Monetary Policy Shocks, Financial Structure, and Firm Activity: A Panel Approach*

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Abstract

This paper assesses the differences in how nonfinancial firms respond to high frequency identified monetary policy shocks conditional on various measures of their financial conditions. In line with the effects of monetary policy shocks on real aggregate activity, the most significant disparities between firms arise slowly, over a horizon of approximately 4 to 12 quarters after a shock. Among the explanatory financial variables considered, both higher leverage and lower liquid asset holdings at the time of a contractionary monetary shock tend to predict relatively lower fixed capital, inventory and sales growth in the cross-section of firms. When simultaneously controlling for both the relevance of leverage and liquid assets, it is the latter that explains the disparities over the longer horizon. Low liquid asset holdings are also shown to be associated with stronger pass-through to borrowing costs.

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1 Introduction

This paper examines the monetary policy transmission mechanism by studying the effects of unexpected monetary policy actions on nonfinancial firm activity. In particular, I assess the differences in firms' responses to monetary policy shocks conditional on their financial characteristics at the time of a shock by employing U.S. individual firm-level data. My aim is to assess whether the financial conditions of nonfinancial firms help to explain their economic activity after a monetary policy shock. Doing so will allow to learn both about the monetary policy transmission mechanism and the financial frictions nonfinancial firms in the U.S. economy might be facing. Also, the

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analysis can potentially help distinguish between different models of the macroeconomy and the financial frictions therein, guiding future research.

My identification of monetary policy shocks builds on a growing literature that leverages high frequency data from financial markets in constructing instruments which provide credible inference from as-if random variation in the shock of interest. More specifically, I use changes in the futures prices of various interest rates in a narrow window around the policy announcements of the Federal Open Market Committee (FOMC) to construct measures of monetary policy shocks to be employed in identification. Several recent papers use this data to study the nature of the monetary transmission mechanism, including Gertler and Karadi (2015), Wong (2018), Gorodnichenko and Weber (2016), Nakamura and Steinsson (2018), to name a few prominent examples. I will contribute to this literature by employing quarterly firm-level data from Compustat in studying how financial conditions might affect nonfinancial firms' behavior after a monetary policy shock.

To tackle the main question of interest, I use an approach in the spirit of local projections as prominently advocated by Jordà (2005). More recently, local projections have been combined with external instruments by Jordà et al. (2015) and Ramey and Zubairy (2018), for example. Of these analyses, the former utilizes a panel of countries, whereas the latter focuses on the state-contingent effects of shocks – both features highly relevant for my analysis. I employ panel data on public U.S. firms to evaluate the relative differences in firm activity after a monetary policy shock, conditional on firm financial characteristics at the time of the shock. In light of conventional estimates for the aggregate economy, for example by Christiano et al. (2005) or Gertler and Karadi (2015), which imply that the effects of monetary policy shocks on real activity appear relatively slowly over time, it is essential to evaluate the differences in firm behavior over a long horizon after the shock. To do so, I project growth rates of firms' measures of performance, such as fixed capital accumulation, inventories and sales at various horizons on monetary policy shocks interacted with financial indicators at the time of the shock. Grouping firms into bins based on these financial indicators allows to unearth possible nonlinearities introduced by financial conditions and also estimate group-specific impulse responses to shocks. I consider estimation both under the assumption that high frequency financial market data yields exact measures of structural monetary policy shocks, and relaxing this assumption by only assuming that the former provide valid instruments for the latter.

The key financial indicators that I focus on are leverage and liquid asset holdings. The former is measured as a firm's total debt to total assets ratio and the latter as the ratio of cash and short term investments to total assets. I find that after a contractionary monetary policy shock the fixed capital, inventories and sales of firms with higher leverage prior to the shock grow relatively slower, with the disparities increasing over the first three years after the shock. During the three years after a monetary policy shock which induces a 25bp increase in the federal funds rate, firms whose leverage ratio is above the 40th percentile in the cross-section experience a cumulative capital growth rate that is about 1 percentage point lower than those with leverage in the two bottom quintiles. Similarly, firms with lower liquid asset holdings just before a contractionary shock perform relatively worse in response, as measured by fixed capital or inventory accumulation and sales growth. A monetary shock inducing a 25bp increase in the federal funds rate leads firms among the 20% with least liquid assets to contract their capital stock by 2% more relative to the quintile with the most liquid asset holdings.

In addition, simultaneously controlling for the relevance of both leverage and liquid asset holdings in explaining differences among firms' responses to monetary policy shocks implies that it is the latter which play a more significant role. In this case, the quantitative and statistical significance of leverage in predicting disparities in firms' responses diminishes considerably. At the same time, there are no noteworthy changes in the estimates related to liquid asset holdings. Surprisingly, these results are unaffected by controlling for other commonly used proxies for the severity of financial frictions and liquidity issues, such as a firm's size, whether it has been issued a Standard & Poor's credit rating or whether it has recently paid dividends. Moreover, these additional indicators do not imply statistically significantly different responses over and above what is explained by leverage and liquid asset holdings.

To put the central results on differences in firms' responses into perspective, I evaluate the total effects of monetary policy shocks on capital accumulation both based on the local projections panel approach and a separate structural vector autoregression (VAR) model for the aggregate U.S. economy. The VAR specification closely follows the work of Gertler and Karadi (2015) and includes measures of aggregate financial conditions and nonresidential fixed investment. The estimates demonstrate that, as found in previous work on monetary VARs, unexpected nominal rate increases lead to contractions in aggregate output and fixed capital investment, alongside a worsening of financial conditions as measured by excess bond premia. The real economy responds to the monetary shock slowly, with output and investment in the VAR both starting a contraction about a year after the impact. The effect on investment becomes statistically significant only after two years. The results thus provide a picture consistent with the findings of Lamont (2000) on the existence of investment lags, with firms' planned investment at the beginning of a year explaining a large part of the variation in actual investment.

Finally, I analyze the dynamics of firms' debt-related financial indicators after monetary policy shocks, conditional on their liquid asset holdings. In line with the observed investment responses, I find that lower liquid asset holdings predict both stronger pass-through to the average nominal interest rates and the total interest expenditures that firms incur.

Related Literature This paper fits into a wide literature which studies how the effects of monetary policy shocks on the macroeconomy might be affected by the financial frictions that firms face. Most prominently, empirical papers exploring evidence for the existence of a financial accelerator mechanism have employed heterogeneity between firms in conjunction with monetary shocks to do so. Early papers in the literature, such as Gertler and Gilchrist (1994), Oliner and Rudebusch (1996), Bernanke et al. (1996) have found that small firms, who are believed to be more likely to be facing constraints in financing, bear the brunt of economic downturns after a contractionary monetary shock. However, Crouzet and Mehrotra (2018) have shown based on a representative sample of U.S. firm-level data that small firms' higher volatility over the business cycle does not seem to be explained by financial factors, such as leverage, liquid asset holdings or access to public debt markets, exposing the drawbacks of using firm size as a proxy for financial frictions.

In this paper I focus on explicit measures of firms' financial positions to study the relevance of financial frictions in shaping their responsiveness to monetary policy shocks.[1] A paper closely related to mine in its analysis is that by Ippolito et al. (2018) who also use firm-level data from Compustat, among other sources, and study the specific channel which emphasizes that changes in monetary policy affect firms' cost of servicing their floating rate debt and as a result directly affect cash flows. If a firm is constrained in acquiring external finance, the implied fluctuations in internal finance will also affect its ability to produce and invest. The authors find evidence of the stock prices of firms with more bank debt, which is usually floating rate, reacting more to high frequency identified monetary policy shocks only if the firms are unhedged against interest rate risk. Moreover, the relation is stronger for firms which are more likely financially constrained as measured by age or the Hadlock and Pierce (2010) index. The authors also present evidence that among firms who do not hedge against interest rate fluctuations, higher bank debt at the time of interest rate increases is associated with relatively lower growth of sales, inventories and fixed capital accumulation thereafter when comparing constrained firms to unconstrained, while such a difference does not arise for interest rate hedgers.[2] My work differs from theirs in that I study the full dynamic effects of high frequency identified monetary policy shocks on real variables over the whole five-year period after a shock, as dictated by the behavior of the aggregate economy, while they focus on the 4- and 6-quarter horizons. Also, due to limitations of data availability on bank debt, the main analysis by Ippolito et al. (2018) only employs data between 2004 and 2008 and thus lacks the power to study differences in responses over longer horizons, shown to be considerable in my work. Furthermore, my results indicate that the assets composition of firms, in the sense of liquid assets held, seems to explain significant differences in firms' responses over and above the structure of their liabilities.

Another highly relevant project is the recent work by Ottonello and Winberry (2019). They study Compustat firms' capital accumulation responses to high frequency identified monetary policy shocks conditional on leverage, credit ratings, and a "distance to default" measure as proxies for default risk. Regarding the explanatory power of leverage, Ottonello and Winberry (2019) focus on differences in firms' capital stocks arising in the shock-impact quarter and the year after that[3], finding that more leveraged firms are less responsive to the monetary shocks, whereas I emphasize the variation in capital accumulation behavior at horizons of four quarters and more – the time frame during which the response of aggregate activity is commonly estimated to peak (Gertler and Karadi, 2015). More importantly, when predicting heterogeneity in capital response dynamics, Ottonello and Winberry (2019) employ deviations in financial positions from firm-specific means, with the goal of controlling for permanent differences between firms, whereas I focus on the heterogeneity predicted by the levels of the firms' financial variables. In Jeenas (2019), I further discuss the usage of firm-level demeaned financial variables based on a structural model, and control for permanent differences by leaving out firms with permanently high or low

[1] Examples of previous papers that have employed firm or industry heterogeneity to analyze financial imperfections and nonfinancial firms' responses to monetary policy shocks using various empirical approaches include Kashyap et al. (1994), Gaiotti and Generale (2002), Ehrmann and Fratzscher (2004), Peersman and Smets (2005), Dedola and Lippi (2005) and Bougheas et al. (2006).

[2] Most of these results are presented using simple interest rate changes and not identified exogenous shocks to monetary policy, thus suffering from potential endogeneity biases. Although they do state that the main qualitative results hold when using high frequency identified measures of monetary policy shocks.

[3] Ottonello and Winberry (2019) do find differences in capital stocks at longer horizons predicted by within-firm variation in the distance to default measure.

leverage or liquid asset holdings.

Finally, my estimation approach differentiates from the two closely related papers above by allowing for nonlinearities in the relationships between a firm's financial characteristics and its performance after a monetary policy shock. It is not clear *ex ante* whether every marginal increase in say, observed leverage, should be associated with an identical marginal worsening of outcomes after an interest rate increase in reality. For example, observing a firm with very low liquid asset holdings could indicate that it is temporarily liquidity constrained, while exceptionally high liquid asset holdings could point towards an preemptive hoarding of cash because the firm might not have access to external funding when in need of liquidity. And it could be the case that both types of firms happen to do worse than others after a contractionary monetary policy shock.

The rest of the paper is organized as follows. Section 2 discusses how the high frequency surprises around policy announcements are measured and how they are used in the identification of structural monetary policy shocks. Section 3 describes the construction of the firm-level data I use, details the empirical specification employed in the panel projection approach, and presents the estimation results for fixed capital accumulation responses to a monetary shock. Additional estimation results for the responses of inventories and sales alongside various robustness tests are reported in Appendices B and C. Section 4 presents the identification approach and estimation results on monetary policy shock effects in a structural vector autoregression of the aggregate U.S. economy. Section 5 studies the dynamics of firms' financial indicators after a monetary policy shock. Section 6 concludes.

2 Identifying Monetary Policy Shocks

To identify shocks to monetary policy, I use high frequency data from futures markets around the time of FOMC meetings.[4] A common approach to identify exogenous changes in monetary policy is to analyze movements in financial market prices in narrow time intervals around FOMC press releases, issued after regularly scheduled meetings. These meetings take place about eight times a year, and occasionally the FOMC issues inter-meeting announcements. As has conventionally been done in previous work, I consider price changes in a window of 10 minutes before until 20 minutes after the FOMC announcement.

To fix ideas and terminology, a note on structural monetary policy shocks and how these can be thought to relate to measurements of unanticipated monetary policy news is in order. Because I will be working with quarterly data, the key object of interest is a quarterly structural monetary policy shock ε_t^p. These monetary policy shocks are understood as primitive, unanticipated economic forces uncorrelated with other structural shocks.[5] The aim of this paper, and the extensive empirical literature on monetary policy shocks, is to assess the effects of such shocks on the aggregate economy and the agents therein. Moreover, the quarterly monetary policy shock can itself be thought to consist of higher frequency structural monetary shocks, such as multiple federal

[4] Prominent pioneering examples of the usage of high frequency data on market interest rates to study monetary policy are papers by Kuttner (2001), Cochrane and Piazzesi (2002), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Gürkaynak et al. (2005).

[5] For further discussion, see Ramey (2016).

funds rate target changes or intentions communicated by FOMC members' speeches within the quarter. Unfortunately, we cannot observe these structural shocks. Yet we can try to measure the unanticipated components of FOMC press releases at specific instances of time. These unanticipated components will then necessarily be correlated with the structural monetary policy shock hitting the economy at that specific moment in time. And when measuring these components in a tight window around the FOMC announcements, one makes the identifying assumption that the measurements are uncorrelated with other structural shocks. The measurements of unanticipated higher frequency components can then be combined into quarterly measures, which are thus correlated with the quarterly structural monetary policy shocks, and uncorrelated with other quarterly structural shocks. To be clear, I will refer to the former, i.e. the objects drawn from the data, as *measures* of monetary policy shocks, and to the actual unobserved shocks as the *structural* monetary policy shocks. The construction of the measures is discussed in the following.

To isolate the unanticipated component of the content in FOMC press releases, federal funds futures are a common financial instrument to study. Federal funds futures have been traded since the end of 1988 and settle on the average effective overnight federal funds rate in any given month. To derive a benchmark measure of a monetary policy shock at the time of the announcement, one option is to construct the change in market expectations of the federal funds rate over the remainder of the month in which the FOMC meeting occurs. This can be done using the price of futures settling on the *current* month's federal funds rate.

To fix notation, let time indices t refer to *quarters* and $\tilde{t}$ to instances of time *within* the quarter, including the *exact dates and times* at which FOMC announcements occur, i.e. there is a continuum of $\tilde{t}$'s inside any period t. Let $\left\{\tilde{t}_k\right\}_k$ be the set of times at which FOMC announcements occur. For a given FOMC press release at $\tilde{t}_k$, let m_k be the number of days in the corresponding month, l_k the day in the month on which the FOMC meeting occurs, $f_{\tilde{t}_k}$ the price of the federal funds contract immediately following the FOMC announcement and $f_{\tilde{t}_k - \Delta\tilde{t}}$ the price immediately before. The implied change in the average federal funds rate for the remainder of the month, arising from the FOMC announcement, can be computed as:

$$\nu_{\tilde{t}_k} = \frac{m_k}{m_k - l_k}(f_{\tilde{t}_k} - f_{\tilde{t}_k - \Delta\tilde{t}})$$

where $\frac{m_k}{m_k - l_k}$ exactly takes into account the fact that the contracts settle on the monthly *average* overnight rate. This method then allows one to construct a series of high frequency measures of monetary shocks $\nu_{\tilde{t}_k}$, each corresponding to an FOMC press release at time $\tilde{t}_k$. I obtain the data on times and dates of the FOMC press releases and the implied measures of shocks from Gorodnichenko and Weber (2016) for the sample period 1994–2008. The data on announcement times and measures of shocks for the sample period 1990–1994 comes from Gürkaynak et al. (2005).[6] I use the convention that a *positive* $\nu_{\tilde{t}_k}$ refers to an unexpected *increase* in the federal funds futures rate, and thus a contractionary monetary policy shock.

[6]Since prior to 1994 the FOMC did not explicitly announce changes in its target federal funds rate, they were implicit in the nature of open market operations conducted following an FOMC meeting. Thus, Gürkaynak et al. (2005) use the date and time of the first open market operation after a meeting as the implicit announcement time. Also, as they elaborate, due to volatility in the federal funds market the Open Market Trading Desk was not able to communicate the FOMC's intentions immediately after the decision on some dates at the beginning of the sample. Because of this, I follow Gürkaynak et al. (2005) and only focus on the sample of announcements after the beginning of 1990.

To construct quarterly measures of monetary policy shocks from the high frequency series for $\nu_{\tilde{t}_k}$, I consider two approaches. As the first measure, I will simply sum up the high frequency $\nu_{\tilde{t}_k}$ within any quarter t to yield a measure ε_t^m of the monetary shock in that quarter, as for example done by Wong (2018). By letting $\underline{\tilde{t}}$ be the exact time of beginning of quarter t and $\bar{\tilde{t}}$ as the ending, this means:

$$\varepsilon_t^m \equiv \sum_{\tilde{t}_k \in \left(\underline{\tilde{t}}, \bar{\tilde{t}}\right)} \nu_{\tilde{t}_k}$$

I will refer to these as *unweighted* quarterly measures of monetary policy shocks. Note that if the $\nu_{\tilde{t}_k}$ are independent of structural monetary policy shocks at other instances of time and other types of structural shocks at any point in time, then the unweighted quarterly measure ε_t^m is also independent of other types of structural shocks at any point in time, and structural monetary policy shocks in other quarters.

Secondly, I follow an analogous approach as Gertler and Karadi (2015) do for monthly data and aggregate the high frequency measures $\nu_{\tilde{t}_k}$ in a *weighted* manner. More specifically, to take into account information about exactly when during the quarter an announcement (and the implied structural shock) took place, I assign each high frequency measure $\nu_{\tilde{t}_k}$ a weight $\alpha_k \equiv \frac{q_k}{Q_k}$, with q_k the number of days until the end of the quarter and Q_k the length of the quarter in which the meeting occurs. I then construct the weighted quarterly measure of a monetary policy shock in quarter t, denoted as $\bar{\varepsilon}_t^m$, as an adequately weighted sum of all the high frequency measures from either the previous quarter or the current quarter. That is:

$$\bar{\varepsilon}_t^m \equiv \sum_{\tilde{t}_k \in \left(\underline{\widetilde{t-1}}, \overline{\widetilde{t-1}}\right)} (1-\alpha_k)\nu_{\tilde{t}_k} + \sum_{\tilde{t}_k \in \left(\underline{\tilde{t}}, \bar{\tilde{t}}\right)} \alpha_{t_k}\nu_{\tilde{t}_k}$$

This is an attempt to account for the fact that, say the announcement of a change in the fed funds target rate at the end of a quarter has a delayed effect on the quarterly measures of economic variables compared to an identical announcement at the beginning of a quarter. However, the construction of these weighted quarterly measures directly introduces correlation of $\bar{\varepsilon}_t^m$ with structural monetary policy shocks in other quarters, and this can lead to issues with the precise identification of the effects of these shocks depending on the estimation approach used, as discussed right below.

The identification assumption for the VAR approach with external instruments, seen in Section 4 equations (8)–(9), is that the external instruments in period t be correlated with the structural monetary policy shock in period t and uncorrelated with other structural shocks in the same period. If the high frequency measures $\nu_{\tilde{t}_k}$ are themselves correlated with structural monetary shocks and uncorrelated with other structural shocks, both the weighted and unweighted quarterly measures above are suitable candidates for instruments in the VAR approach. However, as pointed out by Stock and Watson (2018), when employing local projection methods and instruments to identify the dynamic effects of an imperfectly observable structural shock, the strict conditions for instrument validity also require that the instrument be uncorrelated with the *same* type of structural shock at other points in time. That is, the instrument for a structural monetary policy shock in quarter t must be uncorrelated with structural monetary policy shocks in other quarters. Therefore, the weighted quarterly measure $\bar{\varepsilon}_t^m$ is not fully suitable to directly be used in the panel regressions of Section 3 which rely on a local projections approach.[7] Nontheless, I consider the weighted quarterly measures in robustness analysis and verify that all the central results remain unchanged.

Also, note that an important, yet subtle requirement for the high frequency measures $\nu_{\tilde{t}_k}$ to be uncorrelated with other types of structural shocks at any point in time is that the prices of fed funds futures prior to the monetary policy announcement contain all the relevant information revealed by any structural shocks realized before the announcement. Or at least, the monetary policy announcement itself must not expose information regarding other structural shocks which was not known by financial markets beforehand. If the FOMC's announcements reveal superior information about the realizations of shocks which the private agents in financial markets had not taken into consideration, then the high frequency measures $\nu_{\tilde{t}_k}$ become correlated with such other structural shocks. This issue has been studied in detail by Nakamura and Steinsson (2018) and Miranda-Agrippino (2017), for example. I address this concern in robustness analysis by allowing GDP growth and inflation forecasts from the Greenbook of the Federal Reserve Board of Governors to predict differences in firm behavior alongside the measures of monetary policy shocks. Also, I will instead consider employing measures of monetary policy shocks which have been purged of components that could have been forecastable by the private information contained in the Greenbook forecasts, constructed by Miranda-Agrippino (2017).

As a final note, by employing the changes of only the *current month* federal funds futures prices in measuring monetary policy surprises $\nu_{\tilde{t}_k}$, one is necessarily capturing policy news affecting the currently prevailing short rates. Given that the FOMC tends to move its federal funds target in a persistent manner, any decisions regarding the current federal funds target also contain information about the future expected path of short term rates, thus affecting longer term interest rates and potentially having persistent effects on the economy. However, focusing on the unexpected changes in the current month's rate still misses any information regarding the future expected policy communicated by an FOMC press release over and above the decision on the current federal funds target, i.e. forward guidance. To capture such effects, one can analogously employ changes in futures prices settled on rates at longer horizons than just the current month, as for example done by Gertler and Karadi (2015) or Nakamura and Steinsson (2018). Following the former, I also repeat the analysis for $\nu_{\tilde{t}_k}$ constructed based on the three month ahead monthly fed funds futures prices and comment on the robustness of the main results below.[8]

To recap: the baseline analysis will employ the unweighted measures ε_t^m both as *exact* measures of monetary policy shocks and as instruments for changes in the federal funds rate in the dynamic panel regressions analyzed in Sections 3.3 and 3.4, respectively. And I will use the weighted

[7] As discussed by Stock and Watson (2018), if the method of constructing the quarterly measures/instruments mechanically introduces autocorrelation, one could also solve this issue by including the lagged measures/instruments as controls.

[8] One could also follow Gürkaynak et al. (2005) and decompose the effects of FOMC announcements on interest rate futures of various maturities into two orthogonal principal components: the "target" factor and the "path" factor. The former is restricted to be the only one of the two that affects the current federal funds rate, and the latter to move futures rates at longer horizons without changing the current funds rate (a forward guidance shock). I am leaving this analysis to future research on the topic.

quarterly measures of monetary policy shocks $\bar{\varepsilon}_t^m$ as external instruments in the identification of structural monetary policy shocks in the aggregate VAR of Section 4. I verify that all the main results are robust to making these choices.

3 Firm-level Panel Regressions

3.1 Firm-level data and sample selection

I draw the firm-level dataset from the quarterly Compustat universe of publicly listed U.S. incorporated firms. The sampled firms exclude utilities (SIC codes 4900–4999) and financial firms (SIC codes 6000–6999). I focus on three central measures of firms' performance and their relative responses to monetary policy shocks: accumulation of fixed capital, inventories, and sales.

To construct a measure of the firms' fixed capital stocks, I use a perpetual inventory method, as is commonly done for Compustat data, as for example by Mongey and Williams (2017). The initial value of firm i's capital stock is measured as the earliest available entry of *Property, Plant and Equipment (Gross)* (Compustat quarterly data item 118, denoted $PPEGTQ_{i,t}$), and then iteratively constructed from *Property, Plant and Equipment (Net)* (item 42, $PPENTQ_{i,t}$) as $k_{i,t+1} = k_{i,t} + PPENTQ_{i,t+1} - PPENTQ_{i,t}$. The measures of $PPEGTQ_{i,t}$ and $PPENTQ_{i,t}$ are deflated using the implied price index for gross value added in the U.S. nonfarm business sector beforehand. All the main results are robust to directly using the $PPENTQ_{i,t}$ reported in Compustat as $k_{i,t}$.[9] I measure the stock of a firm's inventories at the end of quarter t as the reported *Total Inventories* (item 38, $INVTQ_{i,t}$). The measure of sales activity is the reported quarterly *Sales* (item 2, $SALEQ_{i,t}$).

As for the main explanatory variables regarding firm financial characteristics in the baseline analysis, I consider book leverage and the holdings of liquid assets. The measure of leverage I employ is total debt over *Total Assets* (item 44, $ATQ_{i,t}$), both measured at book values. Total debt is computed as the sum of *Debt in Current Liabilities* (item 45, $DLCQ_{i,t}$) and *Total Long-Term Debt* (item 51, $DLTTQ_{i,t}$). As the measure of the liquid assets position of a firm, I use the ratio of *Cash and Short-Term Investments* (item 38, $CHEQ_{i,t}$) to total assets. For notational brevity later on, I will refer to a single conditioning financial variable as x and the set of all considered conditioning variables as $\mathcal{X} \equiv \{lev, liq\}$, referring to leverage and the liquid assets ratio. To alleviate possible concerns that these financial indicators might themselves be endogenous to firms' future decisions, such as leveraging up before making a large investment, I will measure a firm's leverage and liquid asset ratios in any quarter as the four quarter rolling means instead. This also eliminates any issues with seasonality in the measurement or reporting of the underlying financial variables. Any reference to firm i's leverage or liquid assets ratio in quarter t below thus refers to the corresponding yearly average $\sum_{j=0}^{3} x_{i,t-j}$, unless specified otherwise.

As a control variable, the analysis will also include firm size, measured as (log) book assets

[9] As pointed out by Chirinko et al. (1999), it may be the case that the book values of property, plant and equipment may understate the current value of the capital replacement value, for example in periods of rapid price changes. However, as I discuss, since the regression specifications will contain industry-quarter dummies, issues arising from mismeasurement due to aggregate trends should be alleviated.

$ATQ_{i,t}$. In robustness analysis, I also test for the relevance of whether a firm has been issued a Standard & Poor's Long-Term Issue credit rating and whether it has recently paid dividends to its owners. I measure dividend payments based on the reported year-to-date *Cash Dividends* (item 89, $DVY_{i,t}$). Additional controls considered in robustness analysis include quarterly sales growth, the sales-to-capital ratio and a firm's market-to-book value ratio.

