DEPARTMENT OF ECONOMICS

Monetary Policy with Firm Heterogeneity

Özgen Öztürk

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

Florence, 17 May 2023

European University Institute
Department of Economics

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Examining Board

Prof. Russell Cooper, EUI, Supervisor
Prof. Árpád Ábrahám, University of Bristol, Co-Supervisor
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I, Özgen Öztürk, certify that I am the author of the work *Monetary Policy with Firm Heterogeneity* I have presented for examination for the Ph.D. at the European University Institute. I also certify that this is solely my own original work, other than where I have clearly indicated, in this declaration and in the thesis, that it is the work of others.

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I confirm that chapter 2 was jointly co-authored with Russell Cooper and I contributed 50% of the work. Chapter 2 draws upon an earlier article that was published as a working paper in the National Bureau of Economic Research, Working Paper Series.
I confirm that chapter 3 was jointly co-authored with Thomas Walsh and I contributed 50% of the work.

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Abstract

This thesis is composed of three essays, and studies how monetary policy transmission is shaped by firm heterogeneity with particular focus on investment, borrowing, and pricing decisions.

In the first chapter, **Debt Contracts, Investment and Monetary Policy**, I study the role of debt contracts on the transmission of monetary policy to firm-level investment and borrowing. Empirically, using information from a detailed loan-level data matched with balance sheet data and stock return data, I document that in response to a contractionary monetary shock, asset-based borrowers –firms with more pledgeable assets, and higher beta– experience sharper contraction in borrowing and investment than cash flow-based borrowers –firms with higher profitability and alpha. To explore the possible channels and provide microfoundation for the coexistence of these debt contracts, I setup a heterogeneous firm New Keynesian model with limited enforceability. The quantitative model suggests that the traditional collateral channel explains this heterogeneous sensitivity as the cash flow based borrowers are less susceptible to collateral damage from changes in asset prices. Results indicate debt contract type affects the severity of financial frictions and also shapes the monetary policy transmission.

The second chapter, **TFPR: Dispersion and Cyclicality**, coauthored with Russell Cooper, studies the determinants of TFPR, a revenue based measure of total factor productivity. Recent business cycle models are built upon the assumption of countercyclical dispersion in TFPQ, a quantity based measure of total factor productivity, based on evidence of countercyclical dispersion in TFPR. But, these can be very different measures of productivity. The distribution of TFPR is endogenous, dependent upon exogenous shocks and the endogenous determination of prices. An overlapping generations model with monopolistic competition and state dependent pricing is constructed to study the factors that shape the TFPR distribution. The empirical focus is on three key data patterns: (*i*) countercyclical dispersion of TFPR, (*ii*) countercyclical dispersion of price changes and (*iii*) countercyclical frequency of price adjustment. The analysis uncovers two interesting scenarios in which

these moments are matched. One arises in the presence of shocks to the dispersion of TFPQ along with a negatively correlated change in the mean of TFPQ. The second arises if the monetary authority responds to shocks to the dispersion of TFPQ by “leaning against the wind". Due to state contingent pricing, the model is nonlinear. Simple correlations mask these nonlinearities of the underlying economy. The real effects of monetary innovations are state dependent, with monetary policy less effective in recessions.

In the third chapter, **Sectoral Volatility and the Investment Channel of Monetary Policy**, written jointly with Thomas Walsh, we investigate how the dispersion of firm-level shocks affect the investment channel of monetary policy. Using firm-level panel data, we construct several measures of dispersion of productivity shocks, time-pooled and time-varying, and interact high-frequency identified monetary policy shocks with these measures of idiosyncratic shock volatility. We document a novel fact: monetary policy has dampened real effects via the investment channel when firm-level TFP shock volatility is high. Our estimates for dampening effects of volatility are statistically and economically significant - moving from the tenth to the ninetieth percentile of the volatility distribution approximately halves point estimates of impulse response functions to contractionary monetary policy shocks. Given that dispersion rises in recessions, these findings offer further evidence as to why monetary policy is weaker in recessions, and emphasize the importance of firm heterogeneity in monetary policy transmission.

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Özgen Öztürk
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Contents

Chapter 1

Debt Contracts, Investment, and Monetary Policy

Abstract This paper studies the effect of asset-based versus cash flow-based debt contracts on the transmission of monetary policy to firm-level investment and borrowing. Using information from detailed loan-level data matched with balance sheet data and stock return data, I document that in response to a contractionary monetary shock, asset-based borrowers experience sharper contractions in borrowing and investment than cash flow-based borrowers. Despite the fact that asset-based borrowers contribute only 15% to aggregate investment, they are responsible for 64% of the total investment *response*. To understand the channels and provide a microfoundation for the endogenous choice of these debt contracts, I set up a heterogeneous firm New Keynesian model with limited enforceability. The quantitative model shows that the traditional collateral channel explains this heterogeneous sensitivity as cash flow-based borrowers are less susceptible to collateral damage from changes in asset prices. This result indicates that the prevalence of asset-based debt contracts increases the strength of the financial accelerator channel and thereby shapes monetary policy transmission.

1.1 Introduction

How does the nature of debt contracts affect the monetary policy transmission to firm-level investment? Using information from detailed loan-level data matched with firm-level balance sheet and stock return data, I document that in response to a contractionary monetary shock, firms with asset-based contracts experience a sharper contraction in investment and borrowing than firms with cash flow-based contracts. I explain this finding by means of a heterogeneous firm model where firms optimally choose their contract type while asset-based borrowing constraints tighten more than cash-flow based constraints after an increase in the policy interest rate.

My focus on the composition of borrower contracts for the transmission of monetary policy is motivated by recent evidence and theory stressing two points. First, in contrast to the conventional, asset-based centered approach in the macrofinance literature, in the data, cash-flow based contracts are more prevalent than asset-based contracts.[1] In fact, around 80% of US corporate debt agreements reference a cash flow measure in determining the borrowing limit (Lian and Ma, 2021). Second, cash flow-based borrowing constraints respond to aggregate shocks differently from asset-based borrowing constraints.[2] The novelty of my approach is to endogenise the firm's choice of contract. In particular, I first empirically show that this choice is endogenous to the stance of monetary policy, then build a model in which firms may switch contract type when asset-based ones become too tight, thereby further weakening the collateral channel of monetary transmission.

The dataset I use in the empirical analyses is the first one to merge loan-level data from DealScan, firm-level balance sheet data from Compustat, and stock return data from CRSP.[3] Using this merged dataset, I first show that firms with higher asset pledgeability ratios (ratio of tangible assets to total assets) and stock beta (more volatile stock return) tend to choose asset-based debt contracts.[4] On the other hand, cash flow-based borrowers tend to have larger profitability as measured by higher Jensen's alpha and EBITDA.[5] However, there is no meaningful difference in terms of loan characteristics (*i.e.* credit spread and maturity) between asset-based and cash flow-based loans.

The second set of empirical findings provides evidence on how firms' investment and borrowing sensitivity to monetary policy shocks depend on their debt contract form. Using high frequency identified monetary policy shocks, I estimate impulse responses of investment and borrowing with local projections method à la Jordà (2005).Three main findings

[1]The financial accelerator literature emphasizes how monetary policy affects the value of asset stock and net worth, which have indirect consequences on the borrowing capacity of firms, which in turn affects their ability to make investments (Kiyotaki and Moore, 1997; Bernanke, Gertler, and Gilchrist, 1999).

[2]Drechsel (2018) shows that a positive investment shock increases investment, boosts aggregate demand and income while lowering the relative cost of capital. Therefore, higher income causes looser borrowing constraints under earnings-based formulation. On the contrary, the lower relative value of capital tightens the borrowing limits under the collateral constraint.

[3]See Section 1.2.3 for the detailed exposition of the dataset and how it compares to Lian and Ma (2021).

[4]To enrich the statistics by two additional stock return measures, I use CRSP stock return data and run a single factor CAPM-type regression with 36-month rolling window. Analysts and investors widely use the Capital Asset Pricing Model (CAPM), which yields two fundamental stock features. *i*) **Stock beta:** the correlation between market and stock volatility (captured by the slope term), *ii*) **Jensen's alpha:** the performance of stock compared to the market (captured by the intercept term). See Appendix A.2.1 for detailed discussion.

[5]EBITDA is a widely used measure of corporate cash flow and stands for **E**arnings **B**efore **I**nterest, **T**axes, **D**epreciation, and **A**mortization.

arise from this exercise. First, conditional on a rich set of firm-level and aggregate control variables, an unexpected interest rate increase causes asset-based borrowers to cut their investment two-times more than cash flow-based borrowers. The gap in the investment response between the two groups lasts up to five years following the shock and indicates wide differences in capital accumulation. Second, in terms of borrowing response, firms with asset-based contracts are approximately four-times more responsive. Third, a small fraction of firms with asset-based contracts switch to cash flow-based contracts, implying that a contractionary monetary shock may more negatively impact asset-based contracts.

Regarding aggregate implications, despite constituting only 15% of the total investment within the sample period, 64% percent of the total investment *response* to monetary policy shocks is initiated by asset-based borrowers. For the total borrowing response, the result is more stunning: 79% of the borrowing response comes from asset-based borrowers.

To explain these empirical patterns and investigate the relevance of the collateral channel in driving the heterogeneous sensitivity and the aggregate implications for the financial accelerator mechanism, I incorporate the cash flow-based borrowing constraints into a macrofinance model consisting of heterogeneous firms, limited debt enforcement, and nominal price rigidity. By employing the model, first, I investigate the relevance of the collateral channel in the heterogeneous transmission of monetary policy shocks. Second, I conduct a counterfactual experiment to demonstrate how this heterogeneous sensitivity implies that the strength of financial accelerator may diminish as more firms in the economy hold cash flow-based contracts.

In the model, firms endogenously choose whether to borrow with an asset-based or cash flow-based contract in each period. I introduce this mechanism by incorporating state contingent borrowing limits resulting from limited debt enforcement. *Ex post*, firms can renege on their promise to repay, thus breaching their contracts. *Ex ante*, by perfectly foreseeing the outcomes, the financial intermediary sets state contingent borrowing limits for both contract types and thus ensures that firms repay in every state of tomorrow. To achieve this, the financial intermediary determines the borrowing limits based upon the incentive compatibility conditions, which require that the value of repayment must be greater than the value of default in all possible states of tomorrow.[6] Typically, the consequences of a contract breach and thus, the value of default depends on the underlying contract.[7] With asset-based contracts, firms lose the pledged portion of their capital stock when they default, which makes the associated borrowing limit a direct function of the

[6]This approach makes borrowing constraints endogenous. As a contribution to the recent growing literature about debt covenants, this paper attempts to provide a microfoundation for the implied borrowing limits of debt contracts.

[7]See Section 1.2.2 and Appendix A.5 for further details.

capital price. Under cash flow-based contracts, lenders have claims against the firm entity. Therefore, the debt limit is dictated by the firm's value, approximated as a multiple of its cash flow.[8] In both contracts, limited enforceability of loan contracts directly maps into the firm's *ex ante* borrowing capacity. Finally, firms select the optimal contract in each period by observing the state-dependent debt limits.

The model is calibrated to match key moments of firm-level investment and borrowing observed in the micro data. To analyze the model's predictions while matching the empirical strategy, I estimate a variant of local projections specification on the simulated data. The model matches the observed empirical patterns and exhibits that firms with asset-based contracts reduce their investment and borrowing more than cash flow-based borrowers. These model-produced impulse responses of investment, output, and consumption at their peak are in line with Christiano, Eichenbaum, and Evans (2005), which can be interpreted as non-targeted empirical moments.

After verifying that the model performs well in terms of targeted (cross-sectional) and non-targeted (magnitude of impulse responses) moments, I analyze how capital price fluctuations drive the differences in responses among asset-based and cash flow-based borrowers by shutting down the asset price channel. When the asset price channel is shut down, the differential response of investment (borrowing) is dampened by 54% (48%).

I also conduct a counterfactual experiment comparing the baseline economy's aggregate investment and borrowing response with three alternative economies. When both types of contracts are available in the economy but the capital price is fixed, the investment (borrowing) response is 28% (41%) lower than the baseline case. When only asset-based contracts are available in the economy (and the capital price is responsive), investment and borrowing responses are larger in magnitude, 35% and 53%, respectively. Finally, the responses are remarkably smaller in an economy with only cash flow-based contracts. These findings suggest that the financial accelerator mechanism is effective, and its strength is tied to the collateral channel and may diminish as more firms in the economy hold cash flow-based contracts. This exercise implies that monetary policy is less effective in the states/countries where cash flow-based contracts are more prevalent.

Finally, I analyze whether the heterogeneous responsiveness among asset-based and cash flow-based occurs only under conventional monetary policy tools or holds for quantitative tightening (QT) as well. To do so, I run the local projections regression in a similar fashion to the baseline empirical framework. The findings about QT policy resemble the conventional contractionary monetary policy as the magnitude of the impulse responses of investment and borrowing among asset-based borrowers is higher than cash flow-based

[8]See Section 1.2.2 for details.

borrowers.[9]

Related Literature. This paper contributes to several strands of the literature. The first strand is the large body of work that studies the role of financial frictions in the transmission of interest rate changes to the economy. Bernanke et al. (1999) introduces the financial accelerator mechanism, and Kiyotaki and Moore (1997) studies the business cycle implications of the collateral channel. I contribute to this literature by evaluating the relative strength of financial accelerator mechanism through asset-based and cash flow-based contract types.

Second, I contribute to the literature that studies the characterization of optimal dynamic financial contracts under various forms of friction. Remarkable examples include implications on conflicting objectives Albuquerque and Hopenhayn (2004), technological innovations on output Cooley, Marimon, and Quadrini (2004), asset pricing (Biais, Mariotti, Plantin, and Rochet, 2007), Q-theory of investment (DeMarzo, Fishman, He, and Wang, 2012; Cao, Lorenzoni, and Walentin, 2019). This paper contributes to this literature branch by providing a rationale for the coexistence of asset-based and cash flow-based debt contracts.

Third, there is a relatively new strand of literature about debt covenants. Lian and Ma (2021) empirically presents that debt covenants are often written as cash flow-based. Sharing similar findings, Drechsel (2023) develops a representative firm New Keynesian model to study the role of borrowing constraints on the transmission of investment shocks. Greenwald (2019) focuses on an environment in which only earnings-based covenants exist and reveals the state dependence of the effectiveness of monetary policy shocks. I contribute to this literature by deriving these borrowing limits from first principles instead of imposing *ad hoc* functional forms, thus endogenising the contract choice.

In spirit, this paper is closely related to the literature body that investigates the heterogeneous sensitivity to monetary policy shocks. The balance sheet liquidity (Jeenas, 2018), age/dividend status (Cloyne, Ferreira, Froemel, and Surico, 2018), leverage/credit spread (Anderson and Cesa-Bianchi, 2020), distance to default (Ottonello and Winberry, 2020), and debt maturity (Jungherr, Meier, Reinelt, and Schott, 2022). I contribute to this literature by focusing on the role of debt contracts, particularly the formulation of borrowing constraints. The results presented in this paper should not be seen as a contradiction to the above-mentioned studies; instead, as a complementary study that focuses on debt contract heterogeneity.

[9]In Appendix A.4, motivated by the empirical evidence about heterogeneous QT transmission, I conduct a QT experiment with the quantitative model. The results suggest that the key mechanism works through the heterogeneous responses of borrowing constraints.

Finally, this paper borrows key insights from the corporate finance literature, focusing on the implications of debt covenants. Prominent examples include Chava and Roberts (2008), Nini, Smith, and Sufi (2009), Roberts and Sufi (2009a), Roberts and Sufi (2009b), Nini, Smith, and Sufi (2012), and Chodorow-Reich and Falato (2017). This paper contributes to this literature by employing a heterogeneous firm model to investigate how debt covenants affect monetary policy transmission.

Road Map. The rest of the paper is organized as follows. Section 1.2 explains the data used in this paper and presents empirical specifications along with the results. Section 1.3 develops the heterogeneous firm model and discusses selected equilibrium properties. Section 1.4 explains the calibration strategy. Section 1.5 covers the role of firm characteristics in selecting the debt contract type. Section 1.6 discusses that firms' heterogeneous sensitivity to monetary policy shocks depends on the contract type and further elaborates that heterogeneity in the responsiveness is associated with the collateral channel. Section 1.7 concludes.

1.2 Empirical Framework

In this section, I discuss the datasets and the empirical strategy employed in the paper. To the best of my knowledge, the final dataset I use in the empirical analyses is the first one that merges loan-level data from DealScan, firm-level balance sheet data from Compustat, and stock return data from CRSP.[10] The underlying reason for bringing together these datasets is twofold. First, to investigate which firm characteristics are at play in debt contract choice, and second, to clearly identify which firm can be classified as asset-based or cash flow-based. Throughout, in Section 1.2.1, I discuss the methodology of identifying the monetary policy surprises. In Section 1.2.2, I briefly describe the loan level DealScan dataset, then elaborate on the relevance of the debt contracts concept from the macroeconomics perspective. In Section 1.2.3, I discuss Compustat, a firm-level balance sheet and income statement dataset, and present cross sectional features of asset-based and cash flow-based borrowers. In Section 1.2.4, I document that compared to the asset-based borrowers, cash flow-based borrowers are less sensitive to monetary policy shocks.

[10]To be clear, Lian and Ma (2021) utilizes a larger dataset by combining DealScan, Compustat, and FISD, along with the hand-collected data from 10-K filings; however, their focus is on the classification of loans into the asset-based and cash flow-based categories. This paper instead focuses on *i*) utilizing Compustat in a more comprehensive way to understand how monetary policy transmits to the firm level-investment and borrowing through the different types of borrowing constraints; *ii*) using CRSP data to bring in the novel stock return implications – profitability and volatility– on the debt contract choice, beyond usual proxies such as age, size, or leverage.

1.2.1 Identification of Monetary Policy Shocks

As well documented by researchers, identifying the unanticipated portion of monetary policy changes requires overcoming the bilateral interaction between the federal funds rate and the aggregate economy. An extensive literature strand utilizes the asset price fluctuations around Federal Open Market Committee (FOMC) announcements to extract its unanticipated component.[11]

Monetary policy shocks are identified by using high-frequency financial market movements that arise around the press releases of Federal Open Market Committee (FOMC).[12] To obtain the monetary policy shocks, Gürkaynak et al. (2005) and Gorodnichenko and Weber (2016), I utilize the change in the implied fed funds rate –obtained from a fed funds futures contract– in a 30-minute window encompassing the issuance of FOMC press release. There are two identifying assumptions: (*i*) Fed funds futures provide a good proxy for the market's expectation for the interest rates, (*ii*) 30-minute window is so narrow that any other factor does not contaminate the market's expectations.

I construct the shock as below.

$$\varrho_{\tau_j} = \text{ffr}_{\tau+\Delta_+} - \text{ffr}_{\tau-\Delta_-} \tag{1.1}$$

where τ is the exact time of FOMC press releases. ffr is the current month fed funds futures rates (at time τ), Δ_- is defined as 10 minutes before the FOMC announcement and Δ_+ is 20 minutes after the FOMC announcement.

Since FOMC meetings are held 8 times a year, the frequency of monetary policy shock is higher than quarterly. Therefore, to obtain quarterly monetary policy shock, ε_t^m, I aggregate the high-frequency measures of the shocks. Process involves summing ϱ_{τ_j} up within quarter t, as presented below:

$$\varepsilon_t^m \equiv \sum_{\tau_j \in (\tau_{j,1}, \tau_{j,2})} \varrho_{\tau_j} \tag{1.2}$$

where $\tau_{j,1}$ and $\tau_{j,2}$ exact dates of the beginning and the ending of quarter t, and τ_j corresponds to the date at which FOMC press release is issued.

Given the fact that ε_t^m is only a proxy for the purely unanticipated quarterly monetary policy shocks ε_t, relatively recent literature indicates that this measure of interest rate surprises are still contaminated because shocks still include signals about the determinants

[11]Using event study based approach to extract monetary policy shocks builds on the influential studies of Kuttner (2001) Cochrane and Piazzesi (2002),Bernanke and Kuttner (2005), Gürkaynak, Sack, and Swanson (2005) and goes back to Cook and Hahn (1989).

[12]I obtain information on the exact timing of FOMC press releases, and implied shock measures from Gorodnichenko and Weber (2016).

of monetary policy (Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2018; Jarociński and Karadi, 2020). These studies state that within each monetary policy shock extracted à la Gürkaynak et al. (2005), the monetary component should be disentangled from another contemporaneous non-monetary component. Therefore, as a robustness exercise, to check if my results are significantly affected by the non-monetary component of the monetary policy shock, I use Nakamura and Steinsson (2018) shocks. The results are less pronounced but qualitatively persist. Details are provided in Section A.1.6.

1.2.2 Loan-level Debt Information

In this section, I explain the data I use for loan-level information and briefly describe the debt contracts and their relevant features to the macroeconomics literature. Specifically, I collect the contract data from the DealScan database and, using the linking file of Chava and Roberts (2008), merge it with Compustat.[13] Although DealScan goes back to older dates, following Greenwald (2019), the sample starts in 1997Q1 since before this date covenant variable in DealScan is sparsely populated. The sample ends in 2017Q3, which is dictated by the most recent version of Chava and Roberts (2008)'s linking file (April, 2018).

In what follows, I provide some background information on debt contracts and discuss how the borrowing method translates into different forms of borrowing constraints. The main variables of interest are the indicator variables for having cash flow-based or asset-based debt contracts. The details about classification procedure is discussed in Appendix A.1.2.

Asset-based Contracts. In these contracts, the borrowing limit is mainly dictated by the liquidation value of the pledged assets. Pledgeable assets could be physical (e.g., machinery, inventory, building *etc.*) as well as suitable intangible assets such as usage rights, patents, etc. The lending procedure is as follows. Before granting the amount requested, lenders employ analysts to appraise the liquidation value of the pledged assets by conducting on-site field examinations and simulating various liquidation scenarios. Then, lenders set a borrowing limit by using their discretion in setting the borrowing limit. During the agreement's lifetime, lenders keep conducting field exams quarterly and update the liquidation value estimates accordingly. Therefore, the borrowing limit is a dynamic object, and its enforcement rule utilizes the most recent estimate.

[13] Details of the merging procedure are presented in the Appendix A.1.4

Given the above procedure, asset-based contract's *ad hoc* contractual borrowing constraint takes the form

$$b' \leq \theta q k \tag{1.3}$$

where θ is the borrowing base, q is the appraised price of capital, and k is the pledged asset stock. Asset-based contracts are the traditional treatment in the classic macrofinance models (Kiyotaki and Moore, 1997).

Cash flow-based Contracts. In cash flow-based contracts, the debt limit is determined by the cash flow generated by the firm's ongoing activities. This is due to the fact that under cash flow-based debt contracts, lenders have claims against the firm entity and have the right to take over the firm's management. A significant share of cash flows based contracts belongs to syndicated loans. Therefore the lending procedure is shaped by loan syndication practice (Lian and Ma, 2021). With cash flow-based contracts, the process is as follows. When the requested loan amount exceeds a single lender's targeted risk exposure level, a consortium of lenders is formed, and they cooperate in providing the money requested. Forming a consortium mitigates the risk undertaken by each lender, as the associated risks are shared between group members. To coordinate the operation, one of the lenders in the consortium takes the lead financial institution role and carries out all the necessary procedures throughout the duration of the loan, such as initial transactions, corresponding fees, and repayments. This leader bank is also responsible for due diligence, monitoring the firm's compliance, and reporting to member banks.

A solitary loan agreement covers the entire lending process. However, depending on each lender's individual condition, terms could vary for each lender. Each bank is liable for its portion of the total loan. The loan amount undertaken by each lender, loan maturity, and collateral requirements could differ for each lender. If more than one of the lenders requires collateral, then the consortium leader assigns different assets of the borrowing firm for each lender.

In cash flow-based contracts, as the lenders have claims against the company entity, the debt limit is calculated via the firm's going-concern cash flow value. However, due to contractibility issues, lenders calculate a firm's going concern cash flow value by taking the multiples of the firm's operating earnings.[14] Due to its verifiability, borrowing limits are calculated based on a cash flow measure called EBITDA. Because of this relative valuation

[14] This valuation method is called relative valuation (multiples of EBITDA) as opposed to absolute valuation (Discounted Cash Flow analysis). The underlying reason and more details about both valuation methods are discussed thoroughly in Appendix A.5.1.

method using multiples, contracts most commonly require a variation of the following formulation

$$b' \leq \phi\pi \tag{1.4}$$

where π is EBITDA and ϕ is the multiple. These cash flow-based agreements are enforced through legally binding financial covenants.[15] As is easy to monitor, max. Debt-to-EBITDA covenant is popular among lenders.[16] Drechsel (2018) states more than 60% of the agreements carry max. Debt-to-EBITDA covenant.[17] As cash flow-based contracts have one master loan agreement; these debt covenants bind at the firm level. Namely, the limit dictated by max. Debt-to-EBITDA is also effective on other types of borrowing, such as issuing bonds. Throughout the loan's lifetime, due diligence is carried out, and -on behalf of all lenders- the consortium leader continuously monitors the borrowing firm's cash flows and debt stock to check its compliance with the covenant.

Prevalence of Cash flow Based Contracts. Compiling the data from various data sources Lian and Ma (2021) shows that (median) share of asset-based lending is less than 20% while cash flow-based is over 80%, and more importantly, the shares are steady over time. The sample set consists of large US non-financial firms, of which the total debt of these firms constitutes over 96% of debt outstanding among Compustat firms. Similarly, by using DealScan data, Drechsel (2018) presents that cash flow-based debt agreements are more common than other practices in the lending markets.

1.2.3 Firm-level Balance Sheet and Income Statement Data

Firm-level balance sheet and income statement items come from the quarterly Compustat database. Apart from being widely accepted in the literature, Compustat has nice features that make it suitable for empirical analyses. Quarterly frequency makes it possible to observe the implications of monetary policy. Furthermore, being a long panel dataset, it is

[15] Debt covenants are terms and conditions that borrowers are obliged to fulfill and written explicitly in the debt contracts. These terms may include limits on financial ratios as well as levels of capital expenditure, leverage, and so on. Although there are various types of covenants in these contracts, this paper focuses on cash flow-based covenants. These loan covenants mandate that throughout the life of the loan agreement, firms must satisfy some financial ratios —most prominently, max. Debt-to-Assets or max. Debt-to-EBITDA. More details can be found in Appendix A.5.

[16] Max. debt-to-EBITDA ratio is in fact the rearranged version of (1.4). It is simply $\frac{b'}{\pi} \leq \phi$ and since b' and ϕ is observable, it is easy for the lender to track the firm's compliance to the covenant.

[17] In fact, cash flow-based covenants also have two broad categories: interest payment-to-total debt or cash flow-to-total debt. Greenwald (2019) exclusively focuses on these two covenants and suggests a state-dependent mechanism in interest rate transmission.

possible to analyze not only cross-sectional variation but also the within firm variation.[18]

To the best of my knowledge, the data set utilized in this paper is the first attempt that assembles loan-level data from DealScan, firm-level balance sheet data from Compustat, and stock return data from CRSP.[19] To merge DealScan and Compustat, I use the linking file provided by Chava and Roberts (2008) and connect the firm identifiers of both datasets. In particular, I extract the available loan data from DealScan and keep the portion matched to the balance sheet data from Compustat. Then, I merge Compustat with CRSP by employing the Compustat/CRSP link table available in WRDS.[20] The aim of merging CRSP data is to measure firm performance with the well-known financial indicators obtained via single factor CAPM-type regression. Below, I briefly discuss the variable construction for some selected variables. Further details on data treatment can be found in Appendix A.1.4.

Corporate finance variables of interest include (but are not limited to) investment (calculated via perpetual inventory method), cash flow (proxied by EBITDA), short-term and long-term debt, interest related expenses, dividend paying status, collateral value, and sales revenue. Using these variables, I construct some firm measures such as size (book value of total assets), age (years since incorporation), leverage (ratio of total debt to total assets), liquidity (short-term cash and investments), and Tobin's Q. Firm size is proxied by the value of total assets rather than employment since Compustat reports employment measures only in the annual frequency. Further, employment related data is less populated than total assets. Following Cloyne et al. (2018) age variable is not taken directly from Compustat's native initial public offering date as it is not well populated. Instead, I blend Compustat's IPO and incorporation dates from the WorldScope database.

Moreover, since some of the Compustat variables are provided as cumulative values within the firm's fiscal year, I calculate the first differences of those variables within the firm's fiscal year to obtain quarterly data. I limit the sample to firms observed for at least 20 quarters since the impulse response functions are estimated over a five-year forecast horizon. Finally, variables in levels are normalized by firm size, and nominal items are deflated by the GVA deflator. Exact data items, variable codes, and corresponding variable construction procedures can be found in Appendix A.1.1.

[18]The only drawback is that Compustat only includes publicly listed firms which restrict the sample set to mostly have relatively large firms. Moreover, large firms are considered more trustworthy and less financially constrained by several studies (Gertler and Gilchrist, 1994; Farre-Mensa and Ljungqvist, 2016). However, within the framework of this paper, the aim is to show that -regardless of their size- asset-based borrowers have relatively impeded access to external financing than cash flow-based borrowers.

[19]See Figure A.1.1 for a succinct depiction.

[20]Wharton Research Data Services.

