionary MP Shock (90% CI)

Note: Building permit data were 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 estimating equation is the same as Equation 1 but with the addition of a quadratic time trend. Regressions include shocks from 1970-2004 and outcomes through 2008.

Jorgenson (1967) and includes more recent examples such as Chirinko et al. (1999). This section shows that while contractionary monetary shocks increase interest rates, they also reduce the relative price of investment, and that the net effect of these shocks is a decline in the user cost of capital for manufacturing firms.

In a neoclassical setting the user cost UC_t can be written as follows:

$$UC_t = \frac{P_t^I}{P_t^Y}\left[i_t + \delta_t - E_t \Delta P_{t+1}^I\right] \tag{2}$$

In this equation P_t^I and P_t^Y are the prices of investment and output, i_t is the gross interest rate, δ_t is the depreciation rate, and $E_t \Delta P_{t+1}^I$ is the expected change in the price of investment. In this setting firms will increase their investment if: 1) the relative price of investment falls, 2) the expected price of future investment rises, or 3) interest rates decline. To estimate the response of the user cost of capital for each sector and its components to a monetary shock I use the following empirical specification:

$$y_{t+h}^i = c_h^i + q_h^i + Trend + y_{t-1}^i + \sum_{j=1}^{4} \Omega_{j,h}^i Z_{t-j} + \gamma_h^i \epsilon_t + \nu_{t,h}^i \tag{3}$$

The baseline specification is tailored for estimating responses of the capital stock, which is a slow-moving variable and thus needs more lags to accurately control for its past dynamics; for more rapidly-adjusting variables like user costs, fewer autoregressive lags are needed, so only one is included. The control vector Z includes one lag of real GDP growth to match my baseline regression and four lags of the Federal Funds Rate. While the results are robust to the choice of interest rate and lag length, including lags of an interest rate measure separately from the lagged user cost is important because the latter responds to changes in non-interest variables, and thus lagged user costs alone are not adequate to control for recent interest rate dynamics.

Data on price indices for investment and rates of economic depreciation are taken from the BEA fixed asset data for the durable, nondurable, and total manufacturing sectors. Effective interest rate measures are not directly observable in the QFR prior to 1998, so to obtain interest rates for the durable and nondurable manufacturing sectors I instead turn to Compustat. These interest rates are derived by first calculating the rate of interest expenses to total debt using the WRDS financial ratio suite, winsorizing the top and bottom 1% of observations, and calculating a mean for each sector in each quarter weighted by total debt. Because these observations are only available starting in 1975, change in yields on AAA bonds between 1970 and 1975 are retroactively applied to the 1975 Compustat series for each sector to get a measure running back to 1970. This assumes that the spread between each sector's average borrowing rate and the AAA yield was constant over this five-year window, though the results are extremely similar to those using a sample that begins after the Compustat interest rates are available.[6]

The empirical user cost estimates are shown in Figure 7. Given that direct estimates of expected changes in the price of investment goods are not observable, and that proxying for such expectations with either lagged or actual future price changes does not make a meaningful impact on the empirical results, I have dropped them from the user cost estimates (which imposes $E_t\left[\Delta P^I_{t+1} = 0\right]$).

The top row shows the baseline estimates, which use the effective Compustat interest rate for each sector described previously. The decline in the total user cost is driven by the nondurable sector, while the changes for the durable sector are both smaller and statistically insignificant. These results look virtually identical to those using the NIPA nonresidential fixed investment price index as the measure of investment prices (shown in the second row) or using BAA bond yields as the relevant interest rate (shown in the third row). The bottom row, which ignores interest and depreciation rates, shows that the decline in the user cost is

[6] Interest rates calculated from Compustat are averages, but Appendix B shows that marginal rates such as AAA or BAA bond yields lead to similar results.

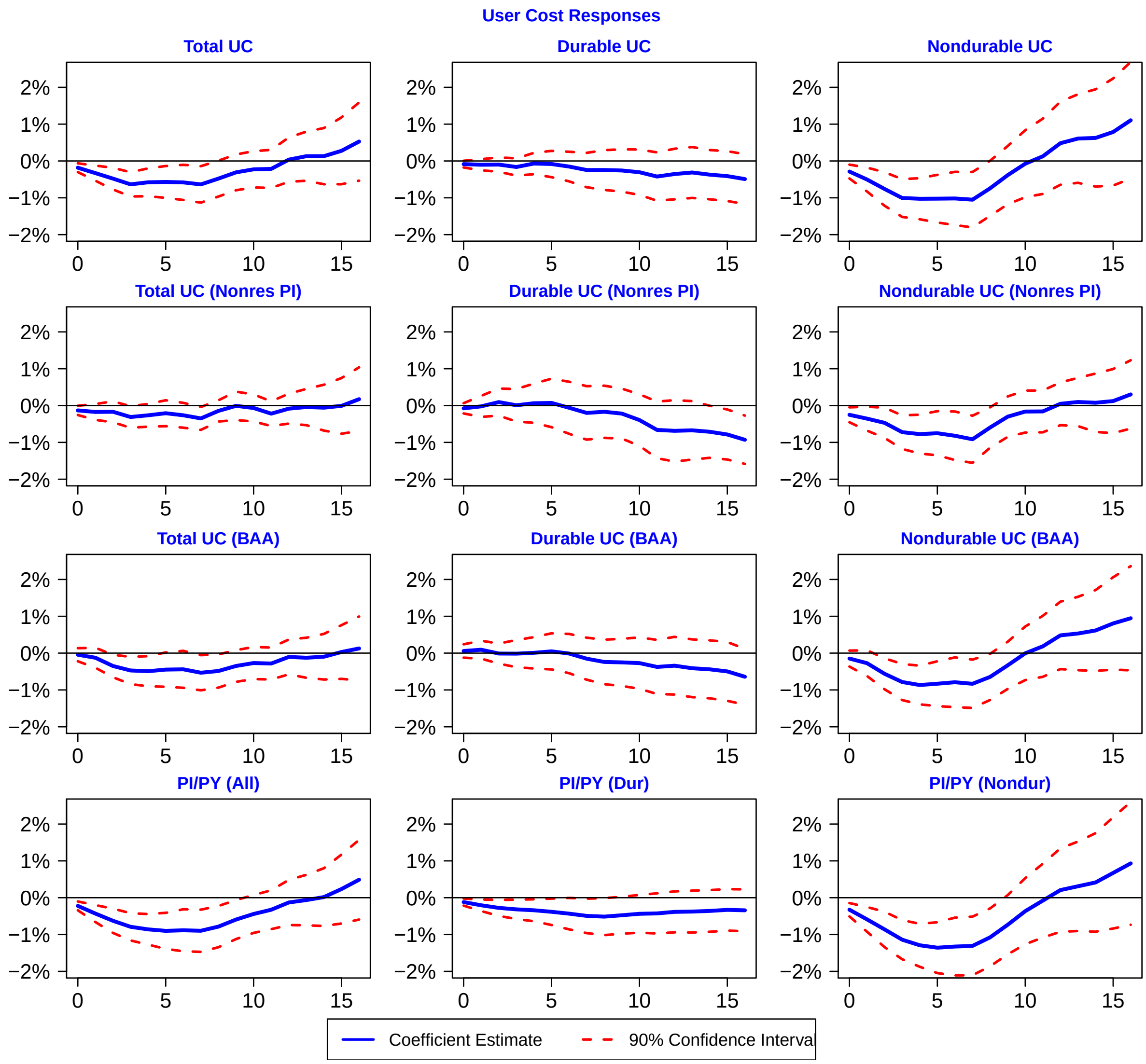

Figure 7: Empirical Responses to 100bp Contractionary MP Shock (90% CI)

Note: All user cost calculations are based on Equation 2 after imposing zero for expected price changes given the lack of data. The estimating equation is Equation 3. All specifications use the BEA manufacturing output deflator for each sector as the measure of P_t^Y and the BEA depreciation rates δ_t as they capture economic depreciation as opposed to accounting depreciation measures used in the QFR. The investment price index P_t^I is taken from the BEA sector-specific manufacturing price indices for the first and third row and the NIPA nonresidential fixed asset price index in the second row. Interest rates for the top two rows are four-quarter moving averages of sector-specific interest rates calculated from Compustat for 1976 and beyond. Interest rates prior to 1976 are calculated by retroactively applying changes in AAA bond yields to the 1976 Compustat level for each sector. Interest rates for the third row use BAA bond yields for the entire time period. The "PI/PY" specification includes only the sector-specific ratios of manufacturing investment prices to manufacturing output prices and ignores interest rates and depreciation. Regressions include shocks from 1970-2004 and outcomes through 2008.

driven by a decline in the relative prices of investment goods.

These empirical user cost estimates do not include direct measures of financial constraints, as they are not directly observed in the data.[7] In the model, the firms face the same

[7]Financial constraints may enter indirectly via interest rate risk premia.

investment good prices and constant depreciation rates, so current and expected financial constraints are a primary driver of the differential responses of user costs across sectors. In the data the user cost does show a smaller and less significant decline for durable producers than nondurable producers; to the extent that monetary shocks also exacerbate the financial constraints on durable producers through falling capital goods prices and hence a tighter investment constraint, a more comprehensive user cost measure should show an even smaller decline for durable producers (or even an increase).

The baseline specification suggests a reduction in aggregate manufacturing user costs of up to 0.6% in the 8 quarters following the shock. The previous section estimated an increase in the capital stock of up to 1.7%, implying a back-of-the-envelope aggregate user cost elasticity of around -3 at its peak.[8] The estimated elasticities for the nondurable sector, which are responsible for the aggregate capital stock increase and which experience a larger drop in user costs, are about -2. To the extent that my user cost estimates do not fully account for changing financial constraints, the estimated user cost elasticity for the nondurable sector is likely to be more reliable than that of the aggregate manufacturing capital stock.[9] The next section shows that financial frictions can help explain why large and nondurable producers take advantage of this decline in user costs while small and durable firms do not.

2.5 Financial Constraints

In this section I show that durable producers are more financially constrained than nondurable producers using QFR income and balance sheet data and argue that these differences can explain the difference in investment behavior across sectors. Durable producers rely more on short-term liabilities, have more volatile cash flow, and pay fewer dividends.

While there is an extensive empirical literature that takes as given that some firms are more constrained than others[10], this paper builds on a research agenda that links the durability of a firm's output to the degree of financial constraint that it faces. Rajan and Zingales (1998), for example, find that six of the eight manufacturing industries with the highest reliance on external finance are durable producers. Almeida and Campello (2007) argue that the assets of durable producers are less liquid than their nondurable counterparts, which reduces their value as collateral. Banerjee et al. (2008) show evidence that durable produc-

[8]These calculations are based on changes in the capital stock over an eight-quarter horizon.

[9]These numbers are larger in magnitude than most past estimates, which range between -0.5 and -1.0 according to Hassett and Hubbard (2002), but they are more in line with the larger estimates found in Zwick and Mahon (2017). It is also aligned with Caballero et al. (1995), who look at plant-level investment data in manufacturing. They find industry-specific elasticities from 0 to -2 with an average around -1 and larger elasticities concentrated in nondurable industries.

[10]See for example Fazzari et al. (1988), Kaplan and Zingales (1997), Almeida and Campello (2001), Whited and Wu (2006), Giroud and Mueller (2017), and Farre-Mensa and Ljungqvist (2016).

ers in bilateral relationships maintain lower levels of leverage than nondurable producers as a way of maintaining bargaining power to prevent holdup problems. Finally, Gomes et al. (2009) find that durable goods manufacturers have a large equity risk premium and argue this is a fundamental consequence of the higher volatility of demand for their products. To my knowledge, this paper is the first to directly consider these effects in the context of monetary policy.

Following Almeida and Campello (2001) and Farre-Mensa and Ljungqvist (2016), I define a firm as being financially constrained if it faces a convex cost of obtaining external capital. This implies that a firm's marginal cost of raising one more dollar of external funding is increasing in the amount raised. In the limiting case in which a firm faces an explicit cap on the quantity of funds it can raise, this curve will be vertical, but in the absence of information about such limits, this will be indistinguishable from the case in which a firm is able to raise additional funds but is deterred by the costs of doing so. While measuring financial constraints in the data is notoriously difficult, there are several commonly cited indicators discussed in the literature. These include higher reliance on short-term debt, more volatile cash flows, and lower dividend disbursements. Figure 8 shows that these measures all point to more binding financial constraints for durable producers relative to nondurable producers.

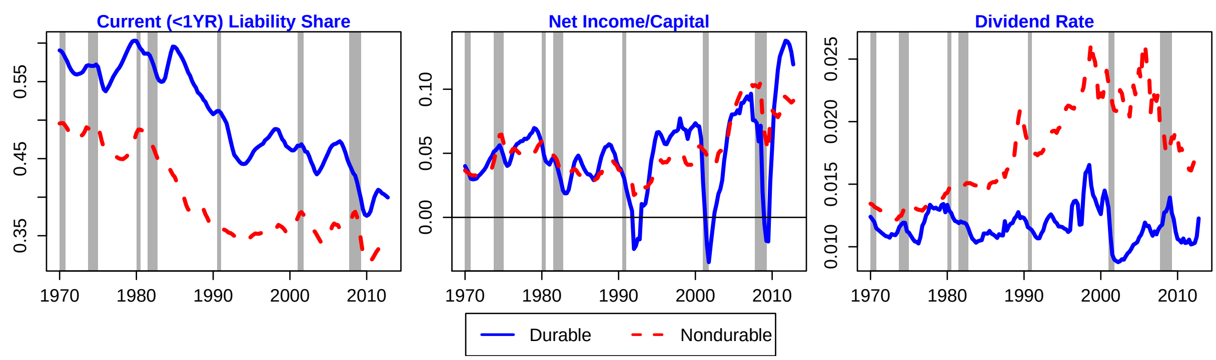

Figure 8: Financial Constraint Measures

Note: All figures show four-quarter moving averages calculated from the QFR. The first panel shows the ratio of each sector's aggregate liabilities with maturity of less than one year to its total liabilities. The second panel shows the ratio of net income after taxes to the stock of property, plant, and equipment net of depreciation. The rightmost panel shows the ratio of dividend payments to the book value of equity. Shaded areas indicate recessions.