In general, one would deflate all variables prior to analysis with industry-specific price indices. However, because the firm activity measures and any control variables included in the main regression will appear in log-levels, industry-quarter dummies will pick up any price level changes at the aggregate and the industry levels. Therefore, the estimation of the baseline panel regression does not require deflating the employed variables beforehand. The details of the employed specifications are presented below in Section 3.2. Nontheless, in cases where deflating is necessary, such as providing summary statistics of firm balance sheets in real terms and deflating the measures of gross and net fixed capital used in the perpetual inventory method, I employ the implied price index of gross value added in the U.S. nonfarm business sector (BEA-NIPA Table 1.3.4. Line 3). Similarly as for deflating, including industry-quarter dummies in regressions allows to control for aggregate and industry-level seasonality. Based on regression estimates, any remaining seasonality seems to be an issue only in regressions for sales measures which are not the main focus of my analysis. To alleviate problems related to seasonality in sales, I will conduct the corresponding estimation only on growth rates over 4, 8, etc., quarters. The aggregate variables which appear in various alternative regression specifications are detailed in Section 4.2.

Motivated by the variables listed above, the sample I employ only includes firm-quarter observations with strictly positive entries of total book assets, and which feature non-negative, measured debt in current liabilities, total long-term debt, and cash and short-term investments. Because of the way I construct each firm's capital stock, I also drop all firm-quarters preceding each firm's first observation of gross property, plant and equipment in the quarterly Compustat database and all firm-quarters with non-positive or missing net property, plant and equipment. Since I measure fixed capital, inventory stock and sales in logs, I also drop all firm-quarters for which sales or total inventories are either reported non-positive or missing.

Due to the fact that the availability of the high frequency identified monetary shock data starts in 1990Q1 and in order to exclude the exceptional conditions around the onset of the Great Recession and the implications of the federal funds rate potentially hitting the zero lower bound, after constructing the necessary growth rates, I focus on the firm-quarter observations for the sample period 1990Q1–2007Q4.[10] This results in an initial unbalanced panel of 272,159 firm-quarter observations, with of course, less effective observations in regressions as the horizon of estimation is increased, outliers are dropped or occasionally missing control variables are added, as will be clear from the regression specification in Section 3.2. Because the baseline regression specification includes firm-level fixed effects and applies the *within* estimator, a reasonably long time-dimension for each cross-sectional unit is necessary to alleviate issues of endogeneity in estimation. Thus, in the estimation of the panel regressions I only include data from firms which are observed for at least 40 quarters during the sample period considered. The results are robust to including all

[10] In robustness analysis below I verify that the results are unchanged when employing measures of monetary policy shocks until 2012Q4 and firm-level data until 2015Q4.

the possible firm-quarter observations from the initial panel in the estimation. The exact number of effective observations for the main regressions can be gauged from the regression tables in Appendix D.

3.1.1 Summary statistics

To give an overview of the basic properties of the data used in the panel regression analysis, Table 1 presents summary statistics of the key variables involved. Because the focus in the regression analysis will be on log growth rates of the firm activity variables of fixed capital ($k_{i,t}$), inventories ($invt_{i,t}$) and sales ($sale_{i,t}$), Table 1 presents the relevant information on quarterly growth rates. In this case, the data for leverage and liquid asset ratios are not rolling averages.

As dictated by the usage of data on public firms only, the average firm size in the sample is large, about $1,700 million over the sample period. The highly right-skewed size distribution of firms motivates the usage of log assets as the relevant measure of size in regressions and when computing correlations. The mean of firms' leverage rates is approximately 30% and the liquid assets ratio approximately 14%. Both exhibit considerable variation in the cross-section, with standard deviations of 42.6% and 18.1%, respectively.

Table 1: Summary statistics for book assets, leverage ratios, liquid asset ratios and activity measures' growth rates

	Size	Leverage	Liquidity	$\Delta \log(k_{i,t})$	$\Delta \log(invt_{i,t})$	$\Delta \log(sale_{i,t})$
Mean	$1725.70	0.297	0.141	1.06%	0.51%	1.21%
Median	$151.65	0.223	0.062	-0.18%	0.63%	1.78%
St. dev	$8866.55	0.426	0.181	13.49%	27.08%	33.30%
$\mathrm{cor}(\cdot, \log(\mathrm{size}_{i,t}))$	–	-0.070	-0.214	0.052	0.043	0.022
$\mathrm{cor}(\cdot, \mathrm{leverage}_{i,t})$	–	–	-0.250	-0.065	-0.049	-0.019
$\mathrm{cor}(\cdot, \mathrm{liquidity}_{i,t})$	–	–	–	0.037	-0.001	0.04

Notes: Size measured as book assets in millions of real 2009 dollars; leverage as total debt to assets; liquidity as cash and short term investments to assets ratio. Statistics involving size, leverage and liquidity computed as time-averages of the corresponding statistics in quarterly cross-section. Statistics for growth rates computed over all firm-quarters. Leverage and liquidity ratio outliers dropped at 99.9% cutoff, growth rates at 0.1% and 99.9% cutoffs.

Based on cross-sectional correlations, firms with higher leverage also tend to hold less liquid assets as a fraction of their balance sheet. However, larger firms tend to have both slightly lower leverage and liquid assets. Of course, one must be careful in interpreting the liquid asset holdings as an effective *liquidity* measure *per se*. Firms with high holdings of liquid assets might choose to hold them as a precautionary measure because of a lack of access to other sources of liquidity, such as trade credit or credit lines extended by financial intermediaries. Possible evidence for this idea is provided by the fact that larger firms, which one expects to have more ease in accessing various sources of finance, tend to hold less liquid assets, on average.

Growth rates of all the activity measures across firms and time exhibit significant variation as well. Most importantly, log sales growth features the most volatility, followed by inventory growth. The implications of this will also be evident in the panel regression results below, resulting in less precise coefficient estimates and wider confidence bands when analyzing the behavior of sales and inventories. Although the correlation coefficients are very small, larger firms and firms with lower leverage tend to experience relatively faster growth on average. The cross-sectional distributions of firms across leverage, liquid assets ratios and balance sheet sizes are also illustrated by Figures 13–15 in Appendix A.1 which depict the time series of the quarterly cross-sectional quintiles.

3.2 Empirical specification of panel regressions

To study whether and how firms respond to a monetary policy shock differently depending on their financial conditions at the time of the shock, I estimate panel regressions, projecting measures of firm activity on interaction terms of the firms' financial indicators and the monetary shock alongside a set of control variables, as elaborated upon below. As a first-pass estimation exercise, I assess the results when one assumes that the ε_t^m constructed in Section 2 is an exact measure of the structural monetary policy shock of interest. This is effectively defining the structural monetary policy shock ε_t^p to only be caused by FOMC decisions revealed in the documented press releases, and assuming that the shock is perfectly measured by the fed funds futures price innovations around the announcements. The corresponding empirical specification for this estimation is presented below and the estimation results documented in Section 3.3 and Appendix B. Alternatively, I will also consider a specification which relaxes these assumptions and instead uses the constructed ε_t^m as external instruments for changes in the federal funds rate. The estimation results from the latter specification can be seen in Section 3.4 and Appendix C.

To analyze possible nonlinearities arising from the financial characteristics of interest, instead of interacting the monetary shock with just a measure of say, a firm's leverage, I interact it with indicators of the firm belonging to a given region of the cross-sectional distribution of leverage in a quarter. That is, in each quarter t the sample of firms in the panel at the time, denoted $\mathcal{I}_t$, is split into groups based on quantiles of the conditioning variable x:

$$\mathcal{I}_t^{x,(a,b)} \equiv \left\{ i \in \mathcal{I}_t | x_{i,t} \in \left[q_{x,t}^a, q_{x,t}^b \right] \right\}$$

$q_{x,t}^a$ refers to the 100a-th percentile of variable x in the cross-section of firms in the sample at quarter t. x refers to either leverage or the liquid assets ratio. For both of these financial indicators I conduct the grouping of firms based on *quintiles*. More specifically, to provide a clearer overview of the main results, I group together the firms below the second quintile (the 40th percentile), and the firms between the second and fourth quintiles (40th and 80th percentiles). Based on the notation introduced above, this yields the set of groups $\left\{ \mathcal{I}_t^{x,(0,0.4)}, \mathcal{I}_t^{x,(0.4,0.8)}, \mathcal{I}_t^{x,(0.8,1.0)} \right\}$ in *both* the leverage and liquid asset ratio cross-sections. Such a grouping might seem arbitrary at first, especially if one were to expect firms with low leverage and high liquid asset ratios to be less financially constrained. The approach is based on prior analysis with finer splits based on quintiles, which indicated that firms below the 40th percentile of the leverage distribution tend to behave similarly in response to monetary policy shocks, as do firms below the 40th percentile of the liquid asset ratios distribution etc. To assure the reader that none of the results are driven by such a choice of groupings, the Appendices reproduce all the main results for when quintile-based groups are used, and when no such grouping is employed. The corresponding quintiles that serve as cutoffs over the sample period are presented in Figures 13 and 14 in Appendix A.1.

For brevity, let $y_{i,t}$ refer to the logarithm of firm i's measure of activity among the considered fixed capital, inventory stock and sales in quarter t.[11] The main goal of my analysis is to estimate how the various outcome variables $y_{i,t+h}$, at horizon $h \geq 0$, behave in response to a structural monetary policy shock at time t, conditional on firm i's characteristics just before the shock, i.e. at the end of $t-1$. Regressions in the spirit of local projections following Jordà (2005), applied to the panel of firms, introducing interaction terms in the monetary policy shock and firm characteristics are a suitable approach for this. To apply local projections in the spirit of Jordà (2005) on panel data, one would like to project $y_{i,t+h}$ on the monetary shock at time t and firm level controls at $t-1$, including $y_{i,t-1}$, to control for persistence in y. However, the inclusion of $y_{i,t-1}$ on the right hand side introduces the standard issue in dynamic panel regressions that either within-individual demeaning or first-differencing to remove fixed effects introduces correlation between the error term and regressors and one will have to resort to GMM and instrumenting with lagged regressors. The simplest way to alleviate this issue and to still be able to use OLS is to instead project the *cumulative difference* $\varDelta_h y_{i,t+h} \equiv y_{i,t+h} - y_{i,t-1}$ on the right hand side variables, *excluding* $y_{i,t-1}$.[12] The same approach has been used in local projections with instrumental variables and panel data by Jordà et al. (2015), for example.

When evaluating the relevance of leverage and liquid asset holdings in characterizing firms' responses to monetary policy shocks, I will first consider each indicator separately. That is, I will regress the firms' measures of activity on cross-terms of leverage indicators and the monetary shock, and other controls, while *not* controlling for liquid asset holdings, and vice versa. Finally, I include the relevant terms in both leverage and liquid assets to evaluate whether either of the two plays a more significant role in explaining firms' performance after a monetary policy shock.

The general form of the baseline panel regression specification looks as follows:

$$\begin{aligned}\varDelta_h y_{i,t+h} =& f_{i,h} + d_{n,h,t+h} + \Theta_h' W_{i,t-1} + \Omega_h' Z_{i,t-1}\varepsilon_t^m + \\ &+ \sum_{x\in\mathcal{X}^s}\sum_{j\in\mathbb{J}^x}\left(\beta_{j,h}^x + \gamma_{j,h}^x\varepsilon_t^m\right)\times \mathbb{1}_{i\in\mathcal{I}_{t-1}^{x,j}} + u_{i,h,t+h} \qquad (1)\\ &\text{with } h = 0,1,\ldots,H;\ \varDelta_h y_{i,t+h} \equiv y_{i,t+h} - y_{i,t-1}\end{aligned}$$

h denotes the horizon at which the relative impact effect is being estimated, $f_{i,h}$ denotes firm i's fixed effect in its cumulative y growth over horizon $h+1$, $d_{n,h,t+h}$ is shorthand for industry-quarter dummies at the SIC 1-digit level for $h+1$-quarter growth measured in period $t+h$, $Z_{i,t-1}$ and $W_{i,t-1}$, with $Z_{i,t-1} \subseteq W_{i,t-1}$, are vectors of lagged firm-level controls not included among the financial indicators in $\mathcal{X}$, $\mathbb{1}_{i\in\mathcal{I}_{t-1}^{x,j}}$ is the indicator of firm i belonging in $\mathcal{I}_{t-1}^{x,j}$, and ε_t^m is the unweighted measure of the quarterly monetary shock as constructed in Section 2. Θ_h, Ω_h, $\beta_{j,h}^x$

[11] Given that sales are a flow variable, the time t measurement will refer to total sales in quarter t, and for the stock variables of fixed capital and inventories, it will refer to the end of quarter t stock.

[12] Note that if the future values of control variables, e.g. leverage, themselves are affected by any firm-level shocks which hit $y_{i,t}$, then the issue of introducing endogeneity when employing the *within* estimator is still present. This is why, as an additional precautionary measure, I only include data from firms who are observed in the sample for at least 40 quarters. Finally, note that even in the case that a control variable $x_{i,t-1}$ is correlated with the firm-level regression error term, if the measures of monetary policy shocks ε_t^m are truly exogenous, then $x_{i,t-1}\varepsilon_t^m$ is *uncorrelated* with both the error term and $x_{i,t-1}$, yielding consistency of the estimates of coefficients on the cross-term $x_{i,t-1}\varepsilon_t^m$, even when the estimates of the coefficients on $x_{i,t-1}$ happen to be inconsistent.

and $\gamma^x_{j,h}$ are regression coefficients.

$\mathcal{X}^s \subseteq \mathcal{X}$ is the set of financial conditioning variables under consideration in a given specification, containing either *lev* or *liq* separately, or both, as explained above. $\mathbb{J}^x$ is the appropriate collection of grouping indicators for variable $x \in \mathcal{X}$. As mentioned, in the baseline case I am splitting firms into three groups, with the cutoffs being the 40th and 80th percentiles. For ease of interpretation, I let the base level of the group indicator dummies for leverage be the *lowest* leverage group, and for liquid assets the *highest* group. That is,

$$\mathbb{J}^{lev} \equiv \{(0.4, 0.8), (0.8, 1.0)\}$$
$$\mathbb{J}^{liq} \equiv \{(0, 0.4), (0.4, 0.8)\}$$

The firm-level controls $Z_{i,t-1}$ and $W_{i,t-1}$ and the grouping indicators are measured as of the end of the quarter before the shock ε^m_t to ensure exogeneity with respect to the shock. In the baseline case, for now, $Z_{i,t} = W_{i,t} = [\log(\text{size}_{i,t})]$, i.e. I only control for total book assets. In robustness analysis, I also test for the relevance of whether a firm has been issued a Standard & Poor's Long-Term Issue credit rating and whether it has recently paid dividends to its owners, among other firm-level controls, as discussed below.

Since the main goal of the analysis is to evaluate *differences* among firms' responses to monetary policy shocks conditional on the variables in $\mathcal{X}$, including a detailed industry-time dummy to control for aggregate effects at any point in time allows for a flexible way to do so. This clearly precludes including a measure of the shock ε^m_t itself on the right hand side of the regression and evaluating the actual, *level* responses of of $y_{i,t}$. I will address this issue and conduct the relevant estimation as a second step in Section 3.5.

Including the cross-term of firm size and the monetary policy shock among the explanatory variables facilitates a more precise evaluation of how financial strength might affect firms' responses to monetary policy shocks. It allows to control for the fact that leverage and liquid asset holdings are themselves correlated with firm size in the cross-section of firms. In addition, as far as size is a proxy for a firm's creditworthiness and the degree of financial constraints it might face, this can also help to alleviate worries about the endogeneity of the financial indicators themselves. If firms hoard cash because they cannot access credit markets or credit lines in case extra liquidity is needed, then any results on the relevance of liquid asset holdings will be inconclusive about the importance of *liquidity per se*. That is, liquid asset holdings are necessarily a flawed measure of the actual liquidity a firm has access to at any given point in time. Controlling for the existence of bond ratings and prior payment of dividends, as I do in robustness tests, will further allow to address these issues, as far as credit market access and credit line usage can be predicted by size, bond ratings and dividend payments.

As is commonly done in the analysis of firm-level data on growth rates and balance sheet ratios, I drop growth rate observations of the three key measures of firm activity below the 1st and above the 99th percentile to control for outliers which might significantly affect the estimates. This is done separately based on each $(h+1)$-quarter log growth rate $\Delta_h \log(k_{i,t})$, $\Delta_h \log(invt_{i,t})$, and $\Delta_h \log(sale_{i,t})$ by quarter t prior to estimation for any given h. I conduct estimation of the firms responses up to the horizon of $H = 20$ quarters.

I consider standard errors clustered at the quarter and firm levels. When applying a local projections approach along the lines of specification (1), it is imperative to remember that the error terms $u_{i,h,t+h}$ for firm i are necessarily correlated across time whenever $h \geq 1$, as discussed in detail by Jordà (2005). For example, if $h = 1$, then any firm-level shock affecting $y_{i,t}$ will be contained in both $\Delta_h y_{i,t+1} \equiv y_{i,t+1} - y_{i,t-1}$ and $\Delta_h y_{i,t} \equiv y_{i,t} - y_{i,t-2}$, making $u_{i,1,t+1}$ and $u_{i,1,t}$ correlated. Clustering by firm allows for fully flexible dependence in the error terms across time within each firm, and has for example also been used in a panel setting by Jordà et al. (2015). The answer to whether one should also cluster the standard errors at the quarter level is not as clear. Given that specification (1) already includes industry-quarter dummies which control for any industry-level and aggregate shocks that could induce correlation across firms, such a clustering would only be necessary if one believed that firm-level shocks themselves might be correlated within any given quarter, over and above any shocks that affect whole industries. I have chosen to cluster standard errors also at the quarter level in order to provide the reader with conservative confidence intervals. When clustering only at the firm level, any confidence intervals on estimates presented below would be considerably narrower.

For interpretability, prior to estimation I rescale the monetary policy shock measures' series ε_t^m by its standard deviation of approximately 12 basis points between 1990Q1–2007Q4. The key coefficients of interest in regression (1) are the $\gamma_{j,h}^x$, measuring the responsiveness of group j in the variable x cross-section, at horizon h, relative to the base group. Because of the dynamic nature of the coefficients $\gamma_{j,h}^x$, it is best to think of them as measures of relative impulse responses of the groups j relative to the baseline group, evolving over horizon h. And thus it is most natural to present the estimation results as graphs, plotting estimates of $\gamma_{j,h}^x$ over $h = 0, 1, \ldots, H$. A positive ε_t^m stands for a fed funds rate *increase*, and thus a contractionary shock. This means that a *negative* estimate for $\gamma_{j,h}^x$ in, say the inventory regression, implies that firms in group j in the variable x dimension prior to the shock experience relatively *lower* inventory growth (or a larger contraction) over horizon h after a contractionary shock. In terms of magnitudes, $\gamma_{j,h}^x$ measures the difference in $\Delta_h y_{t+h}$ for firms in quantile group j compared to the base group, after a contractionary shock in quarter t that is measured in the futures market as a 12bp unexpected increase in the fed funds futures rate, or equivalently, a 1 standard deviation shock ε_t^m.

To verify whether any qualitative findings from estimating specification (1) depend on grouping firms based on the conditioning variables x, I also consider estimating a standard specification which simply interacts $x_{i,t-1}$ with the measures of monetary policy shocks:

$$\Delta_h y_{i,t+h} = f_{i,h} + d_{n,h,t+h} + \Theta_h' W_{i,t-1} + \Omega_h' Z_{i,t-1} \varepsilon_t^m + \sum_{x \in \mathcal{X}^s} (\beta_h^x + \gamma_h^x \varepsilon_t^m) \times x_{i,t-1} + u_{i,h,t+h} \quad (2)$$

with γ_h^x now being the coefficients of interest.

3.3 Panel OLS regression results

3.3.1 Leverage

First of all, I assess the relevance of firms' leverage at the time of a monetary policy shock in characterizing their activity thereafter. That is, the set of financial conditioning variables in specification (1) is just $\mathcal{X}^s = \{lev\}$.

Figure 1 presents the OLS estimates for $\gamma^{lev}_{j,h}$ in the fixed capital regression, alongside the 95% confidence intervals over the horizon of $H = 20$ quarters after a shock. It is evident that firms with more leverage at the time of a contractionary monetary policy shock tend to do relatively worse in terms of fixed capital accumulation over the 20 quarter horizon. Compared to the base group of firms whose leverage is below the 40th percentile, the difference based on the point estimates is negative for both groups of firms with higher leverage starting 4 quarters after the shock. The differences become statistically significant for the (0.4,0.8) group about 5 quarters after, and reach their peak approximately 10 quarters after the shock. For the highest leverage group, the difference is statistically significant about 9 to 14 quarters after. The differences compared to the lowest leverage group start to slowly revert about 3 years after the shock. Table 2 in Appendix D.1 presents the estimation results for the coefficients $\gamma^{lev}_{j,h}$ and $\beta^{lev}_{j,h}$ at selected horizons h in a standard regression table.

It is noteworthy that the differences in fixed capital accumulation arise over a relatively long horizon, in line with the response of aggregate investment seen for the VAR in Section 4.2. Also, among firms with leverage above the 40th percentile, the relationship between leverage and capital accumulation following the monetary shock is not exactly monotonic, with both groups doing virtually equally worse than the lowest leverage firms. In terms of quantitative relevance, the estimates imply that in response to a monetary policy shock which induces a surprise increase of 12bp in the fed funds futures rate, the fixed capital growth of firms with leverage above the 40th percentile is about 1.0% lower than for those with the low leverage, over the 3 years following the shock.

Finally, notice that right after the monetary shock impact, the point estimates for the higher leverage groups are positive, implying a positive relation between capital accumulation and leverage after a contractionary shock, mirroring the results found by Ottonello and Winberry (2019). However, the differences are quantitatively small compared to those at longer horizons and statistically insignificant in the current specification.

For robustness, Figure 17 in Appendix B.1 presents the regression estimates for γ^{lev}_{h} in specification (2), i.e. when firms are not grouped into bins based on leverage quintiles. The estimates still imply that firms with higher leverage at the time of a contractionary monetary policy shock experience lower fixed capital accumulation at horizons longer than a year. Because of the lack of monotonicity in the relation with leverage at these horizons seen in Figure 1, the statistical significance of the coefficient estimates is not too high. In addition, the positive relation between leverage and fixed capital accumulation in the first few quarters after a contractionary shock is embodied by a positive coefficient estimate at $h \in \{0, 1, 2\}$ which is very small and statistically insignificant. The estimates for $\gamma^{lev}_{j,h}$ when splitting firms into five groups based on the quintiles of

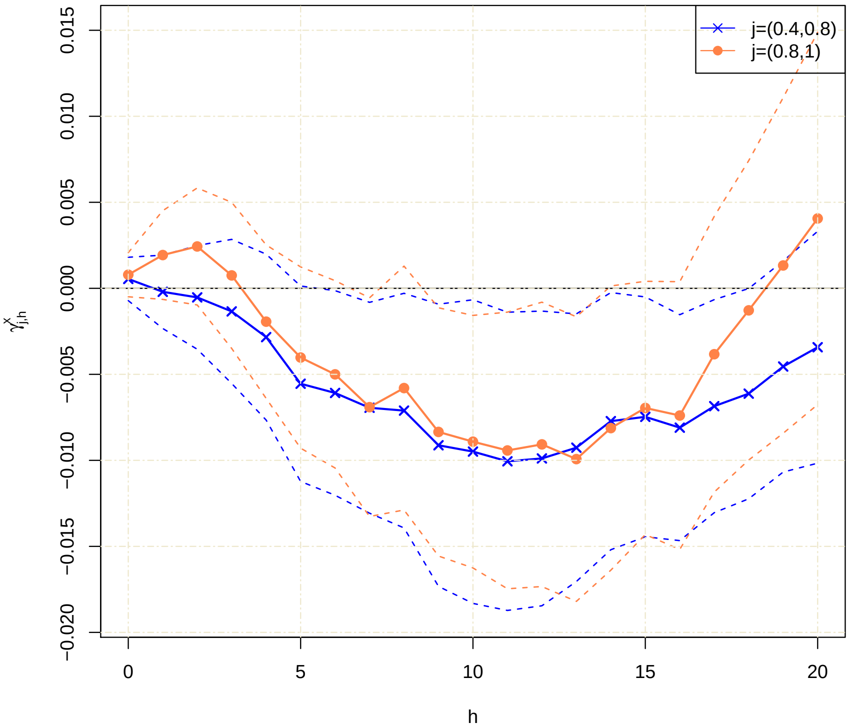


Figure 1: Heterogeneity in responses of capital accumulation conditional on leverage

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $x = lev$, $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

the leverage distribution can be seen in Figure 18 in Appendix B.2.

The estimation results for inventories and sales as the dependent variables when grouping firms based on leverage quintiles are presented in Figures 19 and 20 in Appendix B.3, respectively. For the relative differences in inventory accumulation the general picture looks similar to the disparities in fixed capital, although firms between the 20th and 40th percentiles behave more like the ones with leverage above the 40th percentile. All groups of firms with leverage higher than the 20th percentile do relatively worse after a contractionary monetary shock, and these differences appear slowly over time. The slightly earlier appearance of statistically significant discrepancies in firms behavior is in line with adjustments in inventory stocks being more flexible than in fixed capital. However, there are no noticeable differences in the relative responsiveness across the three groups with leverage between the 20th and 80th percentiles. The firms with highest leverage do the worst during the first two years after a contractionary shock. Over the 8 quarters after a shock that induces a surprise increase of 12bp in the fed funds futures rate firms in the highest leverage group experience approximately 1.7% lower growth in their invetory stock compared to the lowest leverage ones.

To neutralize the issue of considerable seasonal variation in sales affecting estimates, Figure 20 only presents estimates for the impact horizon $h = 0$, and thereafter for $h \in \{3, 7, 11, 15, 19\}$. Based on the definition of $\Delta_h y_{i,t+h}$, this means that the estimation of the dynamic responses only employs 4 quarter, 8 quarter, etc., log growth rates. The estimates for differences in sales dynamics also imply that firms with higher leverage experience lower sales growth after a contractionary monetary shock. All the point estimates are negative for firms with leverage above the 40th percentile. Unlike for the differences in the dynamics of fixed capital and inventories, statistically significant differences in sales appear already 3 quarters after a shock, indicating that the highest leverage group experiences an approximately 0.8% lower growth of sales over this horizon after a monetary policy shock that implies a 12bp surprise increase in the fed funds futures rate. However, since there is a lot of variability in the measures of sales growth, covered above in Table 1, the coefficient estimates are relatively imprecise and feature wide confidence bands.

All in all, the estimates across all three measures of performance indicate that firms which have higher leverage at the time of a contractionary monetary policy shock tend to do worse in the quarters following the shock.

3.3.2 Liquid assets ratio

I repeat the analysis by instead studying the relevance of firms' holdings of liquid assets at the time of a monetary policy shock in explaining their activity thereafter. That is, I estimate regression (1) with $\mathcal{X}^s = \{liq\}$.