Table 1.1
SUMMARY STATISTICS: ASSET-BASED VS. CASH FLOW-BASED

	Asset-Based				
	Mean	SD	P25	Median	P75
Firm Total Assets ($M)	1679.83	3708.59	167.66	527.41	1514.06
Firm Age (years)	32.94	31.86	11.75	21.50	39.50
Firm Leverage	0.32	0.24	0.14	0.28	0.46
Firm Asset Pledgeability	0.70	0.19	0.59	0.74	0.85
Firm Profitability (x10^{-2})	0.15	3.02	-0.63	0.55	1.64
Firm Tobin's Q	1.57	1.50	1.03	1.28	1.73
Firm EBITDA	0.44	1.60	0.02	0.10	0.39
Loan Spread (pp)	2.36	0.95	1.75	2.25	2.75
Loan Maturity (months)	53.62	23.41	36.00	60.00	60.00
Stock Jensen's Alpha (x10^{-2})	-0.54	3.39	-2.00	-0.30	1.15
Stock Beta	1.68	1.06	0.99	2	2.29
Total Observations	8,135				

	Cash flow-Based				
	Mean	SD	P25	Median	P75
Firm Total Assets ($M)	2596.18	4659.20	378.98	973.15	2419.20
Firm Age (years)	34.73	35.05	11.25	22.25	44.25
Firm Leverage	0.32	0.25	0.16	0.29	0.44
Firm Asset Pledgeability	0.57	0.23	0.40	0.59	0.75
Firm Profitability (x10^{-2})	0.75	2.47	0.05	0.97	1.92
Firm Tobin's Q	1.77	1.12	1.15	1.47	2.00
Firm EBITDA	0.84	1.82	0.10	0.30	0.84
Loan Spread (pp)	1.99	1.15	1.25	1.75	2.50
Loan Maturity (months)	59.16	18.37	57.00	60.00	60.00
Stock Jensen's Alpha (x10^{-2})	-0.33	2.80	-1.39	-0.10	0.97
Stock Beta	1.44	0.99	0.82	1	1.89
Total Observations	55,405				

NOTE. Summary statistics for asset-based and cash flow-based contracts in the sample. The sample period is from 1997Q1 and 2017Q3. Asset pledgeability refers to the ratio of tangible fixed assets to total assets as in Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova (2018) and Cloyne et al. (2018). Profitability is measured as Return-on-Assets as widely used in corporate finance literature. Loan spread is measured in percentage points. The sample consists of 2,236 firms of which 614 firms are asset based borrowers and 1602 are cash flow based borrowers. There are 30,591 loans and 11,457 packages.

Summary Statistics. Before starting the dynamic analysis, I report some descriptive statistics depicting the salient features of each firm group to explore the link between firm characteristics and debt contracts. Details about the classification into asset-based or cash flow-based categories are presented in Appendix A.1.2. Table 1.1 presents the descriptive statistics for asset-based borrowers and cash flow-based borrowers.[21] It would be beneficial to state that these statistics are enriched by two additional stock return measures obtained via running a CAPM-type regression.

Summary statistics illustrate that firms with a higher asset pledgeability ratio (measured by the ratio of tangible fixed assets to total assets as in Cloyne et al. (2018) and Dinlersoz et al. (2018)) tend to choose asset-based debt contracts. Furthermore, asset-based borrowers are mainly among the firms with a higher stock beta, implying a positive correlation between more volatile stock returns and collateral dependence in the contracts. Cash flow-based borrowers mostly have larger profitability as measured by higher Jensen's alpha, EBITDA, and Return-on-Assets.

Table 1.1 also shows no serious heterogeneity in the age and leverage dimensions. In line with Lian and Ma (2021), asset-based borrowers are generally smaller (as measured by total assets).

Regarding loan characteristics, asset-based and cash flow-based loans' average credit spreads are close to each other (with only a minor difference of 37 basis points). Loan maturities also don't exhibit heterogeneity as both groups have 60 months maturities at the median (with 5.5 month difference at the mean).

1.2.4 Heterogeneous Sensitivity to Monetary Policy Shocks

The central thought in the empirical analyses is to provide evidence that a firm's debt contract form plays a role in the heterogeneous responsiveness of their investment and borrowing to monetary policy shocks. Following the recent literature on heterogeneous monetary policy transmission (Cloyne et al., 2018; Jeenas, 2018; Anderson and Cesa-Bianchi, 2020; Ottonello and Winberry, 2020), I estimate the impulse response functions using local projection method à la Jordà (2005). I then estimate variants of the baseline empirical specification to better identify the impact of debt contract type.

I start the exercises by estimating the average dynamic effect of monetary policy shock on a variable of interest by borrowing method. The borrowing method indicator splits the

[21] As the final version of data set only includes the observations that could be matched via Chava and Roberts (2008) linking file, the number of observations for the asset-based and cash flow based borrowers are not representative of the population. However, the analyses of Lian and Ma (2021), which includes a more comprehensive dataset suggest cash flow-based borrowers constitute the major portion of all observations. My data set here is in line with their findings in this sense.

entire sample into two, based on whether each firm utilizes an asset-based or cash flow-based debt contract. Regressions are carried out in quarterly frequency. (1.5) presents the baseline empirical specification.

$$y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_1^h \left(\epsilon_t^m \mathcal{I}_{j,t-1}^{Asset}\right) + \beta_2^h \left(\epsilon_t^m \mathcal{I}_{j,t-1}^{Cash}\right) + \sum_{p=1}^{P_Z} \Gamma_p \mathbf{Z}_{j,t-p} + \sum_{p=1}^{P_X} \Gamma_p \mathbf{X}_{t-p} + e_{j,t+h} \quad (1.5)$$

$h = 0, 1, ..., H$ represents the active time horizon where $H = 20$ quarters. $y_{j,t+h}$ is the dependent variable of interest at horizon h: investment and borrowing. α_j^h is the firm fixed effect, ϵ_t^m is the quarterly monetary policy surprise of which calculation is described in Section 1.2.1. $\mathscr{I}_{j,t-1}^{Asset} = 1$ when firm j use asset-based contracts in the prior quarter of the monetary policy shock (otherwise zero) and $\mathscr{I}_{j,t-1}^{Cash} = 1$ when firm j is a cash flow based borrower in the quarter that precedes the monetary policy surprise (otherwise zero). Baseline empirical specification also controls for a variety of idiosyncratic and aggregate factors that may simultaneously affect dependent variables and borrowing method.[22] **Z** is the firm level control variable set including leverage, size, age, and current assets share, with $P_Z = 1$. $\mathbf{X}$ is the aggregate control variable set, including GDP, inflation, unemployment rate, and the VIX volatility index, with $P_X = 4$. β_1^h and β_2^h are the regression coefficients of interest capturing the impulse responses among subgroups.

There are two themes in these exercises: *i*) response of borrowing and investment, *ii*) compositional change between contract groups.

Investment and Borrowing. Figure 1.1 exhibits the estimated impulse responses using (1.5). β_1^h and β_2^h belong to the subgroups asset-based and cash flow based, respectively. The top row, Panel (A) and Panel (B) are for investment, and the bottom row, Panel (C) and Panel (D) are for borrowing. The shaded areas denote the 90 percent confidence intervals based on two-way clustered standard errors at firm and quarter. Impulse response functions are estimated over 20 quarters period.

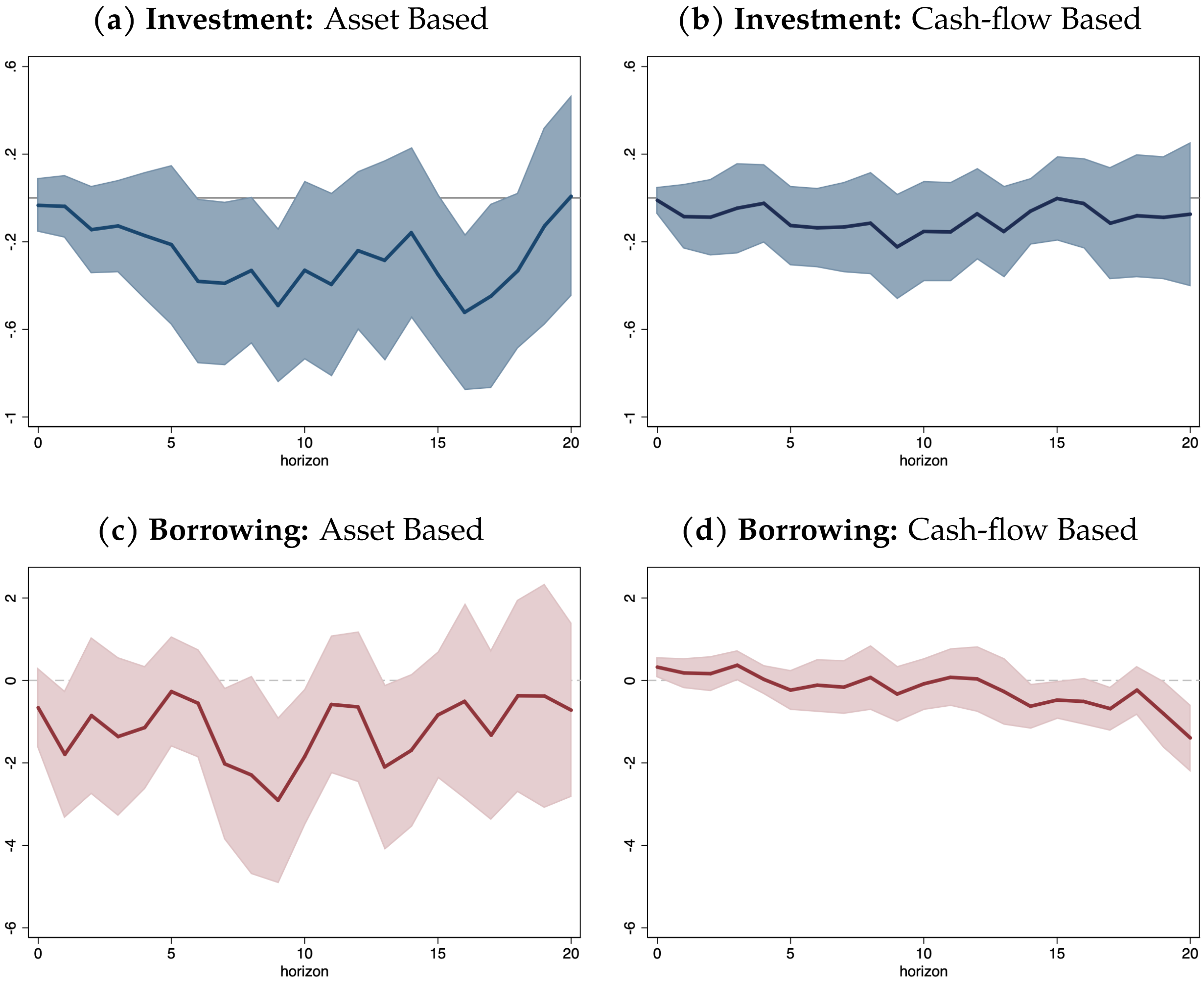
There are three key takeaways from Figure 1.1. First, Panel (A) shows that the decline in investment of asset-based borrowers is statistically significant, while Panel (B) shows that cash flow-based borrowers' response is not statistically significant. Second, the peak response of investment among asset-based borrowers (which occurs 2 years after impact) is almost three times larger than cash flow-based borrowers. Third, these two main points echo in Panel (C) and Panel (D). The borrowing response among cash flow-based bor-

[22]Some of the control variables included in (1.5) are beyond the scope of the quantitative economic model depicted in Section 1.3.

Figure 1.1

IMPULSE RESPONSES:

ASSET-BASED VS. CASH FLOW-BASED



NOTE. Average impulse response functions for the investment and borrowing following a 25 bps increase in 3-month T-bill rate. The responses are estimated with the local projection specification given by (1.5). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

Table 1.2
CONTRIBUTION TO THE AGGREGATE RESPONSE

	Asset-Based	Cash flow-Based
Investment	65.9%	34.1%
Borrowing	78.8%	21.2%

NOTE. This table shows the weighted share of the responses by the asset-based and cash flow-based contract holders. For each group, the discounted percentage changes in borrowing and investment over the forecast horizon is calculated. Then, the investment response of each group is computed by multiplying this value by the level of investment for each group. Each group's contribution to the total investment response is estimated by multiplying this object by the sum of the same statistics for both groups.

rowers is not statistically significant and small in magnitude, while asset-based borrowers respond in a statistically significant way and larger in magnitude. Again the peak response is experienced around 2 years after the impact.

At this point, it is worth mentioning that Compustat firms are publicly listed and thus relatively larger compared to private firms. Literature frequently assumes that large firms have comparatively easy access to external funding and therefore use size as a proxy for the financial constraints (Gertler and Gilchrist, 1994; Farre-Mensa and Ljungqvist, 2016). However, the empirical results suggest that financial frictions are effective even among firms considered relatively unconstrained.

Contribution to the aggregate response According to the evidence in Figure 1.1, firms with asset-based contracts are mainly accountable for the aggregate response of investment and borrowing to monetary policy shocks. To demonstrate more formally, I calculate the shares of investment and borrowing responses of asset-based and cash flow-based contract holders. The procedure is as follows. For each group of firms, I start by calculating the discounted percentage changes in borrowing and investing over the forecast horizon. Then, I compute the investment response of each group by multiplying this value by the level of investment for each group. In the last step, I estimate each group's contribution to the total investment response by multiplying this object by the sum of the same statistics for both groups.

The results are shown in Table 1.2. Despite constituting only 15% of the aggregate investment within the sample period, 64% of total investment *response* to monetary policy shocks are initiated by asset-based borrowers. For the total borrowing response, the result is more stunning. 79% of the borrowing response comes from asset-based borrowers.

Note that these calculations are based on an assumption regarding private firms' borrowing methods. Following the census in the literature about private firms being smaller, and given the descriptive statistics about asset-based contracts are taken mainly by smaller firms, it is likely that private firms mostly borrow with asset-based contracts. Therefore, the results depicted in Table 1.2 would constitute a lower bound for asset-based borrowers' contribution to aggregate investment and borrowing response to monetary policy shocks.

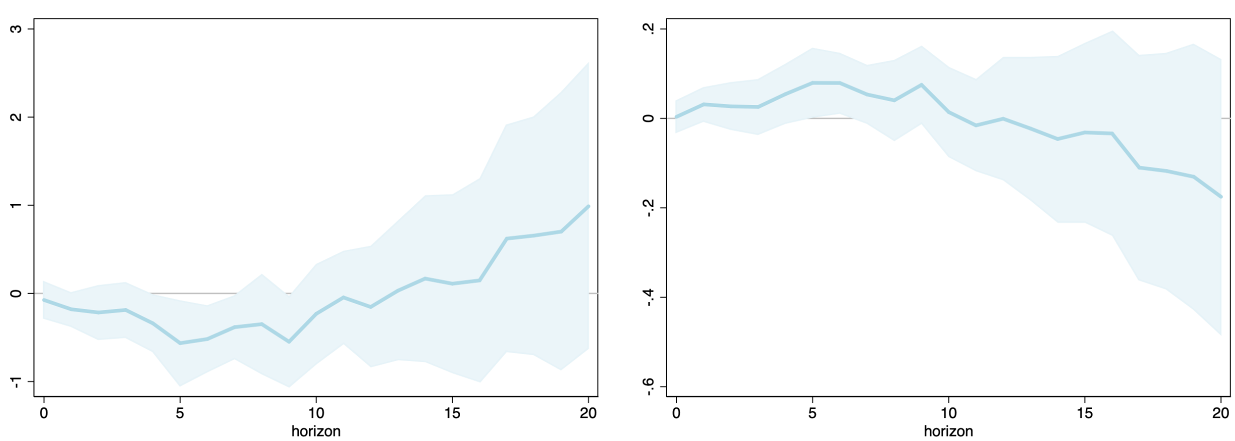
Compositional Change. Figure 1.2 shows that a fraction of firms with asset-based contracts switch to cash flow-based contracts, and the responses are significant. This shows that contract choice is endogenous to the stance of monetary policy. This finding supports the evidence provided above, as asset-based borrowers are severely affected by a contractionary monetary policy shock while cash flow-based borrowers are relatively not responsive. Indeed, the question arises: if there was nothing wrong with asset-based contracts, why would the firms try to switch cash flow-based contracts? Furthermore, the responses are limited in magnitude since monetary policy shocks are not strong enough for most firms to change their contracts. Taken together, Figure 1.2 indicates that the baseline empirical results remain valid.

Figure 1.2

IMPULSE RESPONSES: SHARES

ASSET-BASED VS. CASH FLOW-BASED

(a) Share: Asset Based **(b) Share:** Cash-flow Based



NOTE. Average impulse response functions for the shares of contracts following a 25 bps increase in 3-month T-bill rate. The responses are estimated with the local projection specification given by $y_{t+h} - y_{t-1} = \alpha^h + \beta^h(\epsilon_t^m) + \sum_{p=1}^{P_X} \Gamma_p \mathbf{X}_{t-p} + e_{j,t+h}$. The dependent variable is the share of asset based contract (for panel (a) and cash flow based contract (for panel (b)). The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

Taking stock of the empirical evidence. First set of findings includes descriptive statistics. The comprehensive dataset used in the paper suggests that the majority of firms use cash flow-based borrowing. Firms with higher asset pledgeability ratios and higher beta tend to choose asset-based debt contracts, while cash flow-based borrowers typically have larger profitability.

The second set of findings is obtained via a dynamic monetary policy shock experiment. Three main findings arise from this exercise. First, conditional on a rich set of firm-level and aggregate control variables, an unexpected interest rate increase makes asset-based borrowers cut their investment sharper than cash flow-based borrowers. Second, this investment responsiveness pattern also resembles in the borrowing responses. Third, a small portion of firms with asset-based contracts switch to cash flow-based contracts, as asset-based contracts are affected more severely by the monetary policy shock. Finally, even though the central focus is the debt contract as the main source of firm-level heterogeneity, the main result –the response of borrowing and investment for the asset-based borrowing firms is significantly larger in magnitude– persists after carrying out robustness checks for the possible confounding factors. Particularly, I check whether the baseline results are driven by the spread response, external finance dependence, and regional heterogeneity. See Appendix A.2.3 for further details about the robustness exercises.

Putting together all of this evidence, a likely explanation of the underlying mechanism behind the heterogeneous responses between asset-based and cash flow-based firms is as follows. The firms issuing new debt with asset-based contracts have to rely on the value of their asset stock to serve as collateral. Therefore, by reducing the asset price, contractionary monetary policy shocks tighten the borrowing constraint for these firms and force them to cut back their borrowing and investment. Whereas the debt limits of cash flow-based debt contracts do not depend on asset prices, they are not affected by the decreasing values of asset prices/collateral values. To evaluate the validity of this mechanism, I set up a quantitative model which captures both the cross-sectional and the dynamic empirical patterns; then, I assess the relevance of this asset price/collateral channel by switching it off and comparing the differential responses.

1.3 Model

In this section, I develop a heterogeneous firm New Keynesian model to interpret the empirical findings presented in Section 1.2. The key components of the model are as follows. Production side, which generates heterogeneous responses of investment and borrowing to monetary policy shocks; the financial side, which captures incorporates the state contingent debt contracts; and the New Keynesian components, which help to embed price stickiness.

Heterogeneous production firms are specified in a standard way (Khan and Thomas, 2013; Jeenas, 2018; Ottonello and Winberry, 2020). I extend this structure by including cash flow-based debt contracts. Both asset-based and cash flow-based contracts imply state contingent borrowing limits derived from first principles via limited enforcement. The underlying reason for this modeling strategy is twofold. First, to ensure both asset-based and cash flow-based contracts can coexist in the economy. Second, firms can switch between these contract types in each period depending on their idiosyncratic state.

Moreover, as in typical models of the financial accelerator literature, to generate time-varying capital price, the model economy also inhabits capital good producers subject to the convex adjustment cost of aggregate capital. This agent incorporates the financial accelerator mechanism into the model, resulting in a positive correlation between capital price and aggregate investment.

There is also a retail good producer with some market power to set the price, a representative household that owns all production entities in the model economy, and the monetary authority that follows a Taylor-type rule.

There is no aggregate uncertainty in the model, and I study the perfect foresight transition paths in response to an unexpected monetary policy shock. Finally, I use time subscripts to indicate variations in equilibrium prices and value functions. Prime notation is employed to refer to future values in the choice variables.

1.3.1 Production Firms

Each period, there is a unit mass of heterogeneous production firms investing in capital and participating in the financial markets.[23] Each production firm $i \in [0,1]$ produces an undifferentiated good i, by using labor $l_{i,t}$ and predetermined capital $k_{i,t}$ using a decreasing returns to scale production function given below

$$y_{j,t} = z_{i,t} k_{i,t}^{\theta} l_{i,t}^{\nu}. \tag{1.6}$$

Labor market is perfectly competitive, and firms hire labor at the real wage, w_t. Idiosyncratic firm productivity $z_{i,t}$ follows a log–$AR(1)$ process presented by

[23]For brevity, hereafter, I refer to production firms as "firms" and other firms are distinguished by using their exact names (*i.e.* retailers, capital good producers, etc.).

$$z_t = \rho z_{t-1} + \sigma \epsilon_t; \quad \epsilon \sim N(0,1). \tag{1.7}$$

Since this paper focuses on understanding how different formulations of borrowing constraints shape monetary policy transmission, I incorporate three measures to prevent firms from circumventing financial frictions. The first measure is that each period with probability π_d firms may be hit by an exogenous exit shock which pushes the firm out of the economy regardless of its financial situation. By this method, I prevent all firms from growing to such a size that they are never subject to borrowing restrictions. Exiting firms are replaced by an equivalent mass of new entrants each period to keep the mass constant. The second measure is the existence of operating cost. By incorporating this additional cost of production, firms' dependence on an external finance source increases as some of their cash flow is absorbed by this extra cost of production. The third is imposing a non-negativity constraint on the firms, which prevents firms from raising equity to avoid borrowing limits.

Timing of events Within each period, the following events take place consecutively.

i. The entrant firms with a mass of exiting incumbents enter the economy at the beginning of period t. They hold an initial capital stock k_0, and no initial debt $b_0 = 0$.

ii. Idiosyncratic productivity shock and exogenous exit shock are realized for incumbents and new entrants.

iii. Firms produce intermediate good by using their existing capital stock and hiring labor $l_{i,t}$ from a frictionless, competitive labor market. Firms pay the operating cost Φ and the wage bill at w_t, then sell their undifferentiated goods to the retailers with nominal price p_t.

iv. Firms repurchase all outstanding debt.

v. Exiting firms liquidate their total capital stock and pay the remaining funds as dividends to the households. Conditional on survival, firms decide the following simultaneously. *i*) purchase new capital $k_{i,t+1}$ with capital price q_t, *ii*) purchase new debt $b_{i,t+1}$, and *iii*) contract type of the newly issued debt.

vi. The remaining funds (if any) are distributed to the households as dividend payments.

1.3.2 Debt Contracts

To introduce the coexistence of asset-based and cash flow-based contracts to the model economy, I formulate state contingent borrowing limits derived from limited enforcement. Combined with the heterogeneity across productivity, firms switch between the two contract types depending on the tightness of these endogenous borrowing limits. More elaborately, the borrowing constraints are determined as follows. *Ex post*, firms can renege on their promise to repay, thus breaching their contracts. By having complete information, financial intermediary writes both asset-based and cash flow-based contracts by ensuring that firms repay their debt in every state of tomorrow. To do so, the financial intermediary sets the borrowing limits of both contracts, $\bar{b}^{Asset}(z, nw, k'; q)$ and $\bar{b}^{Cash}(z, nw, k'; \pi)$, to satisfy the relevant incentive compatibility constraints, which mandate that the value of repayment has to be greater than the value of default for all possible states of tomorrow. Therefore, limited enforceability of loan contracts directly maps into the firm's *ex ante* borrowing capacity. Thus, by this method, borrowing constraints become state contingent and derived from first principles rather than imposed exogenously.

Each period, firms are offered two types of debt contracts: asset-based or cash flow-based, which differ in terms of default resolution. By observing the terms of both contracts, firms choose the contract with looser constraints.[24] In this setup, a firm's borrowing decisions have two dimensions: (*i*) in the extensive margin, whether to opt for an asset-based or cash flow-based contract; and (*ii*) in the intensive margin, how much to borrow. Firms can borrow up to the amount which satisfies the relevant enforcement constraint of each contract type.

Asset based contracts. In these contracts, in case of default, firms lose their debt and, as the penalty, lose a fraction Θ of their existing capital stock. Financial intermediary determines the borrowing limit $\bar{b}(z, nw, k'; q)$ to satisfy the below enforcement constraint

$$v_{t+1}^{Asset}\left(z', nw_{t+1}\left(z', k', b'\right)\right) \geq v_{t+1}^{Asset}\left(z', nw_{t+1}\left(z', (1-\Theta)k', 0\right)\right). \tag{1.8}$$

(1.8) states that continuation value under repayment has to exceed (or be equal to) continuation value under default. Also, notice that, since the penalty is based on losing some portion of the capital stock, the associated borrowing limit is closely connected with the capital price.

[24]However, it is possible in the model that given the initial state (z, nw), the financial intermediary may not ensure the repayment with one of the contracts. If that is the case, financial intermediary only offers one type of contract.

Cash flow-based contracts. As explained in Section 1.2.2, lenders have claims against the firm entity and have the right to take over the management in cash flow-based contracts. Therefore the debt limit is dictated by the value of the firm. In the model, following the industry tradition, the firm's value is approximated via its cash flow. If a firm chooses to default on its debt, the penalty is the firm value –as approximated by the multiple of their cash flow. As in asset-based contract, financial intermediary determines the borrowing limit $\bar{b}\left(z, nw, k'; \pi\right)$ to satisfy the below incentive compatibility constraint

$$v_{t+1}^{Cash}\left(z', \hat{nw}_{t+1}\left(z', k', b'\right)\right) \geq v_{t+1}^{Cash}\left(z', \hat{nw}_{t+1}\left(z', k', 0\right)\right) - W_{t+1}\left(z', \hat{nw}_{t+1}\left(z', k', b'\right)\right) \quad (1.9)$$

where

$$W_{t+1}\left(z', \hat{nw}_{t+1}\left(z', k', b'\right)\right) = \varphi[\underbrace{p_{t+1}z'\left(k'\right)^{\theta}\left(l'\right)^{\nu} - w_{t+1}l'}_{\approx \pi}] \quad \text{for all } z'.$$

Below, I recursively characterize the firm's problem, which introduces the relationship between firms and the financial intermediary regarding debt contracts.

Recursive formulation. The set of individual state variables of a firm includes idiosyncratic productivity shock and net worth; (z, nw). Net worth, nw is defined as firms' total funds before acquiring new debt or purchasing new capital. Due to its static nature, given the idiosyncratic productivity shock, the labor choice problem is merged with the definition of net worth.

In this economy, a firm's investment decision is intertwined with its ability to borrow and the terms of debt it carries into the next period. The financial intermediary writes the debt contracts by taking into account their *future* ability of repayment, thus focuses not on today's but instead on the next period's capital. Therefore, it is essential to keep in mind that in this economy, a firm's individual levels of k and b do not directly influence any of its decisions outside of their impact on net worth.[25] The firm value depends only on z and nw and does not depend separately on k and b because nw completely captures earlier choices that influenced its current choice set. This enables us to lower the dimension of the state vector.

[25]This outcome is impossible in the models with capital adjustment frictions since the adjustment cost is a direct function of investment and today's capital.

$$nw = \max_{l} \quad p_t z(k)^{\theta} l^{\nu} - w_t l + q_t(1-\delta)k - b - \Phi \tag{1.10}$$

where Φ is the fixed operating cost to be paid by the firm in order to produce in period t. After production, and dept purchase, conditional on surviving the exit shock, firm chooses between asset-based contract, and cash flow-based contract. This discrete choice of contract is given by the upper envelope:

$$v_t(z, nw) = \left\{ v_t^{Asset}(z, nw), v_t^{Cash}(z, nw) \right\} \tag{1.11}$$

for all states (z, nw).

A firm choosing to borrow with asset-based contract selects the amount of capital (with price q_t) and debt (with $\mathcal{Q}_t$) to solve the below recursive problem:

$$\begin{aligned} v_t^{Asset}(z, nw) = \max_{k',b'} \quad & nw - q_t k' + \mathcal{Q}_t b' + \mathbb{E}_t[\Lambda_{t+1}(\pi_d nw_{t+1}(z', k', b') + \\ & (1-\pi_d) v_{t+1}(z', nw_{t+1}(z', k', b')))] \end{aligned} \tag{1.12}$$

subject to the non-negativity constraint on dividends

$$nw - qk' + \mathcal{Q}b' \geq 0,$$

and the rationality constraint of the asset-based contract

$$v_{t+1}^{Asset}(z', nw_{t+1}(z', k', b')) \geq v_{t+1}^{Asset}(z', nw_{t+1}(z', (1-\mathit{\Theta})k', 0)). \tag{1.13}$$

The recursive problem of the heterogeneous production firm which opt for a cash flow-based contract is as follows.

$$\begin{aligned} v_t^{Cash}(z, nw) = \max_{k',b'} \quad & nw - q_t k' + \mathcal{Q}_t b' + \mathbb{E}_t[\Lambda_{t+1}(\pi_d nw_{t+1}(z', k', b') + \\ & (1-\pi_d) v_{t+1}(z', nw_{t+1}(z', k', b')))] \end{aligned} \tag{1.14}$$

subject to the non-negativity constraint on dividends

$$nw - qk' + \mathcal{Q}b' \geq 0,$$

and the incentive compatibility constraint of the cash flow-based contract

$$v_{t+1}^{Cash}\left(z', nw_{t+1}\left(z', k', b'\right)\right) \geq v_{t+1}^{Cash}\left(z', nw_{t+1}\left(z', k', 0\right)\right) - W_{t+1}\left(z', nw_{t+1}\left(z', k', b'\right)\right) \quad (1.15)$$

and

$$W_{t+1}\left(z', \hat{nw}_{t+1}\left(z', k', b'\right)\right) = \varphi\left[p_{t+1}z'\left(k'\right)^{\theta}\left(l'\right)^{\nu} - w_{t+1}l'\right] \quad \text{for all } z'. \quad (1.16)$$

1.3.3 Financial Intermediary and Capital Good Producers

Financial intermediary. This entity operates in a perfectly competitive market, takes deposits from representative households, and lends these funds to the production firms in need. The household owns financial intermediary, and its recursive problem is

$$v_I(D, B) = \max_{D', B'} \quad D' - B' + \Lambda^h v_I(D', B') \quad (1.17)$$

subject to

$$D' - B' \leq (1 + r^B)B - (1 + r^D)D \quad (1.18)$$

where Λ^h is the household's stochastic discount factor, D stands for the deposit, and B is the loan granted.