The first panel shows that durable producers have a higher share of their total liabilities with a maturity of less than one year. Past studies of the determinants of debt maturity such as Barclay and Smith (1995) and Guedes and Opler (1996) find that smaller, riskier, and more credit-constrained firms are more likely to rely on short-term liabilities. The second panel, which shows net income normalized by the capital stock, offers further evidence that durable producers face a higher risk premium on their debt. Not only is cash flow more volatile for durable producers, but the fluctuations are asymmetric in magnitude; while there is a short stretch in the mid-90s in which the ratio was higher for durable producers, it is far lower during the most recent three recessions.

Another commonly cited indicator of financial constraint in the finance literature (including Whited and Wu (2006)) is the ability of a firm to pay dividends. If firms face a premium to obtain outside financing, it will raise the real value of internal funds relative to dividend disbursements. The third panel shows that the dividend payout ratio is consistently lower for durable producers, particularly since the mid-1980s. The appendix shows that these results hold even when looking at just the largest firms in each sector, suggesting that the results are not driven solely by different firm size distributions across durable and nondurable industries, and that they are also present in Compustat data.

Models that generate a need for finance through agency problems or incomplete contracts usually do not allow first-best levels of investment.[11] To the extent that volatility of cash flow can exacerbate these frictions, durable producers should be more financially constrained in these settings. Appendix C provides a more rigorous theoretical treatment based on Tirole (2010) showing that volatile demand can endogenously reduce the borrowing capacity of a firm compared to one which is otherwise identical. The next section extends my analysis to manufacturing firms in Compustat.

3 Aggregate Evidence from Compustat

The previous section showed the effects of monetary shocks on the aggregate capital stock of the manufacturing sector. I found that contractionary shocks led to increases in investment driven by firms in the nondurable sector. To explain these features I showed that the aggregate user cost of capital fell and provided suggestive evidence that financially unconstrained firms were able to take advantage of the cyclical drop in prices. This section shows that my results can also be seen using aggregated data in Compustat. Throughout this section, I construct capital stocks using the procedure outlined in Ottonello and Winberry (2020), and then aggregate these stocks to the sectoral level. 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.

[11] Holmstrom and Tirole (1997) and Kiyotaki and Moore (1997) are two examples.

3.1 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 further comparison, I use the geographical segment data 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 9. 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.

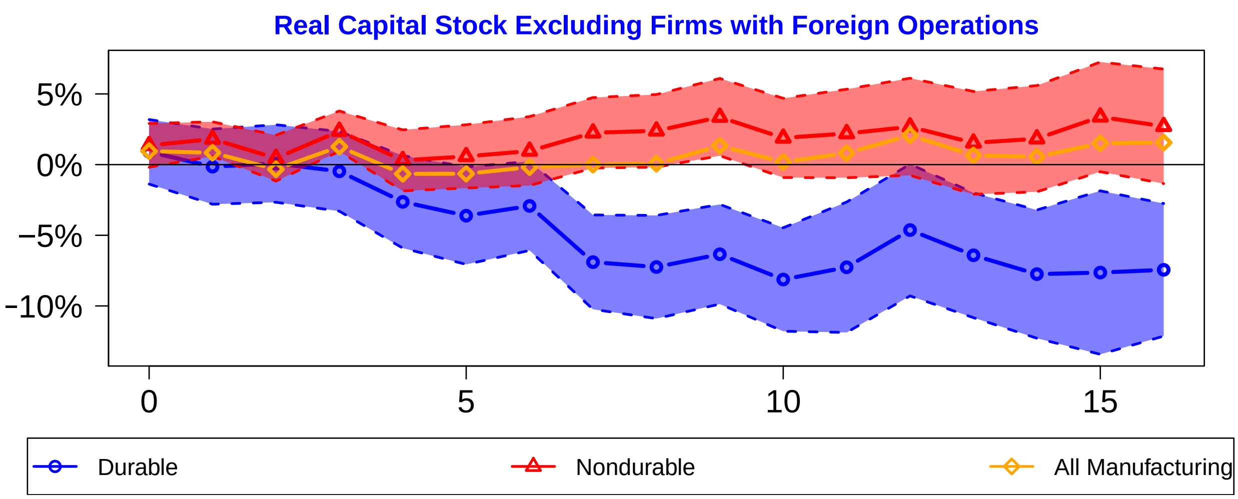

Figure 9: IRFs for Aggregated Compustat Data, Excluding Foreign Operations (90% CI)

Note: This figure shows the coefficient estimates γ_h^i from Equation 1, which correspond to the effects of 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. Because the Compustat data are less reliable prior to 1985 and my baseline specification includes six autoregressive lags, regressions include shocks from 1986Q3-2004Q4 and outcomes through 2008Q4.

3.2 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 don't 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. (2020). 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 (2020), 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

In this section I develop a model that can match the empirical findings in Sections 2 and 3. This model has two key features. First, as shown in past work analyzing price changes in microdata such as Bils and Klenow (2004) and Klenow and Malin (2010), the prices of durable goods are more flexible than those of nondurable goods. Second, in light of the results outlined from the QFR, durable goods producers are financially constrained while nondurable producers are unconstrained. In response to a contractionary monetary policy shock, the flexibility of pricing for durable producers causes the relative price of durables to fall. Durable producers and borrower households are constrained and are unable to take advantage of these lower prices, while nondurable producers and saver households increase their durable purchases. The result is a model which can qualitatively match the responses of durable goods for both consumers and producers to monetary shocks. This intuition is identical to that of the model in Barsky et al. (2007). I include additional frictions such as sticky wages, capital adjustment costs, and habit formation in consumption to allow the model to match the slow and persistent adjustments to the capital stock, but none of these features are necessary to generate the core result that investment increases for the unconstrained sector in response to a contractionary monetary shock. A detailed treatment of the model is provided in Appendix C.

4.1 Households

The household side of the model is based on Chen and Liao (2014). Measure ω are savers with discount factor β_S, while measure $(1-\omega)$ are borrowers with discount factor β_B. Savers are more patient ($\beta_S > \beta_B$), which allows for borrowing in the steady state, and are endowed with ownership of the firms. Households of type $i \in \{S, B\}$ maximize utility over nondurable consumption $C^N_{i,t}$ with habit formation in the manner of Fuhrer (2000), stocks $D_{i,t}$ and flows $C^D_{i,t}$ of durable consumption, labor $H_{i,t}$, and nominal bond holdings $B_{i,t}$:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_i^t \left[\eta \log(C^N_{i,t} - hC^N_{i,t-1}) + (1-\eta)\log(D_{i,t}) - \nu \frac{H_{i,t}^{1+\chi}}{1+\chi} \right]. \tag{4}$$

Durable goods accumulate according to a standard law of motion with depreciation rate δ_D:

$$D_{i,t} = C^D_{i,t} + (1-\delta_D)D_{i,t-1}. \tag{5}$$

Labor is perfectly substitutable between sectors, meaning that households only derive disutility from total labor $H_{i,t}$ and that equilibrium wages will be equal across sectors. The budget constraints are identical for savers and borrowers except for the inclusion of profits in the budget of savers. Relative prices p_t^j are defined as the ratio of the nominal price in sector j to the aggregate price level, with Π_t representing the aggregate inflation rate.

$$p_t^N C_{B,t}^N + p_t^D C_{B,t}^D + B_{B,t} = \frac{(1+i_{t-1})B_{B,t-1}}{\Pi_t} + w_t H_{B,t}^D + w_t H_{B,t}^N, \tag{6}$$

$$p_t^N C_{S,t}^N + p_t^D C_{S,t}^D + B_{S,t} = \frac{(1+i_{t-1})B_{S,t-1}}{\Pi_t} + w_t H_{S,t}^D + w_t H_{S,t}^N + \frac{1}{\omega}\left(Profits_t\right). \tag{7}$$

The Lagrange multiplier on the budget constraint for each household is $\lambda_{i,t}$. Households supply labor through a common labor market so that the same wage w_t applies to both savers and borrowers in both sectors. Real wages are subject to rigidity as in Blanchard and Galí (2007) and will be weighted averages of past real wages and consumers' current marginal disutility of labor times a markup μ^w, which helps prevent the real wage from dropping below the marginal disutility of labor:[12]

$$w_t = \left(\frac{\nu H_{i,t}^{\chi}}{\lambda_{i,t}}\left(1+\mu^w\right)\right)^{1-\rho_w}\left(\frac{w_{t-1}}{\Pi_t}\right)^{\rho_w}. \tag{8}$$

Households are constrained in that they can only borrow up to some exogenous share m of the value of their stock of durable goods. This constraint will bind in the steady state for borrowers but not savers due to the difference in discount factors.

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

Let ψ_t be the Lagrange multiplier on the borrowing constraint. If the constraint doesn't bind, $\psi_t = 0$ and the intertemporal efficiency conditions look the same for both borrowers and savers. If $\psi_t > 0$, then the decisions of borrowers are distorted in two ways. First, the marginal value of one dollar today will be greater than the discounted expected marginal value of a dollar tomorrow. Second, borrowers will receive an additional benefit to buying durable goods because they will ease the borrowing constraint.

[12]This mechanism helps lead to smoother and more persistent model dynamics across all variables in response to shocks, but none of the main results in the paper depend on it (see Figure 12).

4.2 Firms

Each firm produces according to a standard Cobb-Douglas production technology and has a law of motion for capital subject to "second-order" adjustment costs in the manner of Christiano et al. (2005):

$$Y_t^j = A_t \left(K_t^j\right)^{\alpha_j} \left(H_t^j\right)^{1-\alpha_j}, \quad K_{t+1}^j = (1-\delta_K)K_t^j + I_t^j \left[1 - \frac{\theta_j}{2}\left(\frac{I_t^j}{I_{t-1}^j} - 1\right)^2\right]. \tag{10}$$

Output in each sector Y_t^j will be a function of aggregate productivity A_t, capital stock K_t^j, and labor H_t^j. Capital is owned by the firms and depreciates at rate δ_K. The good produced by the durable sector can be used as either a consumer durable good or as productive capital; all durable goods have the same price and can be traded between firms and households. Adjustment costs for investment I_t^j, which are governed by θ_j, help the model generate more realistic persistence in the dynamics of the capital stock but are not necessary for the paper's main results.

Durable goods producers face an intratemporal working capital constraint. Their purchases of labor and investment are constrained to be an exogenous share ξ of the value of their stock of durable goods:[13]

$$w_t H_t^D + p_t^D I_t^D = \xi p_t^D K_t^D \tag{11}$$

The model takes as given the fact that durable producers are financially constrained while nondurable producers are not. This modeling choice is consistent with the empirical results shown in Section 2.5 and the literature regarding financial constraints of durable producers such as Gomes et al. (2009). I also show in Appendix C that a simple model in which durable goods producers face more volatile demand for their product can endogenously lead to more restrictive financial constraints for durable producers relative to nondurable producers with less volatile demand.

Let μ_t be the Lagrange multiplier on the durable firm financial constraint. If the constraint binds, $\mu_t > 0$ and durable producers face an effective wedge on their input prices

[13] For simplicity I allow the producers to borrow at zero net interest. This is a conservative assumption, as increases in the cost of capital will exacerbate the constraints faced by durable producers. In Appendix C I show contractionary monetary shocks have about the same effects on the interest rates of durable and nondurable producers, suggesting that the differential effects on user costs across sectors are driven by prices and not interest rates. Forcing durable producers to borrow at the risk-free interest rate leads to virtually identical model dynamics because variation in interest rates is tiny compared to variation in relative prices.

relative to nondurable producers. In addition to increasing production, expanding their capital stock also eases the working capital constraint faced by durable producers in both the current and future periods.

Firms maximize the expected sum of future dividend payments subject to their production function, the financial and investment frictions discussed previously, the household demand curve, and Rotemberg-style price adjustment costs. Because savers own the firms, their stochastic discount factors are used to value future dividend flows. Define mc^j and mk^j to be the marginal cost and marginal product of capital, respectively, for the firm in sector j. The firm maximization problem can be written:

$$\begin{aligned}\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_S^t \frac{\lambda_{S,t}}{\lambda_{S,0}} \Bigg\{ & p_t^j(i) \left(\frac{p_t^j(i)}{P_t^j} \right)^{-\epsilon_j} Y_t^j - w_t N_t^j - p_t^D I_t^j - \frac{\phi_j}{2} \left(\Pi_t^j(i) - 1 \right)^2 Y_t^j(i) \\ & + mk_t^j \left[I_t^j \left(1 - \frac{\theta_j}{2} \left(\frac{I_t^j}{I_{t-1}^j} - 1 \right)^2 \right) + (1-\delta_j) K_t^j - K_{t+1}^j \right] + \mu_t^j \left[\xi p_t^D K_t^j - w_t N_t^j - p_t^D I_t^j \right] \\ & + mc_t^j \left[A_t (K_t^j)^{\alpha_j} (N_t^j)^{1-\alpha_j} - Y_t^j(i) \right] \Bigg\}. \end{aligned} \tag{12}$$

In the baseline model, durable producers have flexible prices ($\phi_D = 0$) but face credit constraints ($\mu_t > 0$). Nondurable producers, on the other hand, face frictions in adjusting prices ($\phi_N > 0$) but are unconstrained in their expenditure on capital and labor ($\mu_t = 0$). This heterogeneity in financial constraints faced by each sector is crucial for the model's ability to generate empirically consistent investment dynamics.