The OLS estimates for $\gamma_{j,h}^{liq}$ in the fixed capital regression can be seen in Figure 2. The results imply that firms which hold less liquid assets as a share of their balance sheet experience significantly weaker capital growth following a contractionary monetary policy shock. The differences in capital accumulation conditional on liquid asset holdings follow similar general dynamics as the differences conditional on leverage, and the response of aggregate investment seen in Section 4.2. For firms with liquid asset ratios below the 40th percentile, significant differences with the highest group arise about 5 quarters after the shock. And for the (0.4,0.8) group, the difference becomes significant slightly later. The peak in differences is reached approximately 3 years after the shock and thereafter, the disparities tend to dissipate. Table 3 in Appendix D.2 presents the estimation results for the coefficients $\gamma_{j,h}^{liq}$ and $\beta_{j,h}^{liq}$ at selected horizons h in a standard regression table.

Although there does not seem to be too large a difference in the capital accumulation of the two groups with liquid asset holdings below the 80th percentile, a monotonic pattern is evident – lower liquid asset ratios are associated with poorer capital accumulation after a contractionary monetary policy shock. The monotonicity is also evident in Figure 22 in Appendix B.5 which considers splitting firms into five groups based on the quintiles of the liquid assets ratio distribution. Also, the quantitative differences between the two most extreme groups of firms are larger than for leverage. In response to a monetary contraction measured as a surprise increase of 12bp, or one standard deviation, in the fed funds futures rate, the fixed capital growth of firms below the 40th percentile of liquid asset holdings is about 2.2% lower than for those with the most liquid assets over the 3 years following the shock. The regression results with no grouping and instead interacting the negative of the liquid assets ratio with ε_t^m, i.e. estimating (2), seen in Figure 21 in Appendix B.4 support these findings.

The estimation results for inventories and sales as $y_{i,t}$, conditioning on liquid asset holdings and grouping firms based on quintiles, can be seen in Figures 23 and 24 in Appendix B.6, respectively.

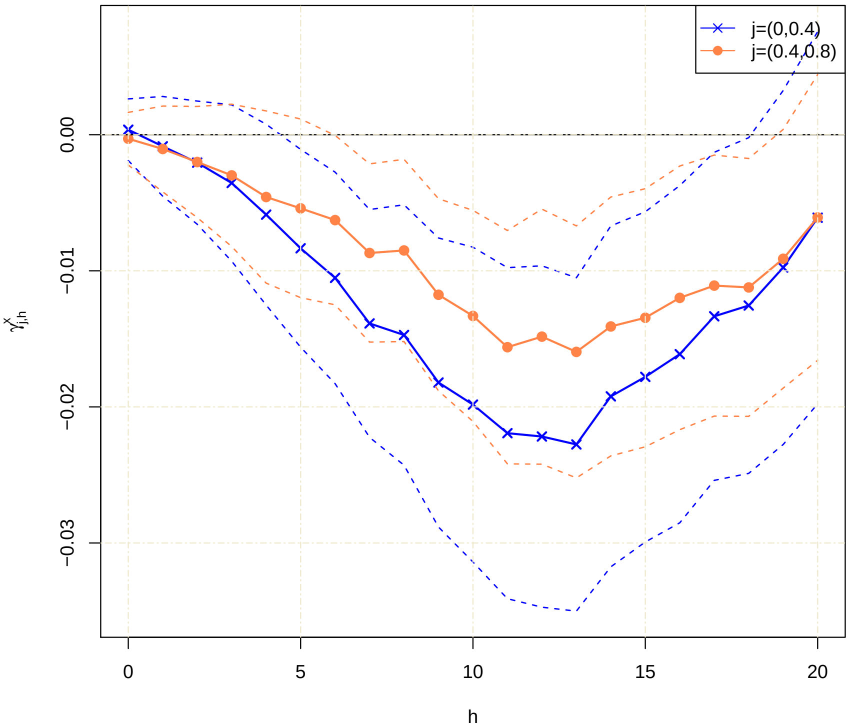


Figure 2: Heterogeneity in responses of capital accumulation conditional on liquid asset holdings
Notes: Point estimates and 95% confidence intervals for $\gamma^{x}_{j,h}$ from estimating specification (1), with $x = liq$, $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

The differences in inventories conditional on liquid asset ratios follow a hump shape that reaches a maximum just slightly earlier than the disparities in fixed capital accumulation. Like for fixed capital accumulation, firms that hold less liquid assets at the time of a contractionary monetary policy shock experience relatively lower inventory growth thereafter. The differences are not perfectly monotonic in liquid assets, with the lowest liquid assets group doing about as well as the firms between the 20th and 60th percentiles. Again, the quantitative differences between the groups are large, with a surprise increase of 12bp in the fed funds futures rate leading to more than 2% lower inventory growth for the firms with lowest liquid asset holdings compared to the highest liquid assets group over the 3 years following the shock.

For the differences in sales dynamics, similar conclusions apply as when conditioning firms' responses on leverage. Firms with lower liquid asset holdings do relatively worse after a contractionary shock although the point estimates do not support a perfectly monotonic relationship between the liquid assets ratio and the sales response. Also, again because of the large variation in sales growth data, the coefficient estimates are relatively imprecise.

To conclude, the estimation results suggest that firms which have lower liquid asset holdings at the time of a contractionary monetary policy shock tend to experience lower growth in fixed capital, inventories and sales over a relatively long period after the shock.

3.3.3 Joint regression

The above regression estimates have shown that both high leverage and low liquid asset holdings predict lower growth of fixed capital, inventories and sales for firms in the Compustat sample after a contractionary monetary policy shock. However, as pointed out in Section 3.1.1, firms that have higher leverage also tend to hold less liquid assets in the cross-section of firms. Therefore, the above estimates focusing on only one financial measure separately might be suffering from omitted variable bias and obscuring the fact that it is actually the other financial indicator that is behind explaining the differences in responses. To test for this, I include both the quantile indicators of leverage and liquid assets in estimating (1), i.e. now $\mathcal{X}^s = \mathcal{X} = \{lev, liq\}$.

The estimates for $\gamma_{j,h}^{lev}$ from the joint regression are presented in Figure 3. When simultaneously controlling for liquid asset holdings, the relevance of leverage in explaining firms' capital accumulation responses is weakened considerably. Although the general picture in terms of the signs and relative positions of point estimates remains similar, the magnitudes of the estimates are markedly smaller and exclusively statistically insignificant. The positive relation between leverage

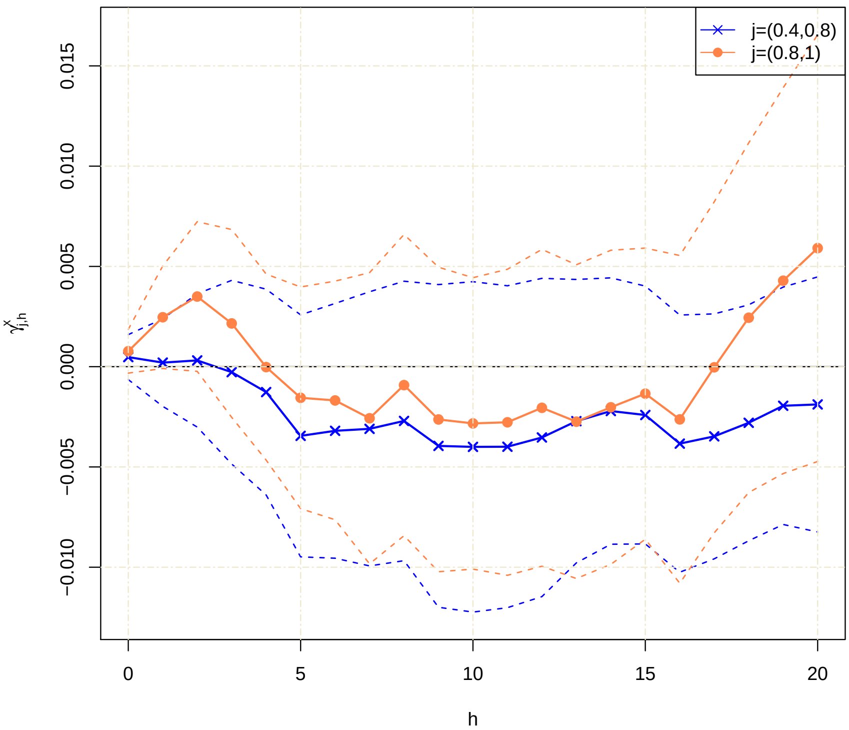


Figure 3: Heterogeneity in responses of capital accumulation conditional on leverage in joint regression

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $x = lev$, $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

and fixed capital accumulation in the quarters right after a contractionary monetary policy shock strengthens slightly yet remains statistically insignificant at the 5% level.

On the other hand, there are no remarkable changes in the relevance of liquid assets in characterizing firms' fixed capital dynamics after a monetary policy shock, as seen from the joint regression estimates for $\gamma_{j,h}^{liq}$ in Figure 4. Although the point estimates are quantitatively slightly smaller in absolute terms, it is still the case that even when controlling for leverage, firms with lower liquid asset holdings do relatively worse after a contractionary shock. The monotonicity in the relation between the liquid assets ratio and capital accumulation in response to a monetary shock remains and is quantitatively significant across the groups of firms. The difference in capital growth rates between the two extreme groups is still about 2% at the 3 year horizon in response to a monetary policy shock that is measured as a 12bp surprise increase in the fed funds futures rate. Similar conclusions regarding the relevance of leverage and liquid asset holdings for fixed capital

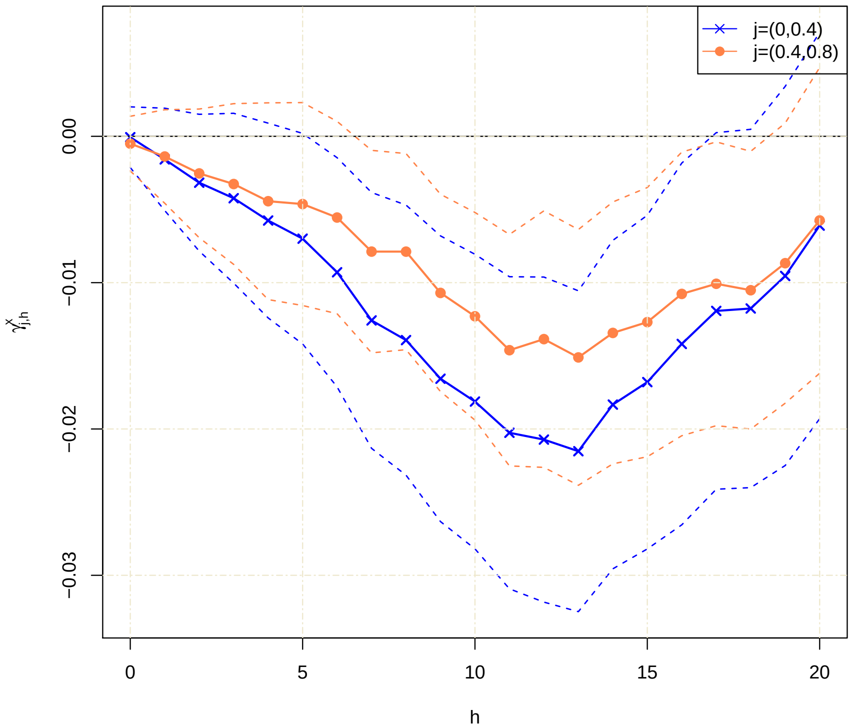


Figure 4: Heterogeneity in responses of capital accumulation conditional on liquid asset holdings in joint regression

Notes: Point estimates and 95% confidence intervals for $\gamma_{j,h}^{x}$ from estimating specification (1), with $x = liq$, $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

responsiveness are implied by the estimation results for when firms are not split into groups and specification (2) is estimated, as seen in Figure 25 in Appendix B.7, or when firms are split into five groups along the leverage and liquid assets ratio dimensions using quintiles, as seen in Figure 26 in Appendix B.8.

The estimation results for inventories and sales from the joint regression, grouping based on leverage and liquid assets ratio quintiles, can be seen in Figures 27 and 28 in Appendix B.9, respectively. The general message from the analysis of disparities in fixed capital dynamics is unchanged. When conditioning the differences in inventory growth on both leverage and liquid asset holdings, the relevance of leverage is diminished considerably and becomes statistically insignificant. At the same time, the conclusions regarding liquid asset holdings remain, implying that a low liquid assets ratio predicts significantly poorer performance in terms of inventory growth after a contractionary monetary policy shock. Again, because of the large volatility in sales growth data, the coefficients are estimated imprecisely and the estimates have wide confidence bands.

3.3.4 Robustness

All of the above qualitative estimation results are robust to instead employing weighted quarterly measures of monetary shocks $\bar{\varepsilon}_t^m$ constructed from the current month fed funds futures prices. Quantitatively, for most regressions, the point estimates of $\gamma_{j,h}^x$ are marginally larger in absolute terms. For brevity, I have omitted the graphs depicting estimation results from various robustness tests. The graphs are available upon request. I have also verified that the main results on capital accumulation are not driven by outliers in the constructed series for ε_t^m. Discarding the three highest and three lowest realizations of the measures of monetary shocks, which stand out among the raw data, causes considerable amplification in the absolute values of the estimates for $\gamma_{j,h}^{lev}$ and $\gamma_{j,h}^{liq}$ in the separate regressions, and for the latter in the joint regression, retaining the irrelevance of leverage.

Because I am employing firm-level data only from the sample period 1990Q1–2007Q4, the dynamic nature of the projection in (1) implies that the longer the horizon h considered, the fewer observations can be included in the estimation. That is, no observations of the measures of monetary policy shocks ε_t^m after 2002Q4 can be included in the estimation for $h = 20$ because this would require measurement of $y_{i,t}$ after 2007Q4. Yet obviously, all observations of ε_t^m between 2002Q4–2007Q4 are included when $h = 0$, leading to a declining number of effective observations as h increases, seen in Table 2 in Appendix D.1, for example. To make sure the results are not generated by this specific type of sample selection, I only include measures of monetary policy shocks prior to 2002Q4 in the regressions for all $0 \leq h \leq 20$. The estimates of $\gamma_{j,h}^{lev}$ and $\gamma_{j,h}^{liq}$ are barely affected in any of the fixed capital regressions.

The qualitative results on capital accumulation above survive even if one conducts the whole analysis on a balanced panel of 630 firms that have no missing data between 1990Q1–2007Q4, and only includes measures of monetary policy shocks prior to 2002Q4. Given that this results in a considerable drop in the number of firm-quarter observations[13], the statistical significance of $\gamma_{j,h}^{lev}$ is not as strong in this case, but the results are evident when we do not split firms into groups and simply estimate specification (2). The corresponding estimates of the coefficients on the cross-terms are seen in Figures 29 and 30 in Appendix B.10.

To check that it is not the case that the constructed monetary policy shock measures series ε_t^m happens to be correlated with the business cycle during 1990Q1–2007Q4 in a manner that causes $\gamma_{j,h}^x$ to instead capture varying cyclicalities of groups of firms over the business cycle, I also consider including terms of the form $\sum_{x \in \mathcal{X}^s} \sum_{j \in \mathbb{J}^x} \mathbb{1}_{i \in \mathcal{I}_{t-1}^{x,j}} \left(\sum_{b=0}^{1} \delta_{j,b,h}^{x\prime} Y_{t-1-b}^a \right)$ in specification (1) for capital accumulation. Y_t^a is a vector of aggregate variables that help forecast the business cycle and $\delta_{j,b,h}^x$ is a vector of coefficients. I have included the quarterly GDP growth and the Gilchrist

[13] For example, approximately 120,000 firm-quarter observations are included in the full sample baseline regression under $h = 8$, and for the balanced panel this number is about 29,000.

and Zakrajšek (2012) excess bond premium in Y_t^a. The corresponding estimates can be seen in Figures 31 and 32 in Appendix B.11. The main results remain, although the confidence bands around the various $\gamma_{j,h}^x$ widen slightly, and the relevance of leverage in predicting heterogeneity in firms' responses decreases to some extent, now significant mainly at the 90% level.

Furthermore, as for example studied by Nakamura and Steinsson (2018), the FOMC's announcements of monetary policy decisions might be communicating its private information or superior forecasting abilities, thus leading to ε_t^m not being fully uncorrelated with other macroeconomic shocks. As emphasized by Ramey (2016), forecasts from the Greenbook of the Federal Reserve Board of Governors indeed do seem to have predictive power over measures of monetary policy shocks measured at FOMC meeting frequency, such as $\nu_{\tilde{t}_k}$. To purge the constructed monetary policy shock measures ε_t^m of such potential correlation and control for whether the differences across firms could have been explained by the Federal Reserve's forecasts, I also consider including terms of the form $\sum_{x\in\mathcal{X}^s}\sum_{j\in\mathbb{J}^x}\mathbb{1}_{i\in\mathcal{I}_{t-1}^{x,j}}\left[\sum_{b=0}^{1}(\delta_{j,b,h}^{x,g}\tilde{g}_{t-1}^{t+b}+\delta_{j,b,h}^{x,\pi}\tilde{\pi}_{t-1}^{t+b})\right]$ in specification (1) for capital accumulation. $\tilde{g}_t^\tau$ and $\tilde{\pi}_t^\tau$ denote Greenbook forecasts of GDP growth and inflation in quarter τ, made in quarter t, respectively, and $\delta_{j,b,h}^{x,g}$ and $\delta_{j,b,h}^{x,\pi}$ are coefficients.[14] The corresponding estimates can be seen in Figures 33 and 34 in Appendix B.12. The qualitative results and their statistical significance for the fixed capital regressions remain largely unchanged, with only the quantitative and statistical relevance of leverage in predicting heterogeneity in firms' responses diminishing slightly. Miranda-Agrippino (2017) studies these issues in detail and develops a measure of monetary policy shocks independent of the Federal Reserve's forecasts and unpredictable by past information. She uses the residuals from a regression of monthly monetary policy shock measures constructed from high frequency changes in financial market prices on the Federal Reserve's forecasts and forecast revisions of output, inflation, and current employment. Employing her measures of shocks constructed based on the three month ahead monthly fed funds futures prices in the capital accumulation regressions, the central results survive, although the statistical significance of the key coefficients is weakened. Firms with more leverage and less liquid assets experience lower capital growth after a contractionary shock and in the joint regression, the relevance of leverage is considerably diminished.

Surprisingly, the above baseline estimation results, both from the separate and joint regressions for capital accumulation are virtually unchanged when one also controls for whether the firms have been issued a Standard & Poor's Long-Term Issue credit rating and whether they have paid dividends at any point in the preceding year – two commonly used proxy measures for the degree of financial frictions and liquidity issues that firms might face.[15] That is, I control for $Z_{i,t-1}=W_{i,t-1}=\left[\log(\text{size}_{i,t-1}),\mathbb{1}_{i\in\mathcal{I}_{t-1}^r},\mathbb{1}_{\sum_{j=1}^4 div_{i,t-j}>0}\right]'$ in (1), with $\mathcal{I}_t^r$ the set of firms which have been assigned an S&P bond rating at time t and $div_{i,t}$ the dividends paid by firm i in quarter t. Moreover, in the joint regression with leverage and the liquid assets ratio included among $\mathcal{X}^s$, the relevance of both the bond rating existence and the dividend payment indicator is statistically insignificant in characterizing capital accumulation after monetary policy shocks. The implied estimates for $\gamma_{j,h}^{lev}$ and $\gamma_{j,h}^{liq}$ when bond ratings and dividend payments are controlled for

[14] I define forecasts made in quarter t as the Greenbook forecasts at the time of the first FOMC meeting in quarter t.

[15] For example, among the financial indicators considered in their analysis, Crouzet and Mehrotra (2018) have found that zero dividend payments seem to be the most promising indicator to predict that constrained firms contract more in recessions.

are presented in Figures 35 and 36 in Appendix B.13. I have also considered controlling for other firm-level variables in the capital accumulation regressions such as annual sales growth, the ratio of cash flows to assets, and the market-to-book value ratio by including them in $W_{i,t-1}$ and $Z_{i,t-1}$ in specification (1) without any considerable changes in the estimates of $\gamma^x_{j,h}$, as seen in Figures 37 and 38 in Appendix B.14.

Figures 39 and 40 in Appendix B.15 present the estimates for $\gamma^x_{j,h}$ in the capital accumulation regressions when ε^m_t is instead constructed in an unweighted manner from unexpected changes in the three month ahead monthly fed funds futures prices. As can be seen, qualitatively the main results hold. However, the quantitative effects are larger than for the baseline case measured based on the current month fed funds futures prices. The unexpected components of changes in the three month ahead fed funds futures might thus also be capturing the effects of forward guidance and the implied changes in rates of longer maturities.

Finally, Figures 41 and 42 in Appendix B.16 present the estimates for $\gamma^x_{j,h}$ in the capital accumulation regressions when ε^m_t is constructed from the changes in the three month ahead monthly fed funds futures prices, and the sample period is extended to include measures of monetary policy shocks up to 2012Q4 and firm-level Compustat data up to 2015Q4. Using the three month ahead fed funds futures prices instead of the current month futures has the potential of alleviating the restrictions imposed by the ZLB on variation in ε^m_t, insofar as looking forward while at the ZLB, there was belief of a non-zero probability that the ZLB would stop binding in the near future. Given that there is little variation in ε^m_t near the ZLB, extending the sample slightly diminishes both the quantitative and statistical significance of the estimates yet leaves the main results unchanged.

3.4 Panel IV regression results

To relax the assumption that the ε^m_t constructed in Section 2 are exact measures of a structural monetary policy shock, I finally consider an instrumental variables approach which instead uses the high frequency measures as exogenous instruments for changes in the federal funds rate. Following Stock and Watson (2018), Appendix E provides a heuristic discussion on why using the change in a policy indicator, such as the fed funds or the one-year Treasury rate in place of ε^m_t in specification (1) and using an IV approach can allow to identify and estimate the coefficients on an unobservable structural monetary policy shock. More specifically, in place of (1), I will now consider estimating the specification:

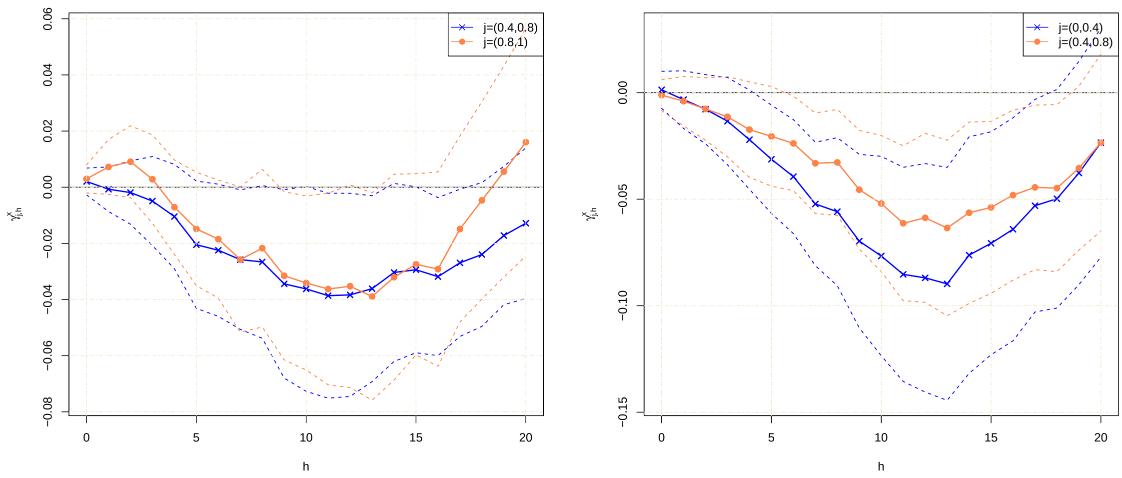
$$\begin{aligned}\Delta_h y_{i,t+h} =& f_{i,h} + d_{n,h,t+h} + \Theta_h' W_{i,t-1} + \Omega_h' Z_{i,t-1}\Delta r_t + \\ &+ \sum_{x\in\mathcal{X}^s}\sum_{j\in\mathbb{J}^x}\left(\beta^x_{j,h} + \gamma^x_{j,h}\Delta r_t\right)\times \mathbb{1}_{i\in\mathcal{I}^{x,j}_{t-1}} + u_{i,t+h} \qquad (3)\\ &\text{with } h=0,1,\ldots,H;\ \Delta_h y_{i,t+h}\equiv y_{i,t+h}-y_{i,t-1}\end{aligned}$$

where Δr_t refers to the quarterly change in the federal funds rate. The estimation employs two stage least squares, using $Z_{i,t-1}\varepsilon^m_t$ and $\left\{\mathbb{1}_{i\in\mathcal{I}^{x,j}_{t-1}}\varepsilon^m_t\right\}_{x\in\mathcal{X}^s,j\in\mathbb{J}^x}$ as instruments for $Z_{i,t-1}\Delta r_t$ and

$\left\{\mathbb{1}_{i\in\mathcal{I}^{x,j}_{t-1}}\Delta r_t\right\}_{x\in\mathcal{X}^s, j\in\mathbb{J}^x}$.

As for how I include the sets of financial conditioning variables $\mathcal{X}^s$ in (3), I repeat the exact same strategy as in the OLS regressions above. I first consider the relevance of leverage and liquid asset holdings separately, and finally jointly. For brevity, I only present the estimation results for fixed capital accumulation as the measure of firm performance here. The implications of using the IV approach for inventories and sales are the same as for capital and are available upon request.