Finally, the financial intermediary's optimality condition reads:

$$r'_B = r'_D \quad (1.19)$$

Capital good producers. There is a representative, perfectly competitive capital good producer which produces next period's capital stock K_{t+1} by using the existing capital stock, K_t and I_t units of final good as inputs to the production technology, $K_{t+1} = \Phi\left(\frac{I_t}{K_t}\right)K_t$. The production of the capital good is subject to adjustment cost, $\Phi\left(\frac{I_t}{K_t}\right)$. Capital good producers' profit maximization problem yields the relative price of capital as

$$q_t = \frac{1}{\Phi'\left(\frac{I_t}{K_t}\right)} = \left(\frac{I_t/K_t}{\hat{\delta}}\right)^{1/\phi} \quad (1.20)$$

where $\hat{\delta}$ is the investment rate at the steady state. Note that full characterization of capital good's problem can be found in Appendix A.3.2.

1.3.4 Retailers, Final Good Producers, and the Monetary Authority

Retailers. Model inhabits a continuum of retailers of which mass is fixed, $i \in [0, 1]$. Each retailer operates in a monopolistically competitive market and thus can set a price with a markup. Retailers buy the undifferentiated intermediate good from the heterogeneous production firm i to produce a differentiated variety $\tilde{y}_{j,t}$ by the production process

$$\tilde{y}_{j,t} = y_{j,t}. \tag{1.21}$$

Having market power, retailers can set a relative price, $\tilde{p}_{j,t}$ for their variety, subject to the quadratic price adjustment cost: $\frac{\varphi}{2}\left(\frac{\widetilde{p}_{j,t}}{\widetilde{p}_{j,t-1}} - 1\right)^2 Y_t$, where Y_t is the final good. Retailers take the demand curve for the differentiated good as given, which is the outcome of the final good producers' problem.

Final Good Producer. The final good producer operates in a perfectly competitive market and thus takes the prices of the retail goods, $\tilde{p}_{j,t}$, and the final good p_t as given. Final good producers use the retail goods as input and bundle them into the final good by using the CES production technology:

$$Y_t = \left(\int \tilde{y}_{j,t}^{\frac{\gamma-1}{\gamma}} \mathrm{d}j\right)^{\frac{\gamma}{\gamma-1}}. \tag{1.22}$$

Note that the final good is the numeraire in this economy. The cost minimization problem of the final good producer generates the retailers' demand curve.

Monetary Authority. Monetary policy is conducted by setting the interest rate on the risk-free bond r_t^f according to the Taylor rule given below.

$$\log r_t^f = \log\frac{1}{\beta} + \varphi_\pi \log \Pi_t + \varepsilon_t^{\mathrm{m}}, \text{ where } \varepsilon_t^m \sim N\left(0, \sigma_m^2\right), \tag{1.23}$$

φ_π is the inflation coefficient in the Taylor rule, and $\varepsilon_t^{\mathrm{m}}$ is the monetary policy shock.

1.3.5 Household and Equilibrium

There is a representative household who consumes the final good c_t and supplies labor l_t in exchange for the real wage w_t. To accumulate their wealth, the household uses two different financial instruments: (i) one-period risk-free bond (issued by financial intermediary), (ii) one-period firm share. Along with the production firms, households own retailers, final good producers, and the financial intermediary in the economy. Furthermore, I assume that the price adjustment cost is rebated lump sum to the household and thus does not exhaust the economy's resources.

Representative household's lifetime utility is governed by the Bellman equation

$$V(a, \eta) = \max_{c,l,a',\eta'} \quad (\log c - \Psi l) + \beta V(a', \eta') \tag{1.24}$$

subject to

$$\begin{aligned} c + a' + \int_{\mathbf{S}} \rho_t^1 (z', nw')\eta' (z', nw') = \\ w_t l + (1 + r_t)a + \int_{\mathbf{S}} \rho_t^0 (z, nw) \eta (z, nw) + \Upsilon + \vartheta. \end{aligned} \tag{1.25}$$

The distribution of the households' ownership over the heterogeneous production firms' shares are represented by the measure η^h. $\rho_t^0 (z, nw)$ is the *cum dividend* price of production firms' shares at the beginning of period t with the state vector (z, nw). $\rho_t^1 (z', nw')$ is the firms' new share price to be inherited to the next period. Υ is the profit of the retail goods producers.[26] ϑ is the lump sum amount the household receives from the price adjustment cost.

In this economy, since households own all firms and financial intermediary, these entities share the stochastic discount factor of households, obtained from the Euler equation of risk-free bonds, which is given below:

$$\Lambda^h = \beta \frac{u_c(c', l')}{u_c(c, l)} \tag{1.26}$$

(1.19) and (1.26) together yields:

$$\Lambda^h (1 + r'_B) = 1 \tag{1.27}$$

Note that full characterization of the equilibrium can be found in Appendix A.3.3.

[26]Note that since financial intermediary, final good producer, and production firms operate in perfectly competitive markets, for brevity, their profits are omitted in the budget constraint.

1.4 Calibration

Calibration strategy involves two main stages: external and internal calibration. In the external calibration, I fix some model parameters *a priori* based on the estimated values in the previous literature. Whereas in the internal calibration, by focusing on the mechanisms of interest at work, the remaining parameters are chosen to match the model's moments at the stationary equilibrium to the observed data moments. The majority of the data moments are calculated based on the merged Compustat/DealScan/CRSP dataset. I also compare the resulting parameter values and moments with their counterparts in the literature. The main anchor in the calibration strategy is to ensure that firms always repay their outstanding debt, and thus there is no equilibrium default.

External Calibration. The length of a model period is one quarter. I set the household discount factor β, to imply an average annual interest rate of 4 percent.[27] and I set $\theta = 0.21$ and $\nu = 0.64$ which imply decreasing returns to scale of 0.85. Quarterly capital depreciation rate is $\delta = 0.025$. The elasticity of substitution between the differentiated intermediate goods (produced by retailers to be sold to the final goods producers) is $\gamma = 10$, which implies a steady state markup of 11% over marginal costs through the formula $\frac{\gamma}{\gamma-1} = 1.11$.[28] Following Ottonello and Winberry (2020) which in turn builds on Kaplan, Moll, and Violante (2018), I set $\varphi = 90$ which yields the NKPC slope $\frac{\gamma-1}{\varphi} = 0.1$. Again, following Ottonello and Winberry (2020) and Bernanke et al. (1999), I set the curvature parameter of the aggregate adjustment costs which govern the price elasticity with respect to investment rate as $\phi = 4$. I set the exogenous exit rate $\eta = 0.087$ to match the exit rates of Jeenas (2018) and Ottonello and Winberry (2020) which are calculated from the survey of Business Dynamics Statistics.

Internal Calibration. I set the parameters in the internal calibration to match the empirical targets depicted in Table 1.4. Targeted empirical moments are calculated from the Compustat/DealScan/CRSP merged sample I used in the empirical exercises in Section 1.2.

First, I set $k_0 = 0.27$ so that new entrants in any given quarter start their lifecycle with a relative size of 0.27 to the average firm size. This calibrated value is higher than its em-

[27]Quarterly discount rate $\beta = 0.99$ corresponds to the 4 percent annual rate of return. This value can be considered as the sum of the risk-free policy rate and the average corporate borrowing spread. For the sample period of the dataset (1997-2018), the average annual fed funds rate is approximately 2 percent. Median corporate borrowing spread the period is 200 basis points (see Table 1.1).

[28]For most production and New Keynesian parameters, I follow Ottonello and Winberry (2020). The resulting moments: the decreasing returns to scale of 0.85 is from Winberry (2021) and the steady state labor share $\frac{\gamma-1}{\gamma}\nu = 0.58$, is in line within range of the labor share of U.S. estimated in Karabarbounis and Neiman (2014)

Table 1.3

PARAMETERS

Parameter	Description	Value
	External Calibration	
β	Discount factor	0.99
θ	Capital share	0.21
ν	Labor share	0.64
δ	Depreciation rate	0.025
ϕ	Capital Adjustment Cost Coeff.	4
γ	Demand elasticity	10
φ_π	Taylor rule coefficient	1.25
φ	Price adjustment cost	90
π_D	Exogenous exit rate	0.087
	Internal Calibration	
ρ	Persistence of TFP	0.90
σ	SD of innovations to TFP	0.05
k_0	Initial capital	0.27
Φ	Operating cost	0.02
Θ	Recoverability parameter	0.71
φ	Value-to-EBITDA ratio	9

pirical counterpart from the Compustat sample (0.25). It is because the model economy includes operating costs, so firms need to have enough capital to survive their first period.[29]

Naturally, each parameter affects all of the model results, but since the novel part of this paper is the borrowing mechanisms –incorporation of cash flow-based contracts– I first discipline the parameters of idiosyncratic productivity shock $AR(1)$, then using these calibrated parameters try to match the empirical moments regarding the borrowing concept. Parameters governing the $AR(1)$ idiosyncratic productivity shock process; persistence parameter ρ and the dispersion of innovations σ to the productivity are chosen to reproduce firm-level investment dynamics (mean and dispersion of investment rate) in the data.

Having set the other parameters, I target the three moments regarding the firm level borrowing: *i*) shares of asset-based and cash flow-based borrowers, *ii*) the percentage of firms having positive debt, and *iii*) mean of the firm-level gross leverage ratio. Here note that for the third target, I choose 0.81 from Crouzet and Mehrotra (2020), not this pa-

[29] The value is still close to 0.23 in Begenau and Salomao (2019) and 0.24 in Jeenas (2018).

Table 1.4
CALIBRATION TARGETS AND MODEL FIT

Moment	Description	Data	Model
k_0	Initial capital	0.25	0.27
$\frac{b}{k}$	Average Gross Leverage Ratio	0.42	0.47
Share (b_A)	Fraction of asset based to total debt	0.16	0.16
Share (b_C)	Fraction of cash flow based to total debt	0.84	0.84
Share $(b > 0)$	Firms with positive debt	0.81	0.63
$\mathbb{E}\left(\frac{i}{k}\right)$	Average investment rate	0.23	0.21
$\sigma\left(\frac{i}{k}\right)$	SD investment rate	0.45	0.48

per's dataset from Section 1.2. The reason is that the merged Compustat/DealScan sample mostly consists of firms with positive debt, thus yielding biased moments.

The calibration strategy leads to the values in Table 1.4. The model performs well in matching the shares of asset-based and cash flow-based debt. Also, the model roughly matches the debt related moments: leverage ratio and firms with positive debt. In terms of investment rate moments, the model overpredicts the dispersion since the model does not include the cost of capital adjustment at the firm level. However, the mean investment rate is lower than the data. The underlying reason could be that in this type of models, firms accumulate capital very quickly and reach their optimal scale (Ottonello and Winberry, 2020). Therefore, the model could be producing the ratio of investment to capital lower than the data.

The calibrated loan recovery rate is 0.71 which is higher than 0.54 in Khan, Senga, and Thomas (2016) and Ottonello and Winberry (2020), and 0.62 in Jeenas (2018). It is because, lower values of Θ lead to underborrowing in the model economy. EBITDA multiple in the cash flow based contract, φ value is 9, lower than 14 in Lian and Ma (2021). The reason is that higher values of φ lead most cash flow-based borrowers to renege on their promise to repay.

In gross leverage ratio, the empirical moment of 0.42 is higher than 0.34 as reported in Crouzet and Mehrotra (2020), since the merged dataset of Section 1.2 is a subgroup that consists of loan borrowers. Therefore, gross leverage ratio is higher than the Census data employed in Crouzet and Mehrotra (2020) which is obtained from the US Census Bureau's Quarterly Financial Report (QFR), a survey that collects income statements and balance sheets of manufacturing, retail, and wholesale trade firms.

About the investment rate moments, it is helpful to compare the moments with the moments of Cooper and Haltiwanger (2006), which is widely used as a benchmark in the literature. Both mean and standard deviation of investment rate are higher than their Cooper and Haltiwanger (2006) counterparts (0.12 and 0.33, respectively). It is because, balanced dataset of Cooper and Haltiwanger (2006) includes large manufacturing plants that operated unceasingly between 1972 and 1988. Therefore, their dataset and results are not contaminated with firm entry/exit, which exists in my Compustat/DealScan dataset. Furthermore, since they only focus on large plants, their need for investment is relatively weaker compared to newly established, younger firms which are also included in my dataset. Putting together, having firm entry/exit and the existence of younger firms in the sample boosts the mean investment rate and its standard deviation.

1.5 Debt Contracts Heterogeneity in the Model

This section discusses the firm's contract choice in the steady state and validates the consistency of the quantitative model with the empirical patterns observed in Section 1.2.3. The central thought in the analyses is to investigate how firm characteristics affect the debt contract choice in the stationary equilibrium.

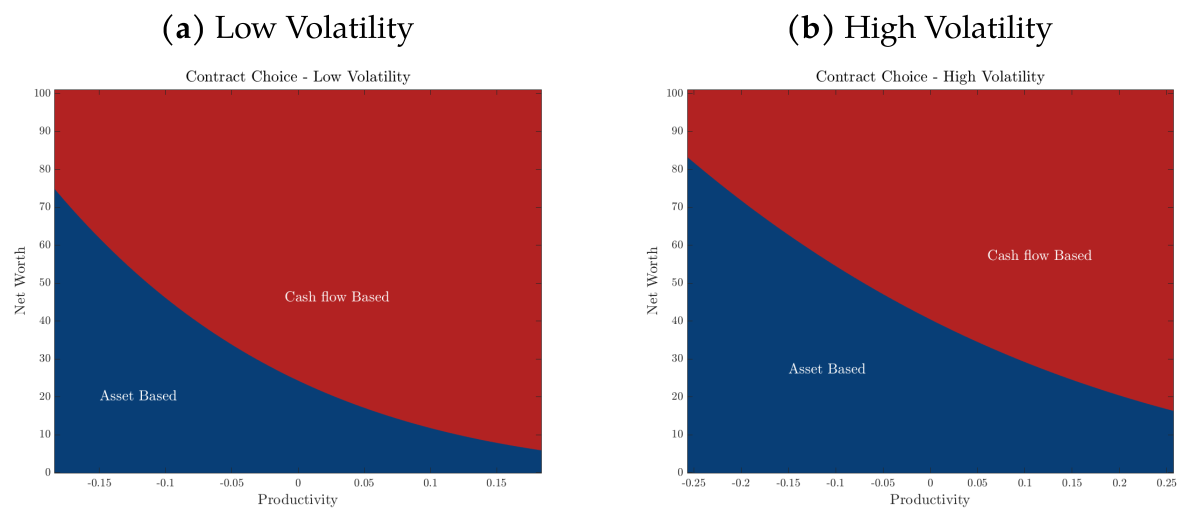
Figure 1.3 depicts the firm's contract preferences in the state space (z, nw). The blue and red areas represent the firms adopting cash flow-based and asset-based contracts, respectively. Note that both Panel (A) and (B) could be used for the exposition as they imply the same mechanisms, however for the sake of consistency, I use Panel (A) in the discussions throughout and employ Panel (B) only when I analyze the impact of volatility.

Before moving on to the underlying mechanisms, it is beneficial to recall how contracts are written. Perfectly foreseeing all possible outcomes (*i.e.* whether to pay or renege), the financial intermediary restricts the borrowing amount to ensure that firms repay in every state of the world next period. As anticipated, the tightness of the borrowing constraints is state contingent. Depending on the firm's place in the state space, one of the contracts could have looser borrowing limit than the other. Then, seeing the contracts, firms choose whether to borrow with an asset-based or a cash flow-based contract.

Here note the dual roles of productivity. First, as the productivity follows a persistent process, having low (high) productivity) increases the chance of having low (high) productivity tomorrow. Therefore, today's productivity constitutes a strong signal about repayment probability in the next period. The second role of productivity comes from the cash flow-based contracts, as the tightness of the borrowing constraint is determined by the multiple of the firm's cash flow in these contracts. Therefore, cash flow-based contracts are more responsive to productivity levels, as they are affected through two distinct channels.

As can be seen from Figure 1.3, steady state analyses reveal that in line with the empirical evidence presented in Section 1.2 and Lian and Ma (2021) as well; the quantitative model well captures the fact that cash flow-based borrowing is the prevalent method for most of the states.

Figure 1.3
CONTRACT CHOICES



NOTE. This figure shows the policy function of debt contracts. High (low) volatility means the dispersion of the error term is high (low) in (1.7). In the high volatility case, dispersion is 10% than the low volatility case.

In order to illustrate the underlying mechanisms at work producing Figure 1.3, it would be helpful to compare the left to the right half. When a firm with higher productivity than average wants to borrow, the financial intermediary offers the contract as follows. The intermediary calculates the two borrowing limits for each point in the state space, i.e. $\bar{b}^{Asset}(z, nw, k'; q)$ and $\bar{b}^{Cash}(z, nw, k'; \pi)$. Given that high productivity means the ability to generate cash flow from the existing capital stock is better and also signals that the firm remains in the high productive state in the next period, for the firms with above average productivity, their repayment is guaranteed for more cases in the state space. Therefore, firms mostly prefer cash flow-based contracts due to having looser borrowing constraint in most cases. On the other hand, if a firm has low productivity, anticipating that firm would default in most cases, the financial intermediary tightens the borrowing constraints under cash flow-based contracts, leading low productive firms to borrow with asset-based contracts. These findings align with the empirical patterns presented in Section 1.2.3, as more profitable firms mostly choose cash flow-based contracts.

Another factor investigated is volatility which is defined as the dispersion of idiosyncratic productivity shock distribution and governed by σ in (1.7). The experiment is increasing σ by 10%. Compared to Panel (A), firms prefer asset-based debt contracts in more states. Again, here the underlying mechanism originates from the financial intermediary. Since the intermediary writes contracts to ensure that firms repay their debt in every state of the next period, when volatility increases, the lowest realization(s) of the idiosyncratic productivity shock becomes crucial. It is because as the dispersion of the shock distribution increases, the left tail of the distribution goes further left, yielding lower outcomes than the low volatility case. In this case, firms are more likely to fail repayment, as their income would not be enough the cover the debt. Therefore expecting an increase in the firm's likelihood of reneging from its promise of payment, the intermediary tightens the borrowing constraints for both contracts, but even tighter for cash flow-based contracts as their borrowing limit is a direct function of productivity. This steer more firms to sign asset-based contracts, as asset-based contracts constitute a larger area in Panel (B).

1.6 Quantitative Monetary Policy Analysis

In this section, I analyze the response of the model economy to a one-time unexpected contractionary monetary policy shock. The quantitative model is designed to validate the proposed asset price channel on the monetary policy transmission while staying consistent with the empirical responses presented in Section 1.2. The layout of this section is as follows. Section 1.6.1 presents the computed the aggregate impulse responses of key variables to a contractionary monetary policy shock. Section 1.6.2 depicts the heterogeneous sensitivity of asset-based and cash-flow based borrowers to a common monetary policy shock. The results are in line with the empirical evidences from Section 1.2, as firms with asset-based debt contracts are more responsive. To show the relevance of the proposed asset price channel, Section 1.6.3 presents the results of an alternative scenario in which there is no capital adjustment cost and thus the price of capital is not time-varying. Consistent with the suggested mechanism, when the capital channel is shut down, asset-based borrowers' responsiveness is substantially reduced compared to cash flow-based borrowers. Finally, Section 1.6.4 discusses the aggregate implications of the debt contract heterogeneity and argues that the strength of the financial accelerator mechanism depends on the share of asset-based borrowers in the economy.

1.6.1 Aggregate Responses to Monetary Policy

The aggregate responses of some selected variables to a contractionary monetary policy shock are shown in Figure 1.4. First row presents the responses of the nominal interest rate, rate of inflation, and the implied changes in the real interest rate—the nominal interest rate increases in response to a contractionary, one-time innovation to the Taylor rule. Second figure shows that innovation lowers inflation by cooling down the economy. As demonstrated by the third figure in the first row, an increase in the nominal interest rate passes through the real interest rate. Since due to the staggered pricing mechanism, prices cannot adapt immediately to the nominal changes.

Second row in Figure 1.4 reports the effects of a contractionary monetary policy shock on consumption, investment, and output. A higher real interest rate cools down the economy, as it depresses consumption and investment, and thus output and inflation.[30] Moreover, the model's impulse responses are in line with the literature. Response of consumption is milder than output due to households' consumption smoothing motive and investment appearing as the most volatile element. Furthermore, the magnitude of the model's impulse responses are consistent with the peak impulse responses to monetary policy shocks estimated in Christiano et al. (2005) and those computed with the heterogeneous quantitative models in Kaplan et al. (2018) and Ottonello and Winberry (2020).

The third row depicts the impulse responses of prices in the economy. First figure shows the impulse response of capital price. Note that a contractionary monetary policy shock mitigates investment demand. In the presence of capital adjustment costs, the marginal cost of capital declines. As can be seen from the second and third figures, lower aggregate demand for goods (whether it comes from consumption or investment) reduces other prices in the economy, such as intermediate good prices and real wages.

Here it is helpful to discuss the lack of hump-shaped responses as opposed to the estimations in the typical New Keynesian literature (Christiano et al., 2005; Smets and Wouters, 2007). Such hump shapes in investment and consumption would require some impedance mechanisms. For instance, habit formation is widely used in the literature to produce hump-shaped consumption responses. Further, one could produce a hump-shaped investment response by formulating costly adjustments as a function of investment rather than capital. The main reason behind excluding these extensions is that the quantitative section of this paper focuses on the role of capital price movements on borrowing constraints and investment. If these extensions had been included, the underlying mech-

[30]Here, note that in Kaplan et al. (2018), a major part of the response to monetary policy shock originates from indirect channels. However, since the heterogeneous household is beyond the scope of this paper, the model relies on the conventional intertemporal substitution channel.

anisms would have been entangled with the collateral channel of monetary policy transmission. Thus it would be challenging to isolate the collateral channel.

In the next section, I decompose the total effect of the monetary shock on aggregate investment and borrowing. To do so, through the lens of the methodology developed in Section 1.2, I compute the impulse responses of these aggregate variables among asset-based and cash flow-based borrowing firms.

1.6.2 Heterogeneous Responses to Monetary Policy

This section presents the model's estimation results on firms' heterogeneous responses to the monetary policy shock experiment. To observe the model's internal dynamics while keeping the comparability to the empirical pattern of Section 1.2, on the simulated data I estimate (1.28) which is a variant of empirical specification (1.5).

$$y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \gamma_t + \beta^h \left(\epsilon_t^m \mathscr{I}_{j,t-1}^{Asset} \right) + \sum_{p=1}^{P_Z} \Gamma_p \mathbf{Z}_{j,t-p} + e_{j,t+h} \tag{1.28}$$

$h = 0, 1, ..., H$ represents the time horizon where $H = 8$ quarters. Dependent variable of interest, $y_{j,t+h}$ is investment and borrowing. α_j^h is the firm fixed effect, ϵ_t^m is the quarterly monetary policy shock. $\mathcal{I}_{j,t-1}^{Asset} = 1$ is the indicator variable when firm j use asset-based borrowing contract at time t (otherwise zero).

Regression yields β^h which captures the relative response (compared to cash flow-based borrowers) of asset-based borrowers to a contractionary monetary shock. To prevent contamination from the firm initial distribution assumption, I only consider the firms surviving at least 28 quarters.[31] Similar to (1.5), firm-level controls include firm size (k), age, and leverage (b), while the macro controls are excluded here, and instead a time fixed effect, δ_t, is employed.[32]

I compare the model output and the data by focusing on the interaction coefficient of indicator variable $\mathcal{I}_{t-1}^{Asset}$ and the monetary shock ϵ_t^m. Dependent variables of interest are firm-level investment and borrowing. The estimation horizon is 8 quarters.[33] I present the model impulse responses as the point estimates of the interaction coefficient β_x^h along with their 90% error bands.

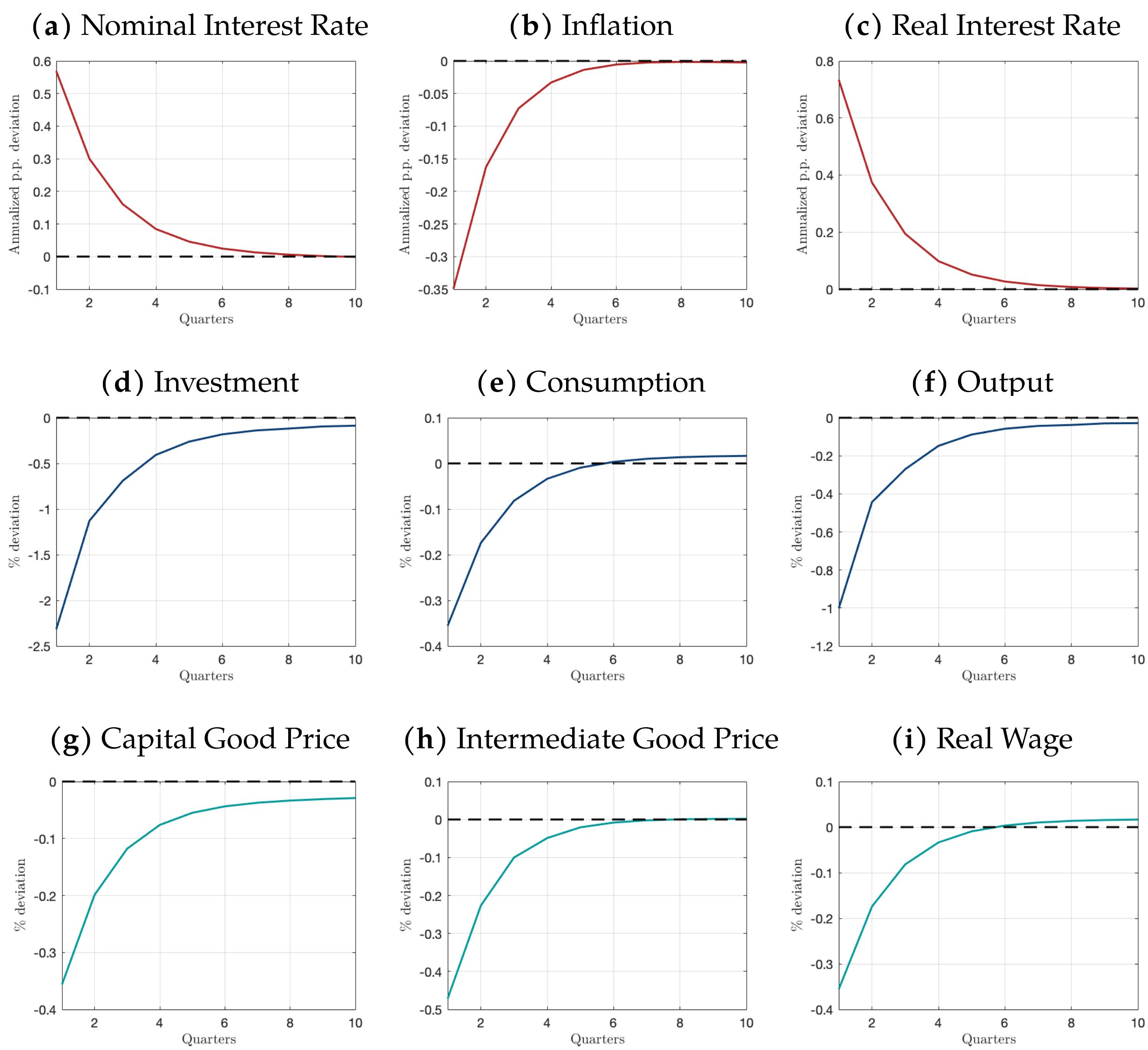
[31] Excluding the earlier periods of firms is a common practice in the literature (Ottonello and Winberry, 2020). The model's results are robust to the cutoff choice.

[32] Here note that (1.5) also includes current assets ratio and Tobin's Q as firm-level controls, but excluded here since these two variables are beyond the scope of the model.

[33] The horizon of the impulse responses on the simulated data is shorter than the actual data. It is because the model does not feature aggregate impedance mechanisms to generate a sluggish response of variables. Therefore, the impact of the shock survives at shorter horizons compared to the data; thus, running the regressions at longer horizons is unnecessary.

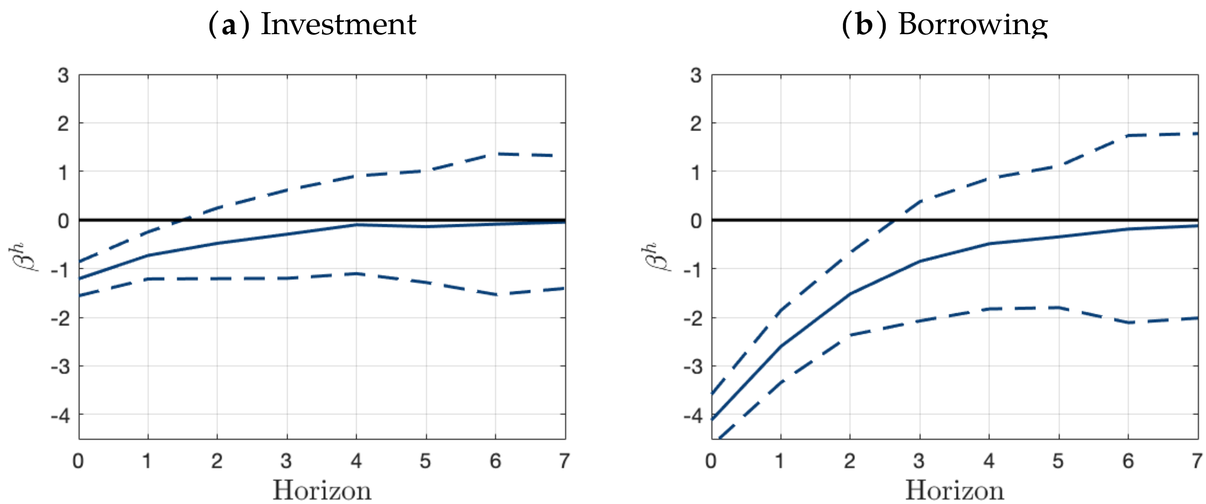
Figure 1.4

AGGREGATE IMPULSE RESPONSES



NOTE. Aggregate impulse response functions following a contractionary monetary policy shock. The shock is applied as an unexpected innovation to the Taylor rule (1.23). The monetary policy shock series starts with $\epsilon_t^m = 0.0025$ and continue as $\epsilon_{t+1}^m = 0.5 * \epsilon_t^m$. The responses are computed as the perfect foresight transition path.