4.3 Equilibrium and Solution

The market clearing conditions for labor in each sector (H_t^N, H_t^D) and household expenditure (C_t^N, C_t^D) require that the aggregates be equal to the sum across different types of households weighted by their measure. Market clearing for household borrowing implies that the total quantity of bonds demanded by borrowing households is supplied by lending households.

$$\omega H_{S,t}^D + (1-\omega) H_{B,t}^D = H_t^D, \quad \omega H_{S,t}^N + (1-\omega) H_{B,t}^N = H_t^N \tag{13}$$

$$\omega C_{S,t}^D + (1-\omega) C_{B,t}^D = C_t^D, \quad \omega C_{S,t}^N + (1-\omega) C_{B,t}^N = C_t^N, \quad \omega B_{S,t} + (1-\omega) B_{B,t} = 0 \tag{14}$$

Market clearing in the durable goods market requires that the total quantity of durable output Y_t^D be equal to total household durable purchases C_t^D plus total investment $(I_t^D + I_t^N)$. Total output in the nondurable sector Y_t^N must be equal to household consumption C_t^N plus any output loss due to price adjustment.

$$C_t^D + I_t^D + I_t^N = Y_t^D, \quad C_t^N + \frac{\phi_N}{2}\left(\Pi^N - 1\right)^2 Y_t^N = Y_t^N \tag{15}$$

To close the model, I specify a standard Taylor Rule for the nominal interest rate:

$$\beta_S(i + i_t) = (\beta_S(i_{t-1}))^{\rho}\left(\Pi_t^{\phi_\Pi}\right)^{1-\rho}\exp(e_t^M). \tag{16}$$

Following Monacelli (2009) and Chen and Liao (2014), I ensure that the calibration results in the constraint binding in the steady state and then linearize around that steady state, assuming that it will continue to bind for small perturbations. Appendix C shows the full set of equilibrium conditions and lists all of the parameter values in Table 2. Most of the parameters related to household borrowing, including the share of borrowers ($\omega = 0.5$) and the discount rates ($\beta_S = 0.99, \beta_B = 0.98$) are taken from Chen and Liao (2014).[14] I also use their values for price stickiness ($\phi_D = 0, \phi_N = 58.25$) and the nondurable share of consumption ($\eta = 0.8$). The parameter governing habit formation ($h = 0.9$) is taken from Fuhrer (2000). The persistence of wage stickiness ($\rho_w = 0.5$) is based on Blanchard and Galí (2007) and the wage markup ($\mu^w = 0.1$) is chosen to generate a 10% steady state markup in the goods markets.

Other parameters including the capital shares of each industry ($\alpha_D = \alpha_N = 0.33$), the Taylor Rule parameters governing the central bank's response to inflation and persistence in the interest rate ($\phi_\Pi = 1.5, \rho = 0.9$), the parameters governing labor supply ($\nu = 4, \chi = 1$), the elasticity of substitution across intermediate goods ($\epsilon_D = \epsilon_N = 11$), depreciation rates ($\delta_D = 0.02, \delta_K = 0.03$), and capital adjustment costs ($\theta_D = \theta_N = 2$) are standard in the literature. The major addition relative to past work is the parameter governing the exogenous working capital constraint ξ, which is set to be 0.1. In addition to resulting in a positive value for the Lagrange multiplier μ in the steady state given the other parameter values, it is also close to the sample averages for the ratios of cash (14.4%) and short-term bank debt

[14] The household borrowing limit is set to $m = 0.7$, which is slightly smaller than their value of 0.75. This helps the model generate more persistent consumption dynamics but is not necessary to match the on-impact consumption responses in the data and has a negligible impact on the behavior of investment.

(8.2%) to the capital stock observed in the QFR.[15]

4.4 Results and Mechanism

The model impulse responses for the capital stocks of producers can be seen in the left panel of Figure 10. When a contractionary monetary policy shock hits, the price of durable goods falls. Nondurable producers, which are unconstrained, take advantage by increasing their capital purchases. Durable producers, whose constraint is exacerbated by the decline in the value of their capital stock used as collateral, are forced to reduce their investment. The increase in capital expenditure by the nondurable sector is larger than the decline from the durable sector, so the aggregate capital stock rises. For comparison, the right panel shows the estimated capital stock responses from the QFR from Figure 1. The model is able to match the empirical dynamics of the manufacturing capital stock quite well.

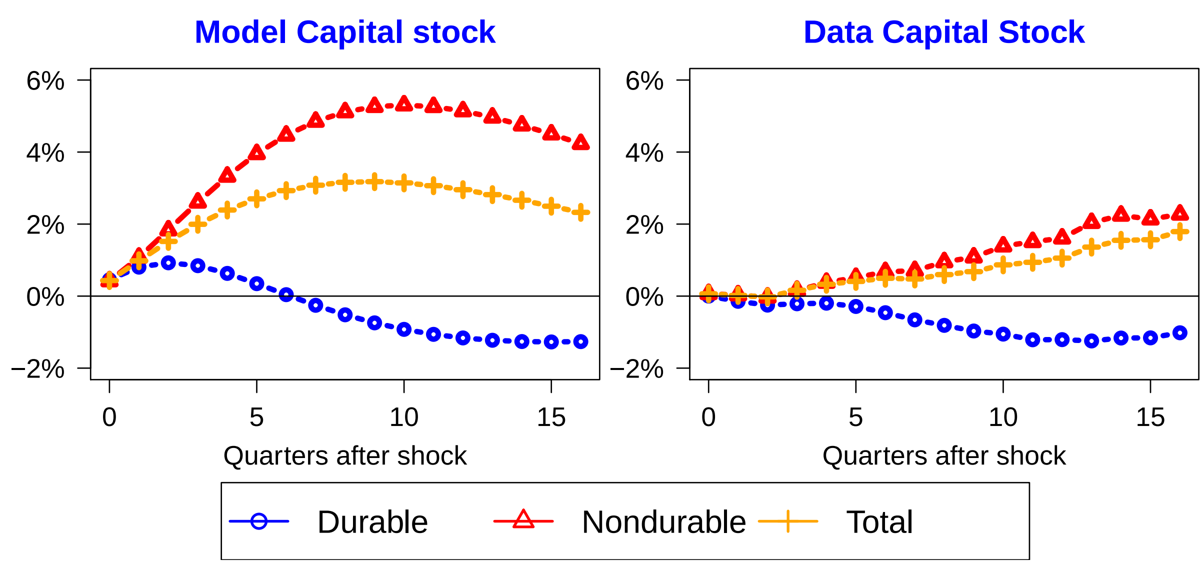

Figure 10: Model and Data Responses to Contractionary MP Shocks

Note: The left panel shows the model responses to a 100bp contractionary monetary shock to the capital stocks for the total manufacturing sector as well as each subsector. The right panel shows the empirical responses to a 100bp contractionary monetary shock shown previously in Figure 1.

The long life of durable goods combined with the decline in their relative price leads investment in my model to increase following a monetary contraction. When a monetary shock hits, both types of producers want to cut prices. Because nondurable prices are sticky, durable producers are able to reduce their prices by a larger amount. Even small drops in

[15] My results are robust to parameter values throughout this range. For large enough changes, however, adjustments to other parameters are necessary to ensure the firm borrowing constraint will bind.

the relative price are able to spur large increases in durable purchases in this model because durables are long-lived; buying the durable good at a low price today is equivalent to getting a discount on a long series of future service flows.

As a result, this drop in the relative price of durable goods is large enough to offset the decline in household consumption and causes nondurable producers to expand their investment. The presence of financial constraints prevents durable producers from increasing investment in two ways. Because they are financially constrained, the fall in the relative price of durables reduces the value of their capital stock and hence the amount of money that they can borrow to fund production. In addition, durable producers experience a drop in demand from the consumer side due to the tightening of the borrowing constraints on impatient consumers that leads to a decline in aggregate household durable expenditure.

The key driver of the empirical results is that the user cost of investment, driven by a decline in the prices of investment goods, falls in response to a contractionary shock. This is also true in the model, where user costs are more complicated and include both current and expected prices, demand, adjustment costs, and, for the durable firms, degrees of financial constraint. For durable producers, the financial constraints are powerful enough to push up the user cost of capital and lead to a reduction in their capital stock. Nondurable producers, undeterred by financial constraints, experience a decline in user costs that leads them to increase their capital stock.

This mechanism can be seen directly by looking at the model responses of the prices of durable goods and the user cost in Figure 11. The orange line shows that the relative price of durable goods falls sharply in response to a contractionary monetary shock before ultimately rising above its pre-shock level. The red and blue lines represent the respective user costs—that is, the implicit rental rate set equal to the marginal product of capital—for the durable and nondurable producers. These expressions are complicated and include both current and expected prices, demand, adjustment costs, and, for the durable firms, degrees of financial constraint. For durable producers, the financial constraints are powerful enough to push up the user cost of capital and lead to a reduction in their capital stock.

The drop in durable goods prices in response to a contractionary monetary shock is usually modeled as a consequence of the assumption that durable prices are more flexible. This assumption is backed by a large body of work in the pricing literature. The benchmark paper on the price flexibility of durables comes primarily from Bils and Klenow (2004), who look at BLS microdata for 350 categories of goods from 1995-1997 and find that durable goods show more frequent price changes than nondurable goods. More recent work by Klenow and Malin (2010) uses the same CPI microdata over a longer range (1988-2009) to show that the mean price duration for durable goods (3.0 months) is much shorter than for nondurables

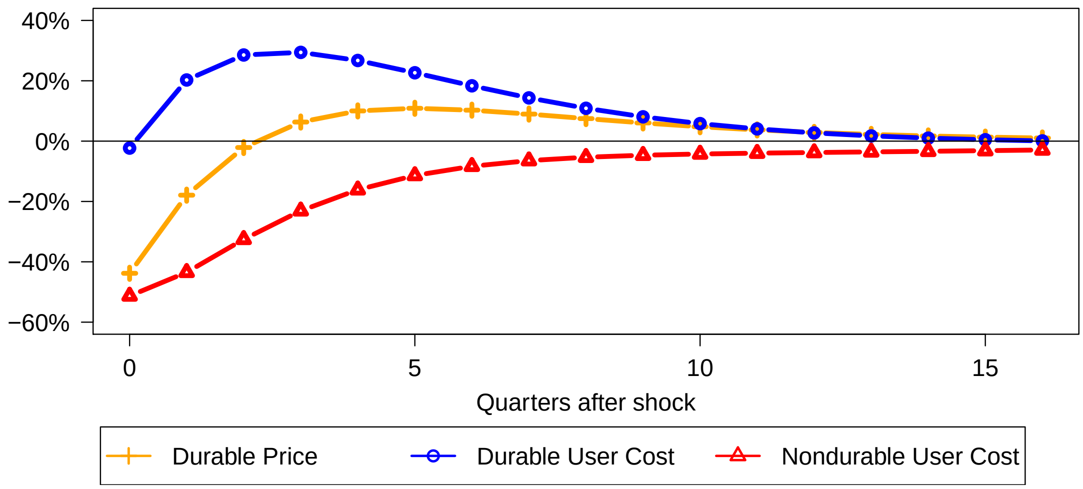

Figure 11: Model User Cost Responses to Contractionary MP Shocks

Note: This figure shows the model response to a 100bp contractionary monetary shock for the relative price of the durable good (which serves as the investment good in both sectors) as well as the user costs for each sector. The user cost in the model can be calculated by rearranging the firm's first order condition on investment to include everything but the marginal product of capital on one side and all remaining variables—including current and expected prices, demand, and financial conditions—on the other.

(5.8 months). Both of these papers abstract from housing and structures in their analysis; including them would likely make durable prices look even more flexible.

This evidence is used as the basis for virtually all other papers in the literature analyzing the effects of monetary shocks on New Keynesian models with durable goods. Some examples of papers assuming perfectly flexible durable prices include Barsky et al. (2007), Monacelli (2009), Carlstrom and Fuerst (2010), Kim and Katayama (2013), and Chen and Liao (2014). In addition to a baseline calibration that assumes durable prices are more flexible, Kim and Katayama (2013) also use Bayesian techniques to estimate the degrees of price stickiness across sectors using their model and finds that the data support parameterizations in which durable producers are able to adjust their prices far more frequently.

Crucially, my model does not depend on a specific parameterization in order to generate its key results because there are multiple channels through which the user cost of investment can fall. The next section shows that the model is able to generate qualitatively similar impulse responses even with perfectly flexible prices ($\phi_D = \phi_N = 0$) in both sectors without changing any other parameter values. In addition, Appendix C shows that the model is able to match the data even if the baseline level of price stickiness is applied to both sectors ($\phi_D = \phi_N = 58.25$) if the financial constraint parameter for durable producers is tightened. This suggests that my results do not depend critically on the assumption of flexible durable prices even if there is substantial empirical evidence to support it.

4.5 Alternative Models and Investment Comovement

The key mechanism in the model that allows it to generate responses to monetary shocks that are consistent with the data for both consumption and investment is the same as the one pointed out in Barsky et al. (2007): Periods of lower demand are a good time to buy durable goods because these goods are cheap and will provide service flows for a long time. This has been termed the "comovement puzzle" and resulted in a literature attempting to generate more empirically accurate responses. I show in Appendix C that the combination of financial frictions on firms and durable producers allows my model to match the empirical dynamics of not only investment, but also consumption. Most alternative approaches to fixing the comovement puzzle do not include endogenous capital accumulation, and those that do include it are unable to generate the investment patterns observed in the QFR data.

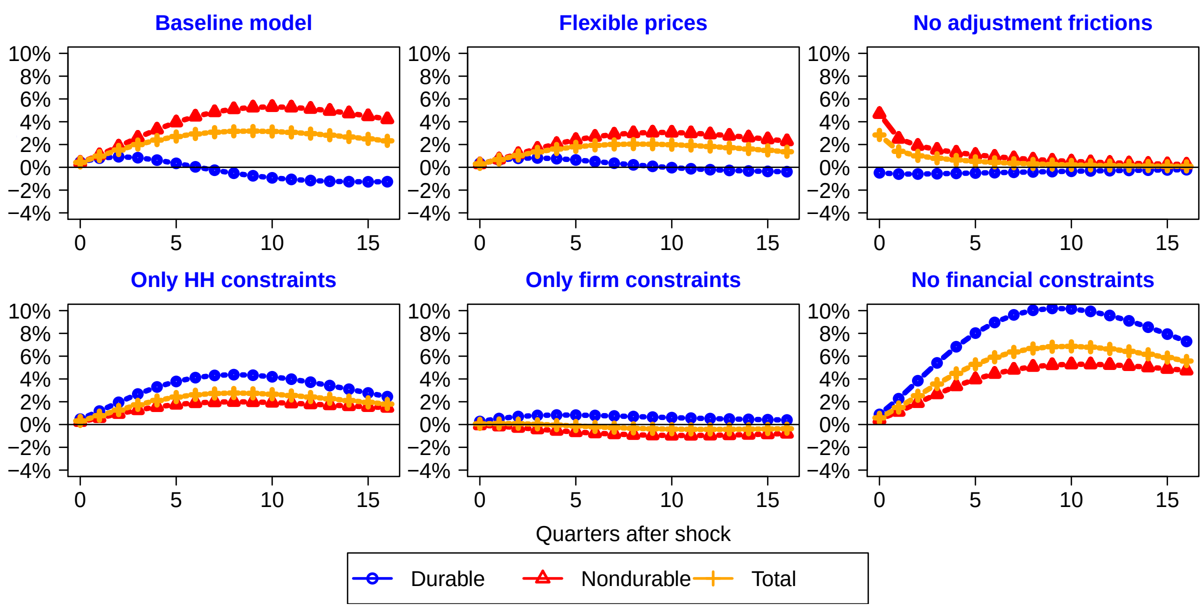

Figure 12: Capital Stock Responses under Alternative Model Assumptions

Note: All responses shown are for the capital stock to a 100bp contractionary monetary shock. The baseline model (top left) shows the same responses as in Figures 10. The flexible price responses (top middle) use the same structure as the baseline model but with no price stickiness in either sector ($\phi_D = \phi_N = 0$). The model without adjustment frictions (top right) is the same as the baseline model (including price frictions) but does not have adjustment costs on investment, wage stickiness, persistence in the Taylor Rule, or habit formation. All responses from the top row are based on models with financial frictions on both firms and households. The responses in the bottom left are from a modification of the baseline model that includes financial frictions on households but has no financial frictions for firms. The model in the bottom middle has financial frictions that apply to firms but none that apply to households. The model in the bottom right includes no financial constraints for either firms or households. All model responses shown on the bottom row include the baseline parameter values for price stickiness and adjustment costs.