Figure 5 presents the estimates for both $\gamma^{lev}_{j,h}$ and $\gamma^{liq}_{j,h}$ from the 2SLS estimation of (3) when only either leverage or liquid asset holdings are included in $\mathcal{X}^s$. The conclusions are virtually unchanged compared to the OLS regression. It is still the case that both high leverage and low liquid asset holdings are associated with lower growth in fixed capital after a contractionary monetary policy shock. And the discussion in Sections 3.3.1 and 3.3.2 above extends directly. The



(a) x = leverage

(b) x = liquid assets ratio

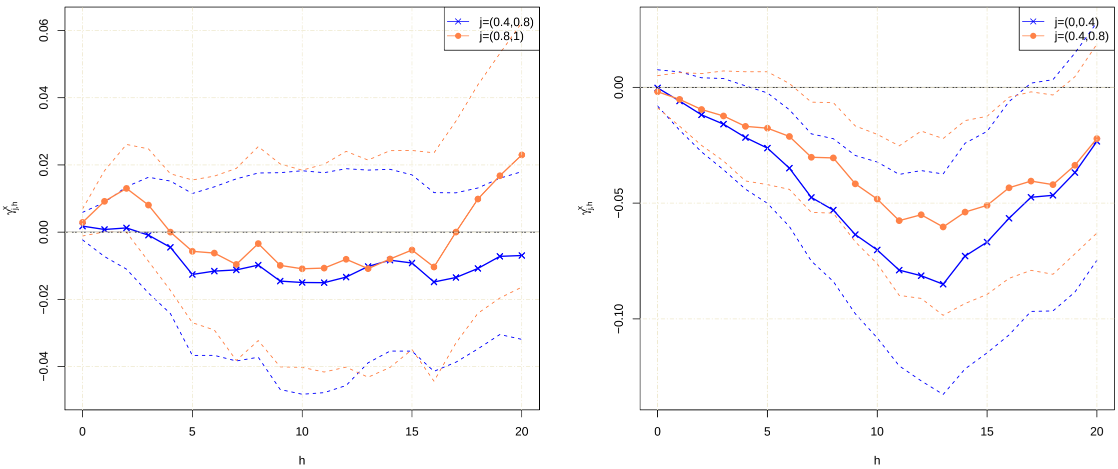
Figure 5: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in separate IV regressions

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (3) using 2SLS and ε^m_t as instruments for Δr_t, with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

main difference with the OLS regression is the fact that now the magnitudes of the coefficients are larger in absolute terms. This is because of the fact that Δr_t is included in (3) in percentage points, so $\gamma^x_{j,h}$ measures the differences in responses to a 100bp change in the annualized fed funds rate. So in response to a monetary policy shock that induces a 25bp increase in the fed funds rate, the fixed capital growth of firms in the three highest leverage quintiles is about 1% lower than for those with the least leverage over the 3 years following the shock. The induced difference between the capital growth of the lowest and highest liquid asset holding groups is almost 2% during the same post-shock horizon.

To relate the magnitudes of the coefficients and the responses to the results seen for the OLS case in Section 3.3, one must keep in mind that an unexpected 1bp change in the *futures'* prices is usually accompanied by a *larger* than 1bp change in the *actual* federal funds rate, due to the discrete nature of how the FOMC sets the federal funds rate target. That is, if the financial markets believe that there is a 50% chance of a 25bp increase in the federal funds rate target and a 50% chance of it remaining unchanged, then an FOMC decision to increase the rate by 25bp will most likely be accompanied by an approximately 12.5bp unexpected increase in the futures rate at the time of the announcement.[16] Put differently, by using the IV approach we are scaling and defining a one unit structural monetary policy shock as one that causes a 100bp increase in the federal funds rate. In the OLS case, a one unit structural monetary policy shock was measured as one that causes a surprise of 12bp in fed funds *futures* rate.

Finally, Figure 6 depicts the estimates for $\gamma^{lev}_{j,h}$ and $\gamma^{liq}_{j,h}$ from the IV estimation of (3) when group indicators for both leverage and liquid asset holdings are included in $\mathcal{X}^s$. Again, the implications of controlling for both financial indicators are unchanged compared to the OLS regressions. Liquid asset holdings at the time of a shock continue to play a significant role in explaining the differences in firms' capital accumulation after a monetary policy shock. During the first 3 years after a contractionary shock which induces a 25bp increase in the fed funds rate, firms with liquid asset ratios below the 40th percentile accumulate about 2% less capital than those in the fifth with the most liquid assets.



(a) x = leverage

(b) x = liquid assets ratio

Figure 6: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint IV regression

Notes: Point estimates and 95% confidence intervals for $\gamma^{x}_{j,h}$ from estimating specification (3) using 2SLS and ε^m_t as instruments for Δr_t, with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

At the same time, the relevance of leverage is considerably diminished. While the point estimates imply that firms with higher leverage tend to accumulate slightly less capital over the longer horizon, none of these estimates are statistically significant. The relation of higher leverage firms accumulating slighly more fixed capital in the first few quarters after a contractionary monetary policy shock is now just barely statistically significant at the 5% level. It implies that a structural

[16] A univariate linear OLS regression of Δr_t on ε^m_t yields a slope coefficient point estimate of approximately 2.2.

monetary shock inducing a 25bp increase in the fed funds rate causes firms in the highest leverage group to accumulate 0.3% more fixed capital than the lowest leverage firms during the first two quarters after the shock.

The results are unchanged, both qualitatively and quantitatively, when instead employing the change in the one-year Treasury rate as Δr_t in the estimation of (3). The estimates are also robust to using weighted quarterly measures of monetary shocks $\bar{\varepsilon}_t^m$ based on the current month fed funds futures as instruments.

Finally, Figures 45 and 46 in Appendix C.1 depict the the estimates for $\gamma_{j,h}^x$ in the IV regressions for capital accumulation when ε_t^m is constructed from the three month ahead monthly fed funds futures price changes and r_t is the one-year Treasury rate. Using the changes in the three month ahead futures rates as instruments implies qualitatively identical conclusions as for the OLS case, yet with slightly smaller quantitative disparities between firms' responses. Note that the marginal decrease in the coefficients' absolute values arises from using different instruments, and not from employing the Treasury rate as the policy indicator.

3.5 Assessing level effects of monetary policy shocks

The analysis employing firm-level data has so far only evaluated *differences* in firms' performance after monetary policy shocks and does not say what happens to the *levels* of firms' activity, i.e. it is still undetermined how the base groups respond to the shocks. It turns out that specializing time dummies by industry in specification (1) for the capital accumulation regressions barely affects the estimates of $\gamma_{j,h}^x$ presented above. So it is enough to control for joint *aggregate*, and not necessarily industry-specific variation to reach similar estimates regarding the differences in firms' responses conditional on leverage and liquid asset holdings. Therefore, following the spirit of local projections, one can assess the effects of monetary policy shocks on the performance of the base groups and continue the approach taken above by simply dropping the industry-quarter dummies from (1), including ε_t^m on the right hand side and directly estimating the corresponding coefficients by OLS.[17] Given that there is significant variation in aggregate capital growth over the business cycle and the small realized monetary shocks most likely constitute a minuscule source of aggregate variation, one can improve the precision of the estimates and control for the usual dynamics of capital accumulation by also controlling for the state of the aggregate economy before a monetary shock, as suggested by Stock and Watson (2018).

It also turns out that the coefficient estimates on the firm size and the monetary shock interaction term in (1) are statistically insignificant and do not considerably affect the estimates of $\gamma_{j,h}^x$ above. Thus, for the rest of this section I will let $Z_{i,t}$ be empty to simplify the interpretation of the estimates below. Also, following the main findings above, I will focus on the capital accumulation regression specification which only controls for liquid asset holdings, i.e. $\mathcal{X}^s = \{liq\}$.[18]

Finally, to make the results more easily interpretable in terms of the response of *aggregate*

[17] Or if we want to relax the assumption of ε_t^m being an exact measure of structural monetary policy shocks, we can include the change in the fed funds rate and instrument it with the former, along the lines of the approach in Section 3.4.

[18] The corresponding results when controlling for leverage can be seen in Appendix B.17.

capital, I will not group firms into bins based on the 40th and 80th percentiles of the liquid assets ratio distribution. Rather, I will group the firms present in quarter t into three bins based on their liquid asset ratios so that the total capital of firms in each bin in quarter t comprises a specific percentage of the capital held by all firms in the sample in t. That is, instead of using the definition of percentile-based bins $\mathcal{I}_t^{x,(a,b)}$ from Section 3.2, I will instead employ the bins defined as:

$$\tilde{\mathcal{I}}_t^{x,(a,b)} \equiv \left\{ i \in \mathcal{I}_t | x_{i,t} \in \left[\tilde{q}^a_{x,t}, \tilde{q}^b_{x,t} \right] \right\}$$
$$\text{where} \quad \tilde{q}^a_{x,t} \equiv \max_{i \in \mathcal{I}_t} \left\{ x_{i,t} \,\middle|\, \sum_{i' \in \mathcal{I}_t : x_{i',t} \leq x_{i,t}} k_{i',t} \leq a \sum_{i' \in \mathcal{I}_t} k_{i',t} \right\}$$

By using the same collection of grouping indicators $\mathbb{J}^{liq}$ as defined in Section 3.2, the bins $\tilde{\mathcal{I}}_t^{x,(0,0.4)}$ and $\tilde{\mathcal{I}}_t^{x,(0.4,0.8)}$ each now represent 40% of total capital held by firms in the sample in quarter t. And naturally, $\tilde{\mathcal{I}}_t^{x,(0.8,1.0)}$ represents the 20% of capital that is held by firms with the most liquid asset holdings. Therefore, a back-of-the-envelope estimate of the response of (log) aggregate capital at horizon h can just be backed out as the weighted average of the responses of each of the three bins at that horizon.

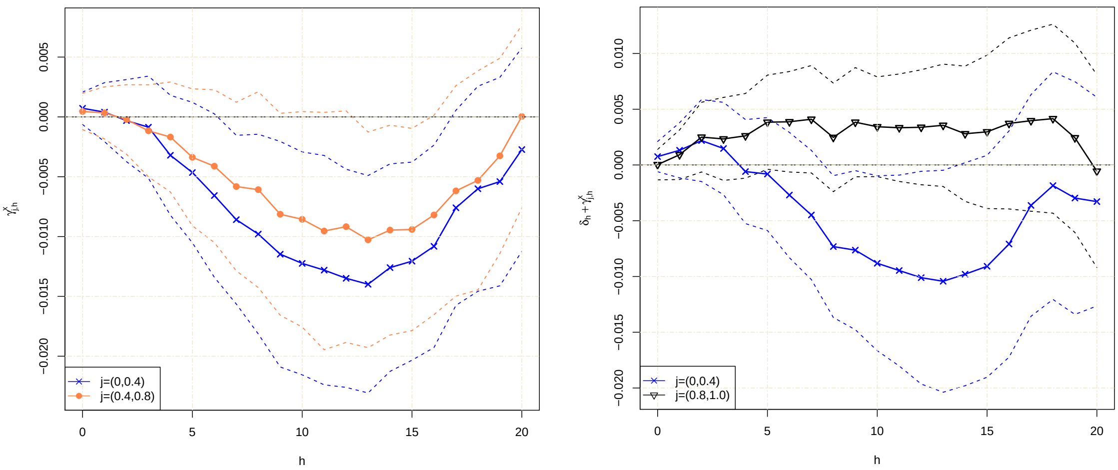
More specifically, I will now estimate the specification:

$$\Delta_h \log(k_{i,t+h}) = f_{i,h} + \delta_h \varepsilon_t^m + \Gamma'_h Y^a_{t-1} + \Theta'_h W_{i,t-1} + \sum_{j \in \mathbb{J}^{liq}} \left(\beta^{liq}_{j,h} + \gamma^{liq}_{j,h} \varepsilon^m_t \right) \times \mathbb{1}_{i \in \tilde{\mathcal{I}}^{liq,j}_{t-1}} + u_{i,t+h} \tag{4}$$

for $h = 0, 1, \dots, H$, with $W_{i,t} = [\log(\text{size}_{i,t})]$. The implied estimates of δ_h then capture the dynamic effects of a contractionary monetary policy shock on the fifth of the total capital stock held by firms with the highest liquid asset ratios. All the other groups' level responses can be backed out by appropriately adding the estimates of $\gamma^{liq}_{j,h}$. Y^a_{t-1} is a vector of economic aggregates in the spirit of the aggregate VAR considered in Section 4. Y^a_t contains the quarterly log difference in CPI, the level of the excess bond premium and the fed funds rate in quarter t. To control for the aggregate capital accumulation activity, I also include the simple cross-sectional mean of the yearly growth rate of the capital stock $\frac{1}{|\mathcal{I}_t \cap \mathcal{I}_{t-4}|} \sum_{i \in \mathcal{I}_t \cap \mathcal{I}_{t-4}} \log\left(\frac{k_{i,t}}{k_{i,t-4}}\right)$ from the Compustat panel. Including quarterly GDP growth does not affect the results. Γ_h is a vector of coefficients.

The estimation results can be seen in Figure 7. The left panel presents the point estimates and 95% confidence intervals for $\gamma^{liq}_{j,h}$ from (4). As one can see, constructing groups based on total capital held instead of the number of firms in each group does not change the main implication that a lower liquid assets ratio at the time of a contractionary shock predicts lower capital growth thereafter.

The right panel in Figure 7 depicts the responses of the *level* of the log capital stock, i.e. that of $[\log(k_{i,t+h}) - \log(k_{i,t-1})]$ to a contractionary monetary policy shock across the two extreme groups of $\tilde{\mathcal{I}}_t^{liq,(0,0.4)}$ and $\tilde{\mathcal{I}}_t^{liq,(0.8,1.0)}$. That is, the black line with triangular markers refers to $\hat{\delta}_h$ and the blue line equals $\hat{\delta}_h + \hat{\gamma}^{liq}_{(0,0.4),h}$, with the corresponding 95% confidence intervals. One can see that based on the point estimates, firms with the highest liquid asset ratios are suggested to respond positively to a contractionary monetary policy shock, although the estimates are statistically insignificant. At the same the the other groups of firms respond negatively, in line with the implications of the VAR on aggregate investment in Section 4.2. Based on the construction of the bins, we can weigh the three groups' responses by 0.4, 0.4 and 0.2 and infer that the implied drop in the aggregate capital stock is about 0.6% over the 3 year horizon in response to a monetary policy shock measured as a 12bp surprise increase in the fed funds *futures* rate, or in response to an unexpected 25bp increase in the fed funds *rate*, following the discussion on the relative magnitudes of the coefficients in Sections 3.3 versus 3.4. The magnitude of the response in the total fixed capital stock among Compustat firms is roughly in line with the VAR implications for investment in nonresidential fixed capital in the whole U.S. economy, presented in Section 4.2.



(a) $\gamma^{liq}_{j,h}$

(b) δ_h and $\delta_h + \gamma^{liq}_{(0,0.4),h}$

Figure 7: Heterogeneity and absolute responses of capital accumulation conditional on liquid asset holdings

Notes: Panel (a): Point estimates and 95% confidence intervals for $\gamma^{liq}_{j,h}$ from estimating specification (4). Panel (b): Point estimates and 95% confidence intervals for δ_h (black solid line) and $\delta_h + \gamma^{liq}_{(0.8,1.0),h}$ (blue solid line) from estimating (4). Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Firms grouped into bins based on the total capital held by firms in each bin.

4 Aggregate Structural Vector Autoregression

4.1 Structural vector autoregression specification

To put the estimation results based on the local projections panel approach into perspective, I will evaluate the effects of a structural monetary policy shock on the aggregate U.S. economy using a structural VAR model that contains both economic and financial variables. Doing so also provides a robustness check for the performance of high frequency identified measures of monetary policy shocks when used in conjunction with quarterly data. Estimating this model and the implied impulse responses is useful in retrieving a benchmark estimate for how the aggregate U.S. economy, especially aggregate nonresidential fixed investment behaves in light of unexpected monetary policy actions.

As for the panel approach, I identify the effects of structural monetary policy shocks in the VAR using external instruments measured from high frequency financial markets data. The estimation approach builds on the methods developed by Stock and Watson (2012) and Mertens and Ravn (2013). More specifically, the VAR specification and identification closely follows the work of Gertler and Karadi (2015), so I will discuss the estimation and data selection details only briefly. The structural form of the VAR under consideration is:

$$A_0 Y_t = \sum_{s=1}^{p} A_s Y_{t-s} + \varepsilon_t \tag{5}$$

where Y_t is a vector of aggregate economic and financial variables, A_s, for $0 \leq s \leq p$, are square coefficient matrices. ε_t is a vector of primitive, structural shocks, assumed to be i.i.d. over time, and satisfy $\mathbb{E}[\varepsilon_t \varepsilon_t'] = \mathbb{I}$. ε_t also contains the structural monetary policy shock ε_t^p, the effects of which on the economy we aim to estimate. For brevity, I have not included a constant vector in (5), although the estimation of all VARs below includes constants.

Multiplying (5) with A_0^{-1}, we get the reduced form representation of the VAR:

$$Y_t = \sum_{s=1}^{p} B_s Y_{t-s} + u_t \tag{6}$$

where $B_s = A_0^{-1} A_s$, for $1 \leq s \leq p$, and u_t is the vector of reduced form shocks, related to the structural shocks by:

$$u_t = D\varepsilon_t$$

with $D = A_0^{-1}$. Let the variance-covariance matrix of the reduced form shocks be Σ. Then, given the assumptions on ε_t, we have that:

$$\Sigma = \mathbb{E}[u_t u_t'] = DD' \tag{7}$$

As Gertler and Karadi (2015), I make the distinction between the policy *indicator* and the policy *instrument*. The instrument of monetary policy is the current period short-term interest rate, which in the U.S. is the federal funds rate. However, as over time the conduct of monetary policy has started increasingly relying on forward guidance, the effects of which one would like the VAR to capture, one can use as the monetary policy indicator a government rate of a longer maturity than the policy instrument. Movements in such a policy indicator reflect both changes in the current funds rate and in the expectations about the future path of the funds rate, i.e. forward guidance. Let the policy indicator be denoted Y_t^p and included in the vector Y_t.

As is the issue in every application of a structural VAR, an OLS estimation of the reduced form VAR in (6) only allows to identify the coefficient matrices $B_s = A_0^{-1} A_s$, for $1 \leq s \leq p$, and the symmetric reduced form shock variance-covariance matrix Σ, and thus DD', but not D itself. Identification of the latter, or the elements within, requires additional restrictions. One column of D, let us denote it d, refers to the impact effect of the monetary policy shock ε_t^p on u_t. Given that my aim is to only compute impulse responses of the variables in Y_t to a monetary shock, I only need to estimate the coefficients $B_s, 1 \leq s \leq p$, and the vector d.

Traditional methods of identifying d using timing restrictions by imposing that the policy rate responds contemporaneously to other variables in the VAR whereas it does not affect them itself, are questionable when financial variables are included. Also, assuming that the policy rate does not respond to financial variables is problematic. Clearly, within a period, policy movements affect financial conditions and may themselves respond to the latter. This is especially true when the length of a time-period considered is a quarter, as delegated by the usage of investment data in the current approach. And even though the focus of my analysis is not necessarily on the responses of financial variables to monetary policy shocks, accounting for their effects on non-financial variables, such as output and investment, can significantly affect the resulting estimates as, for example, demonstrated by the results of Gertler and Karadi (2015) and Caldara and Herbst (2019).

To get around the identification issue, I use high frequency data on the effects of policy surprises on the fed funds futures rate, constructed as discussed in Section 2. Given the identification assumption that the fed funds futures price changes around an FOMC press release are uncorrelated with structural shocks other than the monetary policy shock ε_t^p, both the constructed weighted and unweighted quarterly measures of monetary policy shocks ε_t^m and $\bar{\varepsilon}_t^m$, respectively, can be used as external instruments for identifying the column d in the VAR.

To demonstrate how external instruments can be used in the identification of d, let us suppose that there exists a vector of valid instruments Z_t which are correlated with the policy shock ε_t^p but orthogonal to the vector of other structural shocks in ε_t, denoted ε_t^q. That is, the following identifying moment conditions must be satisfied:

$$\mathbb{E}[Z_t \varepsilon_t^p] = \phi \tag{8}$$

$$\mathbb{E}[Z_t \varepsilon_t^{q\prime}] = 0 \tag{9}$$

Let $u_t^p \in u_t$ denote the reduced form residual from the equation for the policy indicator and $u_t^q \in u_t$ the vector of the remaining reduced form residuals, and analogously, $d^p \in d$ and $d^q \in d$ denote the effects of a unit increase in ε_t^p on u_t^p and u_t^q, respectively. Given the reduced form residuals from estimating (6) by OLS, one can then estimate the ratio d^p/d^q with a two stage least squares regression by regressing u_t^q on u_t^p using Z_t as instruments. Then, an estimate for d^p can be obtained by in addition using (7) and the estimate for Σ from the OLS estimation of (6). Further details and the exact formulas on executing these steps are, for example, presented by Mertens and Ravn (2013) and Gertler and Karadi (2015).

Z_t can potentially contain several instruments derived from futures rates surprises of various market rates such as the current month's fed funds futures, the three month ahead monthly fed funds futures or Eurodollar futures at various horizons. In the interest of brevity, to obtain baseline estimates of impulse responses to structural monetary policy shocks from the VAR, I will just consider the weighted measures $\bar{\varepsilon}_t^m$ constructed based on changes in the current month's fed funds futures price around FOMC announcements as the only source of external variation. As the monetary policy indicator, I will use the one-year Treasury rate. I consider other combinations of monetary policy indicators and high frequency changes in fed funds futures in robustness analysis.

4.2 Aggregate data in the VAR, estimation results

I build the analysis of the aggregate economy on the parsimonious 4-variable structural VAR specification used by Gertler and Karadi (2015), applying it to quarterly data and adding a measure of investment. The aggregate series I include in the 5-variable VAR are a monetary policy indicator, a measure of credit spreads, and three economic variables measuring aggregate economic activity, the price level and aggregate investment. More specifically, as the policy indicator I use the one-year Treasury constant maturity rate, as reported by the Federal Reserve Board. For aggregate activity, I use the log real GDP (BEA-NIPA Table 1.1.6. Line 1). The price level is measured by the log consumer price index as reported by the BLS. And as aggregate investment, I use the log real nonresidential private fixed investment (BEA-NIPA Table 5.3.3. Line 2). The latter three are seasonally adjusted. Finally, as the measure of credit spreads I employ the Gilchrist and Zakrajšek (2012) excess bond premium. This premium gauges movements in the average price of bearing U.S. corporate bond risk over and above the compensation required for expected defaults, and has been shown to have significant power in predicting economic activity.

A useful feature of imposing the VAR structure is that the reduced form (6) can be estimated on data from a longer sample than for which external instruments are available, thus allowing to increase the number of observations. The sample period used to estimate the lag coefficients and the variance-covariance matrix of the residuals in the reduced form VAR is 1984Q1–2007Q4. And the instruments to identify the monetary policy shock vector are used for the 1990Q1–2007Q4 period for which they are available. The baseline estimation only includes data up to the beginning of 2008 in order to exclude the excess financial turbulence around the beginning of the Great Recession and the potentially different aggregate dynamics of the zero lower bound period thereafter.[19] I consider aggregate data starting 1984 because the conduct of monetary policy by the Federal Reserve is widely believed to have changed starting with the appointment of Paul Volcker as Chairman, as for example studied by Clarida et al. (2000), and in order to exclude the volatile times of the Volcker disinflation.[20] In the baseline VAR estimation, I include log GDP, investment, and CPI in first differences and infer the impulse responses of the levels of the former two as cumulative sums. I estimate the VAR including $p = 4$ lags of Y_t.

Figure 8 presents the impulse responses and 95% confidence bands to a one standard deviation contractionary monetary policy shock as identified by the weighted external instruments $\bar{\varepsilon}_t^m$ constructed from current month federal funds futures price data.[21] The shock induces an approximately 30bp increase in the one-year rate which then slowly reverts to pre-shock levels after increasing slightly, reminiscent of the behavior of the fed funds rate in conventional monetary VARs such as estimated Christiano et al. (2005). As found by Gertler and Karadi (2015), the contractionary monetary shock causes a temporary yet persistent worsening of financial conditions

[19] More specifically, including the last two quarters of 2008, i.e. the time around the collapse of Lehmann Brothers in the estimation causes significant changes in the estimates of the effect of monetary policy shocks on financial conditions. This is because the period was a time at which the FOMC announcements induced expansionary surprises, as measured by fed funds futures, while financial markets suffered from significant adverse shocks, leading to outliers in the relations between the reduced-form VAR residuals and external instruments, considerably affecting the first-stage regression estimates.

[20] Including earlier data does not change the point estimates of impulse responses significantly, although the increased parameter uncertainty is reflected in wider confidence intervals.

[21] As Mertens and Ravn (2013) and Gertler and Karadi (2015), I use wild bootstrap to construct confidence bands valid under heteroskedasticity and strong instruments.

evident in the heightened level of the excess bond premium, although the confidence bands are relatively wide. The wide bands do not allow to claim statistically significant effects of monetary policy shocks on output and inflation, although the point estimates of the former suggest a persistent decline in economic activity over time.

Finally, as the focus of the estimation, aggregate investment starts turning down about four quarters after the shock, yet because of the wide confidence bands, the response becomes statistically significant at the 5% level only about 8 quarters after the shock. About 12 quarters after the shock, investment has decreased by approximately 2%. The results thus illustrate the sluggishness of the responses of real economic variables to a monetary shock, again reminiscent of conventional findings in the monetary VAR literature using either identification based on timing restrictions, such as Christiano et al. (2005), or high frequency financial data, including the results of Gertler and Karadi (2015) and Caldara and Herbst (2019).[22] Also, the response of aggregate investment in the VAR is consistent with both the shape and the magnitude of the response of fixed capital accumulation by Compustat firms implied by the local projections panel approach of Section 3.

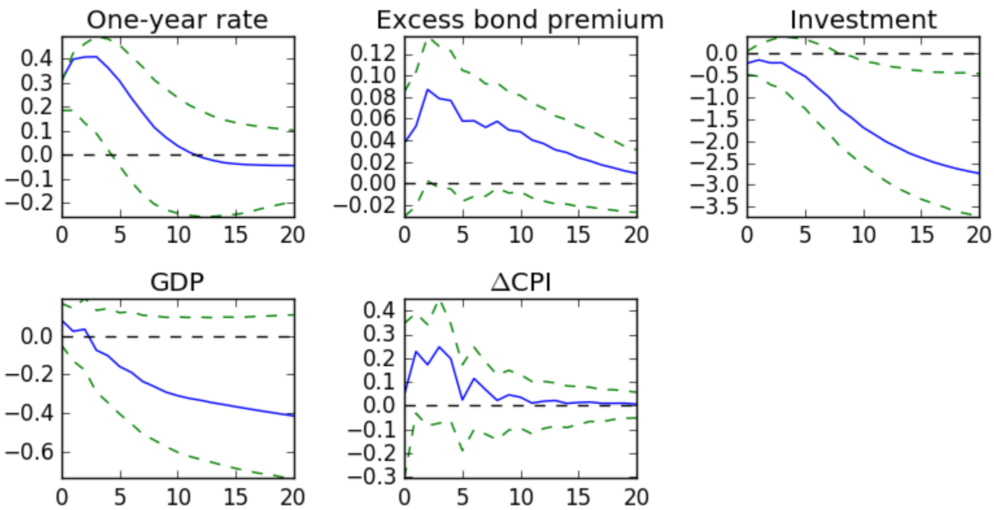


Figure 8: Aggregate impulse responses to 1 sd monetary policy shock from 5-variable VAR
Notes: All in percentages; one-year rate, excess bond premium, and CPI growth annualized. Horizontal axis: quarters after monetary shock. 95% confidence intervals from wild bootstrap. First stage regression: F: 12.27; R^2 14.9 percent; adjusted R^2: 13.7 percent

The above inference regarding the impulse responses of the five variables included in the VAR is robust to: using the fed funds rate as the monetary policy indicator, using the unweighted measures ε_t^m as external instruments and using the three month ahead monthly federal funds futures in constructing the instruments $\bar{\varepsilon}_t^m$ or ε_t^m. I have chosen to use the weighted instruments $\bar{\varepsilon}_t^m$ constructed from the current month fed funds futures prices because they yield the best performance in terms of first-stage relevance and the narrowest confidence bands for impulse responses, but the implications regarding the responses of aggregate investment are virtually unchanged under

[22]When instead including only the more flexible component of private nonresidential fixed investment, namely investments in equipment (BEA-NIPA Table 5.3.3 Line 9), the point stands, although investment does respond slightly more rapidly, with the drop becoming statistically significant 6 quarters after the shock and declining almost 3% in the first 12 quarters after the shock.

all the other specifications.