Figure 1.5
DIFFERENTIAL IMPULSE RESPONSES: INVESTMENT AND BORROWING



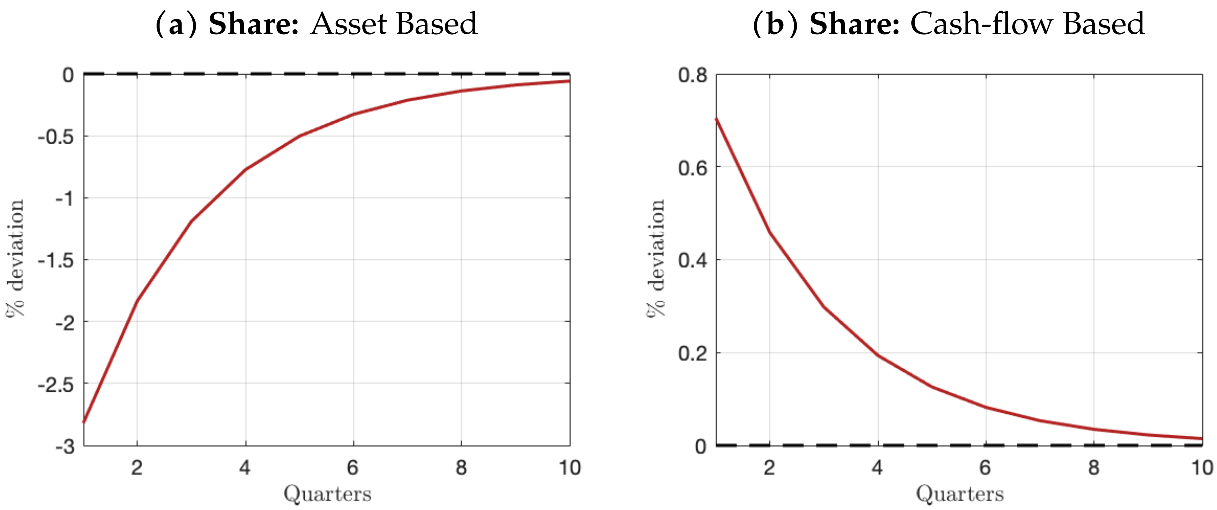
NOTE. Average impulse response functions for the investment and borrowing to contractionary monetary policy shock. The responses are estimated with a variant of the local projection specification given by (1.5). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The dashed lines display 90 percent confidence intervals.

Investment and Borrowing Response Figure 1.5 depicts the relative impulse responses of investment and borrowing in Panel (A) and Panel (B), respectively. Given that both asset-based and cash flow-based borrowers respond by reducing their investment and borrowing, a negative value indicates that the response of asset-based borrowers is larger in magnitude.

Panel (A) depicts that asset-based borrowers decrease their investment relatively more after a contractionary monetary policy shock than cash flow-based borrowers. Panel (B) exhibits that a similar pattern holds for firm borrowing. The differential impulse response is significant, meaning asset-based borrowers cut back on borrowing considerably more than cash-flow-based borrowers.

Compositional Changes Following a similar approach to Section 1.2, I also run an experiment about endogenous changes in group composition. Figure 1.6 shows that indeed, in line with the empirical evidences in Section 1.2, firms respond to a contractionary monetary policy shock by switching from asset-based contracts to cash flow-based contracts. This finding about switching supports the paper's main idea that asset-based borrowers are affected more than cash flow-based borrowers. The magnitudes of compositional changes explain another aspect. If there had not been limited commitment, then we would have seen a much larger switch, but through the limited commitment mechanism, asset-based borrowers only switch to cash flow-based debt contracts if they are able to do so. Here note that since the model does not include portfolio adjustment costs to produce dampened dynamics, the responses are larger than their empirical counterparts (3% in the quantitative model vs 1.2% in the data).

Figure 1.6
IMPULSE RESPONSES: SHARES
ASSET-BASED VS. CASH FLOW-BASED



NOTE. Aggregate impulse response functions for the shares of contracts following a contractionary monetary policy shock. The shock is applied as an unexpected innovation to the Taylor rule (1.23). The monetary policy shock series starts with $\epsilon_t^m = 0.0025$ and continue as $\epsilon_{t+1}^m = 0.5 * \epsilon_t^m$. The responses are computed as the perfect foresight transition path.

As a bottom line, Figure 1.5 shows that asset-based borrowers are affected from an unexpected interest rate increase more than cash flow-based borrowers. The compositional change also favors cash flow-based debt contracts. These responses resemble their empirical counterparts and suggest that the quantitative model well captures the empirical patterns.

At this point, it is worth repeating the primary mechanism in mind. The firms issuing new debt with asset-based contracts have to rely on their capital stock to serve as collateral. Therefore, by reducing the capital price, contractionary monetary policy shocks tighten the borrowing constraint for these firms and force them to cut back on borrowing and investment. Whereas the firms with cash flow-based debt contracts do not have a capital price in their borrowing constraint formulations, therefore, are not affected by the decreasing values of capital price. I assess the relevance of this capital price channel in the next section by switching it off and comparing the differential responses.

1.6.3 Heterogeneous Responses to Monetary Policy in the Absence of Capital Price Movements

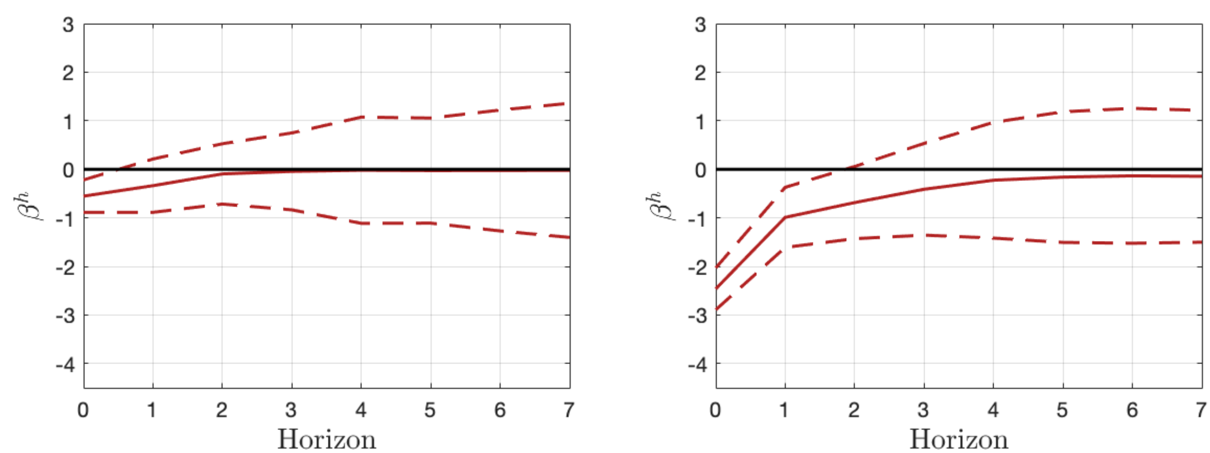
This section discusses why asset-based borrowers are more sensitive to a contractionary monetary shock. The results emphasize that a conventional framework with asset-based borrowing constraint (Kiyotaki and Moore, 1997; Bernanke et al., 1999; Khan and Thomas, 2013) is inadequate to capture the salient aspects of the findings reported in Section 1.2.

In order to show the impact of capital price movements on monetary policy transmission, I compare the impulse responses with and without capital price movements. To shut off the capital price movements, in (1.20) I set the convex adjustment cost parameter $\phi = \text{Inf}$, which yields flexible capital adjustment and time-invariant capital price, $\bar{q} = 1$. Therefore, the collateral constraint of asset-based borrowers is not affected by the extra response of capital price from a monetary shock.

Figure 1.7

Impulse Responses without Capital Price Movements: Investment and Borrowing

(a) Investment **(b)** Borrowing



Note. Average impulse response functions for the investment and borrowing to contractionary monetary policy shock. The responses are estimated with a variant of the local projection specification given by (1.5). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The dashed lines display 90 percent confidence intervals.

On the one hand, if another factor (instead of the asset price channel) is the primary driver of the heterogeneous responses of investment and borrowing, there should be no difference between the results obtained in this section and Section 1.6.2. On the other hand, if the asset price channel is the only driver producing the heterogeneous responses, then the differential responses must be immediately shut off. Figure 1.7 shows that the actual model responses are in between, and thus when the asset price channel is off, the differential response of investment is dampened by approximately 60%. Similarly, the borrowing response difference between these groups is decreased by 50%. The underlying reason about why we don't see a total elimination of differential responses is the general equilibrium effects. More elaborately, by making capital price time-invariant, the indirect channel over the borrowing constraints in the asset-based contracts is shut off. However, for the cash flow-based borrowers, the indirect channel over their borrowing constraint is still effective, as a contractionary monetary shock can still affect the cash flows via aggregate demand.

As a bottom line, this experiment supports the idea that change in asset prices is the primary channel explaining the larger response of asset-based borrowers. This finding is consistent with the proposed primary mechanism, as the debt limits become more stringent when facing a contractionary monetary shock for firms with asset-based borrowing contracts. On the other hand, results indicate that even in the absence of capital price movements, there are still differences between the asset-based and cash flow-based borrowers' responses. This calls for additional analysis and possible model extensions, which is beyond the scope of this paper.

1.6.4 Implications for Financial Accelerator

In the previous parts of this section, I have shown that by incorporating the coexistence of asset-based and cash flow-based borrowing contracts into an otherwise conventional heterogeneous firm model, I explain the empirical findings of Section 1.2. That is, firms with asset-based borrowing contracts exhibit a larger response of investment and borrowing following an unexpected change in interest rates. Furthermore, when the asset price channel is shut off, the difference between the responses of asset-based and cash flow-based borrowers dampens. In the following, I discuss the implications of these findings from the macro perspective by focusing on the financial accelerator mechanism.

A broad literature has investigated the roles of firm balance sheets and their interplay with financial frictions in amplifying the effects of monetary policy. The key trait in these papers is that asset price response triggers a reinforcing channel in monetary policy transmission. However, this mechanism depends on the fact that borrowing constraints (Kiyotaki and Moore, 1997) or equity values (Bernanke et al., 1999) are functions of the liquidation value of tangible assets. The introduction of cash flow-based borrowing constraints to an otherwise conventional macrofinance model shows that the effectiveness of the asset price channel actually depends on the contract type the firm hold.

To illustrate the relevance of asset price channel for the financial accelerator mechanism,

Table 1.5

DEPENDENCE OF AGGREGATE RESPONSE ON CONTRACT TYPE

	w/o Δq	**AB**	**CfB**
Investment	-28.2	35.8	-47.1
Borrowing	-41.4	53.3	-61.5

NOTE. This table shows the aggregate responses of investment and borrowing under various modeling assumptions. The responses are calculated as the discounted percentage changes in borrowing and investment over the forecast horizon. The results presented here are relative to the baseline economy. The baseline case includes when both asset-based and cash flow-based contracts are available in the economy, and asset prices are responsive to monetary policy shocks. **w/o** Δq**:** Both asset-based and cash flow-based contracts are available in the economy but asset prices are time-invariant. **AB:** Only asset-based contracts are available in the economy. **CfB:** Only cash flow-based contracts are available in the economy.

Table 1.5 depicts the aggregate responses of various economies relative to the baseline case. Each column represents a different model. The first column, w/o Δq, corresponds to the case when both types of contracts are available in the economy, but as in Section 1.6.3, capital price is fixed and does not respond to monetary policy shocks. Under this specification, investment is 28% lower, and borrowing is 41% lower than the baseline case. The results are in line with Section 1.6.3, as the absence of asset price responsiveness (*i.e.* collateral channel) leads to less responsive investment and borrowing. This finding supports that the financial accelerator channel is strong and works through the collateral channel. Column 2, presents the model results when only asset-based contracts are available in the economy. Compared to the baseline case, investment and borrowing responses are larger in magnitude, 35.8%, and 53.3%, respectively. Column 3 belongs to an economy with only cash flow-based contracts. The responses are remarkably smaller compared to the baseline economy. Because, in this economy, the borrowing constraints firms face is not a function of capital price, and thus financial accelerator channel is mostly ineffective.

All in all, the three alternative economies' results indicate the collateral channel's active role in the strength of the financial accelerator. As opposed to asset-based contracts, in cash flow-based contracts borrowing limit is not a direct function of the liquidation value of capital. Therefore, cash flow-based borrowers are not vulnerable to the traditional collateral value channel of the financial accelerator mechanism through asset price fluctuations. As the asset price channel is still influential on asset-based borrowers, this implies that the strength of the financial accelerator depends on the share of asset-based borrowers in an economy. Given that most firms borrow using cash flow-based debt contracts, the overall effectiveness of the financial accelerator mechanism may be overstated in the macrofinance models with traditional collateral constraints.

1.6.5 Heterogeneous Transmission of Quantitative Tightening

Since the Great Recession, many central banks have widely used Quantitative Easing (QE) policy tool, which involves the central bank purchasing securities from the open market to reduce longer-term interest rates. The operation injects more liquidity into the banking system, thus stimulates lending and investment. Several studies investigate the macro implications of such large-scale asset purchase programs. Swanson (2021) discusses that large-scale asset purchases have significant effects on asset prices. Curdia and Woodford (2011), Gertler and Karadi (2011), and Boeckx, Dossche, and Peersman (2014) indicates that –as a policy tool– central bank asset purchases is effective in stimulating economy. On the other hand, in the aftermath of Covid-19, most central banks start to sell the assets they hold and thus contract their balance sheet, the operation known as Quantitative Tightening (QT).

This section presents the discussion of the QT transmission by demonstrating the heterogeneous responsiveness of asset-based and cash flow-based contract holders in the data.[34] To do so, I run the local projections regression in a similar fashion to the baseline empirical framework in Section 1.2.4. (1.29) presents the baseline empirical specification.

$$y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \gamma_1^h \left(\epsilon_t^q \mathcal{I}_{j,t-1}^{Asset}\right) + \gamma_2^h \left(\epsilon_t^q \mathcal{I}_{j,t-1}^{Cash}\right) + \sum_{p=1}^{P_Z} \Gamma_p \mathbf{Z}_{j,t-p} + \sum_{p=1}^{P_X} \Gamma_p \mathbf{X}_{t-p} + e_{j,t+h} \quad (1.29)$$

$h = 0, 1, ..., H$ represents the active time horizon where $H = 20$ quarters. $y_{j,t+h}$ is the dependent variable of interest at horizon h: investment and borrowing. α_j^h is the firm fixed effect, ϵ_t^q is the quarterly quantitative tightening policy surprise. The identified QT policy shocks are obtained from Swanson (2021).[35] The empirical framework controls for a rich set of idiosyncratic and aggregate factors that may simultaneously affect dependent variables and borrowing method. γ_1^h and γ_2^h are the regression coefficients of interest capturing the impulse responses among subgroups, asset-based and cash-flow-based, respectively.

[34] I am grateful to Edouard Challe for suggesting to investigate the QT implications of debt contracts.

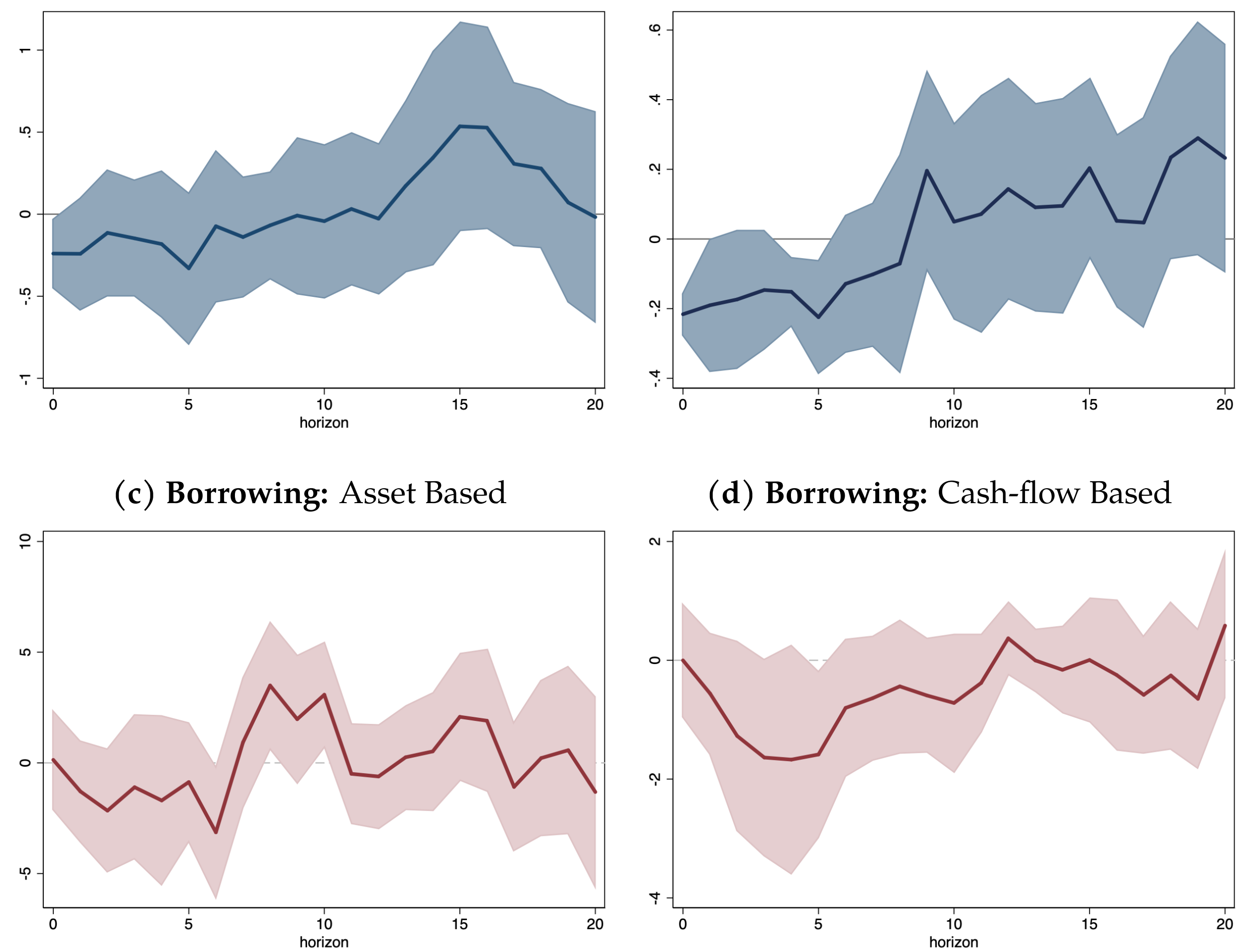
[35] Swanson (2021) identifies the QT shocks by extending Gürkaynak et al. (2005)'s high frequency approach. After calculating the asset price responses (within a 30-minute window) to each FOMC announcement, the author estimates the first three principal components of these asset price responses. To do so, the author chooses the three factors which offer the strongest explanatory power for high-frequency asset price movements. Then, the author identifies the factors as the first factor corresponds to changes in the federal funds rate, the second factor to changes in forward guidance, and the third factor to changes in large-scale asset purchases (*i.e.* QE).

Figure 1.8

IMPULSE RESPONSES TO A QUANTITATIVE TIGHTENING SHOCK:
ASSET-BASED VS. CASH FLOW-BASED

(a) **Investment:** Asset Based (b) **Investment:** Cash-flow Based

(c) **Borrowing:** Asset Based (d) **Borrowing:** Cash-flow Based



NOTE. Average impulse response functions for the investment and borrowing following a QT shock. The responses are estimated with the local projection specification given by (1.29). QT policy shock is interacted with indicator variable based on the firm borrowing status. The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

Figure 1.8 presents the estimated impulse responses using (1.29). The top and bottom rows are for investment and borrowing, respectively. The shaded areas denote the 90 percent confidence intervals based on two-way clustered standard errors at firm and quarter. Impulse response functions are estimated over 20 quarters period.

The results about the QT shock resemble the conventional contractionary monetary policy shock findings as depicted in Section 1.2.4. The magnitude of the impulse responses of investment and borrowing among asset-based borrowers is larger than cash flow-based borrowers. However, unlike the responses to an unexpected interest rate increase, the impulse response of asset-based borrowers is not statistically significant. At this point, it is worth mentioning that Krishnamurthy and Vissing-Jorgensen (2013) points out the role of the expectations channel in QE transmission. The underlying mechanism is that since QE means purchasing assets with long maturities, the value of long-term assets is mainly affected by expectations about future policy stance. Therefore, the authors conclude that the transmission mechanism of QE relies heavily on managing these expectations, namely the announcement (i.e. communication to the investors) of QE policies is effective rather than actual purchasing operations. Given that in the last decade (excluding the Covid-19 period), there were a few announcements of QE policy, the reason behind the insignificant impulse responses may be the insufficient number of announcements).

Finally, in Appendix A.4, motivated by the empirical evidence about heterogeneous QT transmission, I conduct a QT experiment with the model and present the model-produced impulse responses on firms' heterogeneous responses to a quantitative tightening shock.[36] Note that the exercise is designed to see the effect of QT on investment through the collateral channel, not how QT interventions move asset prices. Therefore, the latter mechanism is taken as given. In the experiment, what is measured in the exercise is the impact of an unexpected decrease in capital prices –possibly triggered by QT– on investment and borrowing when there are both asset-based, and cash flow-based contracts, and switching between these debt contract types is allowed. The key mechanism –as in Section 1.6– works through the heterogeneous responses of borrowing constraints.

Regarding QT, an interesting extension of the model in Section 1.3 could be incorporating borrowing constraints which depend on not the future but today's values. As Krishnamurthy and Vissing-Jorgensen (2013) points out, the aim is to disentangle the channels, namely investigating which channel is more effective: through altering expectations about future asset prices or actual asset sales. Although interesting, investigating expectations channel through the different timings of borrowing constraints is beyond the scope of this

[36]Since the effect of a QE shock is symmetric to a QT shock within the model, the results in this section also shed light on the impact of a QE shock.

paper.

1.7 Conclusion

In this paper, I investigate the interactions between the nature of debt contracts and monetary policy transmission to firm-level investment. On the empirical side, by employing loan-level data, firm-level balance sheet data, and stock return data, I first show that firms with more pledgeable assets and high stock beta tend to sign asset-based debt agreements, while more profitable firms with high Jensen's alpha usually opt for cash flow based debt contracts. Second, I show that following a contractionary monetary policy shock, firms with asset-based borrowing contracts cut their investment and borrowing significantly more than firms with cash flow-based debt contracts. Third, despite constituting only a tiny portion of the total investment, the majority of investment *response* to monetary policy shocks are initiated by asset-based borrowers.

To interpret the results about why firms choose one contract over the other and to understand the channels driving the heterogeneous sensitivity to monetary policy shocks, I set up a heterogeneous firm macrofinance model. The model is able to explain the cross sectional heterogeneity on the firm's contract type choice through state contingent borrowing limits. The quantitative results suggest that the traditional collateral channel through asset prices causes this heterogeneous sensitivity as the cash flow-based borrowers are less vulnerable to asset price fluctuations. As for the aggregate implications, the findings suggest that the financial accelerator mechanism is effective, and its strength is tied to the collateral channel and may diminish as more firms in the economy hold cash flow-based contracts.

The results of this paper are of crucial interest to monetary policymakers as these results contribute to understanding how monetary policy transmits to firm investment and borrowing. Furthermore, long-term economic growth requires a healthy rate of birth and death of businesses because it promotes the emergence of new, productive ideas. However, my results show that, while cooling down the economy via increasing rates –through the financial accelerator mechanism– contractionary policy will asymmetrically harm the asset-based borrowing firms, which are already fragile. As the asset-based borrowers are mostly young and small firms, increasing interest rates may have adverse side effects as being detrimental to business dynamism. My results imply that there is room for fiscal policy intervention to asset-based borrowing firms while conducting the monetary policy to fulfill its mandate of keeping inflation steady.

Chapter 2

TFPR: Dispersion and Cyclicality

Abstract This paper studies the determinants of TFPR, a revenue based measure of total factor productivity. Recent business cycle models are built upon the assumption of countercyclical dispersion in TFPQ, a quantity based measure of total factor productivity, based on evidence of countercyclical dispersion in TFPR. But, these can be very different measures of productivity. The distribution of TFPR is endogenous, dependent upon exogenous shocks and the endogenous determination of prices. An overlapping generations model with monopolistic competition and state dependent pricing is constructed to study the factors that shape the TFPR distribution. The empirical focus is on three key data patterns: (i) countercyclical dispersion of TFPR, (ii) countercyclical dispersion of price changes and (iii) countercyclical frequency of price adjustment. The analysis uncovers two interesting scenarios in which these moments are matched. One arises in the presence of shocks to the dispersion of TFPQ along with a negatively correlated change in the mean of TFPQ. The second arises if the monetary authority responds to shocks to the dispersion of TFPQ by "leaning against the wind". Due to state contingent pricing, the model is nonlinear. Simple correlations mask these nonlinearities of the underlying economy. The real effects of monetary innovations are state dependent, with monetary policy less effective in recessions.

2.1 Motivation

There is ample evidence that the cross-sectional dispersion of productivity is countercyclical.[1] Bloom et al. (2018) use this feature of the data as a key input into a model of aggre-

[1] See the evidence and discussion in, for example, Kehrig (2011), Bachmann and Bayer (2014), and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). The evidence is presented as changes in the distribution of total factor productivity and/or the correlation in the dispersion of total factor productivity with a measure of economic activity. Bachmann and Bayer (2014) provide complementary evidence from German data.

gate fluctuations, highlighting the effects of uncertainty.[2] Relatedly, Vavra (2014) provides evidence that in recessions price changes are more dispersed and the frequency of price adjustment is higher.[3] He argues that these patterns can be reproduced in a model with variations in the volatility of firm level productivity as these fluctuations induce some sellers to adjust prices upwards and others to adjust downwards.[4]

While the evidence of countercyclical dispersion of productivity is relatively incontrovertible, debate continues on the source of this pattern. One point of concern, raised for example in Berger, Dew-Becker, and Giglio (2020), is the limited evidence that uncertainty drives these patterns. Further, as argued in this paper, the important distinction between measurement and theory is ignored. This leads to the central question of the paper: what drives the cyclicality of the dispersion in TFPR?

Note that the question pertains to TFPR, a revenue based measure of productivity, and not the quantity-based measure of productivity, TFPQ. The facts presented in Foster, Haltiwanger, and Syverson (2008) make clear that: (i) the distributions of TFPQ and TFPR differ and (ii) the distribution of TFPR is not degenerate. The first point implies that any model attempting to study both of these distributions needs to rationalize the difference between TFPR and TFPQ. Further, that model, following the discussion in Hsieh and Klenow (2009), must explain why the distribution of TFPR is not degenerate.

The distinction between TFPR and TFPQ is important for understanding the existing literature and our contribution. The empirical findings regarding the cyclicality of productivity rely on measurements of TFPR not TFPQ. Yet, the models routinely focus on variations in the dispersion of TFPQ as a driving force and equate these with variations in the dispersion of TFPR. The distinction between the dispersion in TFPQ and TFPR is not a component of the analysis in prominent contributions, such as Bloom et al. (2018) or Vavra (2014). Our analysis instead uncovers conditions for countercyclical variation in TFPR dispersion but does not support the view that it necessarily arises from countercyclical variations in the dispersion of TFPQ.

To be clear, this paper does not contest the cyclicality of TFPR dispersion. Rather, it studies the determinants of this cyclicality along two general possibilities. The first, quite naturally, is that variations in the dispersion of TFPQ underlie variations in the dispersion

[2] There is an important distinction between uncertainty and dispersion. Uncertainty refers to an *ex ante* situation of not knowing, say, some moment of the distribution of a random variable, such as not knowing the future variance. Bloom et al. (2018) contains both uncertainty and dispersion effects.

[3] Bachmann, Born, Elstner, and Grimme (2019) provides comparable evidence for German manufacturing plants.

[4] His calibration relies upon the same measures of dispersion as Bloom et al. (2018). The connection between firm specific shocks and the distribution of price changes is highlighted in Golosov and Lucas (2007) as well.

of TFPR. The second focuses on the effects of price determination directly on the dispersion of TFPR. That is, changes in the distribution of prices can generate movements in the dispersion of TFPR, holding the distribution of TFPQ fixed.

Our model and quantitative analysis explicitly incorporate the distinction between TFPQ and TFPR, building on Foster et al. (2008). As prices form the bridge between the distributions of TFPR and TFPQ, price setting plays a central role in our analysis. From Table 1 of Vavra (2014), the standard deviation of prices is countercyclical. This suggests the possibility that price movements, in response to shocks, contribute to the cyclicality of the dispersion in TFPR. Moreover, price stickiness directly creates a non-degenerate distribution of TFPR, so that other types of frictions or wedges are not needed.[5] Thus, ignoring the distinction between TFPQ and TFPR is not only at variance with the evidence but also misses the contribution of endogenous price setting.

Our central question is addressed through a model of state dependent pricing, with heterogeneous firms, to obtain a mapping from the distribution of TFPQ to the distribution of TFPR. In contrast to the flexible price case, state dependent pricing due to menu costs introduces both extensive and intensive margins of pricing decisions and thus allows for a variety of factors, both monetary and real, to influence the distribution of TFPR.

The framework for analysis is an overlapping generations model with monopolistic competition and sticky prices, specified in section 2.2. Young agents have market power, set prices *ex ante* and can, at a cost, change them *ex post*, once the various shocks (productivity, tastes and monetary) along with the menu cost are realized. Old agents take money earnings from youth as well as monetary policy induced transfers and spend them on a variety of goods. The analysis is conducted through a stationary rational expectations equilibrium for this environment. The model allows aggregate shocks to the dispersion of idiosyncratic demand, the mean and dispersion of productivity and to the money supply.

Admittedly this is not a common framework for studying price determination in an aggregate model, but it has a number of distinct advantages. First, individual choice problems, in particular the state dependent pricing problem of sellers is very tractable. Second, we are able to obtain a full characterization of a stationary rational expectations equilibrium, including a wide variety of shocks to technology, tastes and the money supply. Finally, in contrast to most other papers in this area, there are no approximations in the quantitative analysis. Instead the determination of the effects of the various shocks is through the stationary rational expectations equilibrium. As we shall see, including nonlinear interactions is an integral part of the analysis.