Figure 12 provides insight into the model's ability to match the data by comparing impulse responses under a variety of alternative assumptions. The top row compares my baseline results to models which have perfectly flexible prices in both sectors (the middle panel) and which do not include any non-financial frictions such as sticky wages or habit formation (the right panel). While these changes alter the size and persistence of the investment responses relative to the baseline model, they do not change their direction. The bottom row compares different types of financial constraint and shows that constraints on only one of households (shown in the left panel) or firms (in the middle panel) are unable to match the data. The lower-right panel, which displays the results if neither households nor firms are financially constrained, shows large expansions in the capital stocks of both sectors. To the extent that more financially constrained firms are able to obtain access to funding through reductions in barriers to financing over time, my calibrated model suggests that the responses of constrained sectors should look more like that of the manufacturing sector in the future.

5 Conclusion

Understanding which types of firms are financially constrained and how this affects aggregate dynamics is a crucial research question in macroeconomics and corporate finance. I use a manually digitzed data set to show that the capital stock in the manufacturing sector responds countercyclically to monetary shocks. This behavior is driven by nondurable producers, which display fewer signs of financial constraint. A model in which durable producers and impatient consumers face financial constraints can match the data well. In response to a contractionary monetary policy shock, the relative price of durables falls and the unconstrained firms respond by increasing their investment expenditure. This model suggests that the firms which respond *most* to monetary shocks are actually the *least* financially constrained. Removing financial constraints on all sectors in the model leads to investment dynamics that are even more strongly countercyclical than the baseline.

These findings have two important implications for policymakers. The first is that monetary policy can have a larger impact on the investment of unconstrained producers than constrained producers even when the latter have much more volatile and interest-sensitive demand. The second is that the response of investment to monetary shocks may become more countercyclical over time as financial modernization reduces the number of firms which are financially constrained. Holding all else equal, this means more firms should be expected to purchase capital goods during periods of low prices even if these are also periods of lower demand.

Internet Appendix

A Data Description

A.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 as input to 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.[16] 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 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.

Beyond adjusting for revisions, I have to account for the fact that the data are not seasonally adjusted and in nominal terms. I use calendar quarter fixed effects for each

[16] `https://www.census.gov/econ/qfr/`

regression in my default specification to address these seasonality concerns, though the results are robust to using the Census Bureau's X-13ARIMA-SEATS seasonal adjustment process or a four-quarter moving average. I deflate the stock of net property, plant, and equipment using the nonresidential fixed investment price index. Sales for each sector are deflated using the manufacturing output price deflator for that sector after linearly interpolating it to a quarterly frequency. 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. One issue with using the size data is that the cutoffs are in nominal values and fixed over time; a firm with \$50 million in assets in 1967 is much larger relative to the size of the total manufacturing sector than a firm with \$50 million assets in 2007. One way to address this is to combine many of the smaller bins into one "small" classification. For my baseline specification, I follow Crouzet (2017) in classifying all of the firms with less than \$1 billion in nominal assets as being "small". An alternative approach uses percentiles of sales. This is the approach used in Gertler and Gilchrist (1994) (who use a 30% threshold) and Kudlyak and Sánchez (2017) (who use 25%). My results are robust to calcuating the size cutoffs in this way.

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 provide further evidence that the QFR data are in line with other measures of the capital stock, I can 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 13 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.

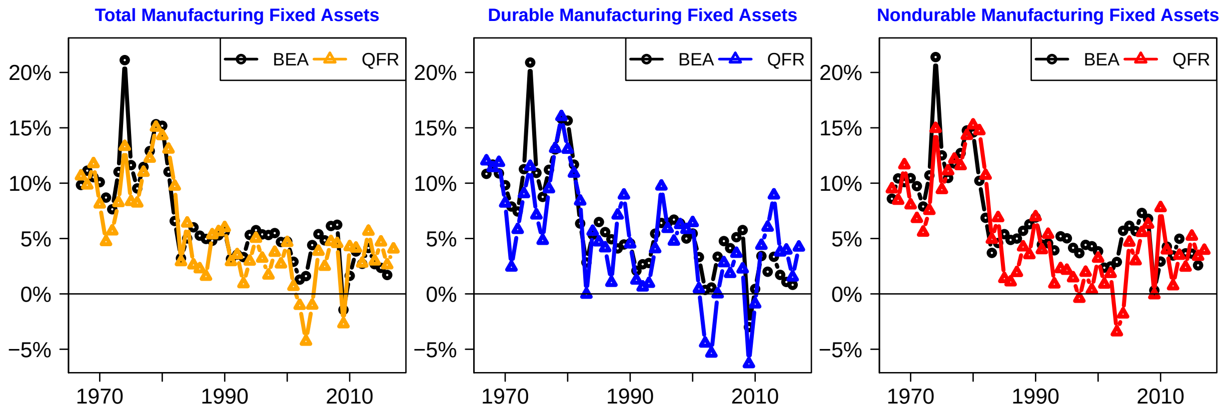

Figure 13: Y/Y % Changes in BEA and QFR Fixed Asset Measures

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).

A.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[17] 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."[18]

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.[19]

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 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.

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

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

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

A.3 Compustat Data

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 1.

	All Manufacturing		**Nondurable**		**Durable**	
Variable	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 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.

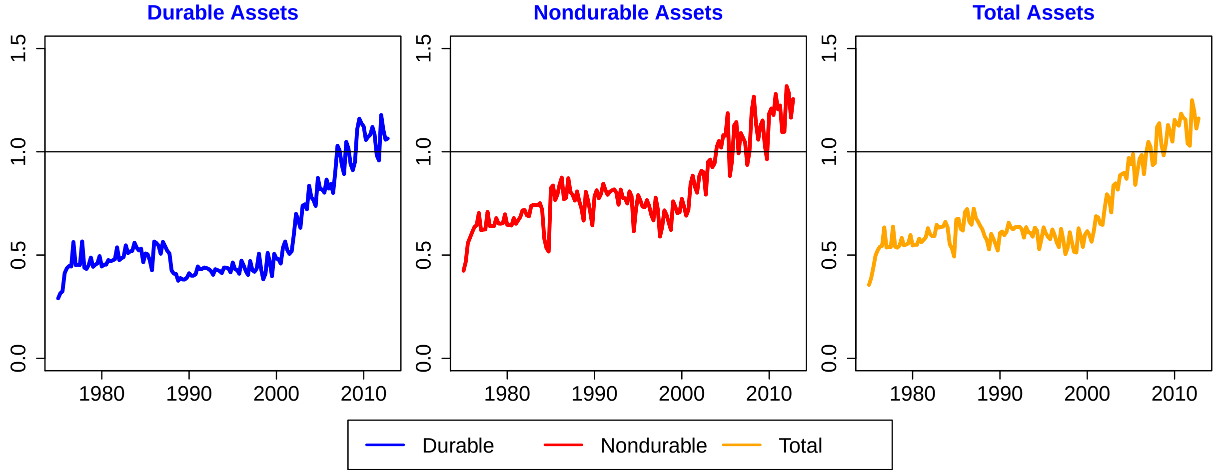

Figure 14: Ratio of Compustat to QFR Measures of Total Assets

Note: This figure shows the ratio of total assets in manufacturing firms in Compustat to total assets for all manufacturing firms from the QFR in each quarter.

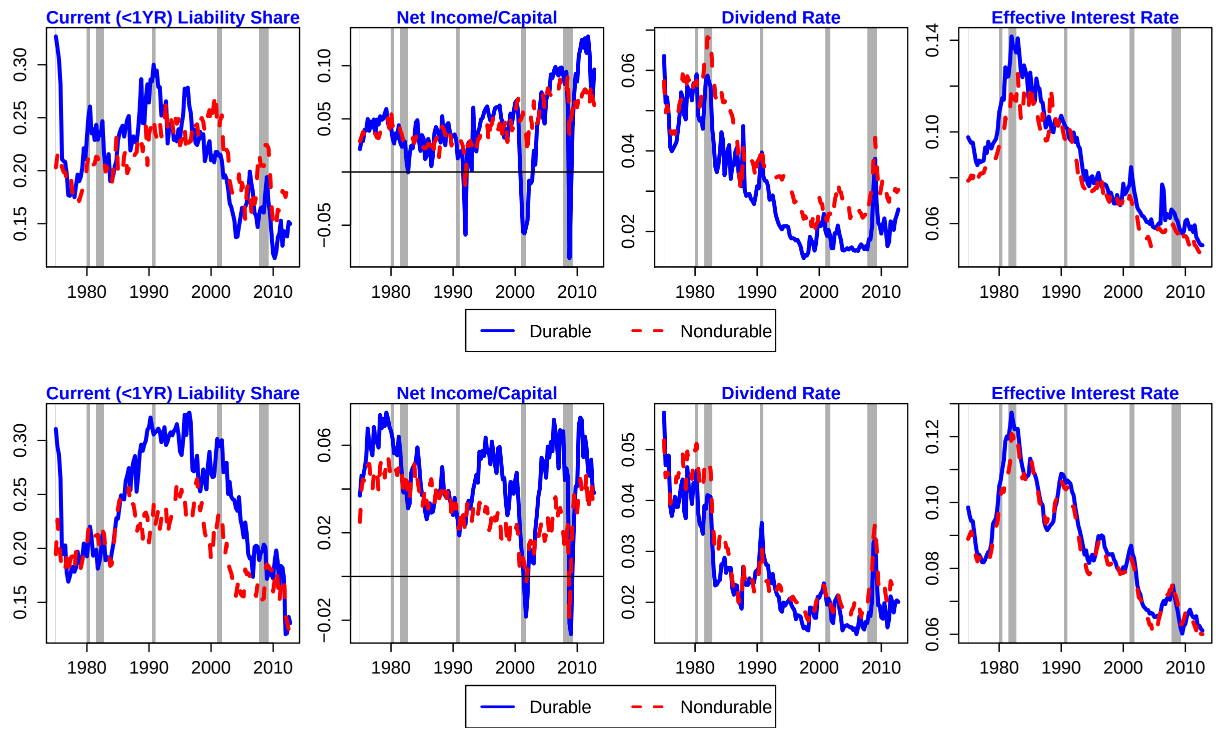

Figure 15: Mean (Top) and Median (Bottom) Compustat Financial Ratios

Note: This figure shows versions of the financial ratios used in the paper calculated from Compustat. The figures in the top row are calculated after winsorizing the top and bottom 1% of observations of each ratio and then weighted by total liabilities (for the short-term liability ratio), the total capital stock (for the net income-capital stock ratio), total equity (for the dividend rate), and total debt (for the effective interest rate). The figures in the bottom row are medians and are not winsorized.

A.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.

$$\Delta i_t = \beta i_{t-1} + \sum_k \phi_x^k E_t x_{t+k} + \sum_k \phi_\pi^k E_t \pi_{t+k} + \epsilon_t^m \tag{17}$$

The time series of shocks is shown in Figure 16 below.

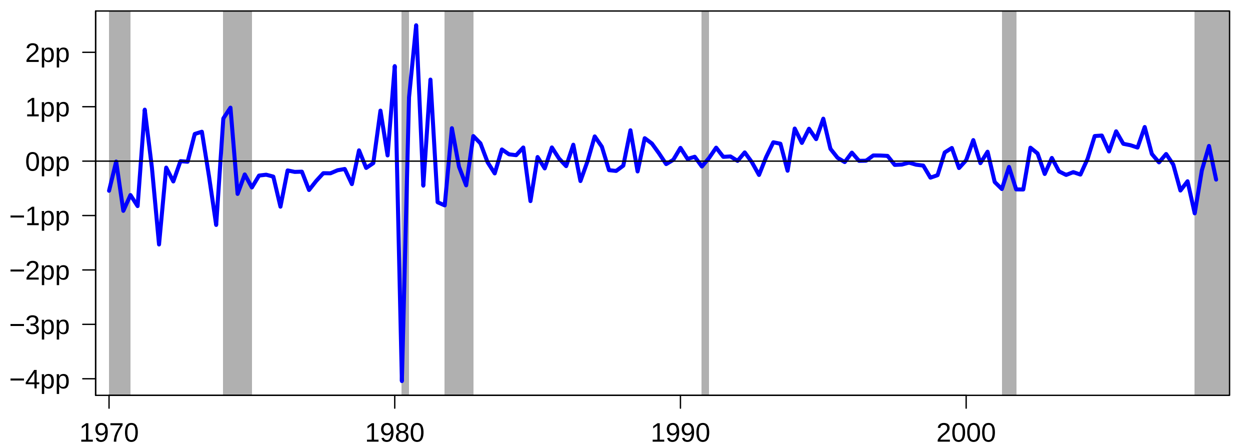

Figure 16: Time Series of Monetary Shocks

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.

B Robustness Checks and Extensions for Main Results

This section outlines robustness checks and shows some extensions using QFR, user cost, and Compustat data.

B.1 QFR Results

This section discusses a variety of robustness checks and extensions of my main results. My findings are robust to using a VAR specification instead of a local projection approach; using the shocks estimated using the identification strategy of Gertler and Karadi (2015) in my local projection specification instead of R&R-style shocks; alternative controls; and using the manufacturing investment price index for each sector from the BEA fixed asset data to deflate the capital stock instead of the nonresidential fixed investment price deflator.