Finally, Figure 16 in Appendix A.2 shows that the main conclusions are unchanged when including log GDP and log investment in the VAR in *levels*. The main differences are that in this case, the negative response of GDP is slightly larger and also statistically significant, reminiscent of the estimates of the response of industrial production by Gertler and Karadi (2015). The response of investment becomes statistically significant after 6 quarters and starts reverting after 12 quarters, having fallen by 2%, instead of continuing its decrease. Yet the main conclusion of a slow yet significant negative response in real investment to a contrationary monetary policy shock remains.

5 Inspecting the Mechanism

To provide a deeper look into what might explain the results reported above, most importantly the fact that liquid asset holdings predict considerable heterogeneity in firms' responsiveness to monetary policy shocks, I conduct a similar analysis of the responses of the firms' financial indicators. More specifically, I study the dynamics of firms' debt-related variables in response to a contractionary monetary policy shock by considering the firms' average interest rates paid, the quantity of debt, and the total cost of servicing the debt. To do so, I utilize the firms' reported *Total Interest and Related Expense* (Compustat item 22, $XINTQ_{i,t}$) as a rough measure of the average interest rate a firm pays, multiplied by the debt on its books.

Let us denote the interest expenses for firm i in quarter t as $\bar{r}_{i,t}d_{i,t-1}$, i.e. the product of the firm's average net nominal interest rate $\bar{r}_{i,t}$ and the book value of debt at the end of the previous quarter $d_{i,t-1}$. Given this view, one can consider splitting interest expenditures into the average rate and the firm's leverage:[23]

$$\frac{\bar{r}_{i,t}d_{i,t-1}}{k_{i,t-1}} = \left(\frac{\bar{r}_{i,t}d_{i,t-1}}{d_{i,t-1}}\right) \times \left(\frac{d_{i,t-1}}{k_{i,t-1}}\right)$$

where

1. $\left(\frac{\bar{r}_{i,t}d_{i,t-1}}{d_{i,t-1}}\right) \equiv \bar{r}_{i,t}$ is a proxy for the firm's average nominal net interest rate, computed as $XINTQ_{i,t}/d_{i,t-1}$, with $d_{i,t-1}$ total debt at the end of quarter $t-1$, as defined in Section 3.1;
2. $\left(\frac{d_{i,t}}{k_{i,t}}\right)$ is a measure of the firm's leverage at the end of quarter t, with $k_{i,t}$ the measure of firm i's capital stock used in all of the above;
3. $\left(\frac{\bar{r}_{i,t}d_{i,t-1}}{k_{i,t-1}}\right)$ measures interest expenses relative to capital, computed as $XINTQ_{i,t}/k_{i,t-1}$.

When analyzing total interest expenditures, I also study the behavior of the firms' interest coverage ratios, defined as:

$$\rho_{i,t} \equiv \frac{\bar{r}_{i,t}d_{i,t-1}}{\bar{r}_{i,t}d_{i,t-1} + c_{i,t}}$$

[23] I scale the financial indicators of interest by the firm's capital stock in order to employ a measure of its scale of operations in the scaling. The main results hold when scaling by total book assets instead.

where $c_{i,t} \equiv IBQ_{i,t}+DPQ_{i,t}$ denotes firm i's cash flow in quarter t, computed as the sum of *Income Before Extraordinary Items* (Compustat data item 8) and *Total Depreciation and Amortization* (item 5).

I study the responses of the financial indicators of interest to monetary policy shocks by estimating identical panel regressions as in Section 3 above, simply using the indicators in place of the outcome variable $y_{i,t}$. To demonstrate the cross-sectional heterogeneity in the responses, I estimate specification (1) defined in Section 3.3 while conditioning on both leverage and the liquid assets ratio, i.e. $\mathcal{X}^s = \mathcal{X}$. To facilitate simpler interpretation of coefficient estimates as level responses, I estimate (4), exactly as defined in Section 3.5, i.e. conditioning only on the firm's liquid assets ratio, with Y^a_{t-1} containing only the excess bond premium, the fed funds rate, and quarterly CPI growth. Focusing on the liquid assets ratio is motivated by the above results on the responses of capital accumulation. Also leverage, as measured by the debt-to-assets ratio does not predict significant heterogeneity in the responses of the average net nominal rate paid nor the debt-to-capital ratio. Naturally, leverage implies cross-sectional heterogeneity in the responses of total interest expenses and the coverage ratio after an interest rate increase since firms who use more debt see their total interest expenses go up if the nominal rates increase. The corresponding responses for the latter two variables when conditioning on leverage can be seen in Appendix B.18. Since the financial indicators respond to monetary shocks relatively faster than real variables, I focus only on analyzing the responses for the first two years after a contractionary monetary shock, i.e. I set $H = 8$.

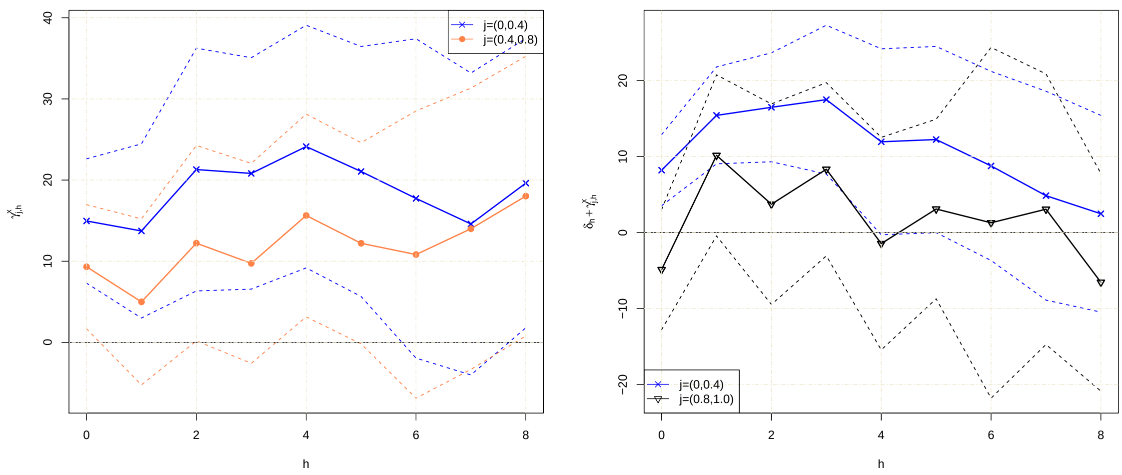
In addition to the data selection procedures covered in Section 3, I drop observations of $\left(\frac{\bar{r}_{i,t}d_{i,t-1}}{d_{i,t-1}}\right)$, $\left(\frac{d_{i,t-1}}{k_{i,t-1}}\right)$, $\left(\frac{\bar{r}_{i,t}d_{i,t-1}}{k_{i,t-1}}\right)$ and $\rho_{i,t}$ above the corresponding 99th percentiles, by quarter. And I only consider observations of coverage ratios $\rho_{i,t}$ which are non-negative.

Interest Rate Pass-through The dynamics of firms' annualized average net nominal interest rates $\bar{r}_{i,t}$ after a one standard deviation, or 12bp, contractionary monetary policy shock as measured by the fed funds futures rate changes can be seen in Figure 9. The left panel simply plots the differences in firms' responses, i.e. the estimates of $\gamma^{liq}_{j,h}$ in specification (1) when $y_{i,t} = \bar{r}_{i,t}$, and $\mathcal{X}^s = \mathcal{X}$. It is evident that firms with lower liquid asset ratios experience a significantly larger increase in the average interest rate paid on their debt, with the differences increasing throughout the first year after the shock. Controlling for firm size and leverage, firms with liquid asset holdings below the 40th percentile are implied to see their annualized average interest rate increase by 25bp more than those with liquid assets above the 80th percentile in response to a 12bp unexpected increase in the fed funds futures rate. As discussed above, on average a monetary shock of this magnitude corresponds to a 25bp increase in the actual fed funds rate.[24]

The right panel in Figure 9 plots the response of the average interest rates for firms in the base group of liquid asset holdings, i.e. those above the 80th percentile, and for the firms below the 40th percentile. The estimate of the base group's response is relatively noisy because this group contains firms with low amounts of debt which can easily lead to imprecise measurement of $\bar{r}_{i,t}$. The average nominal rate for firms with liquid asset ratios above the 80th percentile is estimated

[24]Note that this difference in firms' average rate responses is conditional on keeping firm size and leverage fixed, so no two firms in the sample might actually experience such heterogeneity in their implicit interest rate changes. As can be seen in the right panel of Figure 9, when one does not allow leverage or size to simultaneously explain differences in the responses, the discrepancies predicted by liquid asset holdings are smaller.

not to increase significantly after an unexpected increase in the fed funds futures rate, while the point estimates imply a 10bp increase in the first quarter following the shock. At the same time, firms with liquid assets below the 40th percentile see their average rate increase by almost 20bp three quarters after the shock and then revert to previous levels about 2 years after the shock.



(a) $\gamma^{liq}_{j,h}$ from (1), with $\mathcal{X}^s = \mathcal{X}$

(b) δ_h and $\delta_h + \gamma^{liq}_{j,h}$ from (4)

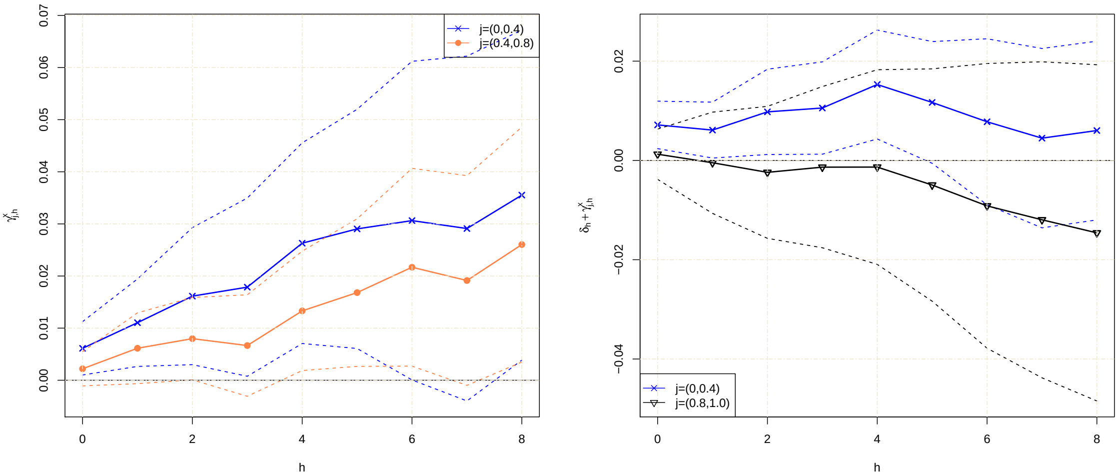
Figure 9: Heterogeneity and absolute pass-through conditional on liquid asset holdings

Notes: Panel (a): Point estimates and 95% confidence intervals for $\gamma^{liq}_{j,h}$ in (1), with $y_{i,t} = \bar{r}_{i,t}$ annualized in basis points, $\mathcal{X}^s = \mathcal{X}$. Panel (b): Point estimates and 95% confidence intervals for δ_h (black solid line) and $\delta_h + \gamma^{liq}_{(0,0.4),h}$ (blue solid line), from estimating (4), with $y_{i,t} = \bar{r}_{i,t}$ annualized in basis points. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

Leverage Dynamics Figure 10 presents the responses of firms' debt-to-capital ratios $\left(\frac{d_{i,t}}{k_{i,t}}\right)$ to a one standard deviation contractionary monetary policy shock as measured by the fed funds futures rate changes. Again, the left panel plots the estimates of $\gamma^{liq}_{j,h}$ in specification (1) when $y_{i,t} = \left(\frac{d_{i,t}}{k_{i,t}}\right)$, and $\mathcal{X}^s = \mathcal{X}$. Firms who hold less liquid assets increase their debt-to-capital ratio relative to those with more liquid balance sheets after a contractionary shock. Controlling for firm size and leverage, the debt-to-capital ratios of firms with liquid asset ratios below the 40th percentile increase by about 3.5 percentage points more than the base group of firms with highly liquid balance sheets during the first two years after a 12bp unexpected increase in the fed funds futures rate.

The responses of the levels of the debt-to-capital ratios of firms with liquid assets below the 40th percentile and above the 80th percentile can be seen in the right panel of Figure 10. For the base group of firms with high liquid assets, the responses of the debt-to-capital ratios are estimated not to change statistically significantly in response to unexpected changes in the fed funds futures rate. The ratios for firms with low liquid asset holdings are estimated to increase by about 1.5 percentage points during the first year after a one standard deviation contractionary monetary policy shock and revert to its previous level thereafter.

Debt Cost Dynamics Given that a contractionary monetary policy shock leads to a relatively larger increase in the average net nominal rates and the debt-to-capital ratios of firms



(a) $\gamma_{j,h}^{liq}$ from (1), with $\mathcal{X}^s = \mathcal{X}$

(b) δ_h and $\delta_h + \gamma_{j,h}^{liq}$ from (4)

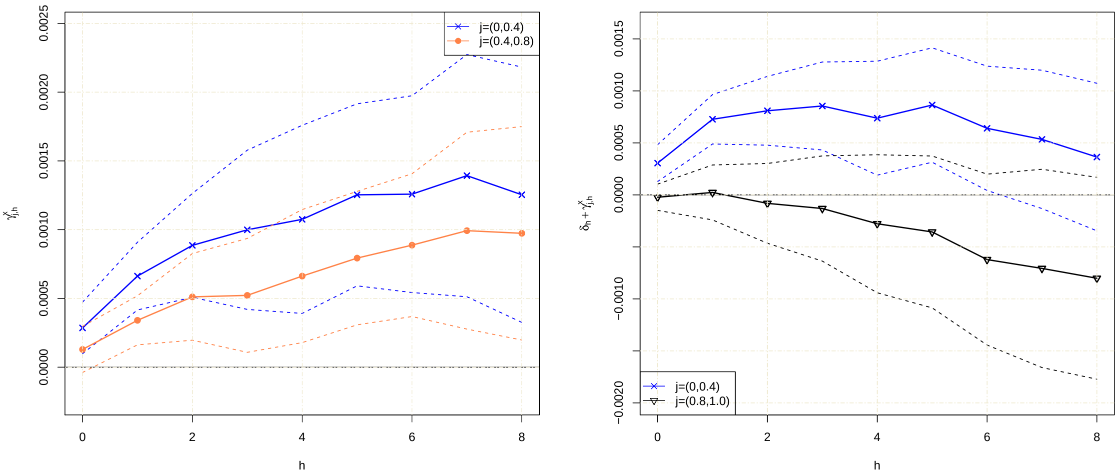
Figure 10: Heterogeneity and absolute responses of leverage conditional on liquid asset holdings

Notes: Panel (a): Point estimates and 95% confidence intervals for $\gamma_{j,h}^{liq}$ in (1), with $y_{i,t} = \left(\frac{d_{i,t}}{k_{i,t}}\right)$, $\mathcal{X}^s = \mathcal{X}$. Panel (b): Point estimates and 95% confidence intervals for δ_h (black solid line) and $\delta_h + \gamma_{(0,0.4),h}^{liq}$ (blue solid line), from estimating (4), with $y_{i,t} = \left(\frac{d_{i,t}}{k_{i,t}}\right)$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

with lower liquid asset ratios, it naturally follows that also the products of the two indicators, i.e. the interest expenditures to capital ratios $\left(\frac{\bar{r}_{i,t} d_{i,t-1}}{k_{i,t-1}}\right)$ for firms with lower liquid asset holdings increase relatively more. The corresponding responses to a one standard deviation contractionary monetary policy shock as measured by the fed funds futures rate changes can be seen in Figure 11. The estimates of $\gamma_{j,h}^{liq}$ in the left panel imply that controlling for firm size and leverage, the interest expenditures to capital ratios of firms with liquid asset ratios below the 40th percentile increase by almost 0.15 percentage points more than those of firms with high liquid asset holdings during the two years after a 12bp unexpected increase in the fed funds futures rate.

The right panel of Figure 11 depicts the responses of the interest expenditures to capital ratios of firms with liquid asset holdings below the 40th percentile and above the 80th percentile. By one year after an unexpected 12bp increase in the fed funds futures rate, the interest expenses of the low liquid asset firms have increased by almost 0.1 percentage points and revert to their prior level about 2 years after the shock. At the same time, the interest expenditures of the base group with highly liquid balance sheets are implied not to respond statistically significantly, with point estimates implying a *decrease* in their interest expenditures to capital ratios.

Finally, the interest expenditures of firms with fewer liquid assets also increase relatively more as a fraction of their cash flows. Figure 12 depicts the responses of the firms' coverage ratios $\rho_{i,t}$ to a one standard deviation contractionary monetary policy shock as measured by changes in the fed funds futures rate. Controlling for firm size and leverage, firms with low liquid asset ratios see their coverage ratios increase relative to those with high liquid asset holdings throughout the first two years after the shock, as seen in the left panel of Figure 12. The right panel of the Figure shows that the coverage ratios also increase in absolute terms for firms with liquid assets ratios



(a) $\gamma^{liq}_{j,h}$ from (1), with $\mathcal{X}^s = \mathcal{X}$

(b) δ_h and $\delta_h + \gamma^{liq}_{j,h}$ from (4)

Figure 11: Heterogeneity and absolute responses of interest expenditures conditional on liquid asset holdings

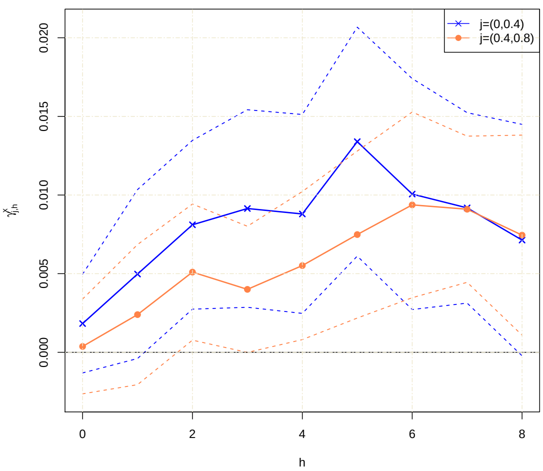
Notes: Panel (a): Point estimates and 95% confidence intervals for $\gamma^{liq}_{j,h}$ in (1), with $y_{i,t} = \left(\frac{\bar{r}_{i,t} d_{i,t-1}}{k_{i,t-1}}\right)$, $\mathcal{X}^s = \mathcal{X}$. Panel (b): Point estimates and 95% confidence intervals for δ_h (black solid line) and $\delta_h + \gamma^{liq}_{(0,0.4),h}$ (blue solid line), from estimating (4), with $y_{i,t} = \left(\frac{\bar{r}_{i,t} d_{i,t-1}}{k_{i,t-1}}\right)$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

below the 40th percentile throughout the first year after the shock and then slowly revert to initial levels. The coverage ratio is not implied to respond statistically significantly for the high liquid assets ratio firms, although the increase is just barely insignificant at the 5% level.

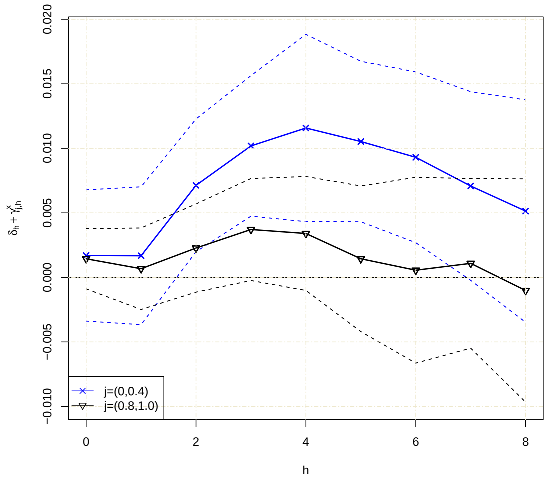
Discussion The above estimates of impulse responses thus imply that after an unexpected increase in the monetary policy rate, the borrowing costs of firms which hold fewer liquid assets increase relatively more both in terms of the average rate and the total interest expenses paid. Given the higher costs of external financing, it is thus natural for these firms to decrease their investments in fixed capital. Although determining the exact reasons behind the observed larger increases in borrowing costs is beyond the scope of this paper, I will discuss the plausibility of a few theories.

First of all, based on the ideas covered by Ippolito et al. (2018), it might be the case that firms which hold fewer liquid assets also happen to utilize floating rate debt to a larger extent. In this case, being relatively more exposed to increases in interest rates when monetary policy is tightened causes firms to cut back on investment either due to increased opportunity costs of investing or decreased cash flows if the firm is constrained from frictionlessly raising external financing. Following Ippolito et al. (2018), one could employ the Capital IQ dataset on debt structure merged with Compustat and use the information on bank debt as a proxy for how much floating rate debt a firm uses.[25] Unfortunately, due to a lack of coverage on bank debt data before 2003, this information cannot be included in the core analysis of the current paper above. Preliminary analysis shows that indeed, firms' liquid asset ratios seem to be negatively correlated

[25] I compute a firm's total bank debt as the sum of drawn credit lines and term loans from the Capital IQ dataset.



(a) $\gamma_{j,h}^{liq}$ from (1), with $\mathcal{X}^s = \{liq\}$



(b) δ_h and $\delta_h + \gamma_{j,h}^{liq}$ from (4)

Figure 12: Heterogeneity and absolute responses of the coverage ratio conditional on liquid asset holdings

Notes: Panel (a): Point estimates and 95% confidence intervals for $\gamma_{j,h}^{liq}$ in (1), with $y_{i,t} = \rho_{i,t}$, $\mathcal{X}^s = \mathcal{X}$. Panel (b): Point estimates and 95% confidence intervals for δ_h (black solid line) and $\delta_h + \gamma_{(0,0.4),h}^{liq}$ (blue solid line), from estimating (4), with $y_{i,t} = \rho_{i,t}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

with bank debt usage in the cross-section. A simple linear regression of a firm's ratio of total bank debt to total debt on the firm's liquid assets ratio, while controlling for industry-quarter fixed effects yields a slope coefficient of -0.31 with a standard error of 0.05. Yet, repeating the estimation of (2), with $\mathcal{X}^s = \{liq\}$ while including the share of bank debt in total debt, or the bank debt to total assets ratio as controls in $W_{i,t-1}$ and $Z_{i,t-1}$ for the 2004Q1–2007Q4 subsample shows that the introduction of bank debt in $Z_{i,t-1}$ does not affect the point estimates of γ_h^{liq} to a considerable degree, and thus does not provide clear evidence of bank debt usage being able to explain the predictive power behind the liquid asset ratios. Also, based on the descriptive statistics presented by Ippolito et al. (2018), bank-borrowers who do not use financial instruments to hedge against interest fluctuations – the subgroup for whom floating rate bank debt should matter most in explaining responses to monetary policy shocks – hold on average *more* liquid assets than hedging bank borrowers. However, because the very low variation of changes in fed funds futures rates around FOMC press releases after 2004Q1[26] does not allow to yield precise estimates of the effects of monetary policy shocks, such an analysis cannot yet conclusively rule out the relevance of the floating rate channel in explaining my findings.

Secondly, it may be the case that firms with fewer liquid assets are the ones which also rely more on short-term debt in financing their liquidity needs. The continuous rolling over of short-term debt could then expose these firms to more pronounced interest rate pass-through if long-term debt is at least partly issued at fixed interest rates. However, it is noteworthy that the cross-sectional correlation between the share of debt in current liabilities[27] in total debt and the liquid assets

[26] The standard deviation of the quarterly ε_t^m between 2004Q1–2007Q4 is 3.7bp. And during 2008Q1-2012Q2 the only non-negligible variation in futures prices around FOMC announcements occurred during the financial crisis.

[27] To be precise, this measure captures the sum of long-term debt due within one year plus short-term debt but

ratio is *positive*. A simple linear regression of a firm's ratio of debt in current liabilities to total debt on the firm's liquid assets ratio, while controlling for industry-quarter fixed effects yields a slope coefficient of 0.18 with a standard error of 0.01.[28]

Another potential explanation for the key findings is that firms with low liquid asset holdings are simply more likely to be financially constrained or close to violating their debt covenants. So when monetary policy tightens and lenders cut back on their supply of funds, a flight to quality mechanism is operative and increases the credit spreads of firms with less liquid assets relatively more. Even though most of the analysis in this paper is conducted controlling for firm size, the fact that size and liquid asset holdings are *negatively* correlated in the cross-section of firms weakens the idea that the liquid assets ratio is a good measure of the degree of financial constraints and access to sources of external finance, if one were to expect large firms to be relatively less financially constrained.

Based on simple descriptive observations, it is thus not necessarily easy to provide evidence of a clear mechanism that could explain the findings on liquid asset holdings predicting considerable heterogeneity in both capital accumulation and borrowing costs in response to monetary policy shocks. Existing macroeconomic models of firms and financial frictions often abstract from firms' liquidity management and the distinct nature of debt and financial assets on firm balance sheets, lumping them together into *net debt*. The explicit modelling of both equity and debt adjustment costs alongside firms' management of liquid and illiquid asset holdings thus seems beneficial in making progress on explaining monetary transmission to investment dynamics, which I plan to pursue in further work on this research agenda.

6 Conclusion

In this paper I have studied how the effect of structural monetary policy shocks on nonfinancial public firms in the U.S. differs conditional on their financial characteristics at the time of the shock. Impulse responses based on conventional vector autoregressions (VARs) with aggregate data suggest that the largest effects on the levels of aggregate economic activity arise over a relatively long horizon. I find that this is also the case for aggregate nonresidential fixed investment when included in a quarterly structural VAR alongside economic and financial variables, identified using instruments from high frequency data on fed funds futures prices around FOMC announcements. To target the main question of interest I employ firm-level data from Compustat and high frequency shock identification in a dynamic panel regression setting inspired by local projections along the lines of Jordà (2005). I find that both firms with higher leverage and lower liquid asset holdings at the time of a contractionary monetary shock tend to experience lower fixed capital, inventories and sales growth after the shock, with the largest disparities occurring about 8–12 quarters after. When controlling for the relevance of both leverage and liquid assets simultaneously, it is the latter that explains the differences in the cross-section of firms over this horizon. Furthermore,

not short-term debt instruments *per se*.