An apparent weakness of the approach is that the *ex post* pricing decisions of sellers

[5]We are grateful to John Haltiwanger for emphasizing this point to us.

have no dynamic component. However, we find that in a parameterized version of the model, the price setting behavior of sellers in this model mimics key features of the price setting from models with infinitely lived sellers. In this sense, while the model misses some dynamic elements of forward looking pricing, it does capture the essence of the state dependent pricing.

The overlapping generations model provides a framework for conducting quantitative experiments in a stochastic equilibrium setting. Section 2.3 presents the quantitative model. The calibration is based on a steady state of the model. The pricing moments for the calibration come from Vavra (2014) while Foster et al. (2008) is used for moments on the dispersion of TFPQ and TFPR. The calibration pins down the elasticity of demand as well as the relative importance of shocks to the dispersion of demand and the dispersion of TFPQ. We find that a much higher dispersion in technology shocks relative to demand is needed to match the moments. The distribution of menu costs comes from Dotsey and Wolman (2019).

The calibrated model has a particularly important feature, common to models of state dependent pricing: a U-shaped hazard of price adjustment. In the parlance of Caballero and Engel (1993), the adjustment rates are very high when the absolute value of the gap between the actual and desired price is large and very low when this gap is near zero. That characterization applies almost directly to our model since price setting is a static problem. This nonlinear hazard creates nonlinear responses in the economy, particularly in the presence of monetary shocks, and this nonlinearity pervades the quantitative analysis.

The model is assessed by its ability to mimic key data features: (*i*) countercyclical dispersion in TFPR, (*ii*) countercyclical frequency of price adjustment and (*iii*) countercyclical dispersion in price changes. Our first set of findings is negative. Taken individually, none of the sources of aggregate variation we consider can reproduce the data patterns of countercyclical dispersion in TFPR, the frequency of price adjustment and the dispersion of price changes.

A natural starting point, in keeping with the literature, is to consider exogenous variations in the dispersion of TFPQ as the source of countercyclical dispersion in TFPR. Consistent with Vavra (2014), shocks to the dispersion of TFPQ do succeed in matching data patterns (*ii*) and (*iii*). But, in our model, shocks to the dispersion of TFPQ are procyclical and produce procyclical variation in the dispersion of TFPR. **Thus, shocks to the dispersion of TFPQ alone are unable to match data patterns.**[6]

The procyclicality of dispersion in TFPQ contrasts with Bloom et al. (2018). In their setting, uncertainty plays a prominent role. However, recent findings of Berger et al. (2020)

[6] Again, keep in mind that there is no direct evidence about the cyclical patterns in the dispersion of TFPQ.

and Dew-Becker and Giglio (2020) casts some doubt on the central role of variations in uncertainty as the source of the countercyclical dispersion.[7] This finding also is at variance with Vavra (2014) who asserts the countercyclical dispersion of TFPQ, without distinguishing it from the distribution of TFPR.

Due to price setting behavior, TFPR dispersion responds to other shocks, including variations in the money supply, the distribution of idiosyncratic demand and the mean of productivity. Analyzed independently, these shocks generate cyclical movements in the dispersion of TFPR, both through effects on the dispersion of prices and, perhaps more interestingly, through the covariance of prices and the firm specific productivity shock. But the model moments produced from these sources of fluctuations do not match data patterns.

The second set of findings relate to experiments that combine these sources of variations. **A shock to the dispersion of TFPQ combined with a perfectly negatively correlated shock to the mean of TFPQ, matches the data patterns.** Essentially the dispersion of TFPR is driven by the dispersion of TFPQ while output movements depend more on the mean of TFPQ. The combination of shocks provides a mechanism that drives a wedge between the dispersion of TFPR and that of TFPQ. Combining these two shocks is crucial: an increase in the dispersion of TFPQ alone cannot capture the empirical pattern of countercyclical dispersion in TFPR.

These results are supportive of findings in the literature. In order to avoid negative correlation between consumption and investment in the face of an uncertainty shock, Bloom et al. (2018), combine a shock to the dispersion of TFPQ with a reduction in average TFPQ. Vavra (2014) employs a variation of this specification. But, again, the mechanisms are different. We do not rely on uncertainty shocks. Further, our shocks relate to the distribution of TFPQ not the endogenous distribution of TFPR so that the pricing decisions impact the TFPR distribution.

In addition to this combination of shocks, we allow the monetary authority to respond to exogenous variations in the mean and dispersion of TFPQ as well as to changes in the dispersion of demand, thus creating a comovement with the money shocks. Through its response to these shocks, the monetary authority induces a correlation between output and money innovations. If the monetary authority "leans against the wind", i.e. tightens monetary policy when output is high, in the face of shocks to the dispersion of TFPQ, then the data patterns of countercyclical dispersion in TFPR, the dispersion of price changes and the frequency of price adjustment emerge.

Section 2.6 looks at additional properties of the model economy. First, we highlight

[7] The effects of uncertainty in our environment are studied in Subsection 2.6.4.

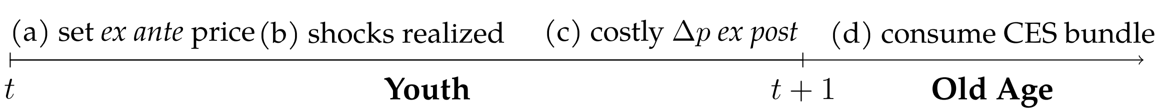
the nonlinear properties of the equilibrium response to shocks, which comes from the U-shaped price adjustment hazard. For this, we compute conditional correlations to indicate how variables comove as a function of the aggregate state (expansion or contraction). Second, we ask whether the model generates state dependence in the effects of monetary shocks, as documented in Tenreyro and Thwaites (2016) and discussed in Vavra (2014) as well. In fact, we do find evidence that money shocks have a bigger impact during expansions. Finally, we introduce uncertainty into the framework, distinguished from *ex post* changes in dispersion. We find no effects of uncertainty.[8]

2.2 Equilibrium Model of State Dependent Pricing

We study the determination of the distribution of TFPR in an infinite horizon overlapping generations model with differentiated products and market power. Agents live for two periods, youth and old age. Generation t young agents produce and, when old, these agents consume a basket of goods produced by the next generation of young producers. Saving occurs through the holding of fiat money. The quantity of fiat money is stochastic, representing monetary shocks.[9]

As noted earlier, this is admittedly not the standard framework for the analysis of state dependent pricing. The benefit of the model is the simplicity of the choice problems coupled with an equilibrium analysis that allows experiments without the introduction of unexpected shocks to money and/or the distributions of productivity and demand. This point is central since understanding how the economy responds to shocks is the key question of the paper. Answering this in a fully articulated stochastic economy is therefore necessary.[10]

Figure 2.1
Time Line: Generation t



[8]This is in line with the relative importance of dispersion relative to "wait and see" effects reported in Bachmann et al. (2019).

[9]This presentation focuses on a version of the model in which there are aggregate shocks to the model supply as well as idiosyncratic shocks to seller productivity and to the cost of price adjustment. The quantitative analysis adds other sources of variation. The extension of the model to include these additional shocks appears in Subsection 2.2.5 and Appendices B.1.2 - B.1.3.

[10]Many other models do not have an equilibrium demand for money and/or do not study the effects of money and other aggregate shocks in an equilibrium framework.

The sequence of choices is shown in Figure 2.1. Generation t young agents set a price *ex ante*, prior to the determination of any shocks but dependent on the history of the economy, summarized in equilibrium by the stock of money inherited from the previous period. This indicated by (a) on the timeline. At point (b) shocks to the aggregate money supply as well as to idiosyncratic productivity and idiosyncratic menu costs are realized. Given these realizations, sellers have an option of *ex post* price adjustment, indicated by point (c). This is the step that generates heterogeneous price setting, both on the extensive margin (to adjust the *ex ante* price or not) and in the event of adjustment, the intensive margin choice of what price to set.

There are a couple of features of the model economy worth highlighting. First, the price setting stage is interdependent in that the optimal price of one seller depends on the *ex post* price of the adjusters as well as the *ex ante* price of the non-adjusters.

Second, the *ex post* decision on price adjustment depends on the realization of all shocks. In this way, the dispersion of the distribution of productivity shocks impacts the frequency of adjustment and thus the real effects of money shocks.

Third, the inclusion of two forms of idiosyncratic shocks, one to productivity and the other to the adjustment costs, creates an interesting tension in the adjustment decision. A seller with a very large productivity shock might be induced to adjust the *ex ante* price but may draw a high adjustment cost and thus not reset its price. This tension has implications for the equilibrium effects of money shocks as the selection into price adjustment depends on all of these shocks. Further, for our purposes, the relationship between the exogenous TFPQ distribution and the endogenous TFPR distribution depends on the price setting behavior of sellers.

Fourth, as in Lucas (1972), in the absence of price stickiness, there would be a stationary rational expectations equilibrium in which money was neutral. This is because money transfers are made to the old in proportion to money holding earned in youth. And, as in that paper, the analysis rests on the coexistence of real and nominal shocks. But, in our setting the friction of costly price adjustment replaces his assumption of imperfect information.[11]

[11]Of course, in his model the real shock was to the fraction of sellers in a particular market while we focus on productivity shocks.

2.2.1 Choice of Old Agents

Lifetime utility is represented by $u(c)-g(n) = \frac{c^{1-\sigma}}{1-\sigma} - g(n)$. Here c is a CES aggregator given by $c = \left(\sum_i c^{i\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$, with $\varepsilon > 1$.[12] The function $g(\cdot)$ is increasing and convex in hours worked, with $0 \leq n \leq 1$. As we shall see, both the substitutability between products as well as the curvature in the disutility of work play important roles in the pricing decisions of young agents, particularly the choice of *ex post* adjustment.

When old, agents take their money holdings from income earned in youth and allocate it across goods to maximize $u\left(\left[\sum_i (c^i)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right)$, subject to a budget constraint of $\sum_i c^i p^i = M$ where M is their nominal income and p^i is the money price of good i.[13]

For these preferences, the demand for good i is given by

$$c^i = d(p^i, P, M) = \left(\frac{p^i}{P}\right)^{-\varepsilon} \frac{M}{P}. \tag{2.1}$$

Here P is an aggregate price index defined as $P = (\sum_i (p^i)^{1-\varepsilon})^{\frac{1}{1-\varepsilon}}$. Note that the only shock to demand is from variations in the stock of money, M.

Let $V(\frac{M}{P})$ be the value of the solution to the optimization problem of an old agent with nominal income of M with prices given by P. Given the definition of c,

$$V(\frac{M}{P}) = u\left(\left[\sum_i \left((\frac{p^i}{P})^{-\varepsilon}\frac{M}{P}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right) = u\left(\left[\sum_i \left((\frac{p^i}{P})^{-\varepsilon}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}} \frac{M}{P}\right) \tag{2.2}$$

with P given above. From this, the marginal value of nominal income is given by $V_M = \frac{u'(c)}{P}$.

At this point, these are generic demands and values for an old age given nominal income and prices. These values summarize the outcome of the choice problem for old agents in period t at point (d) of the time line in Figure 2.1. We will take this structure and use it to study the choices of young agents in the OG framework, summarizing the utility they obtain when old through $V(\frac{M}{P})$.

[12] We normalize the number of young agents and thus products to 1. With the CES assumption, markups are constant. This puts aside another potentially interesting interaction between the level of economic activity and prices.

[13] To simplify the notation, the time subscript is repressed. The money holdings come from income earned in youth as money is the store of value in this economy. Many other general equilibrium models, such as Dotsey, King, and Wolman (1999a), impose money demand. In Golosov and Lucas (2007), money is in the utility function.

2.2.2 Choice of Young Agents

We start with the pricing decisions of generation t young agents. When young agents choose the price of their product *ex ante*, they take into account the option, at a fixed cost, of adjusting their price *ex post*. These are points (a) and (b) in Figure 2.1. Since this is a model of a menu rather than a quadratic cost at the micro-level, the *ex ante* price will influence the frequency of adjustment but not the *ex post* price conditional on adjustment.

As is common in the sticky price literature, see for example Galí (2015), sellers are assumed to meet the demand forthcoming at their price. Thus the prices they set will determine their nominal income in youth, given the aggregate state.

This nominal income is held over time in the form of money to purchase consumption goods when old. Holdings of money are altered through monetary policy. Thus in our framework, money holdings and monetary policy interventions are made explicit.

To study the pricing choice, consider the *ex post* decision of generation t sellers.[14] If they choose to adjust, these sellers choose a price $\tilde{p}$ to solve

$$W^a(z_t, M_{t-1}, x_t, P_t) = max_{\tilde{p}} E_{x_{t+1},P_{t+1}} V((R(\tilde{p}, P_t, M_t))x_{t+1}/P_{t+1}) - g(\frac{d(\tilde{p}, P_t, M_t)}{z_t}). \quad (2.3)$$

Here the demand, denoted $d(\tilde{p}, P_t, M_t)$ and specified in (2.1), is the spending of the old agents on the product of this seller. The function $V((R(\tilde{p}, P_t, M_t))x_{t+1}/P_{t+1})$ is given by (2.2) with, in that notation, $M = R(\tilde{p}, P_t, M_t)x_{t+1}$ being the nominal revenue earned as a seller in period t supplemented by the period $t+1$ money shock and $P = P_{t+1}$, the period $t+1$ aggregate price level.

Since this decision is made *ex post*, the value and the price depend on the current state: (z_t, M_{t-1}, x_t, P_t). Here z_t is the current idiosyncratic productivity shock, M_{t-1} is the aggregate money supply inherited from the previous period, x_t is the money shock and P_t is the aggregate price level, determined in equilibrium as described below.

There is also a seller specific menu cost, denoted F, that influences whether adjustment occurs or not but not the price selected given adjustment. The adjustment cost is written as a utility loss. This specification has a convenient property that the optimal price is independent of the adjustment cost. So, the extensive margin of adjustment will depend on the realized menu cost and idiosyncratic productivity but the intensive margin does not so that the price dispersion of adjusters reflects only heterogeneity in z_t.

In this formulation, the menu cost F has a cumulative distribution function denoted

[14] That is, we solve the agents problem at point (b) and use this solution to study the *ex ante* problem at point (a).

$\Omega(\cdot)$. The inclusion of stochastic menu costs weakens the selection effect, i.e. the dependence of the pricing decision on z. As we shall see with the calibrated model, this implies that the probability of price adjustment is an increasing function of the absolute value of the idiosyncratic technology shock but it is not a step-function. That is, there are no bounds on z such that price adjustment occurs iff z is outside those bounds.

Notice that the price set by these sellers is independent of any price they may have set *ex ante* so that the *ex ante* choice does not appear in the state space. Importantly, once the cost of adjustment is incurred, the price reflects both the monetary shock and seller specific productivity. In this sense, there is an underlying complementarity at work. If a seller pays an adjustment cost to respond to one type of shock, then the marginal cost of responding to another type of shock is zero. This is important for the analysis that follows as it explains why price dispersion and thus TFPR dispersion is influenced by monetary policy.

With the production function of $y = zn$, the labor input of the seller is given by $\frac{d(\tilde{p}, P_t, M_t)}{z_t}$. As the seller meets all demand, the labor input varies inversely with productivity.

The first-order condition is

$$E_{x_{t+1},P_{t+1}}\left(u'(c_{t+1})x_{t+1}\frac{d(p_t,P_t,M_t)(1-\varepsilon)}{P_{t+1}}\right) = g'(\frac{d(p_t,P_t,M_t)}{z_t})\left(-\varepsilon\frac{d(p_t,P_t,M_t)}{p_t z_t}\right). \quad (2.4)$$

Denote this *ex post* optimal price by $p_t = \tilde{p}(z_t, M_{t-1}, x_t, P_t)$ for a seller with realized productivity z_t.

This is the standard condition for optimal price setting, equating marginal revenue with marginal cost.[15] But in this overlapping generations model, marginal revenue is determined by the expected marginal utility of the future consumption that can be acquired with the additional money income. And that income is itself impacted by future monetary policy, through the stochastic transfer x_{t+1}.

Alternatively, if the seller does not adjust, then expected lifetime utility is given by:

$$W^n(z_t, M_{t-1}, x_t, P_t, \bar{p}) = E_{x_{t+1},P_{t+1}}V((R(\bar{p},P_t,M_t))x_{t+1}/P_{t+1}) - g(\frac{d(\bar{p},P_t,M_t)}{z_t}). \quad (2.5)$$

Here, expected utility depends on the preset price, $\bar{p}$.

Given this, consider the *ex ante* choice. When this price is set, the young agent just

[15] To understand this condition in a static setting, let $d = (\frac{p}{P})^{-\varepsilon}y$ be the level of produce demand if the seller sets the price p and the aggregate price is P and the level of real spending is y. So $d_p = -\varepsilon\frac{d}{p}$. Further, revenue is given by $R = pd = p^{1-\varepsilon}(\frac{1}{P})^{-\varepsilon}y$. Hence $R_p = (1-\varepsilon)d$. The left side of (2.4) is the product of R_p and $\frac{u'(c_{t+1})x_{t+1}}{P_{t+1}}$. The right side is the product of d_p and the marginal disutility of work, $g'(\frac{d(p_t,P_t,M_t)}{z_t})\frac{1}{z_t}$.

knows the money supply from the past. Let $W^{xa}(M_{t-1})$ be the value to a young agent of setting the price *ex ante*. The value is given by:

$$W^{xa}(M_{t-1}) = max_{\bar{p}} E_{(z_t, x_t, x_{t+1} P_t, P_{t+1})}[(1 - \Omega(F^*(\Omega_t)))W^n(z_t, M_{t-1}, x_t, P_t, \bar{p}) + \int_0^{F^*(\Omega_t)} W^a(M_{t-1}, x_t, P_t) - F]d\Omega(F) \quad (2.6)$$

where $F^*(z_t, M_{t-1}, x_t, P_t)$ is the critical menu cost in state (z_t, M_{t-1}, x_t, P_t) such that price adjustment occurs iff $F \leq F^*(z_t, M_{t-1}, x_t, P_t)$. Let $\bar{p}(M_{t-1})$ denote the optimal *ex ante* choice.

2.2.3 SREE

The analysis is based on a stationary rational expectations equilibrium (SREE) with valued fiat money.[16] The current aggregate state is represented as (M, x) where M is the inherited money supply and x is the current shock, so that the current money supply is Mx. At the individual supplier level, productivity and the cost of price adjustment are the two elements in the idiosyncratic state: (z, F). At this point of the analysis, the distribution of the idiosyncratic shocks is fixed and thus not in the state vector. An equilibrium is defined and characterized given that distribution.

There are four state dependent functions to be determined. The *ex ante* price set knowing only M is denoted $\bar{p}(M)$. The *ex post* price set by sellers who choose to adjust their price is given by $\tilde{p}(M, z, x)$, indicating the price depends on both the realized money shock and productivity. There is a critical level of the adjustment cost, $F^*(M, x, z)$, such that adjustment occurs iff $F \leq F^*(M, x, z)$. Finally, the *ex post* money price of goods, $P(M, x)$, clears the goods market.

Definition 1 (SREE) A SREE is a set of functions $(\bar{p}(M), \tilde{p}(M, z, x), F^*(M, x, z), P(M, x), W^n(M, x, z), W^a(M, x, z))$ such that:

- $\bar{p}(M)$ solves the *ex ante* pricing problem given the state dependent price index $P(M, x)$;

  $$\bar{p}(M) = argmax_p E_{x,z,x'} V((R(p, P(M, x), Mx)x')/P(Mx, x')) - g(\frac{d(p, P(M, x), Mx)}{z}). \quad (2.7)$$

  for all M.

[16]The more general SREE -including shocks to the distribution of idiosyncratic productivity, as well as other aggregate shocks- is presented in Appendix B.1.2. To avoid confusion with terminology, stationarity means that these functions of the state are not indexed by time.

- $\tilde{p}(M,x,z)$ solves the *ex post* pricing problem:

$$\tilde{p}(M,x,z) = argmax_p E_{x'} V\left((R(p, P(M,x), Mx))x'/P(Mx,x')\right) - g\left(\frac{d(p, P(M,x), Mx)}{z}\right) \tag{2.8}$$

given the state dependent price vector, $P(M,x)$, for all (M,x,z).

- At the critical adjustment cost, $F^*(M,x,z)$, the seller is just indifferent between adjusting and not:

$$F^*(M,x,z) \equiv W^n(M,x,z) - W^a(M,x,z) \tag{2.9}$$

for all (M,x,z), with $W^a(M,x,z)$ given by:

$$W^a(M,x,z) = E_{x'} V\left((R(\tilde{p}(M,x,z), P(M,x), Mx))x'/P(Mx,x')\right) - \tag{2.10}$$

$$g\left(\frac{d(\tilde{p}(M,x,z), P(M,x), Mx)}{z}\right) \tag{2.11}$$

and $W^n(M,x,z)$ given by

$$W^n(M,x,z) = E_{x'} V((R(\bar{p}(M), P(M,x), Mx))x'/P(Mx,x')) - \tag{2.12}$$

$$g\left(\frac{d(\bar{p}(M), P(M,x), Mx)}{z}\right). \tag{2.13}$$

- $P(M,x)$ is the aggregate price index in state (M,x) given by:

$$P(M,x) = [E_z(1 - \Omega(F^*(M,x,z)))\bar{p}(M)^{1-\varepsilon} + E_z(\Omega(F^*(M,x,z))\tilde{p}(M,x,z)^{1-\varepsilon})]^{\frac{1}{1-\varepsilon}} \tag{2.14}$$

where $d(\bar{p}(M), P(M,x), Mx) = \left(\frac{\bar{p}(M)}{P(M,x)}\right)^{-\varepsilon} Y$ and $d(\tilde{p}(M,x,z), P(M,x), Mx) = \left(\frac{\tilde{p}(M,x,z)}{P(M,x)}\right)^{-\varepsilon} Y$. Here $Y = \frac{Mx}{P(M,x)}$ is the equilibrium determined real value of money holdings.

2.2.4 Equilibrium Properties

This section briefly describes properties of a SREE, both at the aggregate and individual seller level. These properties are made more explicit in the quantitative analysis.

Money Non-Neutrality

There are two main properties of a SREE that are verified in the analysis that follows.

Proposition 1 *There exists a SREE in which:* (i) *real quantities are independent of* M *since all prices set ex ante and ex post are proportional to* M *and* (ii) *real quantities are not independent of* x*.*

First, the inherited money supply is neutral: i.e. prices are proportional to M and all real quantities are independent of M. Formally, this amounts to guessing and verifying that there is a SREE in which $\bar{p}(M) = QM$ where Q is an unknown constant and $\tilde{p}(M, x, z) = M\tilde{\phi}(x, z)$. From this all relative prices and thus quantities demanded (and thus supplied) are independent of M.

The second property is money non-neutrality. If prices were not costly to adjust, i.e. the distribution of F was degenerate at $F = 0$, then there would exist a SREE with prices proportional to Mx. In this case, real quantities would be independent of the current money supply, Mx. But, in the presence of non-degenerate menu costs, as long as some sellers choose not to adjustment their prices *ex post*, a SREE with prices proportional to Mx cannot exist simply because the preset price, $\bar{p}$, must be independent of x.[17]

Productivity Measures

Returning to the theme of productivity measures, the difference between TFPQ and TFPR is straightforward to characterize. Here, z corresponds to the TFPQ measure of productivity. It is exogenous to the seller. The variable $\frac{zp}{P}$ is TFPR, where $p \in \{\tilde{p}(M, x, z), \bar{p}\}$ reflects the seller's pricing choice and P is the aggregate price.[18] Though the distribution of TFPQ is exogenous, the distribution of TFPR is endogenous as prices are set by sellers. Thus the distribution of TFPR responds to shocks insofar as sellers adjust prices in response to those shocks.

The price stickiness as well as the limited reallocation of labor across production sites help to shape the distribution of TFPR. To illustrate, consider a static, flexible price version of the model where $TFPR = pz = q^{-\eta}z = z^{1-\eta}n^{-\alpha\eta}$ where the production function is $q = n^{\alpha}$ and η parameterizes the elasticity of demand. From the first order condition with respect to n, if marginal cost of labor is ω, we have

$$(1-\eta)\alpha n^{(-\alpha\eta+\alpha-1)} z^{1-\eta} = \omega.$$

[17]Formally, this requires that the support of menu costs be large enough so that even if all other sellers adjust their prices *ex post*, the remaining seller, for any x, will have a high enough adjustment cost so that adjustment will not occur. See Ball and Romer (1991) for a discussion of this related to multiplicity of equilibria.

[18]Since TFPQ is measured directly in simulated data, there is no need to infer TFPR from revenue and thus no discussion of output or revenue factor shares. See the discussion of these measurement issues in Decker, Haltiwanger, Jarmin, and Miranda (2019).

At $\alpha = 1$, this condition becomes $(1-\eta)n^{-\eta}z^{(1-\eta)} = \omega$ which holds for all z. This implies that TFPR is given by $\frac{\omega}{1-\eta}$ and hence is independent of z. So, in this limiting case, variations in the distribution of TFPQ would not impact the distribution of TFPR. In our model, both price stickiness and non-linear production costs along with labor immobility will contribute to the non-degenerate distribution of TFPR.

Seller Choices

In equilibrium, aggregate real output is given by: $Y(x) = \frac{Mx}{P(M,x)} = \frac{x}{\varphi(x)}$, where, using the first part of Proposition **1**, $P(M,x) = M\varphi(x)$. Thus the response of output to money shocks will depend on $\varphi(x)$, in the absence of other aggregate shocks. This function summarizes the responses by sellers to monetary shocks. It captures both the extensive margin of adjustment, i.e. the fraction of sellers resetting their price *ex post*, as well as the intensive margin of the optimal price to set.

Note that from the first property of the equilibrium, the inherited money supply, M, is completely neutral. It has no effect on either the extensive or intensive margins.

The money shock impacts both margins. In terms of adjustment frequency, more extreme shocks generate a higher fraction of sellers choosing to adjust. Further, for those sellers adjusting, the *ex post* will depend on the money shock. But, importantly, it will not be proportional to x. Thus the non-neutrality arises on both the extensive and intensive margins.

There is an important feature of our model that ties directly with the line of research which studies the frequency of price adjustment as a function of a gap between actual and desired prices. Caballero and Engel (2007) discuss this approach and cite numerous related papers. Our model, with its one time price adjustment, fits exactly into that framework. This can be seem from (2.9), where the difference in the values between adjusting and no adjusting are used to determine the critical adjustment cost. These difference in values is directly related to the gap between the *ex ante* price, $\bar{p}(M)$, and the state contingent *ex post* price, $\tilde{p}(M,x,z)$.[19]

2.2.5 Additional Aggregate and Idiosyncratic Shocks

Thus far the analysis includes only a single aggregate shock. This was simply to enhance the transparency of the presentation. Introducing additional sources of randomness into this framework is direct.

[19]This is explored in the quantitative analysis of the linear quadratic economy.

Appendix B.1.2 presents the more general economy in which there is an aggregate state, S, that includes shocks to the money supply, variations in the distribution of z and relative demand shocks.[20] The optimization problems of agents as well as the definition of equilibrium is directly extended to this enhanced environment. It is the basis of the quantitative analysis that follows.

Two shocks to the distribution of TFPQ are studied. One is the traditional TFPQ shock in which the mean of the z distribution, denoted μ_Q, is stochastic. In this case, the output of a seller becomes $y = \mu_Q zn$. The second, which follows the motivation of the paper is a shock to the dispersion of z, denoted $disp_Q$, holding the mean fixed.

Finally, the model is extended to incorporate idiosyncratic demand shocks.[21] This provides a direct shock to the dispersion of TFPR, through demand, and independent of the dispersion in TFPQ. These are modelled as seller specific shifts in demand. As discussed below, these shocks differ from the idiosyncratic productivity shocks, particularly when prices are sticky. In terms of aggregate shocks, we study mean preserving spreads in the distribution of demand shocks, denoted $disp_D$. Variations in the mean level of nominal spending are studied through the money shocks.

Through all of these extensions of the stochastic framework, the basic structure of the model and the insistence on a SREE is maintained. Further, the numerical solution operates directly on the conditions for a SREE, without the need for linear approximations.

2.3 Quantitative Analysis

The estimation of underlying parameters is best left for an empirical exercise that studies price setting by infinitely lived firms matching high frequency observations on price and quantities. At this point, such an ideal data set is not available. Our goal is more modest and should be considered as an extended quantitative example allowing us to focus on the determination of the distribution of TFPR in an equilibrium model.

That said, the quantitative version of the OG pricing model has features of the standard macroeconomic pricing models, including both the Calvo model and state dependent pricing problems. In the Calvo model, as in the OG structure, the probability of price adjustment and the price set conditional on adjustment, are independent of the previously set price. Further, in some specifications, such as Christiano et al. (2005), price setters who do

[20]The inclusion of the relative demand shocks is motivated by the findings of the importance of this source of variation in Hottman, Redding, and Weinstein (2016). See Sedlacek and Ignaszak (2021) for a discussion of demand vs technology shocks as drivers of firm growth and innovation.

[21]The augmented model is discussed in Appendix B.1.1. See Eslava and Haltiwanger (2020) for discussion of a similar specification.

not adjust get to freely reset prices based upon past inflation. This added feature further reduces the role of history for price setting. In the OG model, this is captured by period t price setters choosing a price that is proportional to the inherited money supply.

Further, as discussed in Klenow and Malin (2010), existing evidence suggests that for individual sellers the likelihood of price adjustment at a particular point in time is independent of the time since last adjustment. Though allowing full state dependence (conditional on paying an adjustment cost), our model also has this history dependent feature as the choices of sellers in period t does not depend on prices in the past.

Price setting in this model also reproduces familiar patterns of state dependent price adjustment. That is the model generates pricing rules for sellers that retain the essential features of the more standard infinitely lived agent specifications. This is made clear in the discussion of the pricing behavior of sellers below.

The calibration of the model serves two purposes. First, it sets the basis for the quantitative assessment of the cyclical properties of the distribution of TFPR. Second, as the model includes both demand and technology shocks, the analysis contributes to the ongoing discussion of the relative importance of these sources of variation.

2.3.1 Calibration

The quantitative analysis rests upon a linear-quadratic economy: $u(c) = c, g(n) = \frac{n^\phi}{\phi}$, where ϕ is the elasticity of labor supply.[22] For the baseline, $\phi = 2$. Varying this elasticity impacts the shapes of marginal cost and thus the benefits of price adjustment, as explored in our robustness section 2.6.1.