B.1.1 Alternative Specification: Vector Autoregression

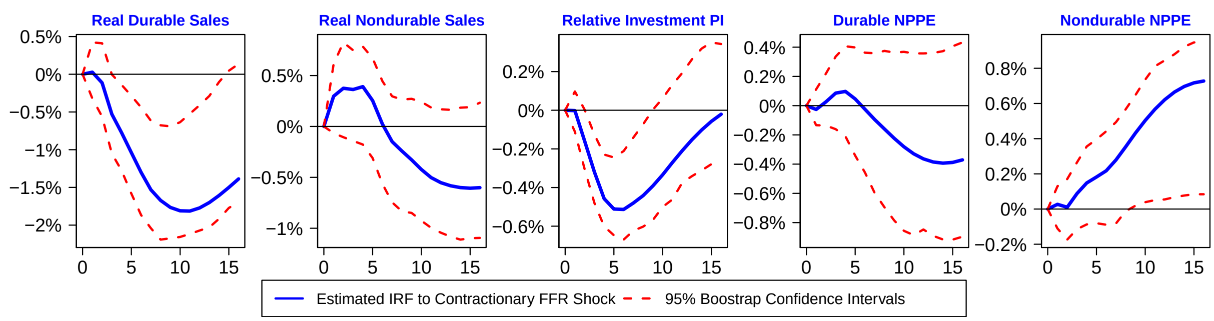

Figure 17: VAR Impulse Responses to Contractionary MP Shock (95% CI)

Note: This figure shows the impulse response to a one standard deviation contractionary FFR shock estimated from a standard recursive SVAR with a constant, linear time trend, seasonal fixed effects, and the following variable ordering: real durable sales, real nondurable sales, the relative price of manufacturing investment to manufacturing output, the real durable capital stock, the real nondurable capital stock, and the Federal Funds Rate. The FFR is in levels and all other data series are in logs. I estimate the responses using up to 8 lags and include seasonal fixed effects. The data span 1970-2004 to match the baseline specification. Bootstrapped 95% confidence intervals are calculated based on 250 draws.

B.1.2 Gertler-Karadi Shocks

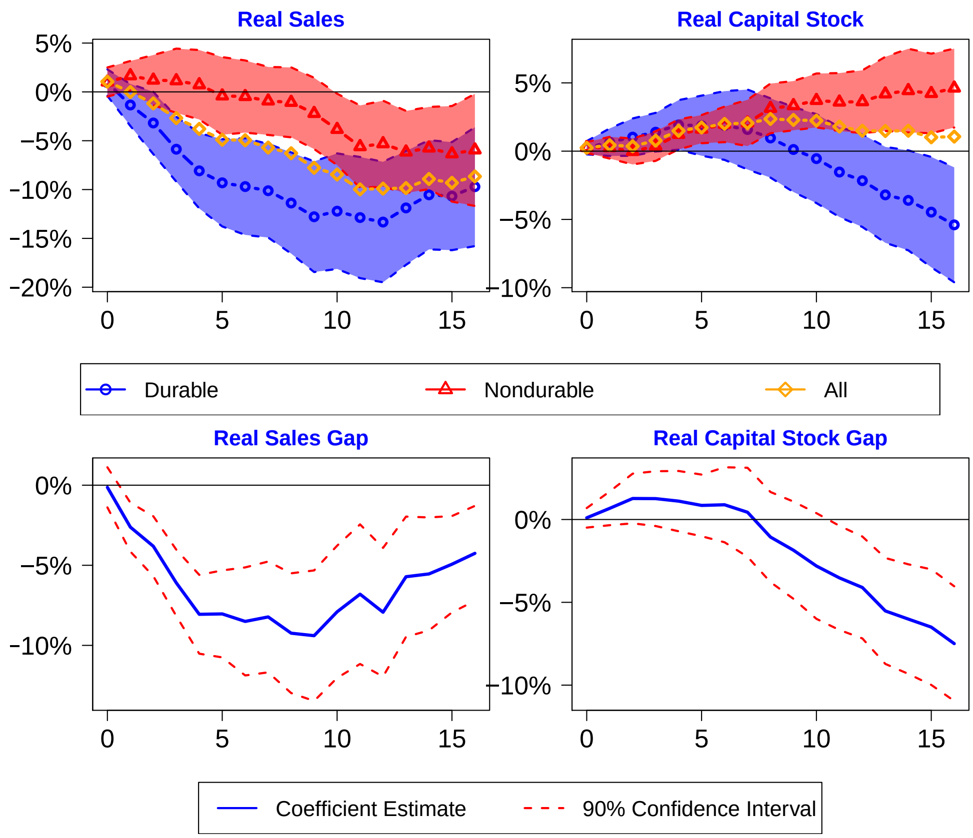

Figure 18: IRFs (top) and Estimated Gaps (bottom) using Gertler-Karadi Shocks

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). Specifically, 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 NIPA manufacturing output price index for each sector. 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 shocks from 1975-2004 and outcomes through 2008.

B.1.3 Number of Autoregressive Lags of Dependent Variable

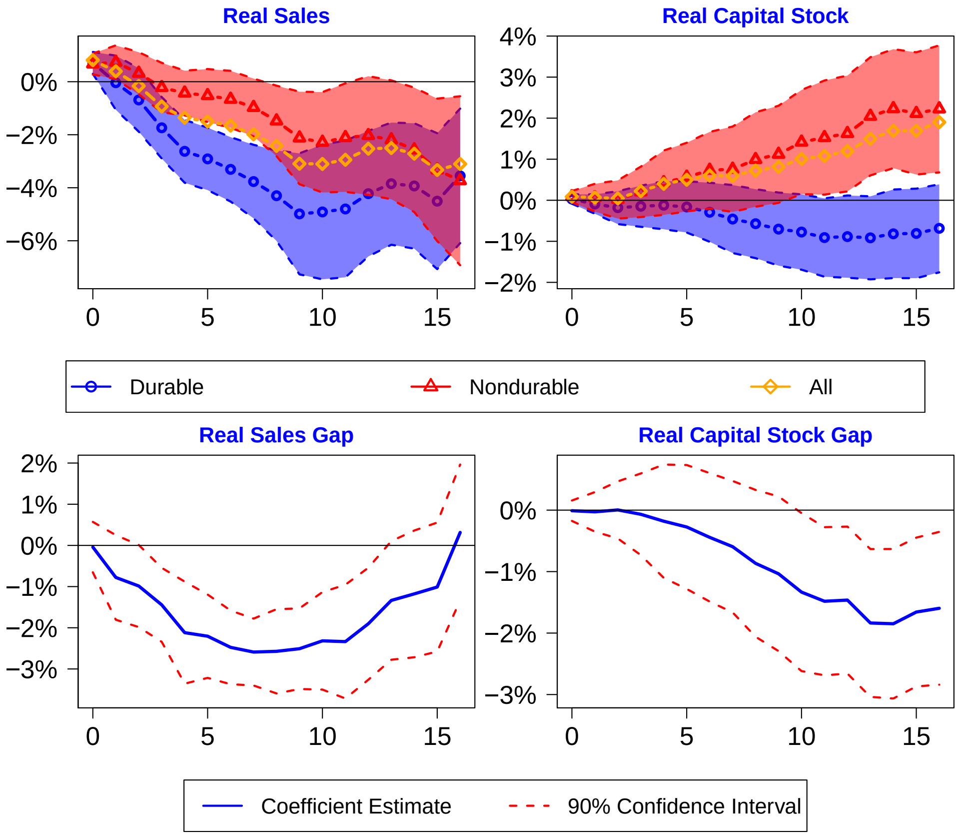

Figure 19: IRFs with 4 Lags of Dependent Variable

Note: This figure shows the coefficient estimates γ_h^i from Equation 1 of the main paper but modified to include 4 lags of the dependent variable. 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 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 shocks from 1970-2004 and outcomes through 2008.

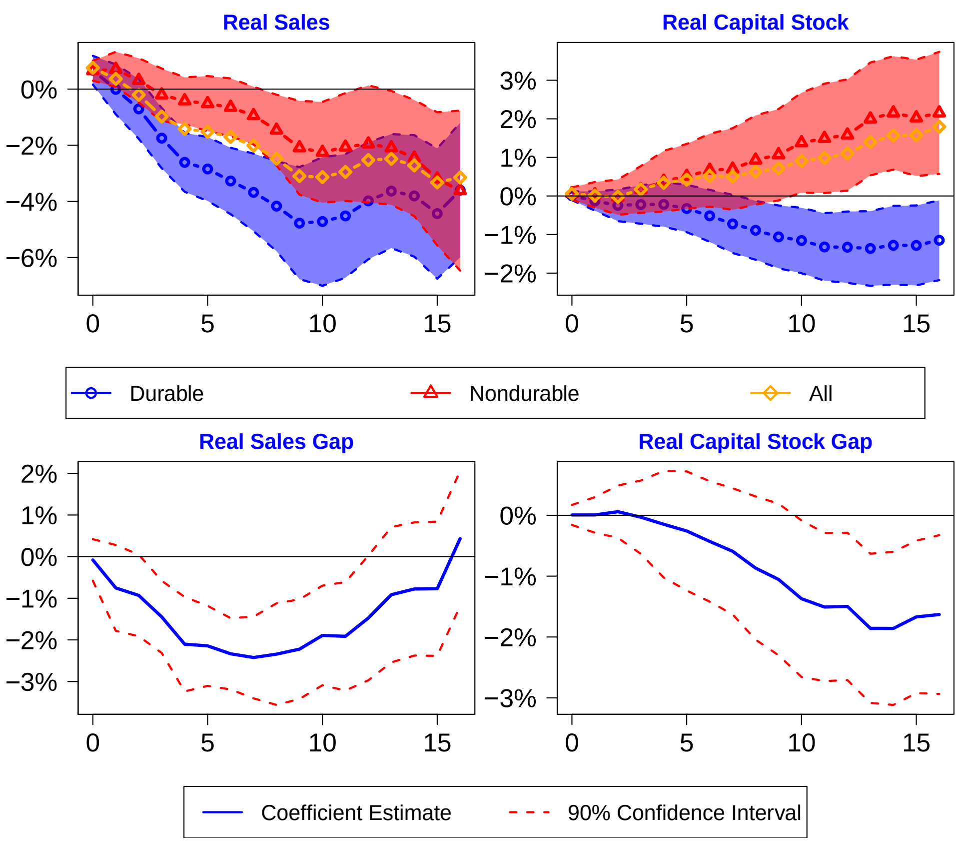

Figure 20: IRFs with 8 Lags of Dependent Variable

Note: This figure shows the coefficient estimates γ_h^i from Equation 1 of the main paper but modified to include 8 lags of the dependent variable. 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 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 shocks from 1970-2004 and outcomes through 2008.

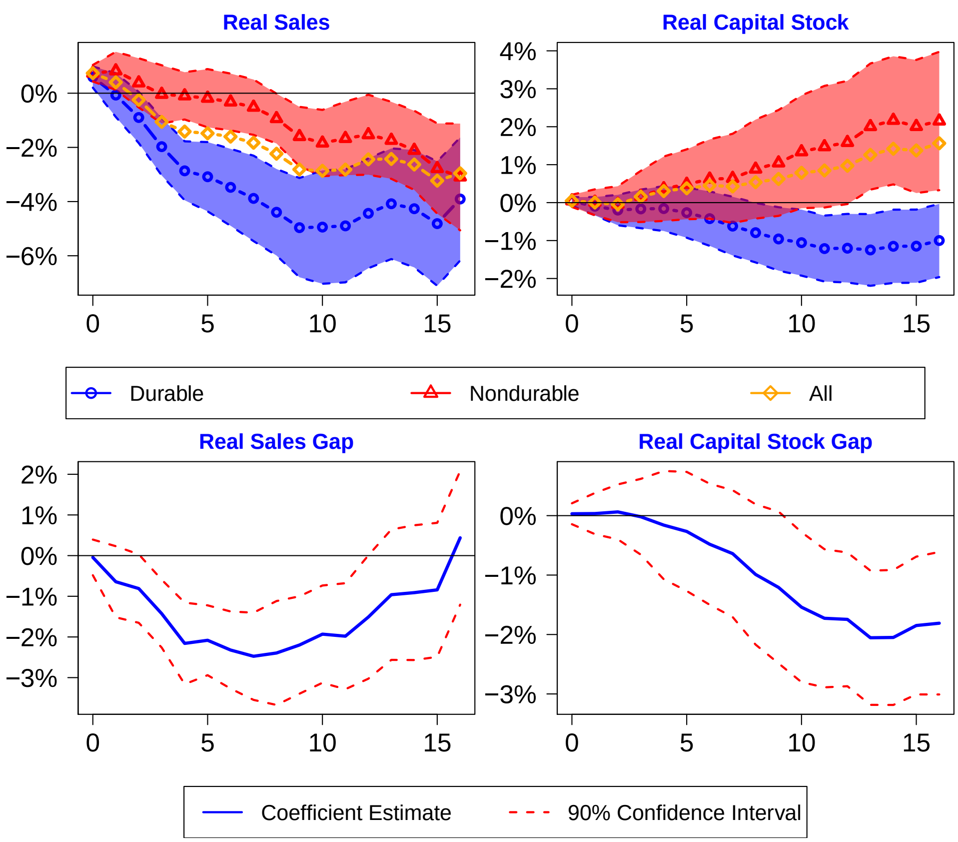

Figure 21: IRFs with 16 Lags of Dependent Variable

Note: This figure shows the coefficient estimates γ_h^i from Equation 1 of the main paper but modified to include 16 lags of the dependent variable. 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 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 shocks from 1970-2004 and outcomes through 2008.