[28] Alternatively, one could regress the ratio of debt in current liabilities to total assets on the liquid assets ratio, and find a *negative* slope, which becomes positive once one also controls for leverage, i.e. the ratio of total debt to total assets, capturing the idea that liquid assets and leverage are negatively correlated in the cross-section.

lower liquid asset holdings predict more pronounced increases borrowing costs after contractionary monetary policy shocks, in line with the observed investment behavior.

It is important to emphasize that the analysis conducted so far does not allow to make definitive causal claims about the *effect* of leverage or liquidity on firms' performance after a monetary policy shock. In measuring a firm's liquidity, the cash-to-assets ratio considered in this paper is likely to suffer from endogeneity because firms which are financially constrained have often been found to preemptively hoard cash with the justification that they cannot access external sources of liquidity when it is needed (Bates et al. 2009). The fact that I find the liquid assets ratio to explain significant differences in firms' capital accumulation after monetary policy shocks even when allowing the responses to differ based on firms' size, possession of bond ratings and recent dividend payments – all commonly used proxies for financial constraints – gives credence to the view that extra liquidity might indeed allow firms to perform better in response to a contractionary shock. Also, simply the fact that the power of liquid asset holdings in predicting heterogeneous capital accumulation behavior across firms is considerably stronger than for leverage motivates the importance of studying firms' asset and liquidity management over and above their methods of financing.

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Appendix

A Additional Figures

A.1 Quintile Time Series

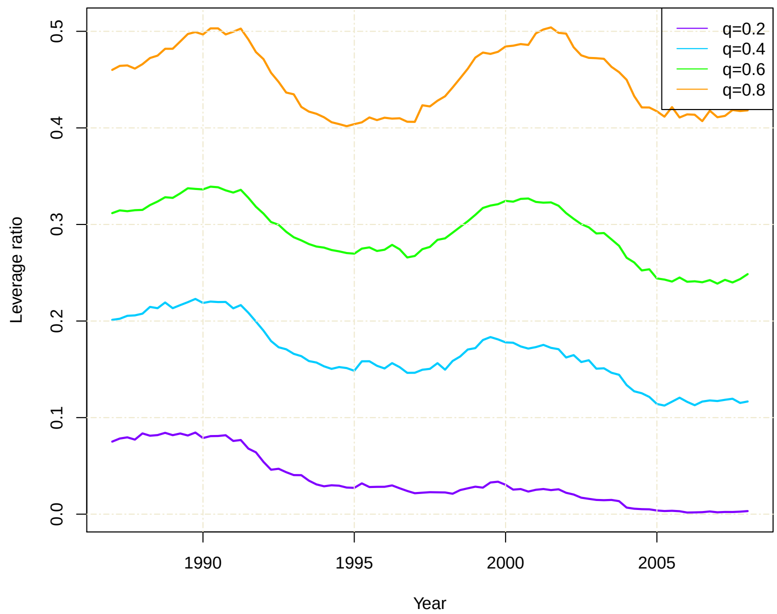


Figure 13: Leverage ratio quintiles, selected Compustat panel, 1986Q4–2007Q4

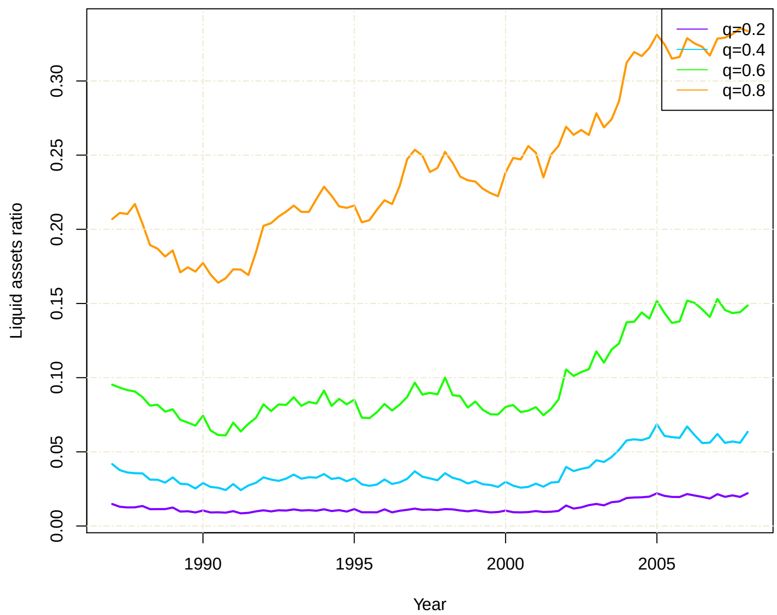


Figure 14: Liquid assets ratio quintiles, selected Compustat panel, 1986Q4–2007Q4

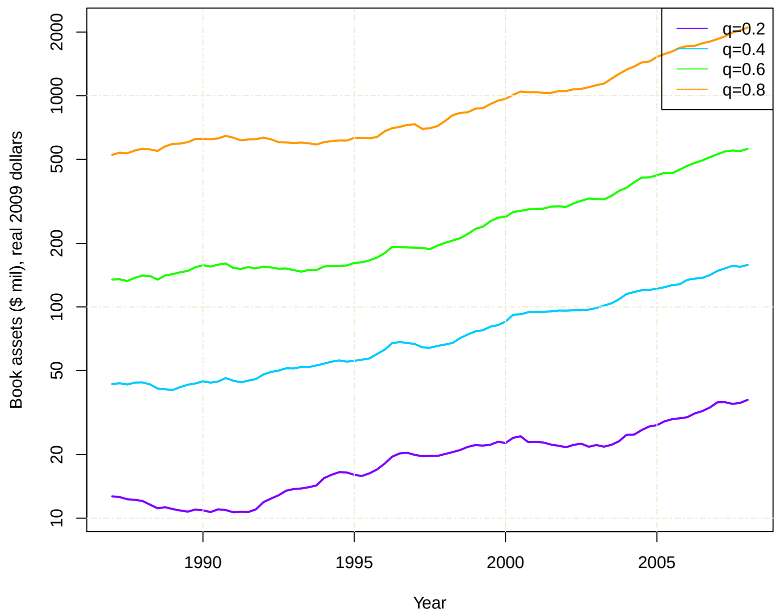


Figure 15: Book assets (in real 2009 $ millions) quintiles, log-scale, selected Compustat panel, 1986Q4–2007Q4

A.2 Aggregate SVAR in levels

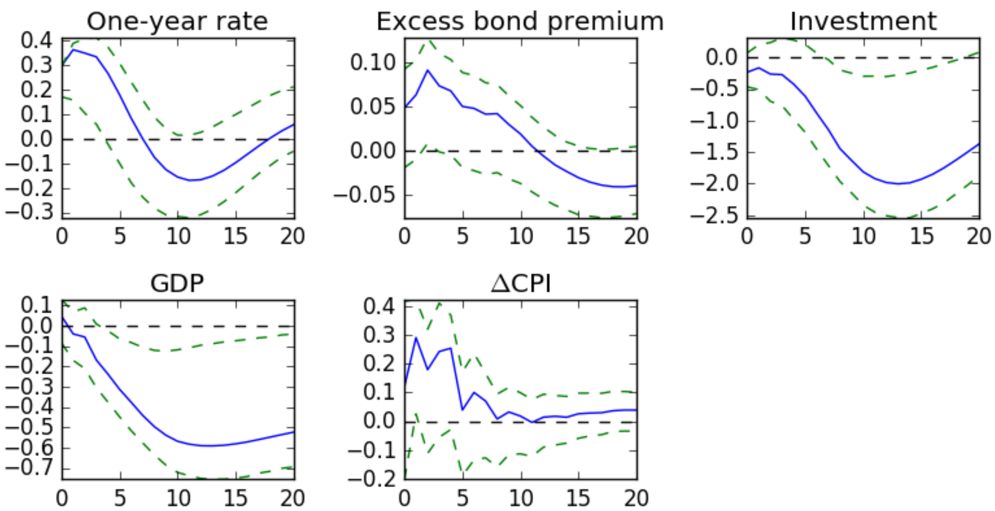


Figure 16: Aggregate impulse responses to 1 sd monetary policy shock from 5-variable VAR in levels

Notes: All in percentages; one-year rate, excess bond premium, and CPI growth annualized. Horizontal axis: quarters after monetary shock. 95% confidence intervals from wild bootstrap. log GDP and investment included in VAR estimation in levels. First stage regression: F: 12.27; R^2 14.9 percent; adjusted R^2: 13.7 percent

B Additional OLS Regression Estimates Figures

B.1 Fixed capital accumulation on leverage, no grouping

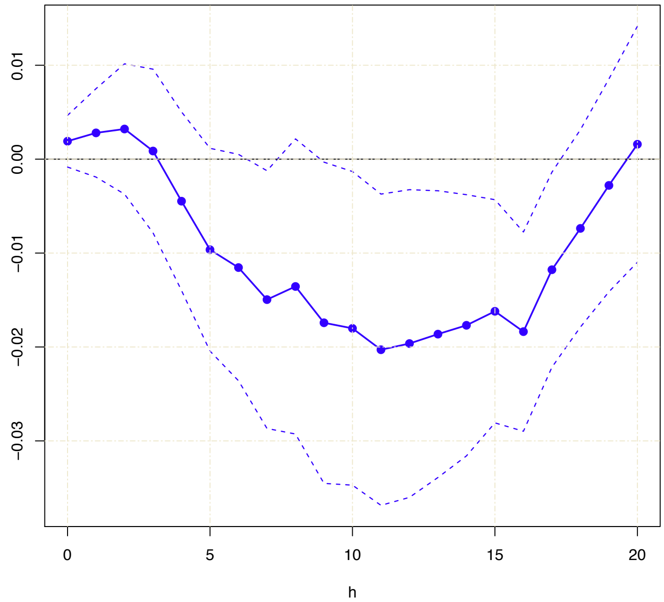


Figure 17: Heterogeneity in responses of capital accumulation conditional on leverage, without grouping based on financials

Notes: Point estimates and 95% confidence intervals for γ_h^x from estimating specification (2), with $x = lev$, $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Data also wisorized at 99% level with respect to leverage and liquid asset ratios by quarter.

B.2 Fixed capital accumulation on leverage, grouping based on quintiles

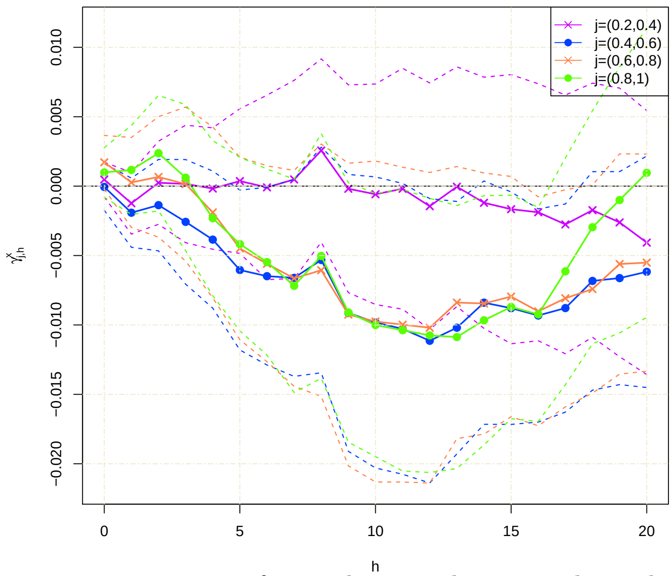


Figure 18: Heterogeneity in responses of capital accumulation conditional on leverage, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma_{j,h}^x$ from estimating specification (1), with $x = lev$, $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev\}$, $\mathbb{J}^{lev} = \{(0.2, 0.4), (0.4, 0.6), (0.6, 0.8), (0.8, 1.0)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

B.3 Inventories and sales on leverage

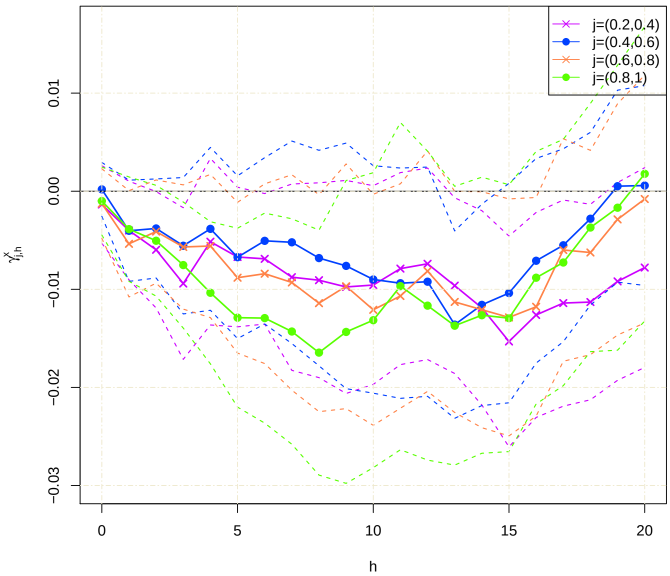


Figure 19: Heterogeneity in responses of inventory accumulation conditional on leverage, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $x = lev$, $y_{i,t} = \log(invt_{i,t})$, $\mathcal{X}^s = \{lev\}$, $\mathbb{J}^{lev} = \{(0.2, 0.4), (0.4, 0.6), (0.6, 0.8), (0.8, 1.0)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

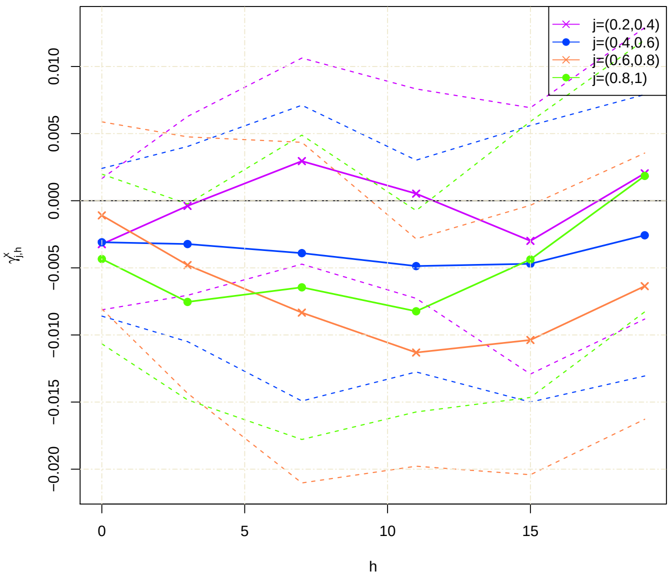


Figure 20: Heterogeneity in responses of sales conditional on leverage, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $x = lev$, $y_{i,t} = \log(sale_{i,t})$, $\mathcal{X}^s = \{lev\}$, $\mathbb{J}^{lev} = \{(0.2, 0.4), (0.4, 0.6), (0.6, 0.8), (0.8, 1.0)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

B.4 Fixed capital accumulation on liquid assets ratio, no grouping

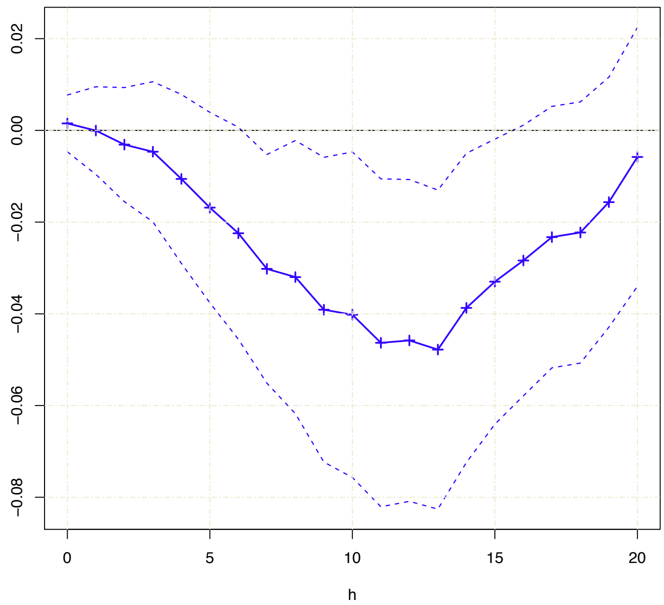


Figure 21: Heterogeneity in responses of capital accumulation conditional on liquid asset holdings, without grouping based on financials

Notes: Point estimates and 95% confidence intervals for γ_h^x from estimating specification (2), with $x = liq$, $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Data also wisorized at 99% level with respect to leverage and liquid asset ratios by quarter.

B.5 Fixed capital accumulation on liquid assets ratio, grouping based on quintiles

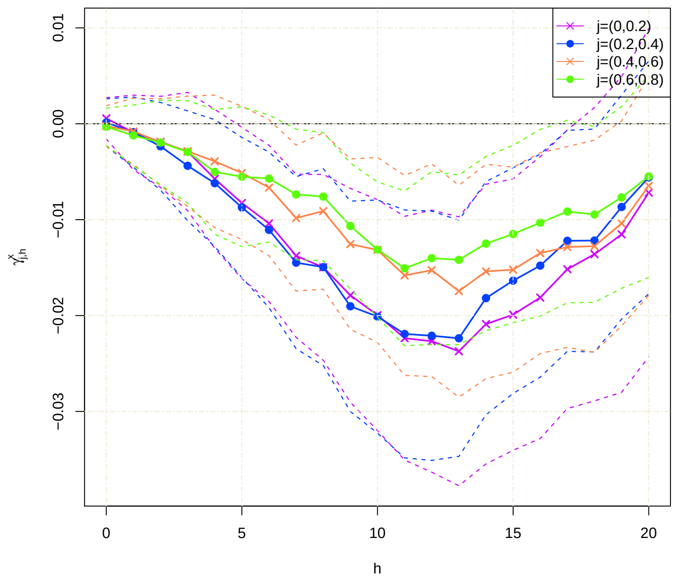


Figure 22: Heterogeneity in responses of capital accumulation conditional on liquid asset holdings, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma_{j,h}^x$ from estimating specification (1), with $x = liq$, $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{liq\}$, $\mathbb{J}^{liq} = \{(0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

B.6 Inventories and sales on liquid assets ratio

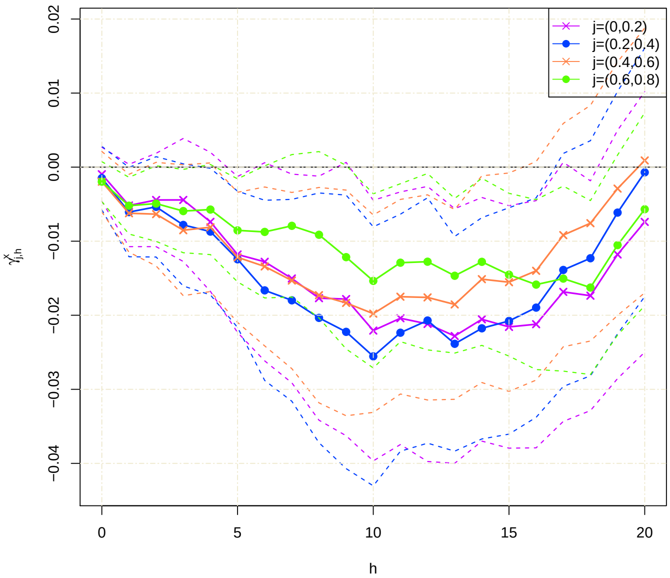


Figure 23: Heterogeneity in responses of inventory accumulation conditional on liquid asset holdings, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $x = liq$, $y_{i,t} = \log(invt_{i,t})$, $\mathcal{X}^s = \{liq\}$, $\mathbb{J}^{liq} = \{(0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

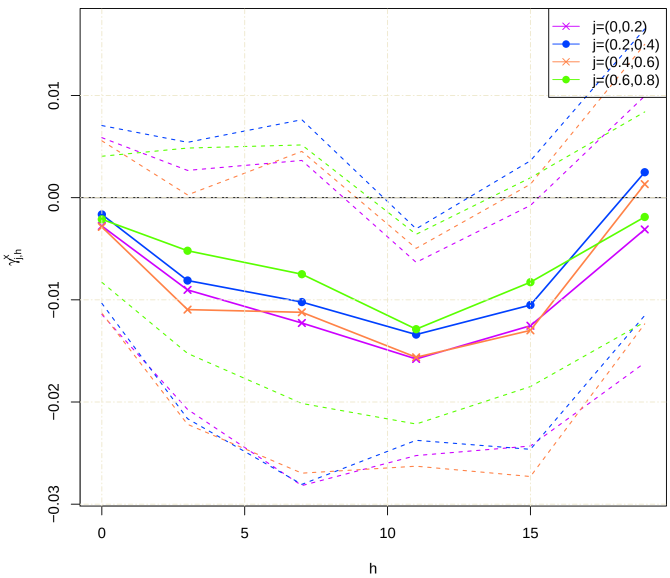
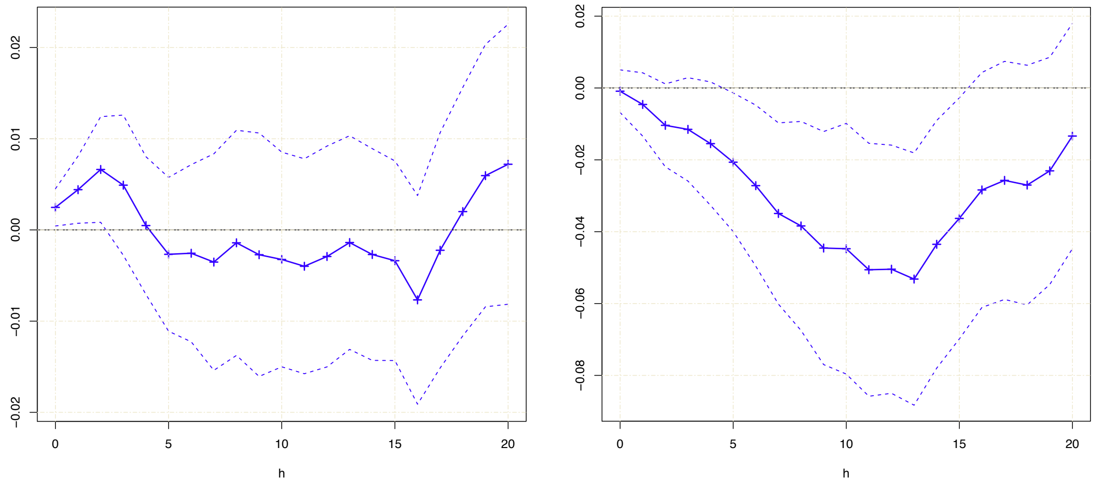


Figure 24: Heterogeneity in responses of sales conditional on liquid asset holdings, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $x = liq$, $y_{i,t} = \log(sale_{i,t})$, $\mathcal{X}^s = \{liq\}$, $\mathbb{J}^{liq} = \{(0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

B.7 Fixed capital accumulation, joint regression, no grouping

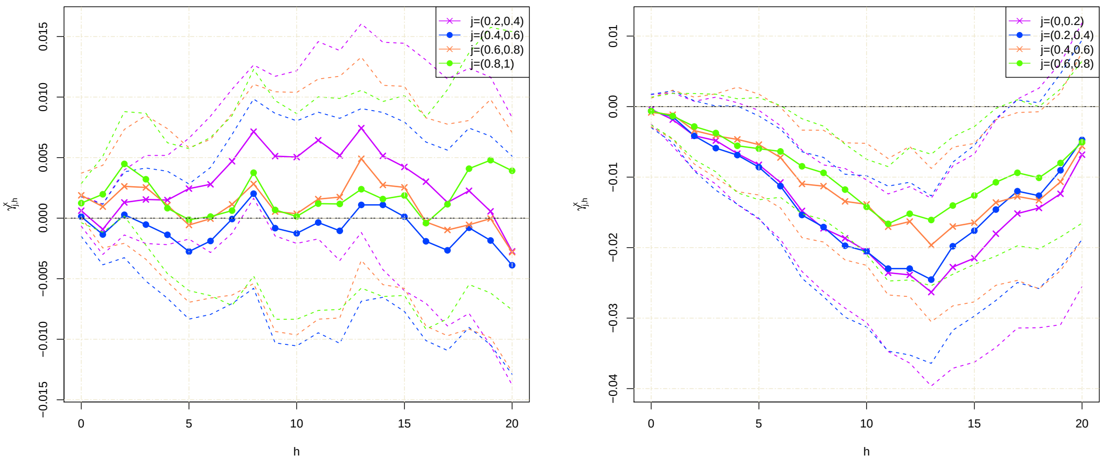


(a) x = leverage (b) x = –liquid assets ratio

Figure 25: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, without grouping based on financials

Notes: Point estimates and 95% confidence intervals for γ_h^x from estimating specification (2), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Data also wisorized at 99% level with respect to leverage and liquid asset ratios by quarter.