The key parameters govern the price adjustment costs and the dispersion of idiosyncratic productivity. These are calibrated so that the steady state of our economy without aggregate shocks matches a set of moments.[23]

Even in the absence of aggregate shocks, the model produces a rich set of cross sectional moments given the presence of idiosyncratic shocks to productivity, idiosyncratic demand shocks and menu costs. The model calibration related to the distributions of the shocks rests on evidence related to the distributions of TFPQ and TFPR as well as the frequency of price adjustment.

The parameters characterizing the distribution of menu costs come directly from Dotsey and Wolman (2019) and are shown in the top panel of Table 2.1.[24] Note that this pa-

[22] Appendix B.1.3 characterizes the SREE for the linear quadratic preferences.

[23] The steady state is just the SREE given above with the restriction that $x = 1$ with probability one.

[24] These are discussed in detail in Appendix B.1.4. In principle, the parameters of the menu cost distribution could have been estimated as well. In practice, this proved difficult along two dimensions: (i) matching moments and (ii) finding an equilibrium. Thus we focus more on the stochastic processes and the elasticity

Table 2.1
Parameterization

Parameter	Value	Description
Menu Cost Distribution		
ψ	0.053	Probability of zero menu cost
$\bar{F}$	0.033	Upper bound on menu cost
ω	41.9	Curvature parameter
ν	2.8	Curvature parameter
Utility Parameters		
ϵ	2.37	Elasticity of substitution between products
ϕ	2	Elasticity of labor supply
Idiosyncratic Productivity Shock		
σ_z	0.0378	Standard Deviation
Idiosyncratic Taste (Demand) Shock		
σ_d	0.0069	Standard Deviation

rameterization allows a free price adjustment with probability slightly over 5%. A period is a month.

The linear-quadratic specification leaves three parameters, $(\varepsilon, \sigma_z, \sigma_d)$ to be determined. To do so, we use moments from Vavra (2014) and Foster et al. (2008) as shown in Table 2.2.

The frequency of price adjustment are taken from Vavra (2014), where the model is calibrated on a monthly frequency. For Vavra (2014), the standard deviation of TFPR on a monthly frequency is set to match the annual measure from Bloom et al. (2018). Vavra (2014) reports the standard deviation of the innovation, the persistence of the shock and the probability of a change in his Table III of calibrated parameters. In our model, all young sellers draw a shock from an ergodic distribution. Thus we infer the standard deviation of TFPR from the standard deviation of the innovation and the persistence reported by Vavra (2014).

Given our focus on the distinction between TFPQ and TFPR, independent observations on these objects is quite informative. From Foster et al. (2008) annual estimates, we take 1.181 as the ratio of the dispersion in TFPQ to the dispersion in TFPR. From experiments, it

of substitution.

Table 2.2
Matching Moments

Moment	Data	Model	Source
$disp_R$	0.102	0.103	Vavra (2014)
$disp_Q/disp_R$	1.181	1.181	Foster et al. (2008)
$freq_{\Delta p}$	0.110	0.127	Vavra (2014)

Note: This table shows basic moments computed from time series averages and the steady state of our model using the parameters in Table 2.1. All variables are logarithms except for frequency of price adjustment.

seems that this ratio is not influenced by time aggregation: simulating a higher frequency model and time aggregating preserves this ratio.[25]

As seen in Table 2.2, the calibration matches the moments well, though we do not quite reproduce the frequency of price adjustment reported in Vavra (2014).[26] The calibrated value of ε is below the level of other studies, such as Vavra (2014) and Golosov and Lucas (2007). Also, the dispersion of demand shocks is significantly lower than the dispersion of technology shocks, in contrast to Hottman et al. (2016) and Eslava and Haltiwanger (2020). We discuss the consequence of these differences in section 2.6.1 on alternative calibrations.

2.3.2 Seller Choices

This section illustrates the quantitative properties of the seller's choices for the linear-quadratic economy. Among other things, it makes clear that the policy functions from the overlapping generations model have properties quite similar to those produced by an infinitely lived seller. Throughout we focus on the response to idiosyncratic shocks, leaving aggregate shocks to the next section.

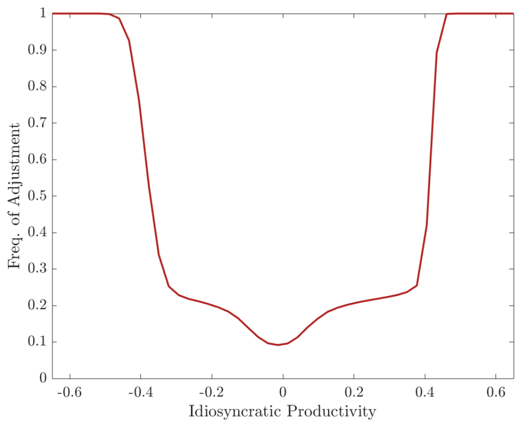
Pricing

As in the traditional state dependent pricing model, prices are adjusted only for sufficiently large shocks and the region of adjustment depends on the adjustment costs. In addition, because of the presence of stochastic menu costs, the probability of adjustment, given z, lies strictly in $(0, 1)$ unless z is in one of the tails. These properties is illustrated in Figure 2.2 in the steady state of our model.

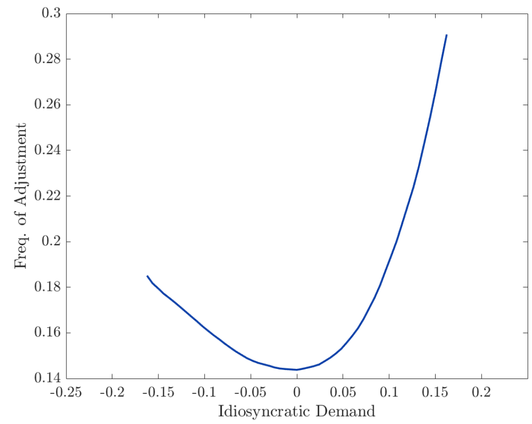
[25]This was studied in a partial equilibrium setting with Calvo price setting.
[26]One point of difference is that Vavra (2014) excludes temporary adjustments.

Two perspectives are shown in the figure. In the top two panels, the adjustment probability depends on the idiosyncratic productivity, on the left, and idiosyncratic demand, on the right. The adjustment probability is U-shaped indicating that adjustment is more likely for extreme values of these shocks.[27]

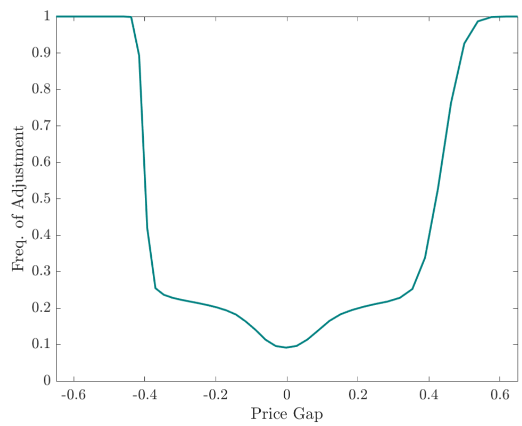
Figure 2.2
Adjustment Probabilities



(**a**) Productivity



(**b**) Demand



(**c**) Price Gap

Note: These figures show the adjustment rates of a seller in a steady state on idiosyncratic productivity, demand and the price gap.

The bottom panel provides an alternative but equivalent expression of the adjustment probability. Here the horizontal axis measures the difference between the log of the price

[27]The adjustment rate does not go to 1 in panel b because of the limited domain of the demand shock displayed.

the seller would set if adjustment was free and the log of the *ex ante* price. This measure, often called the price gap, is the foundation for the extensive research, from Caballero and Engel (1993) and Caballero and Engel (2007), on the relationship between adjustment rates and (price) gaps.[28] The likelihood of price adjustment as a function of the price gap inherits the U-shaped patterns of the responses of adjustment to technology and demand shocks.

This is a natural metric for this analysis. In the overlapping generations model, the price gap is not an approximation for the actual state but is a summary statistic for the gains to adjustment, to be weighed against the costs. That is, the structure of this model fits exactly with the requirements of the approach that summarizes the state through a price gap.[29]

As we shall see, the representation of adjustment rates as a function of the price gap is more convenient. Once aggregate shocks are introduced, the mapping from the idiosyncratic shocks to the likelihood of price adjustment will become state dependent. But, as made clear in Caballero and Engel (1993) and used as well in Vavra (2014), variations in idiosyncratic as well as aggregate states are neatly summarized by the price gap so that the adjustment probability is not a state dependent function of the price gap. Instead, the aggregate shocks impact the distribution of the price gaps across sellers. Interacting with the non-linear hazard, the distribution of these gaps will have aggregate implications.

The fact that the model economy produces this shape for the adjustment rate is important for two reasons. First, it confirms that state dependent pricing in the overlapping generations model produces patterns that are similar to other models. There is nothing special about the OG pricing structure with respect to the shape of this adjustment hazard.

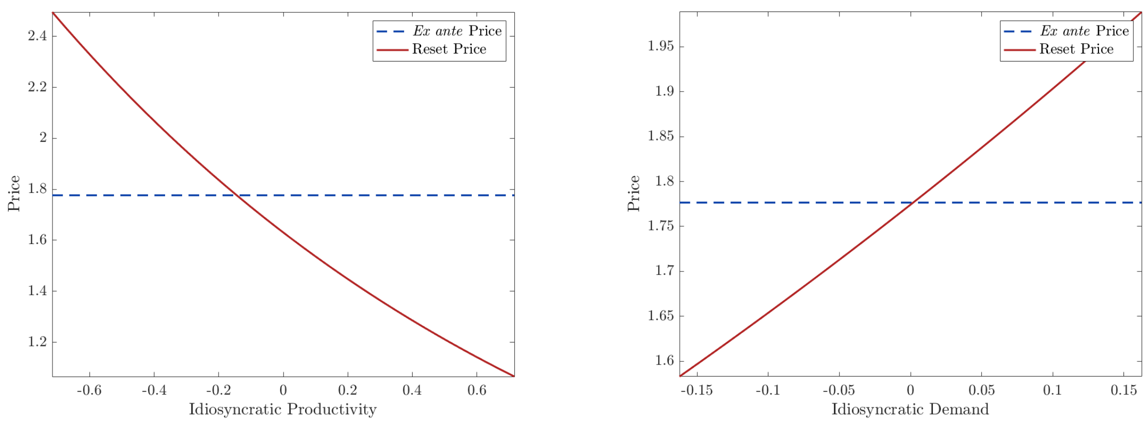
Second, as the analysis develops, the aggregate economy will display non-monotonic responses to various types of shocks. Those patterns can be traced back to the U-shaped adjustment rate. Because the equilibrium of the model is characterized directly, that is without log-linear approximations, the aggregate non-linearities produced through this hazard will be sustained.

Conditional on adjustment, the optimal price of the seller satisfies the first-order condition, (2.8), in the steady state where $x = 1$ with probability 1. In the calibrated model, the *ex post* optimal price is a decreasing function of productivity and an increasing function of demand. This is shown in Figure 2.3.

[28] This is used in Vavra (2014) too.

[29] This is because of the limited time horizon. In an infinite horizon setting, the target price is often defined as the optimal price in the absence of adjustment costs assuming integrated shocks. Here no assumptions on the distribution of future variables are needed and, of course, permanent versus temporary opportunities to adjust are equivalent.

Figure 2.3
Reset Price



(**a**) Dependence on Productivity

(**b**) Dependence on Demand

Note: These figures show the dependence of the reset price on idiosyncratic productivity and idiosyncratic demand.

Output and Employment Responses

This subsection studies the employment and output response to idiosyncratic demand and productivity shocks. The results are enriched by the endogenous pricing decision of sellers.

Table 2.3 reports regression results estimated from simulated data for experiments characterized by the type of shocks: (i) idiosyncratic productivity shocks and, (ii) idiosyncratic demand shocks. The dependent variable is either the (log of) producer employment or output. The columns indicate the response of sellers who did and did not choose to adjust their price.

For the employment column, the negative coefficient for the non-adjusters arises from the fact sellers who do not adjustment their price decrease employment since demand is given. For the adjusters, the effect of productivity on employment is always positive. Because the adjusters raise their price in the face of a demand shock, their employment (and output) response is less than the non-adjusters.

For adjusters, output expands with either productivity or demand shocks. For non-adjusters, idiosyncratic productivity shocks have no output effects again since demand is given. Non-adjusters, given the price, expand output to meet demand.

Table 2.3
Dependence of Employment and Output on Productivity and Demand

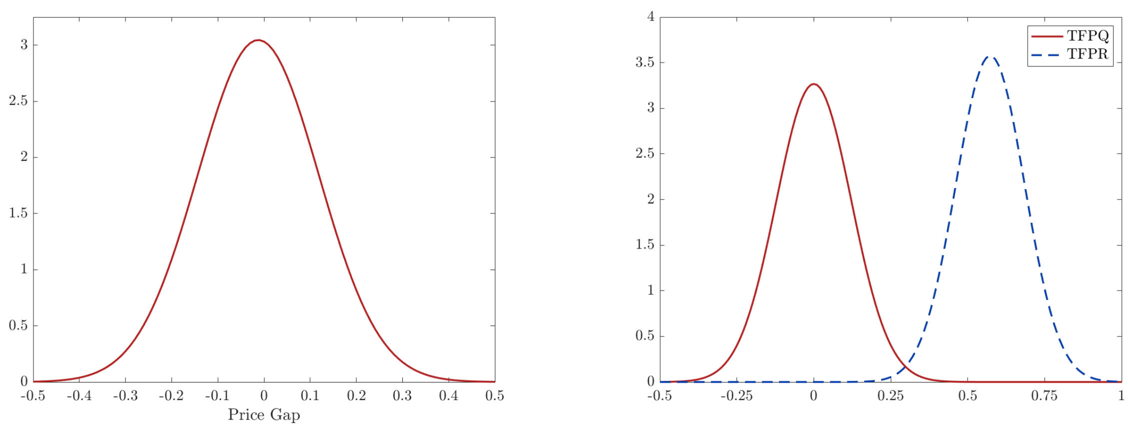
	Employment		Output	
	Adj.	*No Adj.*	*Adj.*	*No Adj.*
Productivity	0.235	-0.573	0.825	0
Demand	0.406	1.367	0.406	1.367

Note: This table shows the effects of idiosyncratic productivity (z) and demand (d) on producer-level employment and output conditioning on price adjustment status.

2.3.3 Aggregate Implications

In the absence of shocks, the only interesting aggregate features are the distributions of prices, the price gaps and TFPR, given the distribution of TFPQ. The pricing itself has an extensive margin, to adjust or not, as well as an extensive margin regarding the response of the reset price to the idiosyncratic state z.

Figure 2.4
Aggregate Implications



(**a**) Gap Distribution: Steady State (**b**) Productivity Distributions: Steady State

Note: This figure shows the price gap and productivity distributions in the steady state.

Figure 2.4a presents the steady state distribution of the price gap, allowing both idiosyncratic productivity and demand shocks. It is centered around zero and reflects the underlying distribution of the idiosyncratic productivity shocks. Clearly there are many sellers with relatively small gaps and who, from the adjustment hazard, are unlikely to adjust their price. Those in the tails have a larger gain to adjustment and thus are more likely to adjust. Compared to Figure 2.2, the distribution puts relatively little weight on gaps which are large enough to warrant adjustment with probability 1. Still there is considerable weight on the nonlinear adjustment rates for intermediate size gaps.

Figure 2.4b shows the distributions of the two measures of productivity in the steady state. The distribution of TFPQ is given while that of TFPR comes from the interaction of the TFPQ distribution and the pricing choices of sellers. Since prices, contingent on resetting, are decreasing in productivity, there is less dispersion in TFPR than in TFPQ, as seen in Figure 2.4b. The distribution of TFPR is shifted to the right of the TFPQ distribution through endogenous prices.

2.4 Cyclicality of TFPR Dispersion

The model of state dependent prices provides a basis to study the cyclicality of TFPR dispersion. As emphasized by Foster et al. (2008), the measurement commonly taken from plant-level studies is TFPR not TFPQ. Output and revenue measures of productivity are not same and their distributions may covary in different ways over the business cycle. Theory exercises that equate TFPR with TFPQ miss the role of price in the mapping between these measures of productivity.

The question is whether the model of price setting can reproduce the countercyclical dispersion in TFPR seen in the data, as well as other pricing facts. This depends both on price setting behavior and exogenous variations. Here the exogenous variations include changes in the dispersion of idiosyncratic productivity, $(disp_Q)$, changes in the dispersion of the idiosyncratic demand $(disp_D)$, aggregate money shocks (x) and changes in the mean of TFPQ (μ_Q).[30]

It is almost immediate that variations in the dispersion of TFPQ will cause variations in the dispersion of TFPR, incorporating optimal price setting. The issue here, as we shall see has to do with the cyclicality of these variations in dispersion. But what about the other shocks? They operate directly on the $disp_R$ given $disp_Q$. Is there any *ex ante* reason to believe they might lead to countercyclical dispersion in TFPR?

For this, consider the following decomposition of the variance in the log of TFPR (*tfpr*):

$$Var(tfpr) = Var(tfpq) + Var(ln(\mathrm{p})) + 2 \times Cov(ln(\mathrm{p}), tfpq). \qquad (2.15)$$

This follows directly from the definition of TFPR: *tfpr*=$ln(\mathrm{p})$+ *tfpq*.

[30]The calibration of these processes is discussed in the Appendix sub-section B.1.4.

Table 2.4 shows this decomposition in the data and in the models, with the latter discussed later. The "FHS" row shows this decomposition for the data from Foster et al. (2008). As noted earlier, the variance of *tfpr* is less than that of *tfpq*. This is a consequence of the negative covariance between prices and *tfpq*. So variations in the dispersion in *tfpr* can be created either by variations in the log of prices or through their covariance with *tfpq*.

The latter effect is directly related to the emphasis on pricing in this paper. As we shall see, prices adjustments are more frequent for extreme values of a money shock. Once the fixed cost of adjustment is paid, the seller can not only align the price to the nominal shock but also to the idiosyncratic component of *tfpq*. Thus, in this example, nominal shocks not only impact the dispersion of prices but also the covariance between prices and *tfpq*, affecting the dispersion of *tfpr*.

The second row labeled recessions is based upon but not taken directly from the data since the evidence in Foster et al. (2008) does not have a cyclical component. It is constructed as a thought experiment where the increase in the variance of *tfpr* during a recession is taken from Bloom et al. (2018). By assumption, the variance in *tfpq* is held fixed. The increased variance in p comes from Table 1 of Vavra (2014). The residual is the covariance of prices and *tfpq*, which is a key to generating cyclical variations in the dispersion of *tfpr*.

Leaving aside shocks to the dispersion in *tfpq*, the challenge is then to find exogenous variations that would create countercyclical dispersion *tfpr* through an increased dispersion of prices along with an increase in the (absolute) value of the covariance. From this exercise, it seems that shock(s) that can create both increased dispersion in prices as well as a higher (in absolute value) covariance of prices and idiosyncratic productivity can indeed increase the dispersion in measured *tfpr*. From our model, variations in these moments come both from the extensive margin of price adjustment as well as the dependence on productivity, conditional on adjustment.

2.4.1 Main Findings: a Preview

Table 2.5 summarizes our main findings and serves to organize the more detailed discussion that follows. It displays, by source of variation, the cyclical patterns of dispersion in TFPR, the dispersion of price changes, and the frequency of price adjustment. For this part of the analysis, a recession (expansion) refers to output below (above) its steady state value.

The table is discussed in detail in this section, first by looking at each shock independently. We then consider some shocks in tandem, as in Bloom et al. (2018) and Vavra (2014). Finally, we allow the monetary authority to respond to variations in the mean and

Table 2.4
Variance Decomposition: Data

	$Var(tfpr)$	$Var(tfpq)$	$Var(ln(\text{p}))$	$Cov(ln(\text{p}), tfpq)$
FHS	0.0484	0.0676	0.0324	-0.0258
recessions	0.0618	0.0676	0.0506	-0.0282

Note: This table shows the decomposition of the variance of *tfpr*. FHS data are annual (Foster et al. (2008)). The percent changes for recession $var(tfpr)$ comes from Bloom et al. (2018), the recession $var(ln(\text{p}))$ is from Vavra (2014), the $cov(\cdot)$ is solved. Recessions are calculated assuming $disp_Q$ is fixed. All variables are logarithms.

dispersion of TFPQ and study the implications for the dispersion of TFPR.

The results are best evaluated relative to moments from the data. **From various studies, $disp_R$ is countercyclical, the dispersion of price changes and frequency of price changes are countercyclical.**[31]

By choice, we do not use correlations to summarize business cycle properties. The model, as suggested by the U-shaped hazard and discussed further in sub-section 2.6.2, has very non-linear responses to shocks. Looking at these through the lens of correlations leads to the omission of the rich interactions produced by the model.

2.4.2 Dispersion in TFPQ Shocks

The analysis of countercyclical variation in TFPR dispersion starts with an obvious hypothesis: variations in $disp_Q$ drive the cyclicality of $disp_R$. To order for this explanation to be consistent with data patterns, it must be that: (i) increased dispersion in TFPQ creates increased dispersion in TFPR and (ii) increased dispersion in TFPQ causes economic downturns. We demonstrate that the model does not produce these patterns: **variations in the dispersion of TFPQ do not generate countercyclical fluctuations in the dispersion of TFPR.**

Specifically, here we study the effects on $disp_R$ of an increase in $disp_Q$, modelled as a mean preserving spread in the distribution of z.[32] To be clear, the effects highlighted here

[31] The negative correlation of output (growth) and $disp_R$ comes from Bloom et al. (2018). Kehrig (2011) finds that the correlation of (detrended) output and the dispersion of productivity is -0.293 for non-durables and -0.502 for durables, in Table 2. His Table 4 makes clear that the countercyclicality is robust to various output measures. Evidence on the dispersion and frequency of price changes comes from Vavra (2014), Table 4: the dispersion of price changes is higher in recessions as is the frequency of price changes.

[32] As discussed in Appendix sub-section B.1.4, these variations are about the same size as those explored

Table 2.5
Cyclical Variations

Shock	Moments					
	$disp_R$		$disp_{\Delta p}$		$freq_{\Delta p}$	
	Contraction	Expansion	Contraction	Expansion	Contraction	Expansion
			Baseline Parameterization			
$disp_Q$	0.047	0.131	0.020	0.167	0.065	0.294
x	0.088	0.095	0.125	0.114	0.278	0.221
$disp_D$	0.103	0.103	0.073	0.078	0.145	0.150
μ_Q	0.090	0.102	0.129	0.136	0.266	0.298
$disp_Q, \mu_Q$	0.126	0.057	0.208	0.082	0.328	0.164
			Leaning Against the Wind			
$disp_Q$	0.093	0.057	0.192	0.062	0.527	0.157
μ_Q	0.082	0.076	0.141	0.141	0.365	0.500

Note: This table shows the cyclical patterns of the dispersion in TFPR, $disp_R$, the dispersion in price changes, $disp_{\Delta p}$ and the frequency of price adjustment, $freq_{\Delta p}$. The moments are displayed as columns, for contractions and expansions. The rows refer to the model economies distinguished by the source of exogenous variation as developed in the sections below.

come from realized changes in the distribution of TFPQ, there is no uncertainty effect in the analysis.

Variations in $disp_Q$ will impact $disp_R$ in two ways. First, of course, there is the direct effect: given prices, an increase in $disp_Q$ will translate into an increase in TFPR dispersion. Second, pricing behavior will adjust, potentially magnifying (reducing) the effects of the increase in $disp_Q$. The sign and size of this latter effect will depend on the properties of the revenue function and, as emphasized by our model, the pattern of price adjustment.

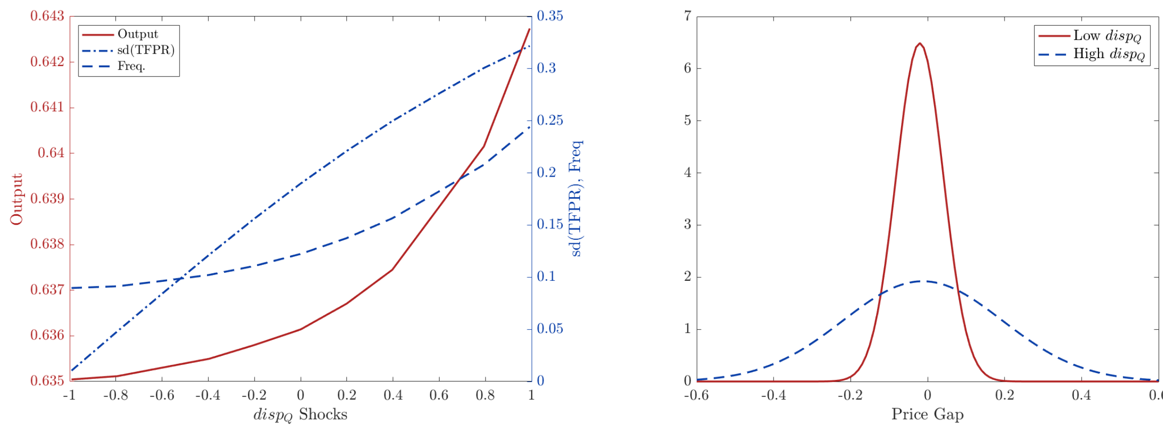
Figure 2.5a shows the response of output, the frequency of price adjustment and $disp_R$ in response to variations in $disp_Q$. Clearly output is an increasing function of this dispersion, allowing sellers with high productivity to expand.[33] The frequency of price adjustment itself increases as the increased dispersion in z puts more weight on the tails of the price gap distribution, inducing more price adjustment. This is clearly evident in Figure 2.5b where the price gap distribution is shown for two levels of $disp_Q$.

Overall, for this case, drawing on Figure 2.5a and Table 2.5, $disp_R$ is monotonically increasing in $disp_Q$ and hence in output. A key element is that $disp_Q$ is procyclical in the

in Bloom et al. (2018).

[33]Importantly, these reallocation effects are hampered by both price rigidity and the immobility of labor.

Figure 2.5
$disp_Q$ Shock



(**a**) Responses (**b**) Gap

Note: This figure shows the relationship between output, $disp_R$ and the frequency of price adjustment as well as the price gaps as a function of shocks to $disp_Q$

model. This is not necessarily inconsistent with evidence since the negative correlation found in numerous studies between output and dispersion relates to measured $disp_R$ **not** $disp_Q$.

The findings about the cyclicality of the dispersion in price changes and frequency are consistent with Vavra (2014) if $disp_R$ was countercyclical. **But the model is inconsistent with the data in terms of the motivating observation of countercyclical dispersion in TFPR.** Consequently, from Table 2.5, the variations in price change dispersion and frequency are counter to the data.

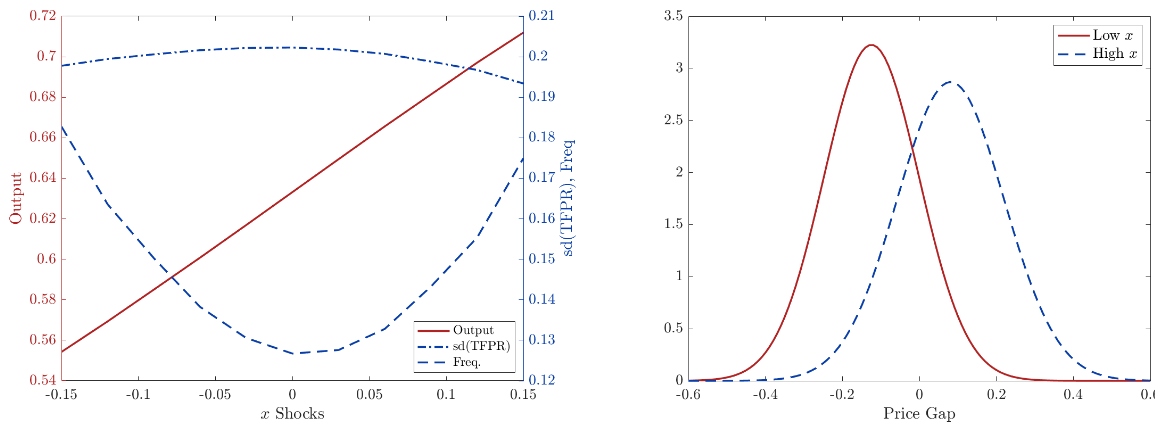
2.4.3 Money Shocks

A second aggregate shock comes from monetary innovations, x. Due to price rigidities, monetary shocks impact real output. Further, the distribution of TFPR is impacted by monetary shocks, given the distribution of TFPQ, due to both the intensive and extensive margins of price adjustment.

From Table 2.5, for this source of variation, $disp_R$ is procyclical. As for the moments characterizing pricing, both the dispersion of price changes and the frequency of adjustment are countercyclical, in line with data patterns.

Figure 2.6a shows the response of output, $disp_R$ and the frequency of price adjustment to monetary shocks. Reflecting price rigidities, output is a monotone function of the inno-

Figure 2.6
Money Shock



(a) Responses **(b)** Gap

Note: This figure shows the relationship between output, $disp_R$, the frequency of price adjustment and the price gap as a function of money shocks.

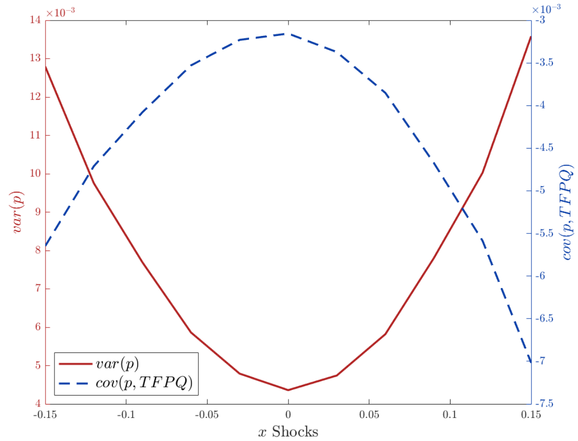
vation to the money supply. As highlighted in Figure 2.2, the frequency of adjustment is a U-shaped function of the price gap. That is reflected here in the U-shaped frequency of adjustment in response to the money shocks. Importantly for our analysis, this translates into an inverse U-shaped relationship between $disp_R$ and the money shock. At extreme values of the shock, price adjustment is much higher. Since price setters are responding to the common realization of x, there is a reduction in the dispersion of TFPR. Though the realized idiosyncratic productivity, z, is independent of x, the selection into adjustment, again using Figure 2.2, will be those in the tails of the productivity distribution.