B.1.4 Alternative Controls

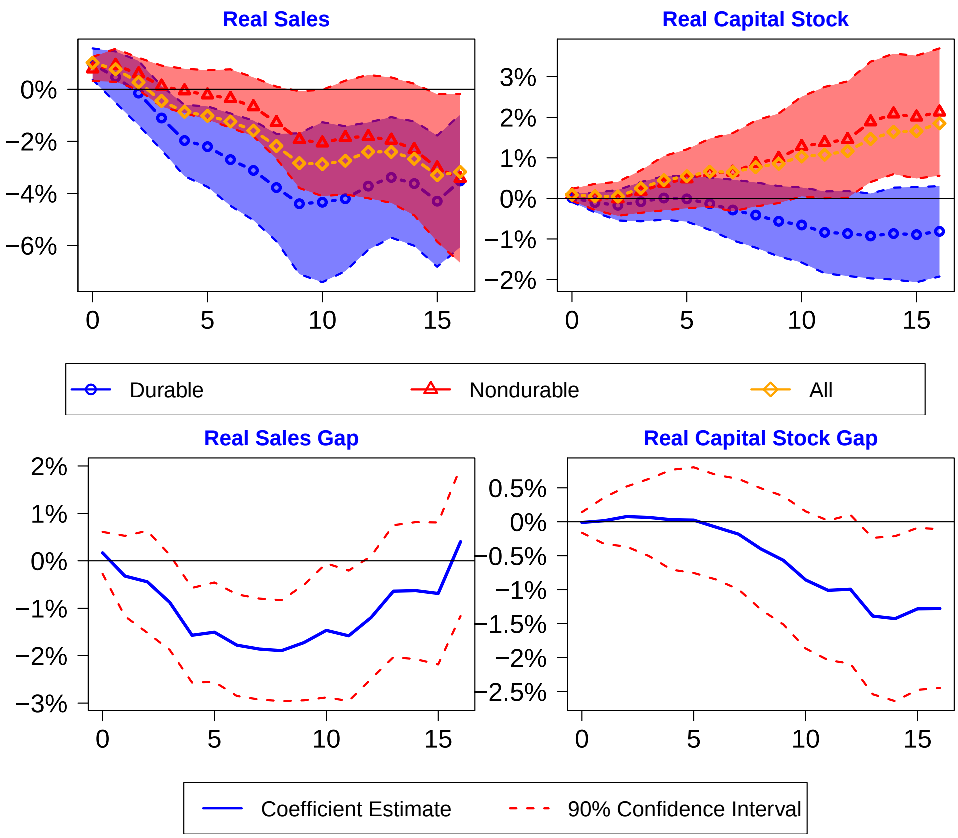

Figure 22: IRFs Excluding Lagged Real GDP Growth as Control

Note: This figure shows the coefficient estimates γ_h^i from Equation 1 of the main paper but excludes lagged real GDP growth as a control. 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 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 shocks from 1970-2004 and outcomes through 2008.

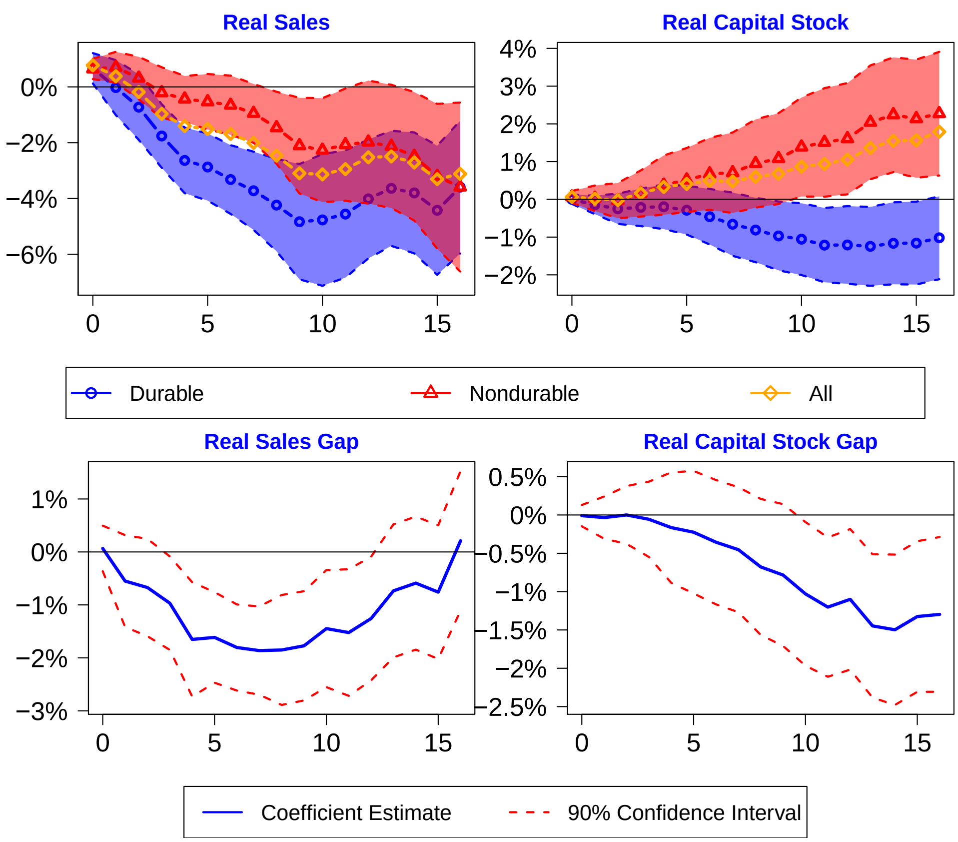

Figure 23: IRFs Excluding Lagged Shock as Control

Note: This figure shows the coefficient estimates γ_h^i from Equation 1 of the main paper but excludes ϵ_{t-1}^m as a control. 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 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 shocks from 1970-2004 and outcomes through 2008.

B.1.5 BEA Sector-Specific Investment Price Deflators

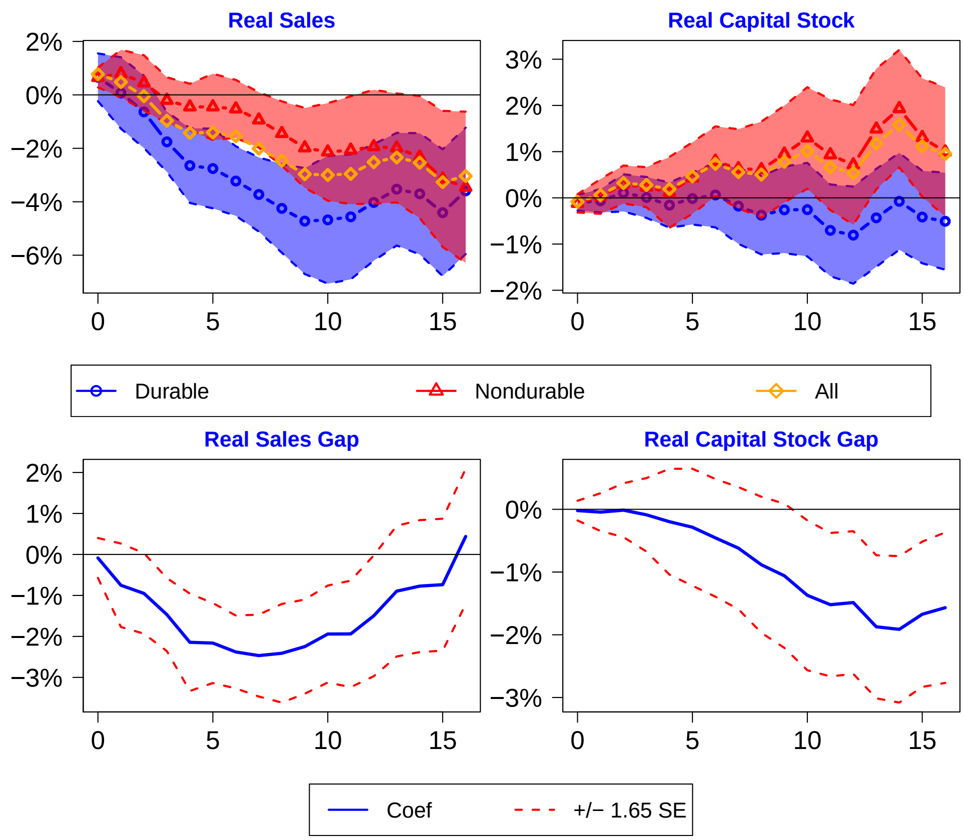

Figure 24: IRFs to 100bp Contractionary Shock Using BEA Investment Deflators (90% CI)

Note: This figure shows the coefficient estimates γ_h^i from Equation 1 of the main paper. The top row shows the responses of NPPE, which is measured by the QFR item "Stock of Property, Plant, and Equipment Net of Depreciation" deflated using the BEA sector-specific investment price index for each sector, 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 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 shocks from 1970-2004 and outcomes through 2008.

B.2 User Cost Results

Effective interest rate measures are not directly observable in the QFR prior to 1998. To obtain the sector-specific interest rates I use in my main analysis, I use data from Compustat. To calculate these interest rates, I first calculate the rate of interest expenses to total debt using the WRDS financial ratio suite. I Winsorize the top and bottom 1% of observations and then calculate a mean for each sector in each quarter weighted by total debt.

Because these observations are only available starting in 1975, I retroactively apply the change in yields on AAA bonds between 1970 and 1975 to get a series running back to 1970. This effectively assumes that the spread between each sector's average borrowing rate and the AAA yield was constant over this five-year window, though the results are extremely similar if I start the regressions after the Compustat data are available. One issue with this approach is that the Compustat calculations only give the *average* interest rate, whereas the *marginal* rate is the one relevant for the user cost calculation. In practice this does not appear to make a large difference, however, as user costs estimated using AAA or BAA bond yields as well as the Federal Funds Rate all yield similar results.

The estimated interest rates are shown in Figure 25. In general, the average interest rates calculated from Compustat behave quite similarly across sectors; contractionary monetary shocks lead to small on-impact effects that gradually increase to a peak of about 50bp between two and three years after the shock, consistent with the idea that it takes time for higher marginal rates to increase average rates as debt based on old rates expires and new debt is issued. The bottom panel shows that while the effect on the Federal Funds Rate is large, the effects on corporate bond yields are more muted. Aside from a slightly larger increase on impact, the responses are very similar to those measured in the Compustat data.

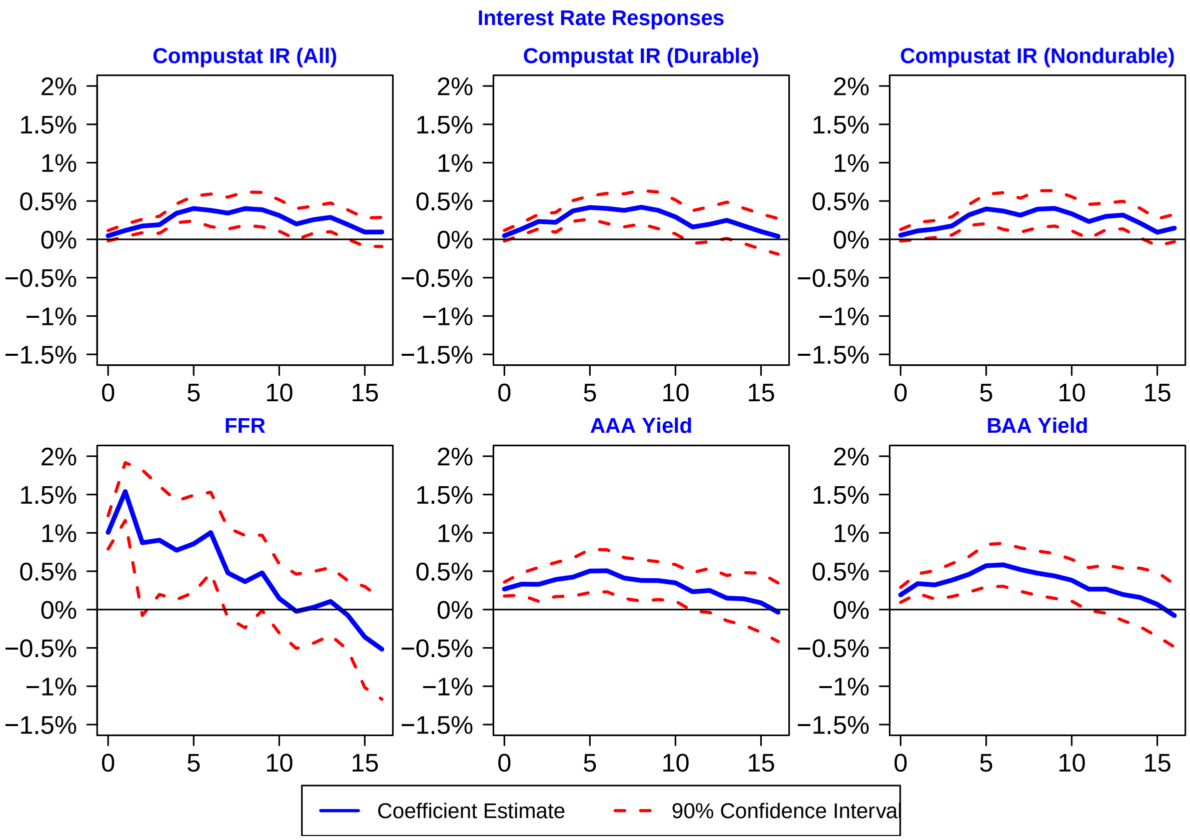

Figure 25: Impulse Responses to 100bp Contractionary Monetary Shock (90% CI)

Note: This figure shows the responses of interest rates to monetary shocks. The top row shows average interest rates calculated from Compustat as total interest payments divided (and weighted) by total debt after winsorizing the top and bottom 1% of observations. Because Compustat interest rates are only available starting in 1975, I calculate levels by retroactively applying changes in the AAA yield rate from 1970-1975. The bottom row shows the responses of the Federal Funds Rate as well as AAA and BAA corporate bond yields.

C 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.