B.8 Fixed capital accumulation, joint regression, grouping based on quintiles

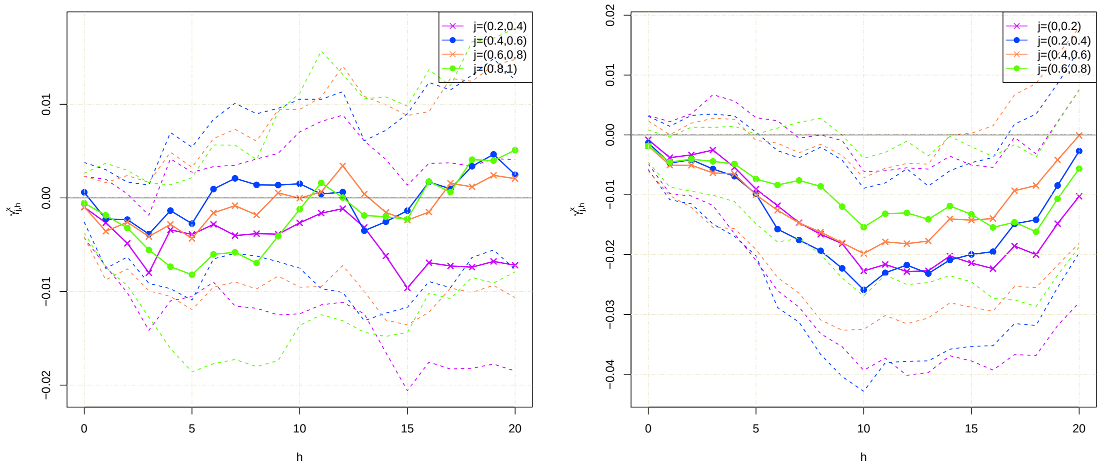


(a) x = leverage (b) x = liquid assets ratio

Figure 26: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma_{j,h}^x$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$, $\mathbb{J}^{lev} = \{(0.2, 0.4), (0.4, 0.6), (0.6, 0.8), (0.8, 1.0)\}$, $\mathbb{J}^{liq} = \{(0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

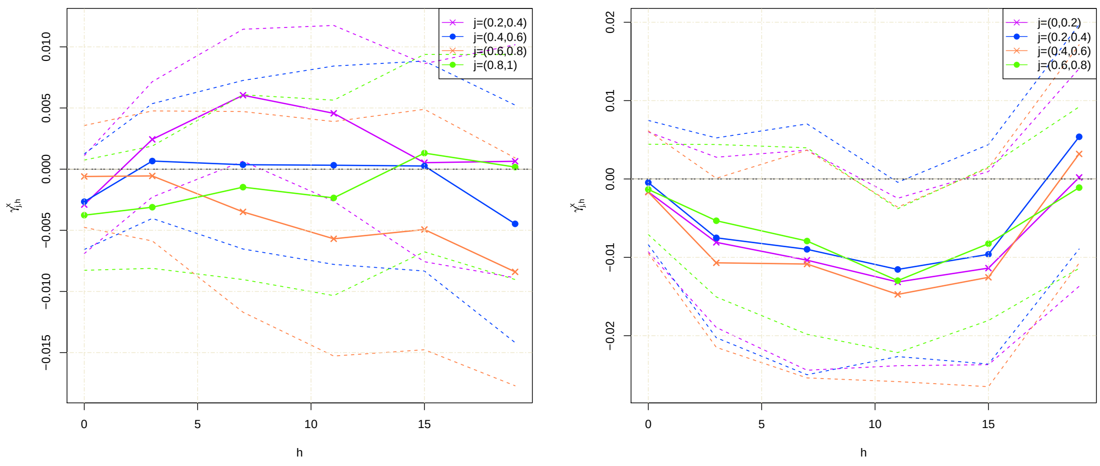
B.9 Inventories and sales, joint regression



(a) x = leverage (b) x = liquid assets ratio

Figure 27: Heterogeneity in responses of inventory accumulation conditional on leverage and liquid asset holdings in joint regression, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(invt_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$, $\mathbb{J}^{lev} = \{(0.2, 0.4), (0.4, 0.6), (0.6, 0.8), (0.8, 1.0)\}$, $\mathbb{J}^{liq} = \{(0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

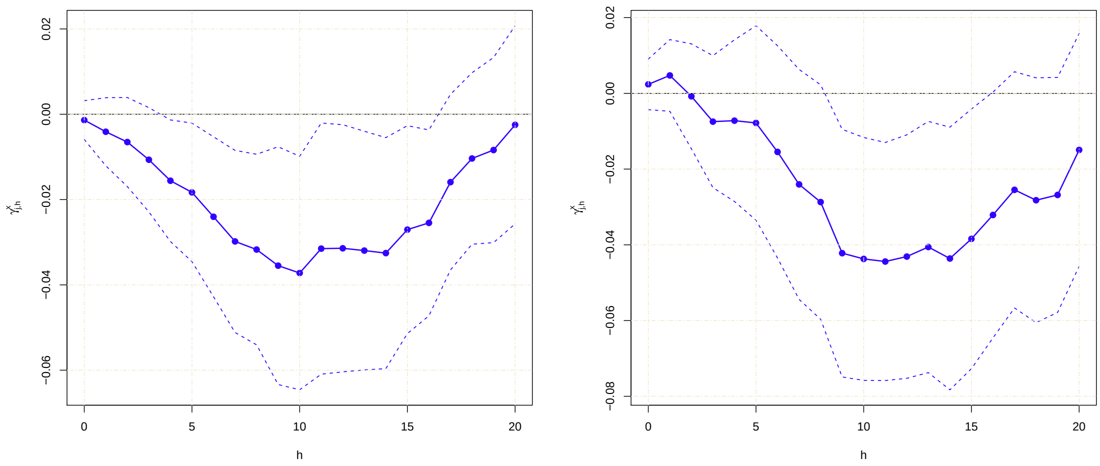


(a) x = leverage (b) x = liquid assets ratio

Figure 28: Heterogeneity in responses of sales conditional on leverage and liquid asset holdings in joint regression, grouping based on quintiles

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(sale_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$, $\mathbb{J}^{lev} = \{(0.2, 0.4), (0.4, 0.6), (0.6, 0.8), (0.8, 1.0)\}$, $\mathbb{J}^{liq} = \{(0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8)\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

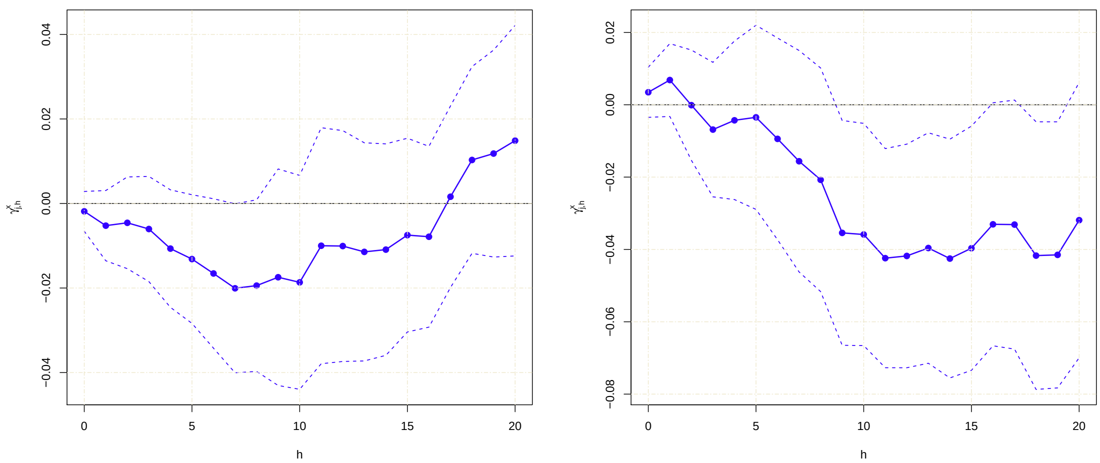
B.10 Fixed capital accumulation, no grouping, balanced sample



(a) x = leverage (b) x = -liquid assets ratio

Figure 29: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings, without grouping based on financials, balanced sample

Notes: Point estimates and 95% confidence intervals for γ_h^x from estimating specification (2), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{x\}$. Only including 630 firms which had no missing data during 1990Q1–2007Q4. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Data also wisorized at 99% level with respect to leverage and liquid asset ratios by quarter.

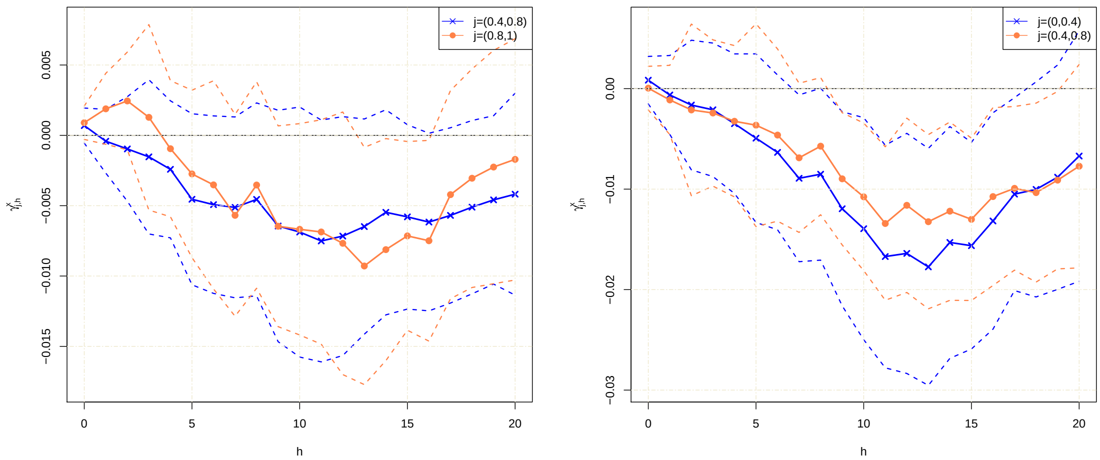


(a) x = leverage (b) x = -liquid assets ratio

Figure 30: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, without grouping based on financials, balanced sample

Notes: Point estimates and 95% confidence intervals for γ_h^x from estimating specification (2), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$. Only including 630 firms which had no missing data during 1990Q1–2007Q4. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Data also wisorized at 99% level with respect to leverage and liquid asset ratios by quarter.

B.11 Fixed capital accumulation, controlling for heterogeneous cyclicalities

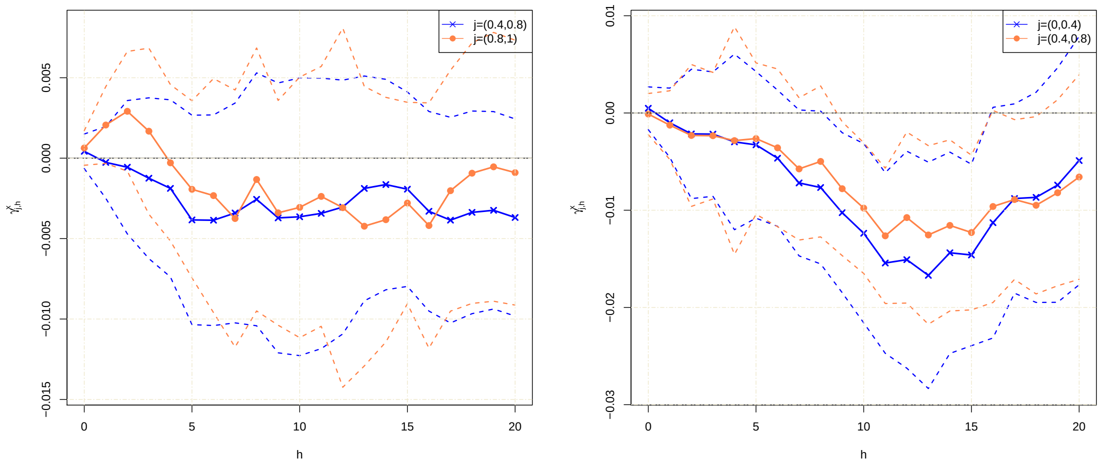


(a) x = leverage

(b) x = liquid assets ratio

Figure 31: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings, controlling for bond ratings and dividend payments

Notes: Point estimates and 95% confidence intervals for $\gamma^{x}_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{x\}$, and added terms $\sum_{x\in\mathcal{X}^s}\sum_{j\in\mathbb{J}^x}\mathbb{1}_{i\in\mathcal{I}^{x,j}_{t-1}}\left(\sum_{b=0}^{1}\delta^{x\prime}_{j,b,h}Y^a_{t-1-b}\right)$, with Y^a_t containing quarterly GDP growth and the Gilchrist and Zakrajšek (2012) excess bond premium. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.



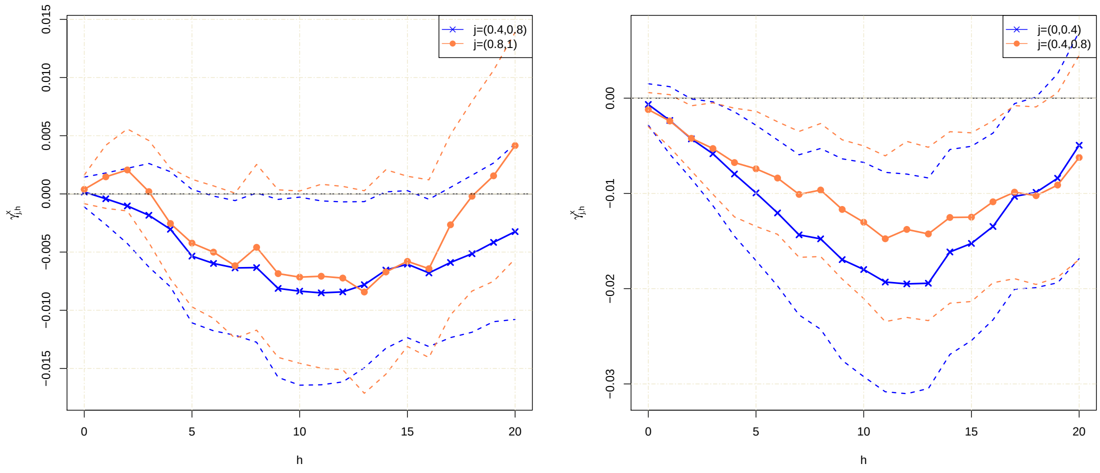
(a) x = leverage

(b) x = liquid assets ratio

Figure 32: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, controlling for bond ratings and dividend payments

Notes: Point estimates and 95% confidence intervals for $\gamma^{x}_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$, and added terms $\sum_{x\in\mathcal{X}^s}\sum_{j\in\mathbb{J}^x}\mathbb{1}_{i\in\mathcal{I}^{x,j}_{t-1}}\left(\sum_{b=0}^{1}\delta^{x\prime}_{j,b,h}Y^a_{t-1-b}\right)$, with Y^a_t containing quarterly GDP growth and the Gilchrist and Zakrajšek (2012) excess bond premium. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

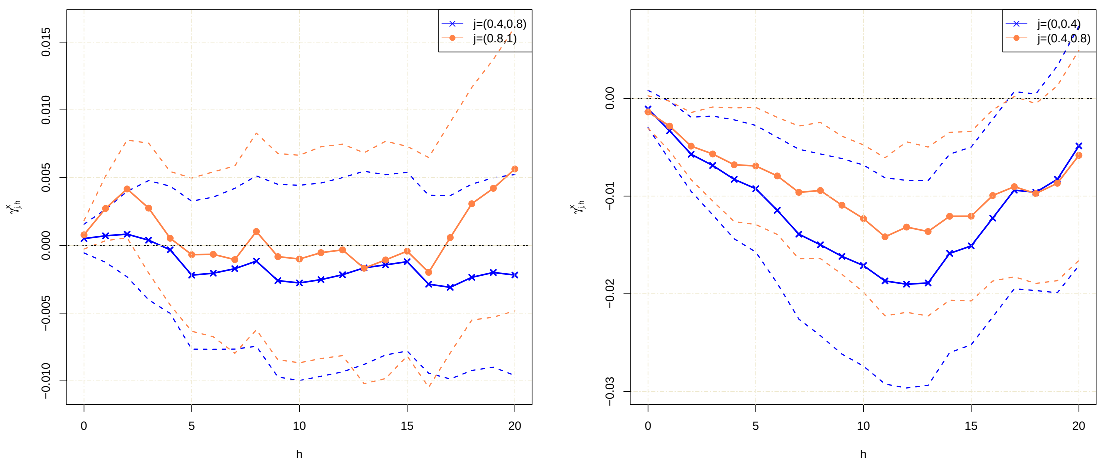
B.12 Fixed capital accumulation, controlling for Greenbook forecasts



(a) x = leverage (b) x = liquid assets ratio

Figure 33: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings, controlling for bond ratings and dividend payments

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{x\}$, and added terms $\sum_{x\in\mathcal{X}^s}\sum_{j\in\mathbb{J}^x}\mathbb{1}_{i\in\mathcal{I}^{x,j}_{t-1}}\left[\sum_{b=0}^{1}(\delta^{x,g}_{j,b,h}\tilde{g}^{t+b}_{t-1}+\delta^{x,\pi}_{j,b,h}\tilde{\pi}^{t+b}_{t-1})\right]$, with $\tilde{g}^{\tau}_t$ and $\tilde{\pi}^{\tau}_t$ denoting Greenbook forecasts of GDP growth and inflation in quarter τ, made in quarter t, respectively. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

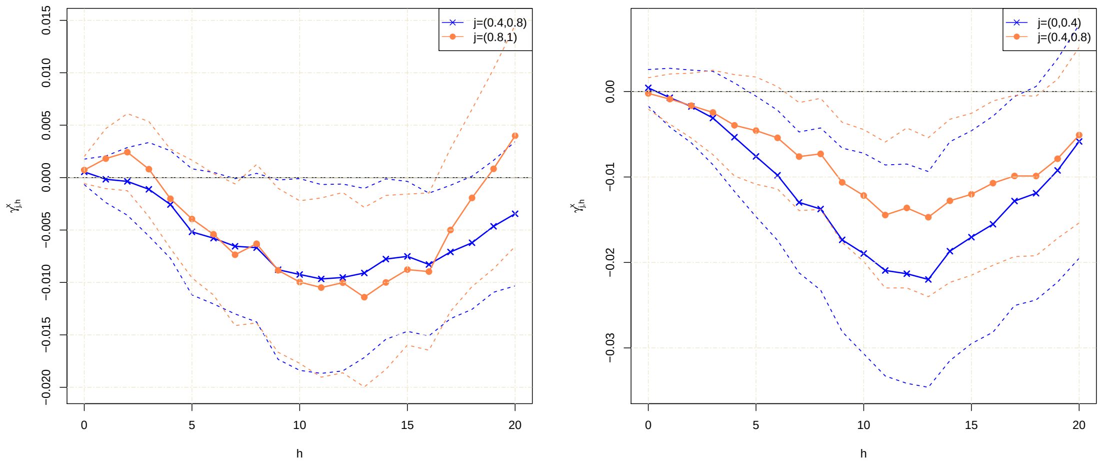


(a) x = leverage (b) x = liquid assets ratio

Figure 34: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, controlling for bond ratings and dividend payments

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$, and added terms $\sum_{x\in\mathcal{X}^s}\sum_{j\in\mathbb{J}^x}\mathbb{1}_{i\in\mathcal{I}^{x,j}_{t-1}}\left[\sum_{b=0}^{1}(\delta^{x,g}_{j,b,h}\tilde{g}^{t+b}_{t-1}+\delta^{x,\pi}_{j,b,h}\tilde{\pi}^{t+b}_{t-1})\right]$, with $\tilde{g}^{\tau}_t$ and $\tilde{\pi}^{\tau}_t$ denoting Greenbook forecasts of GDP growth and inflation in quarter τ, made in quarter t, respectively. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

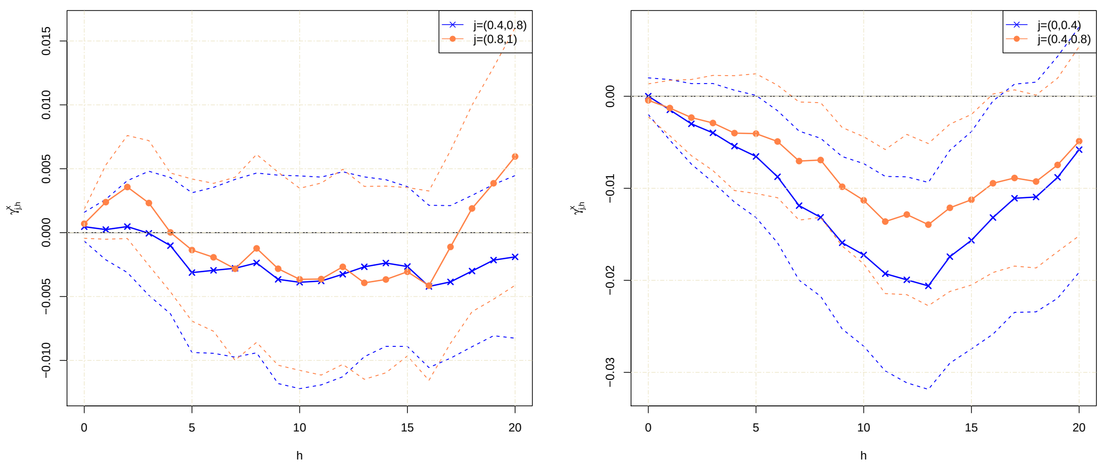
B.13 Fixed capital accumulation, controlling for bond ratings and dividend payments



(a) x = leverage (b) x = liquid assets ratio

Figure 35: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings, controlling for bond ratings and dividend payments

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{x\}$, and $Z_{i,t} = W_{i,t} = \left[\log(\text{size}_{i,t}), \mathbb{1}_{i\in\mathcal{I}^r_t}, \mathbb{1}_{\sum_{j=0}^{3} div_{i,t-j}>0}\right]'$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

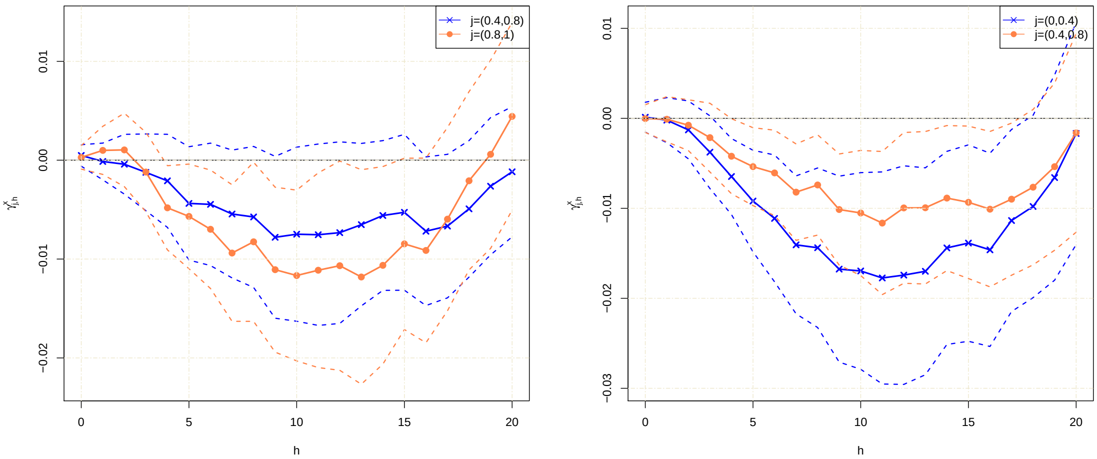


(a) x = leverage (b) x = liquid assets ratio

Figure 36: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, controlling for bond ratings and dividend payments

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$, and $Z_{i,t} = W_{i,t} = \left[\log(\text{size}_{i,t}), \mathbb{1}_{i\in\mathcal{I}^r_t}, \mathbb{1}_{\sum_{j=0}^{3} div_{i,t-j}>0}\right]'$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

B.14 Fixed capital accumulation, controlling for sales growth, cash flows, and market-to-book ratio

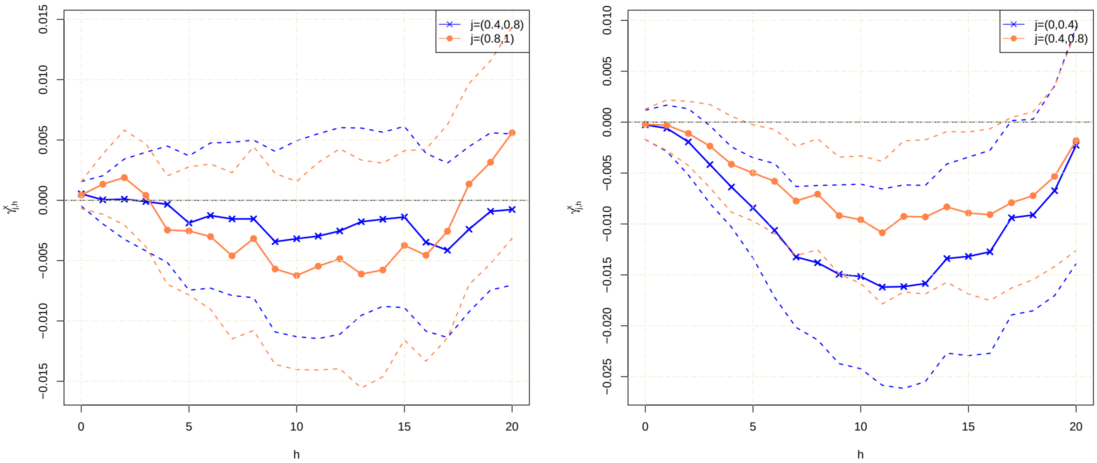


(a) x = leverage

(b) x = liquid assets ratio

Figure 37: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings, controlling for bond ratings and dividend payments

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{x\}$, and $Z_{i,t} = W_{i,t} = [\log(\text{size}_{i,t}), \Delta_3 \log(sale_{i,t}), c_{i,t}/\text{size}_{i,t}, q_{i,t}]'$, where $c_{i,t}$ are i's cash flows in t, computed as defined in Section 5; $q_{i,t}$ is i's market-to-book value ratio. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.