The effects of the money shock on the gap distribution is shown in Figure 2.6b. In contrast to the increased dispersion of the gap distribution from a $disp_Q$ shock, the monetary shock causes a rightward shift. The additional weight on the right tail from a high value of x will increase the frequency of upward price adjustments.

It is useful to understand how a money shock influences the distribution of TFPR. From the decomposition of (log) TFPR in (2.15), with the dispersion in TFPQ fixed, variations in $disp_R$ come from two sources: (i) changes in the dispersion of prices and (ii) changes in the covariance between prices and productivity. Both of these components are effected by the endogenous price adjustment.

The mechanism is illustrated in Figure 2.7 which shows how two cross-sectional moments, the variability of prices and the covariance of prices and productivity, vary with the money shock. Both of these moments are nonlinear functions of the money shock.

Figure 2.7
Price Dispersion and Covariance of Prices and Productivity



Note: This figure shows response of the variance of price, the standard deviation of prices and the covariance of prices and productivity at the micro-level to money shocks.

From this figure, for extreme values of the money shock, the standard deviation of prices is higher and the covariance of price and productivity is higher in absolute value. This reflects the increased frequency of adjustment, as in Figure 2.6a, as well as the dependence of prices on z for those sellers who choose to reset. This is in keeping with the role of dispersion and covariance brought out in Table 2.4.

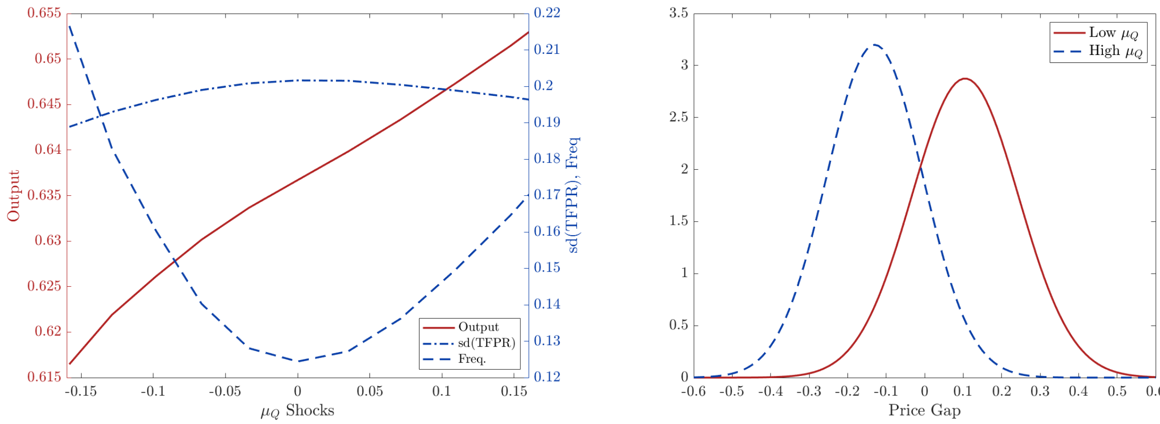
Overall, as real output increases with the money shock, the model implies that the standard deviation of TFPR is not a monotone function of economic activity when fluctuations are induced by money shocks. It can be lower in recessions and also lower in expansions when the money shocks take relatively extreme values. **Thus, the model can produce countercyclical dispersion in TFPR, for a given distribution of TFPQ, when money shocks are extremely large**. Importantly, the change in the dispersion of prices and their covariance seen in this experiment follows the qualitative pattern of the data, as shown in Table 2.4.

2.4.4 Shocks to the Mean of TFPQ

The another leading source of variation is the more standard shock to the average productivity, i.e. the mean of TFPQ, denoted μ_Q. As before, the interest is in the cyclicality of the dispersion in TFPR induced by this shock. For now, we study its impact in isolation. Experiments below couple this with a shock to $disp_Q$ as well as a monetary response.

Figure 2.8a summarizes the findings. As in standard RBC models, output is an increasing function of mean productivity. The frequency of price adjustment is again U-shaped,

Figure 2.8
μ_Q Shock



(a) Responses **(b)** Gap

Note: This figure shows the relationship between output, $disp_R$, the frequency of price adjustment and the price gap as a function of shocks to the mean of TFPQ.

reflecting the larger gains to adjust for more extreme realizations of mu_Q along with the shift in the price gap distribution, shown in Figure 2.8b. The dispersion in TFPR is almost flat, decreasing slightly for realizations in the tails where there is more price adjustment.

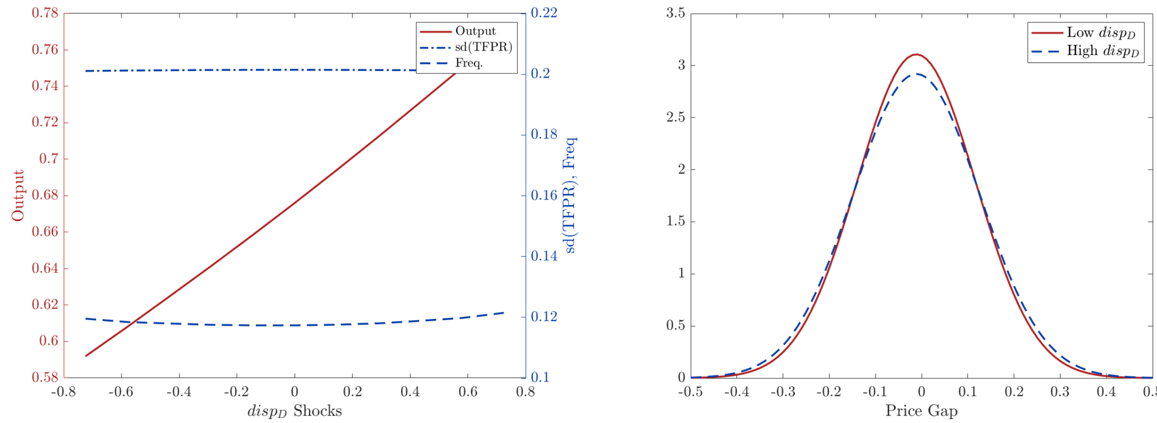
Thus this case does not produce the data pattern of countercyclical dispersion in TFPR. Further, from Table 2.5, for this source of variation, both the dispersion of price changes and the frequency of adjustment are procyclical, in contrast with data patterns. But, as discussed below, this source of variation is of more interest when combined with a shock to $disp_Q$.

2.4.5 Dispersion of Demand Shocks

A final source of aggregate variations arises from changes in the dispersion of idiosyncratic demand shocks. As with variations in $disp_Q$, this is a mean preserving spread in demand shocks. The money shocks can be interpreted as variations in the mean of demand.

As shown in Figure 2.9a, output increases with demand dispersion, as it did with increased dispersion in TFPQ. In response to increased dispersion in demand shocks, $disp_R$ is slightly countercyclical. This is quite different than the response of $disp_R$ to an increase in $disp_Q$. Part of the explanation lies in the response of output and employment to a demand shock at the producer level, summarized in Table 2.3. From Table 2.5, the frequency

Figure 2.9
$disp_D$ Shock



(a) Responses

(b) Gap

Note: This figure shows the relationship between output, $disp_R$ and the frequency of price adjustment as a function of shocks to $disp_D$.

of price adjustment and its dispersion increase with this shock, so that both of these moments are procyclical.

2.4.6 Shocks to the Dispersion and Mean of TFPQ

In many studies, such as Bloom et al. (2018) and Vavra (2014) the shock to dispersion and to the mean of TFPQ are studied jointly. Given the prominence of this case in the literature, it is important to study this case in detail.[34] Here we follow the baseline model in Vavra (2014) and assume the shocks are perfectly negatively correlated: $corr(disp_Q, \mu_Q) = -1$. Interestingly, as the shocks are lognormally distributed, the skewness of the cross-sectional distributions of TFPQ is changed by this experiment. Specifically, as μ_Q decreases and $disp_Q$ increases, the skewness increases as well.

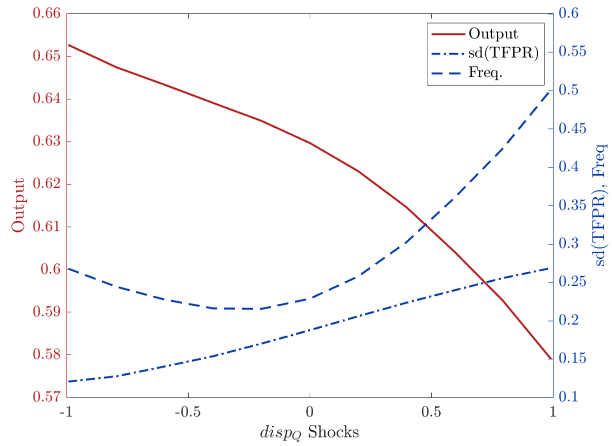
From Table 2.5, this is the experiment that brings the model and data patterns closest together. All three moments, $disp_R$, the dispersion of price changes and the frequency of adjustment are countercyclical.

The results from Figure 2.10 illustrates the effect of combining these shocks. The horizontal axis shows $disp_Q$. By construction, as it increases μ_Q decreases. From the graph, the dispersion in TFPR rises with $disp_Q$ while output falls.

This is quite different from the case in which only $disp_Q$ varies, shown in Figure 2.5a,

[34]Other combinations were studied without success in matching moments.

Figure 2.10
Combined $disp_Q$, μ_Q Shocks



Note: This figure shows the relationship between output, $disp_R$ and the frequency of price adjustment as a function of shocks to the $disp_Q$. By construction, as the dispersion increases, the mean of TFPQ falls.

where output was increasing in $disp_Q$. Further, in contrast to that case, with the combined shock, there is much more response in the frequency of price adjustment to variations in $disp_Q$.

This result does not emerge because of negative comovement between $disp_R$ and $disp_Q$. The dispersion in TFPR increases, albeit modestly, driven by the increase in $disp_Q$. Instead, the decrease in mu_Q has a stronger effect on output than the increase in $disp_Q$. This creates the countercyclical variation in both $disp_Q$ and $disp_R$.

Still, the moments are not monotone. For example, the frequency of price adjustment, due to the U-shaped hazard, is also relatively high for low values of $disp_Q$ when output is high. We return to these nonlinearities below.

2.5 Monetary Feedback Rules

One important theme of the analysis is the nonlinearity produced by the U-shaped frequency of price adjustment. This was shown to matter in the response of the economy to money shocks x. Building on this, we enrich the setting to allow interactions between the shocks, focusing on monetary policy responses. As we see, allowing the monetary authority to link the distribution of x to the aggregate state can alter the cyclicality of $disp_R$. In this way, the implications of the model can be brought closer to some features of the data.

Specifically, suppose that the evolution of the money supply is given by:

$$M_{t+1} = M_t x_{t+1} = M_t[\Phi(s_{t+1}) + \tilde{x}_{t+1}]. \tag{2.16}$$

In this specification, the money stock follows the same stochastic process as above, with x_{t+1} representing the period $t+1$ money shock that is not predictable given period t information.[35] But here, the growth of the money supply, $[\Phi(s_{t+1}) + \tilde{x}_{t+1}]$ has two components. The first is the feedback rule where $\Phi(s_{t+1})$ allows money growth to depend on the period $t+1$ state of the economy. The second is the money shock, denoted $\tilde{x}_{t+1}$ above.

We focus on two specific cases, distinguished by the source of fluctuations in the aggregate economy. These cases produced variations in the dispersion of TFPR that are qualitatively similar to data moments.[36]

In the first, the monetary authority responds to changes in the dispersion of TFPQ. Let μ_{disp_Q} be the average value of $disp_Q$ and consider

$$\Phi(disp_Q) = \zeta \times (disp_Q - \mu_{disp_Q}). \tag{2.17}$$

In a similar fashion, let μ_{μ_Q} be the average value of the mean of TFPQ and consider

$$\Phi(\mu_Q) = \zeta \times (\mu_{\mu_Q} - \mu_Q). \tag{2.18}$$

In both formulations, the feedback is characterized by a single parameter, ζ.

Given a monetary feedback rule, it is straightforward to extend the analysis of a SREE from Appendix B.1.3 to include (2.16). Note that the monetary feedback rule impacts agents both as young price setters and as old agents, both in terms of the distribution of the stochastic transfer and the equilibrium prices they face as buyers. As in the previous analysis, all of the newly created money is distributed as a proportional transfer. But in this specification, it is feasible for the monetary authority to link these transfers to the current state of the economy. If prices were perfectly flexible, there would be no real effects of this monetary policy. Further, since private agents share the information of the monetary authority, there is no information transmitted to the private sector by this policy.

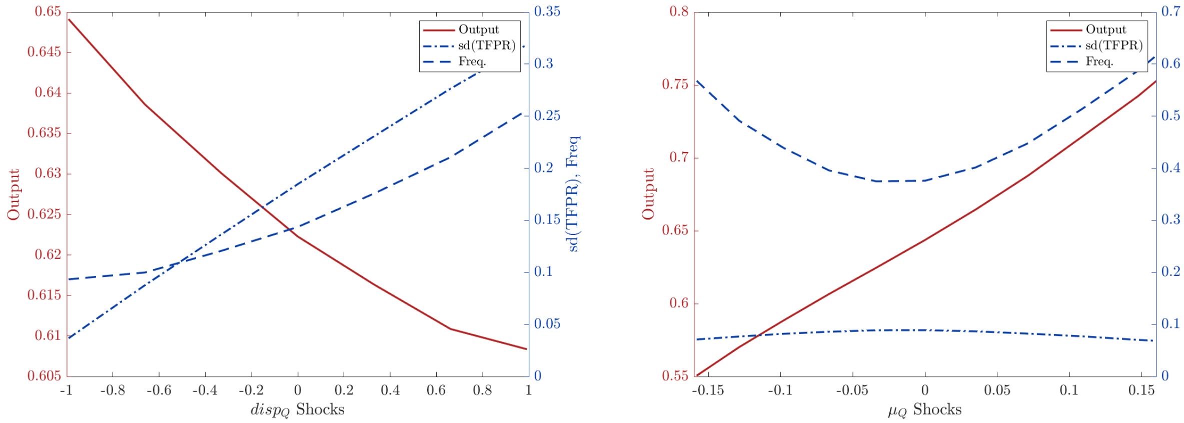
The SREE was characterized for both shocks to μ_Q and $disp_Q$. The formulation that created countercyclical dispersion in TFPR had $\zeta < 0$ so that the monetary authority was "leaning against the wind".

Consider first the results when the economy is driven by variations in $disp_Q$, along with money shocks. Figure 2.11a illustrates the outcome and Table 2.5 summarizes the

[35] This is again one of many possible specifications of a feedback rule intended to illustrate this potential channel.

[36] This was not the case for monetary policy interacting with $disp_D$ shocks.

Figure 2.11
Monetary Responses



(a) $disp_Q$ Shocks **(b)** μ_Q Shocks

Note: This figure shows the effects of a response in monetary policy to $disp_Q$ and μ_Q shocks.

moments.

In this case, the patterns in the simulated data match those in the actual data. A feedback rule with $\zeta = -0.05$ generates countercyclical dispersion in $disp_R$. With this policy, the monetary authority responds to higher than average dispersion in idiosyncratic profitability shocks by reducing the average growth of the money supply. In the absence of the intervention, output would be positively correlated with $disp_Q$. So, the monetary authority appears to be leaning against the wind. But in this case, the response to the policy outweighs the direct effect of $disp_Q$ so that increased dispersion in z is associated with an economic downturn. The dispersion in TFPR follows that of TFPQ, so that $disp_R$ is countercyclical. Note that this result does not occur without monetary feedback. As noted earlier, with $\zeta = 0$ the model creates procyclical dispersion in TFPR.

From Table 2.5, the frequency of price adjustment is higher in the recession. Further, the dispersion of price changes is also higher in recessions. These patterns match those in the data.

A second interesting case arises from the response of the monetary authority to mu_Q shocks. This is illustrated in Figure 2.11b. In this setting, the nonlinear response of price setting to the state is important. Despite the monetary authority leaning against the wind, output increases with the mean of TFPQ. But, in contrast to the case with no monetary feedback in Figure 2.8a, now $disp_R$ varies considerably with the aggregate productivity shock. This is because of the response of price setters interacting with the money shock.

From Table 2.5, $disp_R$ is countercyclical, but not nearly as much as in the case of monetary feedback to variations in $disp_Q$. A difference with the data appear in the pricing moments. In particular, the frequency of adjustment is procyclical, produced by the asymmetry in the U-shaped hazard from Figure 2.8a.

2.6 Additional Properties

This section looks at additional properties of the model. The presentation starts with a discussion of the sensitivity of moments to parameters. The second point highlights the nonlinearities of the economy by presenting correlations conditional on the output gap. The third uses the model to understand the findings of Tenreyro and Thwaites (2016) concerning the nonlinear effects of monetary policy. The final part introduces uncertainty and, as in Vavra (2014), finds no role for it.

2.6.1 Sensitivity to Calibration

Here we study the mapping from parameters to moments. There are three key parameters: (i) the elasticity of substitution between products, ε, (ii) the convexity in the disutility of work, $g(n) = \frac{n^\phi}{\phi}$, (iii) the distributions of the shocks and (iv) the upper support of the menu cost distribution, $\bar{F}$. The point is to understand how the shapes of these functions impact the results in Table 2.5.[37]

The first experiments influence the gains to price adjustment. For that, we increase ε from its baseline value of 2.36 to 4 and decrease ϕ from 2 to 1.5, thus reducing the slope of marginal cost. Finally, we look at how the results depend on the relative magnitudes of technology and demand shocks. For the baseline, σ_d was about 18% of σ_z. For the robustness exercise, we set $\sigma_d = \sigma_z$, close to the findings reported in Eslava and Haltiwanger (2020), with σ_z remaining at its baseline value.

For the distribution of menu costs, we reduce the upper support by 50%. Thus we eliminate the high adjustment cost region of the distribution. This implies that the frequency of price adjustment more than doubles and the dispersion of TFPR fall by about 20% in the steady state.

For these experiments we focus on the case of money shocks alone. This allows us to isolate the effects of these parameter variations most succinctly. Table 2.6 summarizes our findings. The rows indicate the parameters that have been altered relative to the baseline,

[37] Vavra (2014) has linear disutility of work and an elasticity of substitution of 6.8. Golosov and Lucas (2007) also have linear disutility with an elasticity of substitution of between 6 and 10. They also include money in the utility function.

Table 2.6
Cyclical Variations: Robustness

Case	$disp_R$		$disp_{\Delta p}$		$freq_{\Delta p}$	
	Contraction	Expansion	Contraction	Expansion	Contraction	Expansion
Baseline	0.088	0.095	0.125	0.114	0.278	0.221
$\varepsilon = 4$	0.086	0.098	0.086	0.069	0.323	0.264
$\phi = 1.5$	0.120	0.117	0.116	0.118	0.094	0.094
$\bar{F} = 0.016$	0.114	0.108	0.113	0.110	0.183	0.165
$\sigma_d = \sigma_z$	0.577	0.582	1.024	1.215	0.875	0.776

Note: This table shows cyclical patterns for alternative parameters (rows) with fluctuations driven by monetary shocks.

reproduced as the first row of each block. Each entry represents a simulation setting all other parameters at baseline levels.

As indicated in the first row of Table 2.6, the model with money shocks alone did not produce countercyclical dispersion in TFPR. The property, inconsistent with the data, is retained for the alternative parameterizations except for the experiment with less curvature in the disutility of work.

With a higher value of ε relative to the baseline, the frequency of price adjustment is higher. As goods are more substitutable, the incentive to adjust prices when others do is higher. The dispersion in price changes is lower since the optimal price is driven more by the aggregate money shock compared to the idiosyncratic shock.

With $\phi = 1.5$, the moments are essentially acyclical. Notice that the frequency of price adjustment is much lower than the baseline since the cost of meeting variations in demand induced by money shocks is considerably lower. Accordingly, $disp_R$ is also much higher that in the baseline since variations in z are not being offset by price adjustments.

Increasing the dispersion of demand relative to productivity shocks has a large impact on these moments. With this increased source of variability in demand, the frequency of price adjustment is almost four times that of the baseline. The dispersion of price changes is also much larger. This alternative parameterization though does not bring the model with monetary shocks alone closer to the data.

With the lower value of $\bar{F}$, $disp_R$ becomes countercyclical, as does the dispersion of price changes and the frequency of price adjustment. These differences though are relatively small compared to both the data and the other leading cases. Further, as noted, the lower $\bar{F}$ produces a much higher frequency of price adjustment compared to the data.

2.6.2 Nonlinearities

As noted earlier, correlations have not been used to summarize model properties given the inherent nonlinearities created by the price adjustment hazard. Thus in our consideration of the various sources of fluctuations in $disp_R$, we have focused more on moments conditional on the state of aggregate activity, either contractions or expansions.

One way to highlight the importance of this is to compute correlations conditional on the business cycle, measured by the difference between aggregate output and its steady state value. Table 2.7 presents correlations of key variables with output conditional on whether output is above (expansion) or below (contraction) its stationary level. This is shown for the various sources of fluctuations, including cases with the monetary feedback rules. The fact that these correlations are state independent reflects both the nonlinear decision rules and that the simulated distributions put non-negligible weight on these areas.

Table 2.7

Cyclical Variations: Conditional Correlations with Output

Shock	$disp_R$			$disp_{\Delta p}$			$freq_{\Delta}p$		
	Unc.	Cont.	Exp.	Unc.	Cont.	Exp.	Unc.	Cont.	Exp.
				Baseline Parameterization					
x	-0.086	0.421	-0.478	0.027	-0.962	0.925	-0.191	-0.648	0.977
$disp_Q$	0.721	0.322	0.952	0.893	0.787	0.952	0.911	0.799	0.842
$disp_D$	0.023	0.028	-0.034	0.403	0.122	0.337	0.032	-0.066	0.131
μ_Q	0.076	0.241	-0.167	-0.118	-0.883	0.911	0.068	-0.613	0.663
$disp_Q, \mu_Q$	-0.812	-0.740	-0.815	-0.906	-0.902	-0.965	-0.810	-0.961	-0.800
				Leaning Against the Wind					
$disp_Q$	0.062	0.173	-0.418	0.011	-0.118	-0.168	-0.006	-0.023	-0.153
μ_Q	0.015	0.055	-0.065	-0.036	-0.161	0.123	-0.059	-0.070	0.052

Note: This table shows the conditional correlation with output of the dispersion in TFPR, $disp_R$, the dispersion in price changes, $disp_{\Delta p}$ and the frequency of price adjustment, $freq_{\Delta p}$. Here contractions (Cont.) and expansions (Exp) are defined in levels relative to steady state and Unc. is the unconditional correlation.

First, looking at the monetary shock case, the frequency of price adjustment is negatively correlated with output in a contraction and positively correlated with output in an expansion, -0.648 and 0.977 respectively. This is a direct consequence of the U-shaped hazard, as in Figure 2.6a. So when the money shock is above average, so is output. Within this region, higher realizations of the money shock increase the frequency of price adjustment and, at the same time, output expands. But, for values of the money shock below the mean (so that output is below its mean), the opposite occurs. For progressively lower values of x, again the frequency of price adjustment rises but output falls, producing a negative correlation in this region.

The unconditional correlation is slightly negative. It masks the positive comovement between output and the frequency of price adjustment in expansionary periods.

The dispersion of TFPR has an inverted U shaped in Figure 2.6a. This produces a negative correlation with output in expansions as $x > 0$. But the correlation switches sign when x is below its mean. Again, this is not captured by the unconditional correlation.

Second, note that in many cases other than money shocks, the correlations change sign with the state of the economy. This pattern of a positive (negative) correlation of price adjustment and output in expansions (contractions) is seen in the other cases except for $disp_Q$ shocks. In that case, the frequency of price adjustment is higher in expansions but, from Table 2.7, the correlation with output is negative, conditional on being in an expansion. And for some experiments, such as the μ_Q shock the correlations are quite high, conditional on the state.

Third, variations in shocks to x, $disp_D$ or μ_Q can each produce countercyclial $disp_R$ but only during expansions. The combination of $disp_Q, \mu_Q$ shocks generate this negative correlation in all states of the business cycle.

To be clear, these nonlinearities are a direct consequence of the U-shaped hazard. As that is a central feature of state dependent pricing models, these properties are not peculiar to our specification. Given that, model and data statistics ought to be treated in a manner that is consistent with the inherent non-linearities of these economies.

2.6.3 Nonlinear Effects of Monetary Policy

This section continues this theme and looks at the nonlinear effects of monetary policy. This is an underlying feature of the economy whereby the endogenous frequency of price adjustment depends on the magnitude of the shocks. This is part of the mechanism that links $disp_R$ to the state of the economy. It has implications for the effects of monetary policy.

To some extent, Vavra (2014) addresses this question.[38] He argues that shocks to nominal spending will have a smaller effect on output when the dispersion of firm level productivity is higher, which by his assumption arise in a recession. This comes from his

[38] Klepacz (2021) distinguishes between aggregate and idiosyncratic volatility and finds that increases in aggregate volatility do not reduce the effects of monetary policy. We do not study the case of changes in aggregate volatility in this paper.

finding that the dispersion and frequency of price changes is countercyclical. Hence, recessions are associated with more frequent price adjustment and thus a smaller impact of monetary policy.

For our analysis, we decompose this into two distinct points. First, how do the effects of monetary policy depend on the dispersion of idiosyncratic shocks? This is in the spirit of the Vavra (2014) exercise but without the link between dispersion and the business cycle. Here we study variations in the dispersion of both productivity and demand shocks.

The second exercise, building from the evidence in Tenreyro and Thwaites (2016), looks at the cyclical effectiveness of monetary policy. In this case, we do not focus on cycles driven by $disp_Q$ since increases in dispersion are pro- not counter-cyclical in our environment.

For both of these exercises, we study the following regression:

$$E[y_t|x_t, s_t] = \gamma_1 x_t + \gamma_2 s_t + \gamma_3 (x_t \times s_t) \tag{2.19}$$

where y_t is output, x_t is the monetary innovation and s_t is the state of the economy. In the first exercise, s_t denotes the value of $disp_Q$ or $disp_D$, depending on the case. In the second exercise, s_t is a dummy variable indicating if the economy is in an expansion or a recession. The focus of the analysis is on γ_3 which measures the state dependent effectiveness of monetary policy.

Monetary Policy Effectiveness and Variations in Dispersion

Table 2.8 reports the results for two exercises estimating the parameters on simulated data. In the first exercise, $s_t = disp_{Qt}$ and in the second $s_t = disp_{Dt}$. So here we study how the effectiveness of monetary policy is impacted by changes in the dispersion of TFPQ and demand.

From the table for the $disp_Q$ experiment, the estimated value of γ_3 is negative and significantly different from zero. The effects of a money shock on output are smaller when $disp_Q$ is high. This is consistent with the increased frequency of price adjustment when $disp_Q$ increases.

The effects of a money shock are slightly larger when $disp_D$ is higher. The estimate of γ_3 in this case is positive and statistically significant, but this interaction is economically very small. Interestingly, $\gamma_3 > 0$ even though the frequency of price adjustment, from Figure 2.9b, is almost independent of $disp_D$.

Monetary Policy Effectiveness over the Business Cycle

Tenreyro and Thwaites (2016) argue output is less responsive to monetary policy during

Table 2.8
Dispersion Dependent Effects of Money shocks

	$disp_Q$	$disp_D$
γ_1	0.680	0.293
	(0.001)	(0.002)
γ_2	0.038	0.007
	(0.001)	(0.001)
γ_3	-0.037	0.008
	(0.001)	(0.001)

This table reports the coefficients of (2.19). Standard errors are in parentheses.

recessions. We use our model, with its explicit distinction between TFPQ and TFPR, to study the state dependent effects of monetary shocks. The question is whether the model provides support for the findings of Tenreyro and Thwaites (2016).[39]

Table 2.9 quantifies the interaction between the state of economic activity and the response of output to a monetary innovation. It does so by regressing (log) real output on the (log) monetary shock, distinguishing recessions from expansions. The specification follows (2.19) except that for this exercise s_t indicates either expansion or contraction.

This experiment is built upon two models which match the moments best: (i) with shocks to $(disp_Q, \mu_Q)$ jointly, as in section 2.4.6 and (ii) the case of monetary feedback with $disp_Q$ shocks alone. For the first case, there are additional shocks to x and we assess the impact of those shocks.

From the table, when monetary shocks are added to the economy driven by shocks to $(disp_Q, \mu_Q)$, the response of output to a monetary innovation is larger during expansions compared to recessions. The mechanism is best understood from Figure 2.10. A recession is associated with a large value of $disp_Q$ coupled with a reduction in mu_Q. From the figure, during the recession the frequency of price adjustment is higher. With more price flexibility in a recession, the real effect of the money shock is reduced. Therefore we see this countercyclical effectiveness of monetary shocks.

Sub-section 2.5 found that a monetary policy response to $disp_Q$ shocks could match the moments. Here it is possible that the feedback itself could produce additional nonlinearity.

[39] By a recession they are referring to negative growth in output and not a level of output below trend. In fact, they find that the response of output to money shocks does **not** depend on the level of output relative to trend. In fact, the baseline estimates of Tenreyro and Thwaites (2016) use a 7 quarter moving average of GDP growth to construct their indicator. Our model does not have a rich stochastic process for output and has not growth. So we focus on expansions vs contractions as defined above.

The results in the second block of the table indicate that this is indeed the case. The effects of the money shock are higher in the expansionary state.

Table 2.9
State Dependent Regression of output on monetary shock

	$disp_Q$	$disp_Q, \mu_Q$
γ_1	0.611	0.641
	(0.001)	(0.001)
γ_2	0.265	0.458
	(0.002)	(0.010)
γ_3	-0.267	-0.523
	(0.002)	(0.009)

This table reports the coefficients of (2.19), where $s_t = 1$ indicates a contraction. Standard errors are in parentheses.