C.1 Parameter Values

Parameter	**Value**	**Description**
β_S, β_B	0.99, 0.98	Discount factors
ω	0.5	Share of savers
η	0.8	Nondurable consumption share
ρ_w, μ_w	0.5, 0.1	Wage rigidity and markup
h	0.9	Habit formation
ν	4	Labor disutility scale
m, ξ	0.7, 0.1	Borrowing limits
ϕ_D, ϕ_N	0, 58.25	Price adjustment costs
θ_D, θ_N	2	Investment adjustment costs
δ_D, δ_K	0.02, 0.03	Depreciation rates
ϵ_D, ϵ_N	11	Substitution elasticities
α_D, α_N	0.33	Capital shares
ϕ_π, ρ	1.5, 0.9	Taylor Rule

Table 2: Parameter Values

C.2 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.

$$\begin{aligned}\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta_S^t \frac{\lambda_{S,t}}{\lambda_{S,0}} \Bigg\{ & p_t^j(i) \left(\frac{p_t^j(i)}{P_t^j}\right)^{-\epsilon_j} Y_t^j - w_t N_t^j - p_t^D I_t^j - \frac{\phi_j}{2} \left(\Pi_t^j(i) - 1\right)^2 Y_t^j(i) \\ & + mk_t^j \left[I_t^j \left(1 - \frac{\theta_j}{2}\left(\frac{I_t^j}{I_{t-1}^j} - 1\right)^2\right) + (1-\delta_j) K_t^j - K_{t+1}^j \right] + \mu_t^j \left[\xi^j p_t^D K_t^j - w_t N_t^j - p_t^D I_t^j\right] \\ & + mc_t^j \left[A_t (K_t^j)^{\alpha_j} (N_t^j)^{1-\alpha_j} - Y_t^j(i)\right] \Bigg\}\end{aligned} \tag{18}$$

The full set of equilibrium conditions are as follows:

$$\eta \left(\frac{1}{C_{B,t}^N - hC_{B,t-1}^N} - h\beta_B E_t \left[\frac{1}{C_{B,t+1}^N - hC_{B,t}^N} \right] \right) = \lambda_{B,t} p_t^N \tag{19}$$

$$w_t = \left(\frac{\nu H_{B,t}^{\chi}}{\lambda_{B,t}} (1+\mu^w) \right)^{1-\rho_w} \left(\frac{w_{t-1}}{\Pi_t} \right)^{\rho_w} \tag{20}$$

$$\lambda_{B,t} p_t^D = \frac{(1-\eta)}{D_{B,t}} + m\psi_t p_t^D \lambda_{B,t} + \beta_B E_t \left[\lambda_{B,t+1} p_{t+1}^D (1-\delta_D) \right] \tag{21}$$

$$(1+i_t)\psi_t = 1 - \beta_B E_t \left[\frac{\lambda_{B,t+1}(1+i_t)}{\lambda_{B,t}\Pi_{t+1}} \right] \tag{22}$$

$$D_{B,t} = C_{B,t}^D + (1-\delta_D) D_{B,t-1} \tag{23}$$

$$(1+i_t) B_{B,t} = m p_t^D D_{B,t} \tag{24}$$

$$p_t^N C_{B,t}^N + p_t^D C_{B,t}^D + \frac{(1+i_{t-1}) B_{B,t-1}}{\Pi_t} = B_{B,t} + w_t H_{B,t}^D + w_t H_{B,t}^N \tag{25}$$

$$\eta\left(\frac{1}{C^N_{S,t}-hC^N_{S,t-1}}-h\beta_S E_t\left[\frac{1}{C^N_{S,t+1}-hC^N_{S,t}}\right]\right)=\lambda_{S,t}p^N_t \tag{26}$$

$$w_t=\left(\frac{\nu H^{\chi}_{S,t}}{\lambda_{S,t}}\left(1+\mu^w\right)\right)^{1-\rho_w}\left(\frac{w_{t-1}}{\Pi_t}\right)^{\rho_w} \tag{27}$$

$$\lambda_{S,t}p^D_t=\frac{(1-\eta)}{D_{S,t}}+\beta_S E_t\left[\lambda_{S,t+1}p^D_{t+1}(1-\delta_D)\right] \tag{28}$$

$$D_{S,t}=C^D_{S,t}+(1-\delta^D)D_{S,t-1} \tag{29}$$

$$\lambda_{S,t}=\beta_S E_t\left[\frac{\lambda_{S,t+1}(1+i_t)}{\Pi_{t+1}}\right] \tag{30}$$

$$w_t(1+\mu_t)=(1-\alpha^D)mc^D_t A_t(K^D_t)^{\alpha_D}(H^D_t)^{-\alpha_D} \tag{31}$$

$$w_t=(1-\alpha^N)mc^N_t A_t(K^N_t)^{\alpha_N}(H^N_t)^{-\alpha_N} \tag{32}$$

$$\begin{aligned}(1+\mu_t)p^D_t=mk^D_t&\left[1-\frac{\theta_D}{2}\left(\frac{I^D_t}{I^D_{t-1}}-1\right)^2-\theta_D\left(\frac{I^D_t}{I^D_{t-1}}-1\right)\left(\frac{I^D_t}{I^D_{t-1}}\right)\right]\\&+\beta_S E_t\left[mk^D_{t+1}\theta_D\left(\frac{I^D_{t+1}}{I^D_t}-1\right)\left(\frac{I^D_{t+1}}{I^D_t}\right)\right]\end{aligned} \tag{33}$$

$$\begin{aligned}p^D_t=mk^N_t&\left[1-\frac{\theta_N}{2}\left(\frac{I^N_t}{I^N_{t-1}}-1\right)^2-\theta_N\left(\frac{I^N_t}{I^N_{t-1}}-1\right)\left(\frac{I^N_t}{I^N_{t-1}}\right)\right]\\&+\beta_S E_t\left[mk^N_{t+1}\theta_N\left(\frac{I^N_{t+1}}{I^N_t}-1\right)\left(\frac{I^N_{t+1}}{I^N_t}\right)\right]\end{aligned} \tag{34}$$

$$mk^D_t=\beta_S E_t\left[\left(\frac{\lambda_{S,t+1}}{\lambda_S}\right)\left(A_{t+1}\alpha_N {K^D_{t+1}}^{\alpha_D-1}{H^D_{t+1}}^{1-\alpha_D}mc^D_{t+1}+mk^D_{t+1}\left(1-\delta_K\right)\right)+\xi p^D_{t+1}\mu_{t+1}\right] \tag{35}$$

$$mk^N_t=\beta_S E_t\left[\left(\frac{\lambda_{S,t+1}}{\lambda_S}\right)\left(A_{t+1}\alpha_N {K^N_{t+1}}^{\alpha_N-1}{H^N_{t+1}}^{1-\alpha_N}mc^N_{t+1}+mk^N_{t+1}\left(1-\delta_K\right)\right)\right] \tag{36}$$

$$w_t H^D_t+p^D_t I^D_t=\xi p^D_t K^D_t \tag{37}$$

$$\left[(1-\epsilon_D)p_t^D+\epsilon_D mc_t^D\right]-\phi_D\left(\Pi_t^D-1\right)\Pi_t^D+\beta_S\phi_D E_t\left[\left(\frac{\lambda_{S,t+1}}{\lambda_{S,t}}\right)\left(\Pi_{t+1}^D-1\right)\Pi_{t+1}^D\left(\frac{Y_{t+1}^D}{Y_t^D}\right)\right]=0 \tag{38}$$

$$\left[(1-\epsilon_N)p_t^N+\epsilon_N mc_t^N\right]-\phi^N\left(\Pi_t^N-1\right)\Pi_t^N+\beta_S\phi_N E_t\left[\left(\frac{\lambda_{S,t+1}}{\lambda_{S,t}}\right)\left(\Pi_{t+1}^N-1\right)\Pi_{t+1}^N\left(\frac{Y_{t+1}^N}{Y_t^N}\right)\right]=0 \tag{39}$$

$$Y_t^D=A_t\left(K_t^D\right)^{\alpha_D}\left(H_t^D\right)^{1-\alpha_D} \tag{40}$$

$$Y_t^N=A_t\left(K_t^N\right)^{\alpha_N}\left(H_t^N\right)^{1-\alpha_N} \tag{41}$$

$$K_{t+1}^D=(1-\delta_K)K_t^D+I_t^D\left[1-\frac{\theta_D}{2}\left(\frac{I_t^D}{I_{t-1}^D}-1\right)^2\right] \tag{42}$$

$$K_{t+1}^N=(1-\delta_K)K_t^N+I_t^N\left[1-\frac{\theta_N}{2}\left(\frac{I_t^N}{I_{t-1}^N}-1\right)^2\right] \tag{43}$$

$$\omega H_{S,t}^D+(1-\omega)H_{B,t}^D=H_t^D \tag{44}$$

$$\omega H_{S,t}^N+(1-\omega)H_{B,t}^N=H_t^N \tag{45}$$

$$\omega C_{S,t}^D+(1-\omega)C_{B,t}^D=C_t^D \tag{46}$$

$$\omega C_{S,t}^N+(1-\omega)C_{B,t}^N=C_t^N \tag{47}$$

$$\omega D_{S,t}+(1-\omega)D_{B,t}=D_t \tag{48}$$

$$\omega B_{S,t}+(1-\omega)B_{B,t}=0 \tag{49}$$

$$K_t^D+K_t^N=K_t \tag{50}$$

$$C_t^D+I_t^D+I_t^N+\frac{\phi_D}{2}\left(\Pi^D-1\right)^2Y_t^D=Y_t^D \tag{51}$$

$$C_t^N + \frac{\phi_N}{2}\left(\Pi^N - 1\right)^2 Y_t^N = Y_t^N \tag{52}$$

$$A_t = A_{t-1}^{\rho^A} \exp\left(e_t^A\right) \tag{53}$$

$$\beta_S(i + i_t) = (\beta_S(i_{t-1}))^{\rho}\left(\Pi_t^{\phi_\Pi}\right)^{1-\rho} \exp(e_t^M) \tag{54}$$

$$\Pi_t^D = \frac{p_t^D}{p_{t-1}^D}\Pi_t \tag{55}$$

$$\Pi_t^N = \frac{p_t^N}{p_{t-1}^N}\Pi_t \tag{56}$$

$$1 = (p_t^N)^{\eta}(p_t^D)^{1-\eta} \tag{57}$$

C.3 Model with Interest Rate Wedge

In the baseline model, firms are able to borrow at zero net interest and thus are not directly affected by changes in the cost of capital. This is a conservative assumption, as increases in the cost of capital will exacerbate the constraints faced by durable producers. In practice, as shown in Figure 25, contractionary monetary shocks have about the same effects on the interest rates of durable and nondurable producers. As a result, sectoral differences in the empirical user cost responses are driven mostly by changes in relative prices.

The model can easily be modified to allow for borrowing costs of constrained firms to increase in response to the monetary contraction. 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:

$$w_t(1+\mu_t)(1+i_t) = (1-\alpha^D) mc_t^D A_t (K_t^D)^{\alpha^D} (H_t^D)^{-\alpha^D} \tag{58}$$

$$\begin{aligned}(1+\mu_t)p_t^D(1+i_t) = mk_{D,t}&\left[1 - \frac{\theta_D}{2}\left(\frac{I_{D,t}}{I_{D,t-1}} - 1\right)^2 - \theta_D\left(\frac{I_{D,t}}{I_{D,t-1}} - 1\right)\left(\frac{I_{D,t}}{I_{D,t-1}}\right)\right] \\ &+ \beta_S E_t\left[mk_{t+1}^D \theta_D \left(\frac{I_{D,t+1}}{I_{D,t}} - 1\right)\left(\frac{I_{D,t+1}}{I_{D,t}}\right)\right]\end{aligned} \tag{59}$$

$$(1+i_t)\left(w_t H_t^D + p_t^D I_t^D\right) = \xi p_t^D K_t^D \tag{60}$$

The impulse responses incorporating these modifications are shown in Figure 27 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.

C.4 Model with 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 non-durable 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 Figure 26. This suggests that imposing equal degrees of price stickiness will not automatically lead to behavior inconsistent with the main mechanisms described in my paper.

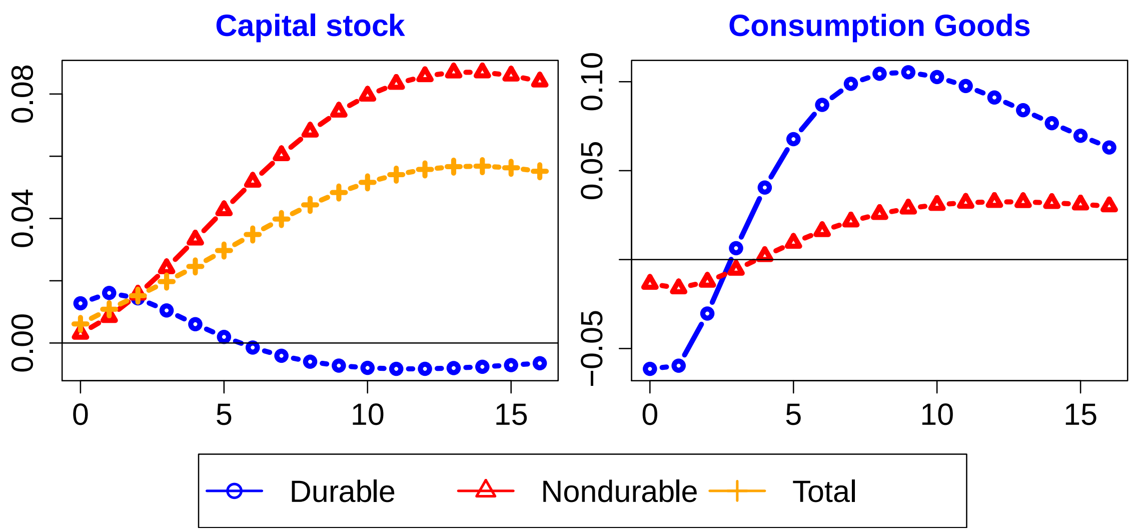

Figure 26: Model IRFs with Sticky Prices in Both Sectors

Note: This figure shows the impulse responses to a 100bp contractionary monetary shock 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 $\eta = 0.4$. All other parameters remain the same as in Table 2.