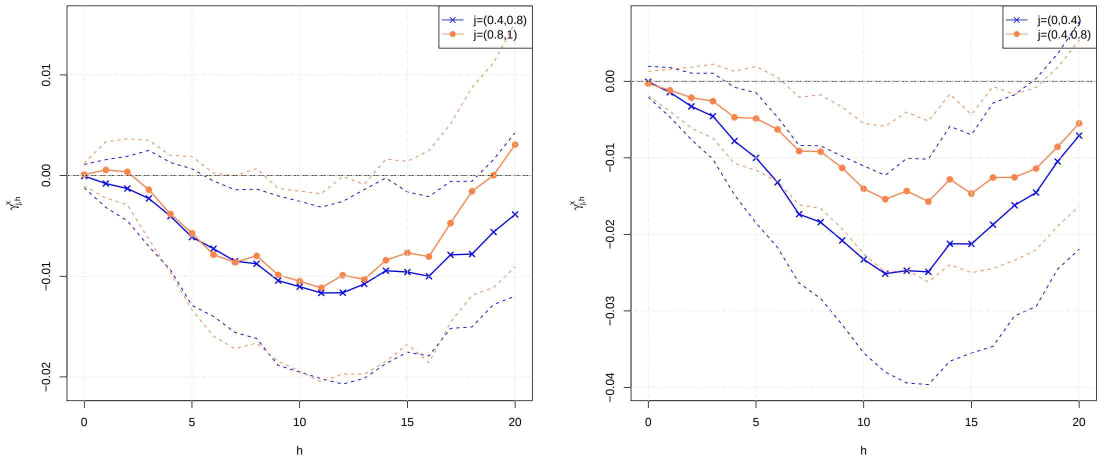
(a) x = leverage

(b) x = liquid assets ratio

Figure 38: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, controlling for yearly sales growth, cash flow to assets ratio, and market-to-book ratio

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$, and $Z_{i,t} = W_{i,t} = [\log(\text{size}_{i,t}), \Delta_3 \log(sale_{i,t}), c_{i,t}/\text{size}_{i,t}, q_{i,t}]'$, where $c_{i,t}$ are i's cash flows in t, computed as defined in Section 5; $q_{i,t}$ is i's market-to-book value ratio. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

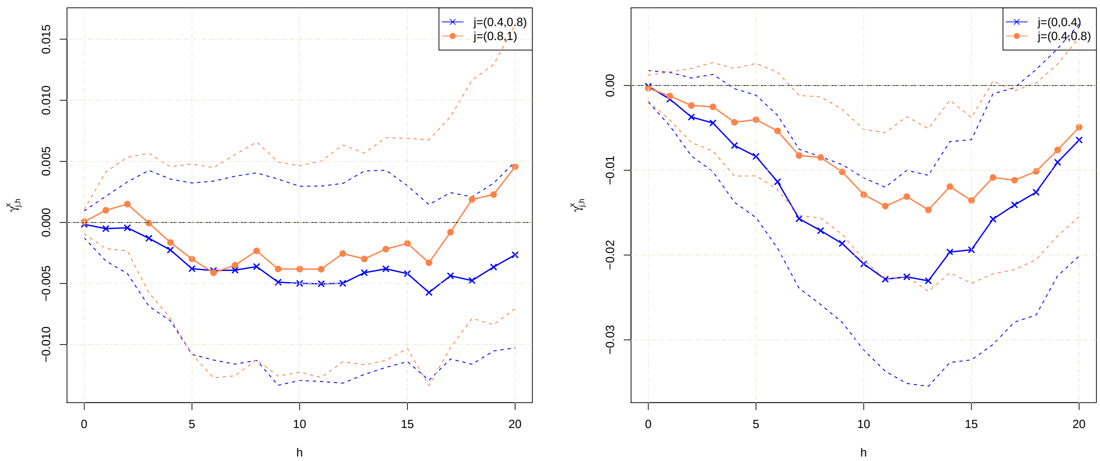
B.15 Fixed capital accumulation, 3m ahead fed funds futures shocks



(a) $x =$ leverage (b) $x =$ liquid assets ratio

Figure 39: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings, shocks based on 3m ahead fed funds futures

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{x\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Measures of monetary policy shocks ε^m_t constructed from unexpected changes in 3m ahead fed funds futures rates in 30 minute window around FOMC announcements.

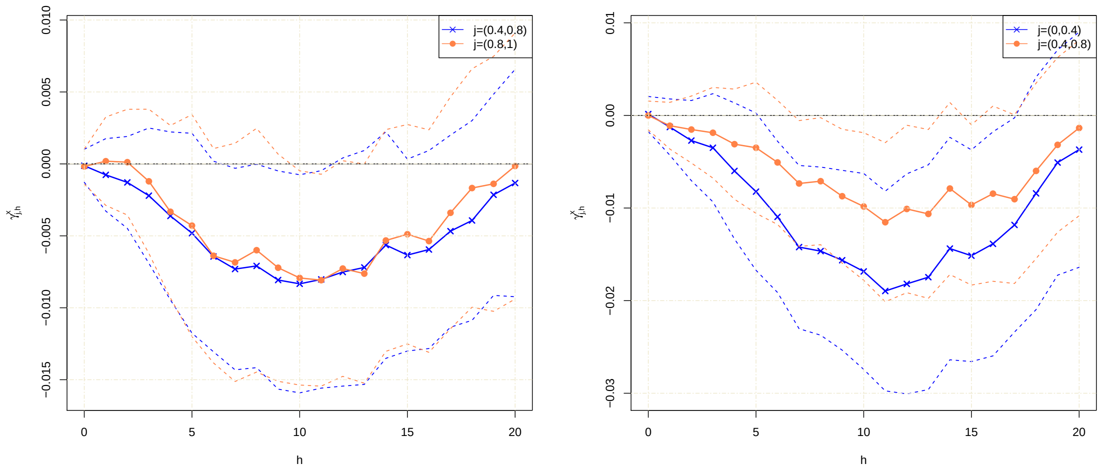


(a) $x =$ leverage (b) $x =$ liquid assets ratio

Figure 40: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, shocks based on 3m ahead fed funds futures

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Measures of monetary policy shocks ε^m_t constructed from unexpected changes in 3m ahead fed funds futures rates in 30 minute window around FOMC announcements.

B.16 Fixed capital accumulation, 3m ahead fed funds futures shocks, 1990Q1–2012Q2 (2015Q4)

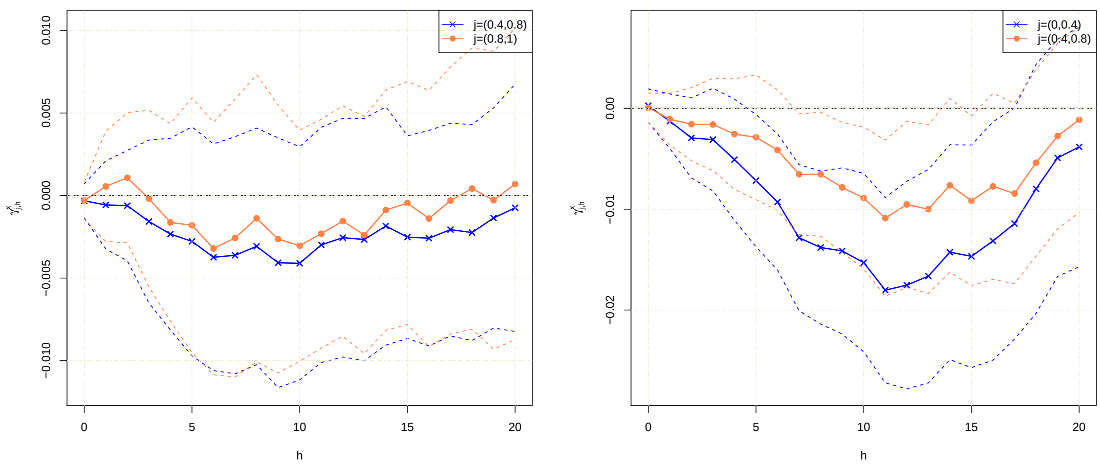


(a) x = leverage

(b) x = liquid assets ratio

Figure 41: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings, shocks based on 3m ahead fed funds futures, long sample

Notes: Point estimates and 95% confidence intervals for $\gamma^{x}_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{x\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Measures of monetary policy shocks ε^m_t constructed from unexpected changes in 3m ahead fed funds futures rates in 30 minute window around FOMC announcements. Data on ε^m_t for sample 1990Q1–2012Q2, firm-level data for 1990Q1–2015Q4.



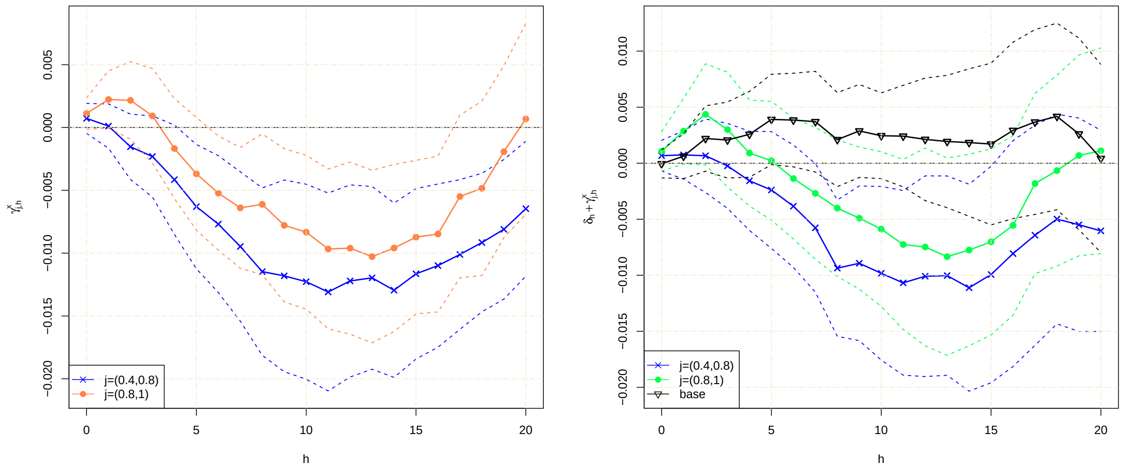
(a) x = leverage

(b) x = liquid assets ratio

Figure 42: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint regression, shocks based on 3m ahead fed funds futures, long sample

Notes: Point estimates and 95% confidence intervals for $\gamma^{x}_{j,h}$ from estimating specification (1), with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Measures of monetary policy shocks ε^m_t constructed from unexpected changes in 3m ahead fed funds futures rates in 30 minute window around FOMC announcements. Data on ε^m_t for sample 1990Q1–2012Q2, firm-level data for 1990Q1–2015Q4.

B.17 Level effects: Fixed capital accumulation on leverage



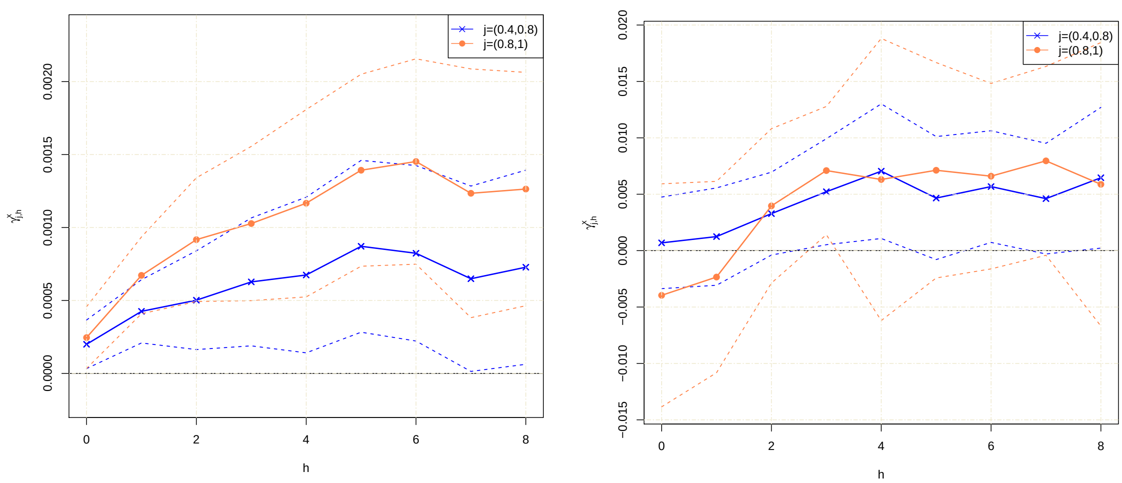
(a) $\gamma_{j,h}^{lev}$ (b) δ_h and $\delta_h + \gamma_{j,h}^{lev}$

Figure 43: Heterogeneity and absolute responses of capital accumulation conditional on leverage
Notes: Panel (a): Point estimates and 95% confidence intervals for $\gamma_{j,h}^{liq}$. Panel (b): Point estimates and 95% confidence intervals for δ_h (black solid line) and $\delta_h + \gamma_{j,h}^{liq}$ (blue solid line). All estimates from estimating

$$\Delta_h \log(k_{i,t+h}) = f_{i,h} + \delta_h \varepsilon_t^m + \Gamma_h' Y_{t-1}^a + \Theta_h' W_{i,t-1} + \sum_{j\in\mathbb{J}^{lev}} \left(\beta_{j,h}^{lev} + \gamma_{j,h}^{lev}\varepsilon_t^m\right) \times \mathbb{1}_{i\in\tilde{\mathcal{I}}_{t-1}^{lev,j}} + u_{i,t+h}$$

Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Firms grouped into bins based on the total capital held by firms in each bin.

B.18 Interest expenses on leverage

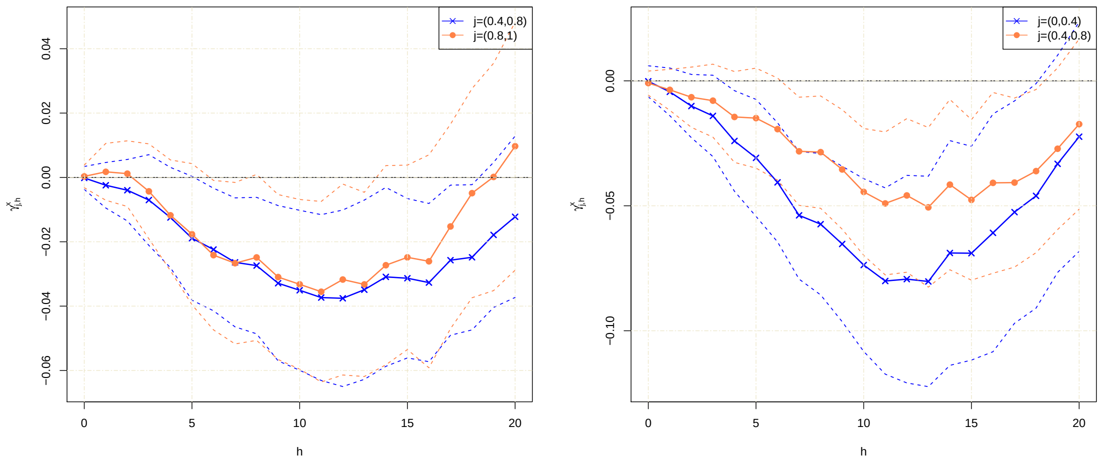


(a) $\gamma_{j,h}^{lev}$, with $y_{i,t} = \left(\frac{\bar{r}_{i,t} d_{i,t-1}}{k_{i,t-1}}\right)$ (b) $\gamma_{j,h}^{lev}$, with $y_{i,t} = \rho_{i,t}$

Figure 44: Heterogeneity in responses of interest expenses conditional on leverage
Notes: Point estimates and 95% confidence intervals for $\gamma_{j,h}^{lev}$ in (1), with $\mathcal{X}^s = \{lev\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels.

C Additional IV Regression Estimates Figures

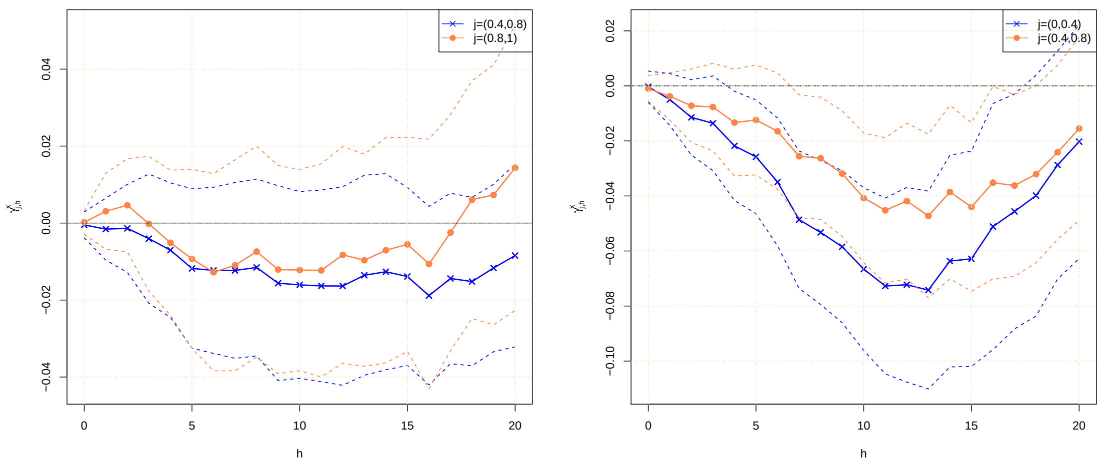
C.1 Fixed capital accumulation, 3m ahead fed funds futures shocks



(a) x = leverage (b) x = liquid assets ratio

Figure 45: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in separate IV regressions, instruments based on 3m ahead fed funds futures

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (3) using 2SLS and ε^m_t as instruments for Δr_t, with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{x\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Instruments ε^m_t constructed from unexpected changes in 3m ahead fed funds futures rates in 30 minute window around FOMC announcements. Δr_t is the quarterly change in the one-year Treasury rate.



(a) x = leverage (b) x = liquid assets ratio

Figure 46: Heterogeneity in responses of capital accumulation conditional on leverage and liquid asset holdings in joint IV regression, instruments based on 3m ahead fed funds futures

Notes: Point estimates and 95% confidence intervals for $\gamma^x_{j,h}$ from estimating specification (3) using 2SLS and ε^m_t as instruments for Δr_t, with $y_{i,t} = \log(k_{i,t})$, $\mathcal{X}^s = \{lev, liq\}$. Confidence intervals constructed based on two-way clustered standard errors at firm and quarter levels. Instruments ε^m_t constructed from unexpected changes in 3m ahead fed funds futures rates in 30 minute window around FOMC announcements. Δr_t is the quarterly change in the one-year Treasury rate.

D OLS Regression Tables for Baseline Specification

D.1 Fixed capital accumulation on leverage

Table 2: Coefficient estimates of baseline OLS regression specification (4), with $y_{i,t} = \log(k_{i,t})$, x =leverage

	Dependent variable:				
	$\Delta_h \log(k_{i,t+h})$				
	$h = 0$	$h = 4$	$h = 8$	$h = 12$	$h = 16$
$\beta^x_{(0.4,0.8),h}$	-0.013^{***}	-0.067^{***}	-0.103^{***}	-0.119^{***}	-0.122^{***}
	(0.001)	(0.005)	(0.008)	(0.010)	(0.012)
$\beta^x_{(0.8,1),h}$	-0.025^{***}	-0.130^{***}	-0.205^{***}	-0.231^{***}	-0.229^{***}
	(0.001)	(0.008)	(0.013)	(0.016)	(0.019)
$\gamma^x_{(0.4,0.8),h}$	0.001	-0.003	-0.007^{**}	-0.010^{**}	-0.008^{**}
	(0.001)	(0.002)	(0.003)	(0.004)	(0.003)
$\gamma^x_{(0.8,1),h}$	0.001	-0.002	-0.006	-0.009^{**}	-0.007^{*}
	(0.001)	(0.002)	(0.004)	(0.004)	(0.004)
Observations	154,694	140,659	127,313	114,610	102,413
R^2	0.118	0.231	0.336	0.442	0.548
Adjusted R^2	0.098	0.212	0.318	0.425	0.533

Notes: *p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the firm and quarter level in parentheses

D.2 Fixed capital accumulation on liquid assets ratio

Table 3: Coefficient estimates of baseline OLS regression specification (4), with $y_{i,t} = \log(k_{i,t})$, x =liquid assets ratio

	Dependent variable:				
	$\Delta_h \log(k_{i,t+h})$				
	$h = 0$	$h = 4$	$h = 8$	$h = 12$	$h = 16$
$\beta^x_{(0,0.4),h}$	-0.029^{***}	-0.144^{***}	-0.218^{***}	-0.256^{***}	-0.268^{***}
	(0.002)	(0.008)	(0.014)	(0.018)	(0.020)
$\beta^x_{(0.4,0.8),h}$	-0.019^{***}	-0.091^{***}	-0.134^{***}	-0.165^{***}	-0.181^{***}
	(0.001)	(0.007)	(0.011)	(0.015)	(0.017)
$\gamma^x_{(0,0.4),h}$	0.0004	-0.006^{*}	-0.015^{***}	-0.022^{***}	-0.016^{**}
	(0.001)	(0.003)	(0.005)	(0.006)	(0.006)
$\gamma^x_{(0.4,0.8),h}$	-0.0003	-0.005	-0.009^{**}	-0.015^{***}	-0.012^{**}
	(0.001)	(0.003)	(0.003)	(0.005)	(0.005)
Observations	154,694	140,659	127,313	114,610	102,413
R^2	0.119	0.233	0.337	0.444	0.550
Adjusted R^2	0.100	0.214	0.319	0.427	0.535

Notes: *p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the firm and quarter level in parentheses

E Heuristic justification for the IV regression specification

Let us follow Stock and Watson (2018), and suppose that the dynamics of the aggregate variables in the macroeconomy, represented by a vector Y_t of macroeconomic variables with length n_Y, have a linear structure and are driven by a collection of structural shocks ε_t, a vector of length n_ε. The path of the observed Y_t can be thought of as arising as a linear combination of current and past ε_t:

$$Y_t = \Theta(L)\varepsilon_t \tag{10}$$

where L is the lag operator and $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \ldots$, where Θ_s is an $n_Y \times n_\varepsilon$ coefficient matrix. I am assuming that Y_t has been transformed so that it is stationary. Note that in the general case, the vector ε_t may also contain measurement errors and $n_\varepsilon > n_Y$ is possible.[29]

The vector ε_t contains the structural monetary policy shock ε_t^p, the effect of which on the economy we would like to assess. Let us suppose that ε_t^p is ordered as the first element in ε_t. Note that the scale of the structural shocks is indeterminate. That is, (10) holds if the j-th component $\varepsilon_{j,t}$ is replaced with $c\varepsilon_{j,t}$ and the j-th column of $\Theta_s, \forall s \geq 0$ is divided by c. Stock and Watson (2018) propose to normalize the scale of the shock of interest by assuming that a unit increase in ε_t^p increases some specific variable $Y_{j,t}$ in Y_t by one unit.[30] Given that a monetary policy shock should affect the federal funds rate, it is natural to assume that this $Y_{j,t}$ is the fed funds rate r_t, for example.[31] If we order the fed funds rate as the first variable in Y_t, this implies the normalization $\Theta_{0,11} = 1$, i.e. that the top left element of Θ_0 has a value of unity.

With this normalization, the can rewrite the first row of (10) as:

$$r_t = \varepsilon_t^p + \{\varepsilon_{\bullet,t}, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\} \tag{11}$$

where, directly following Stock and Watson (2018), I am using the notation $\varepsilon_{\bullet,t} \equiv [\varepsilon_{2,t}, \ldots, \varepsilon_{n_\varepsilon,t}]'$ and $\{\ldots\}$ to denote linear combinations of the terms in braces. Or alternatively,

$$\Delta r_t = \varepsilon_t^p + \{\varepsilon_{\bullet,t}, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\} \tag{12}$$

The usefulness in considering *differences* stems from the fact that ε_t^m is a highly more suitable instrument for Δr_t than for r_t.

Now, suppose one wanted to estimate a panel regression such as (1) and include the *actual* structural monetary policy shock ε_t^p, i.e. estimate

$$\begin{aligned}\Delta_h y_{i,t+h} =& f_{i,h} + d_{n,h,t+h} + \Theta_h' W_{i,t-1} + \Omega_h' Z_{i,t-1}\varepsilon_t^p + \\ &+ \sum_{x\in\mathcal{X}^s}\sum_{j\in\mathbb{J}^x}\left(\beta_{j,h}^x + \gamma_{j,h}^x\varepsilon_t^p\right) \times \mathbb{1}_{i\in\mathcal{I}_{t-1}^{x,j}} + u_{i,t+h}\end{aligned}$$

[29] If we define $\Sigma_\varepsilon \equiv \mathbb{E}[\varepsilon_t\varepsilon_t']$ and order structural shocks before measurement errors, then Σ_ε is block-diagonal, with the block corresponding to the structural shocks diagonal and the block corresponding to the measurement errors positive definite.

[30] Note that this normalization is different from the one used in the structural VAR of Section 4.1 following Gertler and Karadi (2015), where $\mathbb{E}[\varepsilon_t\varepsilon_t'] = \mathbb{I}$ imposes that each structural shock has a standard deviation of 1.

[31] Alternatively, one could use the one-year Treasury rate instead of the fed funds rate, in which case the structural monetary policy shock is defined as one which moves the government rate by one unit.

where $u_{i,t+h}$ is a function of firm-level structural shocks up to time $t+h$, and the time-dummy $d_{n,h,t+h}$ captures any aggregate and industry-level structural shocks up to time $t+h$.

One can then use (12) to substitute out ε_t^p and get

$$\begin{aligned}\Delta_h y_{i,t+h} =& f_{i,h} + d_{n,h,t+h} + \Theta_h' W_{i,t-1} + \Omega_h' Z_{i,t-1} \Delta r_t + \\ &+ \sum_{x \in \mathcal{X}^s} \sum_{j \in \mathbb{J}^x} \left(\beta_{j,h}^x + \gamma_{j,h}^x \Delta r_t\right) \times \mathbb{1}_{i \in \mathcal{I}_{t-1}^{x,j}} + \tilde{u}_{i,t+h} \\ \text{where} \quad \tilde{u}_{i,t+h} = & u_{i,t+h} + \left[\Omega_h' Z_{i,t-1} + \sum_{x \in \mathcal{X}^s} \sum_{j \in \mathbb{J}^x} \gamma_{j,h}^x \times \mathbb{1}_{i \in \mathcal{I}_{t-1}^{x,j}}\right] \times \{\varepsilon_{\bullet,t}, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\}\end{aligned}$$

which is exactly the specification set up in (3). Given that the ε_t^m constructed in Section 2 are correlated with ε_t^p and thus Δr_t, and are uncorrelated with $\tilde{u}_{i,t+h}$, this implies that (3) can be estimated by two stage least squares, using ε_t^m as an instrument for Δr_t.[32] Note also that it is because of Δr_t being correlated with $\{\varepsilon_{\bullet,t}, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\}$ that simple OLS does not work.

[32] More specifically, note that ε_t^m is uncorrelated with $\{\varepsilon_{\bullet,t}, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\}$, $Z_{i,t-1}$, and $\mathbb{1}_{i \in \mathcal{I}_{t-1}^{x,j}}$ since all of the latter are functions of shocks realized prior to t. Therefore, for some $z \in \left\{Z_{i,t-1}, \left\{\mathbb{1}_{i \in \mathcal{I}_{t-1}^{x,j}}\right\}_{x \in \mathcal{X}^s, j \in \mathbb{J}^x}\right\}$ and any v among the terms in $\{\varepsilon_{\bullet,t}, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\}$, we have that

$$\mathbb{E}\left[\left(\varepsilon_t^m z\right)(vz)\right] = \mathbb{E}\left[\underbrace{\mathbb{E}[\varepsilon_t^m v | z]}_{=0} z^2\right] = 0 \tag{13}$$

And therefore, $Z_{i,t-1}\varepsilon_t^m$ and $\left\{\mathbb{1}_{i \in \mathcal{I}_{t-1}^{x,j}} \varepsilon_t^m\right\}_{x \in \mathcal{X}^s, j \in \mathbb{J}^x}$ are valid instruments for $Z_{i,t-1}\Delta r_t$ and $\left\{\mathbb{1}_{i \in \mathcal{I}_{t-1}^{x,j}} \Delta r_t\right\}_{x \in \mathcal{X}^s, j \in \mathbb{J}^x}$.