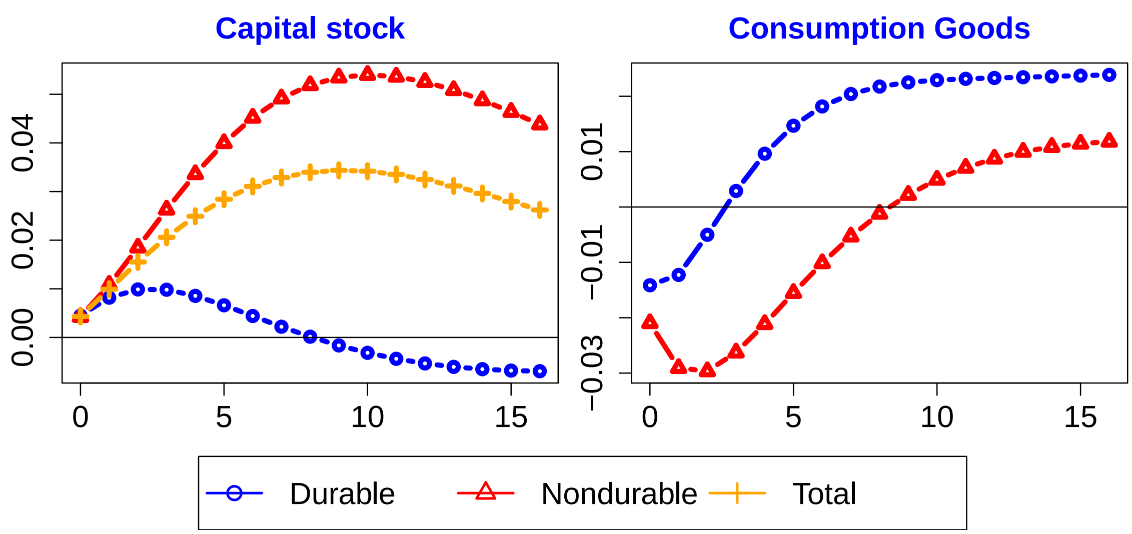

Figure 27: Model IRFs with Interest Rate Wedge

Note: This figure shows the impulse responses to a 100bp contractionary monetary shock when durable producers must pay the risk-free rate on their loans. The modified equilibrium conditions are described in Section C.3. All parameters remain the same as in Table 2.

C.5 Additional Model Figures

This section shows several additional impulse responses from the model. A comparison of the responses of consumption and investment is shown in Figure 28. The left column reproduces the analysis from the main paper by showing the responses of the capital stock of each type of producer in both the model (the top row) and the data (the bottom row). The right column shows the responses of nondurable consumption expenditure and the stock of consumer durable goods. The bottom-right panel shows that the responses of both nondurable consumption and the stock of durable goods decline by about 1% before returning to their pre-shock level. The model matches the responses of nondurable consumption relatively well, though with a larger peak effect. The on-impact decline in the stock of durable goods matches the peak effect seen in the data, though it recovers quickly and ends up stabilizing at a level above where it started. This is due to the combination of the persistent drop in prices and the lack of adjustment frictions on the part of consumer durables.

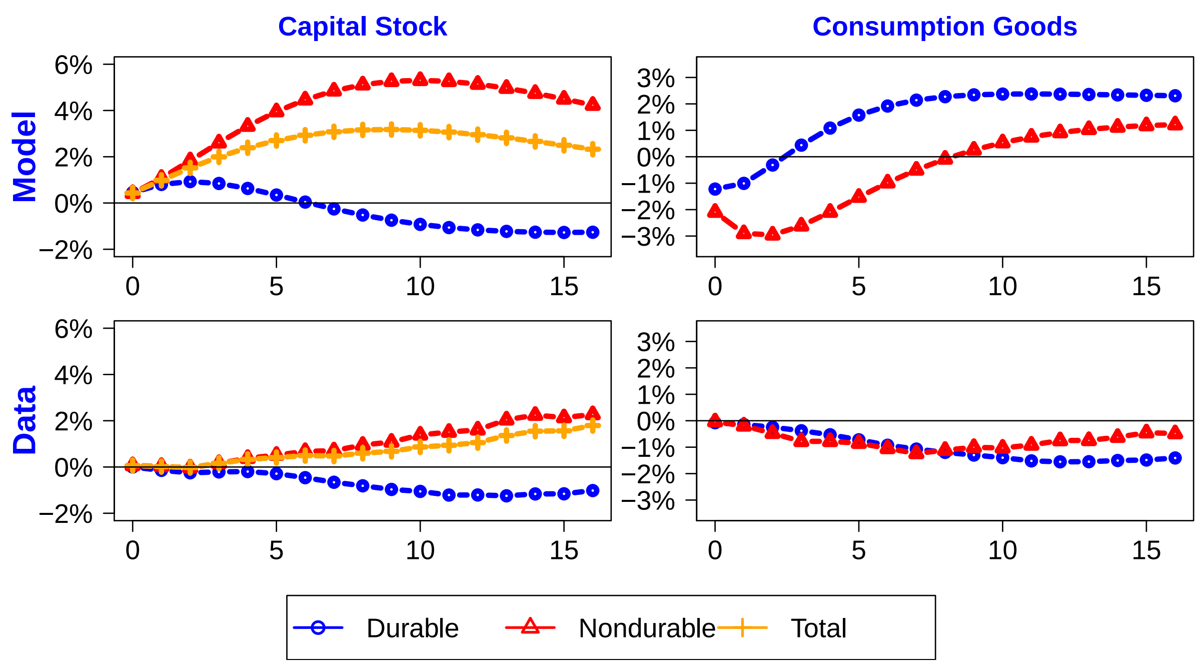

Figure 28: Model and Data IRFs to Contractionary MP Shock

Note: The top row shows the model responses to a 100bp contractionary monetary shock for the capital stock (left side) as well as the level of nondurable consumption and stock of consumer durable goods (right side). The bottom row shows the empirical estimates to a 100bp contractionary monetary policy shock. Empirical measures of consumer durables are reported as stocks while consumer nondurables are reported as expenditure flows. The capital stock estimates on the left are the same as those shown in the baseline empirical results. The nondurable consumption series comes from the BEA's real personal consumption expenditure data. The data for the stock of consumer durable goods come from the BEA's real fixed asset accounts and do not include housing.

C.6 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.

C.6.1 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:

$$R_b(e_h)X \geq R_b(e_l)X \implies p_h R_b X \geq p_l R_b X + BX \implies R_b X \geq \frac{BX}{\Delta p} \tag{61}$$

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 $(1 + i)$:

$$(1+i)L \geq p_h R_l X \implies (1+i)(X - A) \geq p_h \left[RX - R_b X\right] \tag{62}$$

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 61 and 62 leads to following condition:

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

$$\implies X\left[1 - \frac{p_h}{1+i}\left(R - \frac{B}{\Delta p}\right)\right] = A \implies X = \left(\frac{1}{1 - \frac{p_h}{1+i}\left[R - \frac{B}{\Delta p}\right]}\right) A \tag{63}$$

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:

$$U^B = (p_h R - 1)X = \left(\frac{p_h R - 1}{1 - \frac{p_h}{1+i} \left[R - \frac{B}{\Delta p} \right]} \right) A \tag{64}$$

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.

C.6.2 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.[20]

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

[20] 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.

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 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:

$$(1+i)(X-A) = X\left(1 - \frac{B}{\Delta p R_1}\right)\hat{R} \implies X = \left[\frac{1}{1 - \left(\frac{1-\frac{B}{\Delta p R_1}}{(1+i)}\hat{R}\right)}\right] A \tag{65}$$

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:

$$p_h \bar{R} - \hat{R} = p_h\left(\theta R_0 + (1-\theta)R_1\right) - \left(\theta p_l R_0 + (1-\theta) p_h R_1\right) = \theta \Delta p R_0 \tag{66}$$

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.

C.6.3 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:

$$\left(\frac{1}{1 - \frac{p_h}{1+i}\left[\bar{R} - \frac{B}{\Delta p}\right]} \right) > \left(\frac{1}{1 - \left(\frac{1 - \frac{B}{\Delta p R_1}}{(1+i)} \hat{R} \right)} \right) \tag{67}$$

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:

$$w_t H_t^D + p_t^D I_t^D = \xi p_t^D K_t^D \tag{68}$$

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.

References

Almeida, H. and M. Campello (2001). Financial constraints and investment-cash flow sensitivities: New research directions.

Almeida, H. and M. Campello (2007). Financial constraints, asset tangibility, and corporate investment. *The Review of Financial Studies 20*(5), 1429–1460.

Arredondo, A. (2020). Time to deliver: Financing constraints of capital goods producers and investment dynamics. Mimeo.

Banerjee, S., S. Dasgupta, and Y. Kim (2008). Buyer–supplier relationships and the stakeholder theory of capital structure. *The Journal of Finance 63*(5), 2507–2552.

Barclay, M. J. and C. W. Smith (1995). The maturity structure of corporate debt. *the Journal of Finance 50*(2), 609–631.

Barsky, R. B., C. L. House, and M. S. Kimball (2007). Sticky-price models and durable goods. *American Economic Review 97*(3), 984–998.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics 1*, 1341–1393.

Bils, M. and P. J. Klenow (2004). Some evidence on the importance of sticky prices. *Journal of political economy 112*(5), 947–985.

Blanchard, O. and J. Galí (2007). Real wage rigidities and the new keynesian model. *Journal of Money, Credit and Banking 39*, 35–65.

Buera, F. J., J. P. Kaboski, and Y. Shin (2011). Finance and development: A tale of two sectors. *American Economic Review 101*(5), 1964–2002.

Caballero, R. J., E. M. Engel, J. C. Haltiwanger, M. Woodford, and R. E. Hall (1995). Plant-level adjustment and aggregate investment dynamics. *Brookings Papers on Economic Activity*, 1–54.

Carlstrom, C. T. and T. S. Fuerst (2010). Nominal rigidities, residential investment, and adjustment costs. *Macroeconomic Dynamics 14*(1), 136–148.

Chen, B.-L. and S.-Y. Liao (2014). Capital, credit constraints and the comovement between consumer durables and nondurables. *Journal of Economic Dynamics and Control 39*, 127–139.

Chirinko, R. S., S. M. Fazzari, and A. P. Meyer (1999). How responsive is business capital formation to its user cost?: An exploration with micro data. *Journal of Public Economics 74*(1), 53–80.

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), 1–45.

Cloyne, J., C. Ferreira, M. Froemel, and P. Surico (2019, December). Monetary policy, corporate finance and investment. Mimeo.

Coibion, O. (2012, April). Are the effects of monetary policy shocks big or small? *American Economic Journal: Macroeconomics 4*(2), 1–32.

Crouzet, N. (2017). Aggregate implications of corporate debt choices. *The Review of Economic Studies 85*(3), 1635–1682.

Crouzet, N. and N. R. Mehrotra (2020, January). Small and large firms over the business cycle. Mimeo.

Erceg, C. and A. Levin (2006). Optimal monetary policy with durable consumption goods. *Journal of Monetary Economics 53*(7), 1341–1359.

Farre-Mensa, J. and A. Ljungqvist (2016). Do measures of financial constraints measure financial constraints? *The Review of Financial Studies 29*(2), 271–308.

Fazzari, S. M., R. G. Hubbard, B. C. Petersen, A. S. Blinder, and J. M. Poterba (1988). Financing constraints and corporate investment. *Brookings Papers on Economic Activity 1988*(1), 141–206.

Fuhrer, J. C. (2000). Habit formation in consumption and its implications for monetary-policy models. *American Economic Review 90*(3), 367–390.

Gertler, M. and S. Gilchrist (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *The Quarterly Journal of Economics 109*(2), 309–340.

Gertler, M. and P. Karadi (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics 7*(1), 44–76.

Giroud, X. and H. M. Mueller (2017). Firm leverage, consumer demand, and employment losses during the great recession. *The Quarterly Journal of Economics 132*(1), 271–316.

Gomes, J. F., L. Kogan, and M. Yogo (2009). Durability of output and expected stock returns. *Journal of Political Economy 117*(5), 941–986.

Greenwald, D. L., J. Krainer, and P. Paul (2020). The credit line channel. Federal Reserve Bank of San Francisco Working Paper.

Guedes, J. and T. Opler (1996). The determinants of the maturity of corporate debt issues. *The Journal of Finance 51*(5), 1809–1833.

Guo, X. (2020). Identifying aggregate shocks with micro-level heterogeneity: Financial shocks and investment fluctuation. Mimeo, Bank of Canada Working Paper.

Hadlock, C. J. and J. R. Pierce (2010). New evidence on measuring financial constraints: Moving beyond the kz index. *The Review of Financial Studies 23*(5), 1909–1940.

Hall, R. E. and D. W. Jorgenson (1967). Tax policy and investment behavior. *The American Economic Review 57*(3), 391–414.

Hassett, K. A. and R. G. Hubbard (2002). Tax policy and business investment. In *Handbook of public economics*, Volume 3, pp. 1293–1343. Elsevier.

Holmstrom, B. and J. Tirole (1997, August). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics 112*(3), 663–691.

Jeenas, P. (2019, July). Monetary policy shocks, financial structure, and firm activity: A panel approach. Mimeo.

Jordà, Ò. (2005, March). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Kaplan, S. N. and L. Zingales (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics 112*(1), 169–215.

Kim, K. H. and M. Katayama (2013). Non-separability and sectoral comovement in a sticky price model. *Journal of Economic Dynamics and Control 37*(9), 1715–1735.

Kiyotaki, N. and J. Moore (1997). Credit cycles. *Journal of Political Economy 105*(2), 211–248.

Klenow, P. J. and B. A. Malin (2010). Microeconomic evidence on price-setting. In *Handbook of monetary economics*, Volume 3, pp. 231–284. Elsevier.

Kudlyak, M. and J. M. Sánchez (2017). Revisiting the behavior of small and large firms during the 2008 financial crisis. *Journal of Economic Dynamics and Control 77*, 48–69.

Leamer, E. E. (2015). Housing really is the business cycle: what survives the lessons of 2008–09? *Journal of Money, Credit and Banking 47*(S1), 43–50.

Monacelli, T. (2009). New keynesian models, durable goods, and collateral constraints. *Journal of Monetary Economics 56*(2), 242–254.

Ottonello, P. and T. Winberry (2020, June). Financial heterogeneity and the investment channel of monetary policy. Mimeo.

Rajan, R. and L. Zingales (1998). Financial dependence and growth. Technical Report 3.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. In *Handbook of macroeconomics*, Volume 2, pp. 71–162. Elsevier.

Romer, C. D. and D. H. Romer (2004, September). A new measure of monetary shocks: Derivation and implications. *American Economic Review 94*(4), 713–727.

Tirole, J. (2010). *The Theory of Corporate Finance*. Princeton University Press.

Whited, T. M. and G. Wu (2006). Financial constraints risk. *The Review of Financial Studies 19*(2), 531–559.

Zorn, P. (2018, February). Investment under rational inattention: Evidence from us sectoral data. Mimeo.

Zwick, E. and J. Mahon (2017). Tax policy and heterogeneous investment behavior. *American Economic Review 107*(1), 217–48.