2.6.4 Effects of Uncertainty

The distinction between uncertainty and dispersion is often blurred. The main effect of uncertainty, again expressed in Bloom et al. (2018), is to create an incentive to wait and allow the uncertainty to be resolved before making an irreversible choice, such as changing a price. To the extent this leads to a decrease in spending, largely on durables, the uncertainty can be recessionary. This is often quite different from the positive effects of dispersion which can lead to an expansion in output, as discussed above.

The previous discussion highlighted the effects of dispersion on the frequency of price adjustment and thus the real effects of monetary shocks. Here we focus on how *ex ante* prices respond to uncertainty over a distribution, not the realization of that change.

Our analysis includes distributions over four dimensions: (i) idiosyncratic productivity, (ii) idiosyncratic demand, (iii) money shocks, and (iv) aggregate productivity. Thus in principle one can study the effects of uncertainty with respect to each of these four distributions.

To do so, it is natural to create a Markov switching process for the dispersion of, say, idiosyncratic productivity. Price setters in period t would know the distribution of these shocks last period but in setting their *ex ante* price, the period t distribution, as well as that for period $t+1$ would not be known. Further, for those who adjust *ex post*, the uncertainty would remain over the distribution in the following period when they are consumers.[40] This is the nature of the uncertainty.

One extreme version of this Markow switching process is for the dispersion to be permanently high (low). **For the price setting problem of young agents, the *ex ante* price is essentially the same with high dispersion of the idiosyncratic productivity shock as it is for the low dispersion case.** In fact, this is true when the uncertainty is over the money transfer or the aggregate productivity distributions.

Given this, it is unlikely that *ex ante* uncertainty matters for the price setting problem. This is verified explicitly for the case of uncertainty over idiosyncratic productivity. Even if there is a positive probability of a regime shift in the distribution of z, the *ex ante* price is essentially unchanged.

This is an important finding. It makes clear that the effects come from dispersion not uncertainty. This is consistent with Berger et al. (2020) who argue, at least for aggregate shocks, that uncertainty *per se*, had a negligible effect on real activity.

2.7 Conclusion

The analysis characterizes the properties of the distribution of TFPR in a stationary rational expectations equilibrium of a monetary economy with state dependent pricing. A quantitative version of the model is used to determine the cyclicality of the dispersion in TFPR as well as other key pricing moments, the cyclicality of both the frequency of price changes and their dispersion. This is studied by determining pricing decisions and thus the distribution of TFPR in the face of aggregate shocks to: (i) the money supply, (ii) the dispersion of TFPQ, (iii) the mean of TFPQ and (iv) the dispersion of demand. These are very conventional shocks for an aggregate economy, with recent attention given to variations in the dispersion of TFPQ and demand.

The moments are generated from a stationary rational expectations equilibrium without the need for linearization. This matters as the firm-level non-linearities in the state dependent pricing model carry over to the aggregate economy.

Looking at these shocks alone as well as combinations and allowing monetary feedback, there are a few cases in which the data patterns of countercyclicality in the dispersion of TFPR, the frequency of price adjustment and dispersion in price changes are matched. One case arises when there are negatively correlated shocks to the mean and dispersion of TFPQ. This combination was highlighted in Bloom et al. (2018) to match aggregate fluc-

[40] Thus the expectation on the left side of (B.1.8) is extended to include the conditional expectation over the future dispersion.

tuations. Here the combination actually creates the countercyclical dispersion in TFPR assumed in that paper. Also, a monetary authority that leans against the wind in face of shocks to the dispersion of TFPQ creates an equilibrium that matches data patterns.

Admittedly these results are suggestive rather than definitive. The OG model, with only one period of price setting, misses some of the forward looking aspect of price adjustment. But, as argued in the text, the pricing behaviour in the model is similar to that produced by other state dependent pricing models. On the data side, it would be desirable to have higher frequency observations on both prices and quantities upon which to base a structural estimation exercise.

Throughout these exercises, one theme emerges: non-linearities in the response of the economy to monetary and dispersion shocks. Regardless of the source of aggregate fluctuations, the dispersion of TFPR is generally lowest for extremely low and high realizations and highest for the average state. This property of the model, driven by the U-shaped response of the frequency of price changes to money surprises, makes it useful to study the impact of monetary and productivity shocks using non-linear statistical models.

This suggests empirical exercises that goes beyond the traditional focus on correlations, say between output and the dispersion of TFPR. Tenreyro and Thwaites (2016) exemplifies this approach. There is certain value in looking further at price adjustment frequency as well as employment and output responses, at both the firm and aggregate levels, in a non-linear setting. For this, high frequency data on prices, output and employment is needed.

Finally, the model is used to study the effects of uncertainty on pricing. It seems clear that the effects highlighted in our analysis stem from dispersion not uncertainty. One interesting extension of our model would be to include some of the adjustment cost structure that creates a real options effect, as in Bloom et al. (2018), **coupled with** state dependent pricing.

Chapter 3

Sectoral Volatility and the Investment Channel of Monetary Policy

Abstract How does the dispersion of firm-level shocks affect the investment channel of monetary policy? Using firm-level panel data, we construct several measures of dispersion of productivity shocks, time-pooled and time-varying, and interact high-frequency identified monetary policy shocks with these measures of idiosyncratic shock volatility. We document a novel fact: monetary policy has dampened real effects via the investment channel when firm-level TFP shock volatility is high. Our estimates for dampening effects of volatility are statistically and economically significant - moving from the tenth to the ninetieth percentile of the volatility distribution approximately halves point estimates of impulse response functions to contractionary monetary policy shocks. Given that dispersion rises in recessions, these findings offer further evidence as to why monetary policy is weaker in recessions, and emphasize the importance of firm heterogeneity in monetary policy transmission.

3.1 Introduction

Firms' investment is a key transmission channel from monetary policy operations to the real economy. This aggregate response of business capital formation is shaped by firm heterogeneity in a number of dimensions (for example: firm's age and dividend status (Cloyne et al., 2018); financial position and liquidity (Jeenas, 2018); leverage (Anderson and Cesa-Bianchi, 2020), and distance to default (Ottonello and Winberry, 2020)). In this work, the dimension of heterogeneity we focus on is idiosyncratic firm risk.

Idiosyncratic firm risk is large and matters for firm adjustment decisions. Firms exhibit large variation in their measured total factor productivity, and most of that productivity variation comes from idiosyncratic shocks (Syverson (2011); Castro, Clementi, and Lee (2015)). We document substantial differences in idiosyncratic shock variance across sectors in the cross-section, and through time within sectors. Dispersion of firm-level shocks influences investment behaviour because it affects the triggering of the extensive margin of adjustment, and therefore plays a key role in firm investment, hiring, and production decisions. In this paper we study how dispersion of idiosyncratic productivity shocks affects the investment channel of monetary policy.

The study of this interaction is important for two reasons. Firstly, investment is the most volatile component of GDP, and is strongly procyclical. Secondly, the business investment response is a major component of the total macroeconomic response to monetary policy operations. A better understanding of the drivers of heterogeneous investment responses at the micro-level is important for the study of the business cycle dynamics, and for a better understanding of what constitutes effective countercyclical macroeconomic policy.

Our empirical strategy involves constructing firm-level productivity, and its shocks, according to several methodologies in the literature. We compute second moments of firm shocks to measure idiosyncratic risk at the sector and sector-year levels. Our empirical analysis involves regressing firm investment on an identified monetary policy shock interacted with our measures of volatility. This approach allows us to use both cross-sectional variation (making comparisons across sectors with high and low overall volatility) and panel variation (following a given sector through time, comparing when its volatility is high versus low).

This work contributes in two ways to our understanding of the interaction between idiosyncratic firm shocks and their variance, firm capital adjustment decisions, and asymmetric monetary policy transmission over the business cycle. Firstly, our results document new evidence on the role of dispersion of idiosyncratic shocks in determining firms' investment response to monetary policy actions. Regression analysis implies qualitatively significant dampening of the investment channel of monetary policy. Moving from the 10th to the 90th percentile of sectoral volatility implies up to approximately a 50 percent reduction in response point estimates. Combining findings across three measures of productivity, and by both time-pooled and time-varying volatility measures, the majority of our volatility interaction coefficients imply a volatility-dampening effect on the investment channel that is statistically significant and economically meaningful in relative size. Secondly, our results also offer an explanation as to why monetary policy is weaker in recessions. As shown by Tenreyro and Thwaites (2016), this asymmetry along the business cycle is particularly strong in business investment. Our results suggest this weakening of monetary policy in bad times is (in part) due to higher idiosyncratic risk, making firms reluctant to take the extensive-margin step of investment. Overall our findings reiterate the importance of firm heterogeneity at the micro-level in monetary policy transmission to the real economy and its effectiveness at fighting recessions.

Related Literature This work is connected to several branches of the existing literature. Firstly work focusing on investment and uncertainty, especially the so-called "options approach" of Bernanke (1983) and Dixit and Pindyck (1994) which emphasizes the timing margin of firm investment decisions, and not just simple NPV rules[1] usually based on one-period investment opportunities. The options approach is discussed in more detail in the following section. Bloom et al. (2018) argue that uncertainty drastically dampens firm-level investment and hiring decisions when subject to rich factor adjustment costs, featuring convex and nonconvex costs of adjustment as well as partial irreversibility. They indicate that firms freeze their capital/labor adjustment decisions and enter a "wait-and-see" mode, due to the “real options” effect induced by increased uncertainty.

We add to this important finding by providing empirical evidence that firms are reluctant to make capital adjustments in response to aggregate monetary policy shocks when they face higher dispersion of idiosyncratic shocks.

Relatedly, by employing a menu cost model[2], Vavra (2014) links volatility in nominal income to price adjustment behavior, and shows that firms are forced to change their prices more frequently when there is higher volatility. Vavra (2014) further argues that due to this fact price change dispersion and frequency of price adjustment are counter-cyclical. On the empirical side, Bachmann et al. (2019) provide additional evidence on the interaction between volatility and firm behaviour. They point out that higher volatility is associated with a higher probability of price adjustment, and the likelihood of this price adjustment is higher in recessions.

Our work is related to the literature that studies the cyclicality of monetary policy effectiveness. Tenreyro and Thwaites (2016) indicate that the macroeconomy is less responsive to monetary policy shocks during recessions compared to expansionary periods - “pushing on a string" as they phrase it - with an especially pronounced asymmetry in the reaction of investment. Our work complements these findings and offers an explanation: elevated dispersion of idiosyncratic shocks in bad times leads to lower responsiveness to monetary policy operations because of stronger real options effects and a greater share of adjustment occurring through nominal as opposed to real channels.

[1] Dixit and Pindyck (1994) define the net present value rule as: invest if the net present value of an investment opportunity is greater than zero, without accounting for irreversibility, and the possibility to delay the decision.

[2] Dotsey, King, and Wolman (1999b); Golosov and Lucas Jr (2007)

This paper also relates to the literature that studies heterogeneity in monetary policy transmission. In recent years there has been an increased focus on examining macroeconomic questions with microdata, looking at firm-level responses to monetary policy operations, and how those responses are patterned across heterogeneous firms. After employing rich firm-level controls, recent work finds significant heterogeneity along the dimensions: distance to default Ottonello and Winberry (2020), liquidity position Jeenas (2018), heterogeneity in markups Meier and Reinelt (2019), leverage Anderson and Cesa-Bianchi (2020) and Ferrando, Vermeulen, and Durante (2020). Closely related to our paper is Fang (2020), who studies volatility's effects on the investment channel in a rich theoretical framework, and provides empirical results using the interquartile range of sales growth as his volatility measure. Our paper acts as a complementary study focusing on a novel channel —idiosyncratic firm risk, and provides a detailed analysis of TFP shock dispersion's dampening effects on the investment channel of monetary policy.

All employ high-frequency identified monetary policy shocks (in the spirit of Gertler and Karadi (2015)) with firm-level panel data. We employ a similar econometric methodology.

Road Map In Section 3.2, we describe our firm-level data and empirical strategy. Section 3.2.1 discusses the approaches we employ to estimate firm level productivity. Then, Section 3.2.2 presents our constructed volatility measures. Section 3.3 motivates our empirical analysis through the lens of two theoretical models in the literature. Section 3.3.1 stresses that increased dispersion of shocks leads to less effective monetary policy through the real options channel, while Section 3.3.2 focuses on the nominal adjustment channel. Section 3.4 presents our baseline regressions identifying average investment response to monetary policy. We then present regression analysis interacting the monetary policy shock with measures of volatility to identify patterns of heterogeneity in the investment response to monetary policy. Section 3.5 concludes. The appendix contains further robustness checks.

3.2 Cross-Sectional Distribution of Productivity across Sectors

This section describes how we measure idiosyncratic firm risk in productivity. Our empirical strategy involves three main parts. First, we compute firm level productivity, and fit an autoregressive process to productivity in order to fit productivity shocks. Second, we pool these shocks in order to construct moments of the shock distribution by 2-digit sector.

Finally in our local projection regression analysis we interact monetary policy shocks with measures of shock dispersion.

Data We use Compustat firm-level panel data to conduct our empirical analysis. This dataset provides rich financial information for a broad range of firms, and is relatively high frequency, with most data reported quarterly, as opposed to yearly for other similar datasets. The principal drawback in the use of the Compustat data relates to representativity – only listed firms are included in the sample. As noted by Axtell (2001) Compustat firms are approximately lognormally distibuted, while the population of firms in census data is more accurately modelled by a power law (Gabaix (2016)) meaning Compustat has too few small firms relative to the population of firms. Moreover, the number of firms sampled in sector-cells do not correspond with the aggregate sector shares. We do not see this as problematic for the following reasons: (i) our empirical strategy exploits variation both across and within sectors (ii) aggregates calculated from explicitly summing the microdata yield time series which behave very similarly to the national accounts aggregates (investment growth, for example, Cloyne et al. (2018)) (iii) our focus is on the investment channel of monetary policy, as such relatively small firms are not likely to hold enough capital to be meaningful to aggregated dynamics at the sector or economy-wide level.

Sample Following similar work in the literature (e.g. Ottonello and Winberry (2020)) we exclude the so-called "FIRE" sectors (finance and real estate) due to the very different balance sheet composition of firms in these sectors, as well as utility firms. We drop any of the following firms: not based in USA, not trading in USD, making acquisitions above 5 percent of the value of total assets in nominal values. Nonsensical values such as negative capital or negative sales are also dropped. Where gaps in series are only one quarter we use linear interpolation to fill in the gaps following similar papers in the literature.

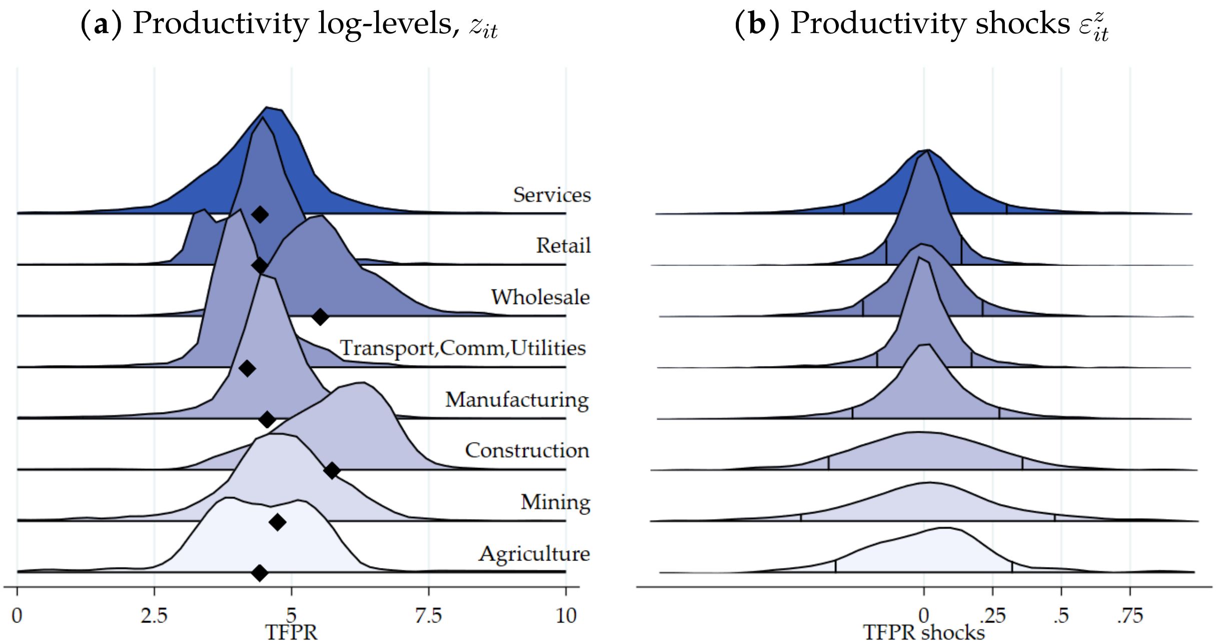
3.2.1 Firm Productivity

Estimating Firm Productivity Among several approaches to estimating firm productivity, we begin by using a Cost Share approach: imposing a functional form on production and computing functional parameters based on observed factor usage shares. We check the robustness of such a measure using Generalized Method of Moments and the Olley and Pakes (1996) Control Function approach.

The distributions of TFP and its innovations are show in Figure (3.1), pooling firms according to broadly defined sector groups. Sectors exhibit significant variation in both the mean and dispersion of productivity (left panel) as well as significant differences in the dispersion of shocks in TFP (right panel). We investigate what are the monetary implications of sectoral differences like these, but at a more disaggregated 2-digit level.

Figure 3.1

Total Factor Productivity by Sector



Note. Pooled TFP levels and innovations calculated according to Cost Share method. Filled diamonds mark sectoral means (left) and vertical lines mark the tenth and ninetieth percentiles respectively (right

Cost-Share approach

We take a Cost Share approach following works such as Foster et al. (2008),Bloom et al. (2018), Decker, Haltiwanger, Jarmin, and Miranda (2018) and we identify productivity via structural assumptions on the production function. We impose a Cobb-Douglass production function, and assume inputs of capital and labor only. We calculate factor intensity parameters from median cost-shares within sector-years. This is done for two reasons. At the firm level this method is vulnerable to measurement error, while the median helps filter out extreme values. Moreover, even though in any given period adjustment costs are likely to induce a fraction of firms not to adjust either factor, over many firms we can recover average cost-shares. We construct this measure with time-varying parameters. For a given firm i in sector s in year t productivity in logs, z_{ist}, is constructed as the following, where y_{ist} is observed log sales revenue[3].

[3]For notational clarity we report k_{ist} however Compustat reports end of period values after adjustment, hence k_{ist} refers to last period's end-of-period capital brought into period t

$$z_{ist} = y_{ist} - \alpha_{s,t}^{(N)} n_{ist} - \alpha_{s,t}^{(K)} k_{ist} \tag{3.1}$$

Generalized Method of Moments

As a robustness check we calculate TFP according to several other methodologies to gauge how sensitive the main results are to TFP computation methods. Following Cooper and Haltiwanger (2006), we assume z_{it} follows an AR(1) process we can make the following quasi-first-difference transformation. To allow for trends in TFP we detrend log sales using sector-year and firm fixed effects.

$$\tilde{y}_{ist} - \rho_s \tilde{y}_{it-1} = (1-\rho_s)c_s + \alpha_s(k_{ist} - \rho_s k_{ist-1}) + \beta_s(n_{ist} - \rho_s n_{ist-1}) + \varepsilon_{ist} \tag{3.2}$$

Parameters $\theta_s = (c_s, \rho_s, \alpha_s, \beta_s)$ are then estimated using the moment condition $E(z_{ist}\varepsilon_{ist}) = 0$, setting the innovation term orthogonal to current and lagged values of k_{ist}, since it is taken as predetermined, and lagged n_{ist}. In this approach production function parameters are constant over time and can only vary across sectors.

$$\hat{\theta}_{GMM} = \arg\min_{\theta} \left\{ N^{-1} \sum_{i,s,t} z_{ist}\varepsilon_{ist}(\theta) \right\}' W \left\{ N^{-1} \sum_{i,s,t} z_{ist}\varepsilon_{ist}(\theta) \right\} \tag{3.3}$$

In economic terms, this moment condition enforces that the innovation in TFP behaves like a shock - unforecastable with $t-1$ information. The weighting matrix is set to minimize estimate variation.

Olley-Pakes Control Function

The above methods may suffer from two problems: simultaneity and selection bias. Simultaneity problems arise due to the fact some portion of the productivity shock is known to the firm, but not to the econometrician. More productive firms may invest more or hire more labor with the expectation of higher returns. The second issue is the selection bias which originates from the correlation between negative productivity shocks and the probability of exiting the market. Namely, firms with a larger capital stock are more likely to stay in the market despite a low productivity shock. This situation will cause the coefficient of the capital variable to be biased downward. By employing the methodology in Olley and Pakes (1996), we account for both the endogeneity of factor inputs as well as selection bias due to low productivity firms exiting the sample. If we assume firm investment is a function of state variables age, capital stock, and productivity, provided investment is not zero we can invert the investment function $z_{ist} = h(a_{ist}, k_{ist}, i_{ist})$. Making this substitution we can then recover β_n

$$y_{ist} = \beta_0 + \beta_a a_{ist} + \beta_k k_{it} + \beta_n n_{ist} + h(a_{it}, k_{ist}, i_{it}) \tag{3.4}$$

$$= \beta_n n_{ist} + \phi(a_{ist}, k_{ist}, i_{ist}) + e_{ist} \tag{3.5}$$

Finally, accounting for selection, the Olley-Pakes method estimates the following by non-linear least squares:

$$E\left(y_{ist} - \beta_n n_{ist} | a_{ist}, k_{ist}, \text{exit}_{it-1} = 0\right) = \beta_a a_{ist} + \beta_k k_{ist} + E\left(z_{ist} | z_{ist-1}, \text{exit}_{ist-1} = 0\right) \tag{3.6}$$

To close the estimation section: all measures of productivity are computed separately for each 2-digit sector. However only the Cost Share method allows for time and sector variation in parameters. Olley Pakes and GMM both estimate parameters which are fixed for the duration of the sample. We do not see this as problematic given our final regression sample only runs from the 1990s to 2010 based on the availability of the monetary policy shock variable we employ.

3.2.2 Volatility

We estimate a process for firm-level productivity in logs (z_{ist}). The AR(1) component determines the speed with which shocks decay and productivity returns to its trend, while sector-year dummies (λ_{st}) account for systematic comovement among firms within a given sector, but allow those stochastic trends to vary freely. This component is potentially non-stationary. Firm-level fixed-effects (f_i) control for permanent differences in productivity between firms. Finally we also control for size and age effects in the level of productivity. A separate regression is run for each 2-digit sector. Volatility is taken as the standard deviation of ε_{ist}, pooling firms at the sector- and sector-year levels[4]:

$$z_{isy} = \rho_s z_{isy} + \beta_s \left(\text{log size}_{isy}\right) + \gamma_s \left(\text{log age}_{isy}\right) + \lambda_{sy} + f_i + \varepsilon_{isy} \tag{3.7}$$

We define volatility as:

[4] Our strategy to pool at the 2-digit sector level is to avoid imprecisely measuring volatility at finer levels of aggregation, for example at the firm level

$$\text{sectoral volatility: } \sigma_s = sd(\varepsilon_{isy}|s) \tag{3.8}$$

$$\text{time-varying sectoral volatility: } \sigma_{s,y} = sd(\varepsilon_{isy}|s, y) \tag{3.9}$$

Productivity Distributions within Sectors TFP calculated this way shows high levels of dispersion at the firm level (Table C.2.1). Firms in the unconditional 95th percentile are more than twice as productive (in sales revenue), for given inputs, than firms in the 5th percentile. On average this ratio is tending towards 5 if we compare the top and bottom one percent of firms overall, and within some sectors this number is over 7. This qualitatively matches many other papers in the firm productivity literature which find significant dispersion of firm productivity.

Productivity Distributions across Sectors Figure (3.1) plots the cross-sectional distributions of TFP, pooling firms across time. Significant heterogeneity in the moments of TFP (mean level, dispersion, and moments governing shape) are clear from the left panel. The right panel displays significant variation across sectors in TFPR shock dispersion. 10th and 90th percentiles are marked.

3.3 Stylized Theoretical Framework

Having constructed measures of firm-level productivity dispersion, and established stylized facts, we now turn to motivating our empirical analysis of monetary policy's ability to affect firm-level investment, based on two mechanisms highlighted in the literature.

We rationalize our empirical findings by drawing a line from the results of Tenreyro and Thwaites (2016), who show that monetary policy has asymmetric effectiveness in booms and recessions, through the work of Bloom et al. (2018) and Vavra (2014) to our own results.

Monetary policy may have dampened effectiveness via the investment channel of transmission during periods of higher dispersion of shocks due to (1) a real options/option value channel (Bloom, 2009; Bloom et al., 2018) and (2) a nominal adjustment channel (Vavra, 2014). Our results can be interpreted through the lens of both models, and are consistent with model predictions, however we remain agnostic between the two channels.

Firstly, Bloom et al. (2018) links recessions with periods of higher uncertainty and more dispersion of firm-level productivity shocks, and we would expect to see more wait-and-see behaviour and a postponement of firms' labour and capital input adjustments. The downstream consequence of this insensitivity to prices and market conditions is that firms will likely respond less to monetary policy when shock dispersion is high, which tends to be the case in recessions.

Leading on from this inaction in factor choices, work by Vavra (2014) would suggest more adjustment to shocks will occur through nominal as opposed to real channels when volatility is high. Greater price flexibility has implications for monetary policy transmission. If prices were fully flexible, monetary stimulus would have no real effects.

3.3.1 Real Options Channel

The first mechanism through which our work can be seen is the "options approach" to firm investment in work such as Bernanke (1983) and Dixit and Pindyck (1994), in which the interaction of irreversibility and uncertainty plays a key role in investment dynamics. A simple NPV approach of whether to invest or not ignores the timing dimension of the firm's problem. The "when" of investment matters if such outlays are costly to unwind in the future if things go wrong. Moreover, a firm with an opportunity to invest is essentially holding a call option - the right but not the obligation to invest. The opportunity cost of investing is to give up the option value of waiting.

Recent work by Bloom (2009) and Bloom et al. (2018) emphasizes the role of uncertainty in firms' factor input choices, especially in recessions. Empirical evidence shows that uncertainty, or measures of shock dispersion more generally, goes up in recessions.

The uncertainty effect acts through changes in the expected future distribution of idiosyncratic shocks, which combined with time-to-build can induce wait-and-see behaviour in firms if they expect the chance they are ejected from the inaction region of the state-space next period is higher. High dispersion of shocks, and with it a higher option value of inaction, makes firms temporarily insensitive to factor prices and causes them to freeze hiring and investment decisions in order to avoid double-paying nonconvex adjustment costs.

In these two models of firm dynamics with fluctuations in uncertainty, firms learn today that tomorrow's shock distribution will be more dispersed. There is no direct effect today, since the variance of today's shocks hasn't changed, however the firm now forms expectations over a wider distribution of shocks.

Bloom et al. (2018) setup a rich, heterogeneous firm environment to capture the several impacts of uncertainty shocks observed in the data. The model incorporates nonconvex adjustment costs of capital and labor, to create a real options channel of uncertainty shocks in their model. The capital adjustment cost includes a fixed disruption cost, as well as partial irreversibility of investment. Irreversibility is integrated via an asymmetric price of capital, which depends on whether the transaction is a capital purchase or sale. A sale only receives a partial share of capital's full price. Irreversibility results in an asymmetric behavior, making negative shocks more important as capital sales cause extra losses.[5]

This is an Ss type model, therefore if the productivity (combination aggregate and idiosyncratic components) falls into the inaction region, firms do not hire and invest and thus do not suffer the corresponding adjustment cost. However, if productivity reaches the boundary of this region, then the firm pays the necessary costs, and adjusts its capital and/or labor inputs.

The authors first state that the presence of adjustment costs in the above-mentioned formulation causes real options effects. The authors argue that an increase in uncertainty widens the inaction region, making any adjustment decision more difficult than before. This leads to an economy-wide freeze in extensive margin adjustments of hiring and investment decisions and making all firms insensitive to any policy changes (or shocks more generally).

Secondly, the authors argue for the existence of an Oi-Hartman-Abel effect, that is, in the absence of adjustment costs, and output is convex in productivity, then an increase in the standard deviation of the productivity distribution affects the economy positively, (*i.e.* output and investment increases, unemployment decreases). Moreover, if uncertainty is resolved, the Oi-Hartman-Abel effect is triggered, and firms start to invest and hire again, and output rises.

As noted by Bloom (2009), it is plausible that such wait-and-see effects have consequences for monetary policy transmission, and macroeconomic stabilisation more broadly. Higher uncertainty in recessions would make firms much less sensitive to monetary policy operations directly, that is, where monetary policy variables enter the firm's dynamic problem becomes less important. This however would still allow monetary policy to act via other indirect channels.

Our findings are in line with the predictions and explanations of Bloom et al. (2018). The authors' predict that firms freeze their investment and hiring decisions when facing higher uncertainty. According to our empirical findings, if a sector has higher dispersion of idiosyncratic productivity shocks, then in that sector, firms' investment response to a monetary policy shock is weaker.

[5]Labor adjustment costs also include a very similar fixed disruption cost, and a partial irreversibility mechanism. For the sake of brevity, we are omitting labor adjustment discussion here. Interested readers may refer to the relevant section of Bloom et al. (2018).

3.3.2 Nominal Adjustment Channel

Dispersion of shocks also plays a role in the frequency of price changes.The nominal adjustment mechanism acts through price adjustments counteracting monetary policy actions. Vavra (2014) shows empirically that during recessions typical volatility measures rise, and the cross-sectional standard deviation of price changes increases. He then argues that with higher dispersion of firm-level shocks, firms adjust their prices more frequently, and so more firm adjustment takes place through the nominal margin rather than through quantities. Any nominal stimulus attempt induced by the monetary authority generates more inflation and gives less of a boost to the real economy when volatility is high in recessions.

Vavra (2014) discusses that there are both direct and indirect effects of second moment shocks. The direct effect is the notion that more dispersed shocks increase the likelihood of pushing firms to the action region of the state space, thus firms adjust their prices more frequently. If the firm faces a choice of adjusting in several dimensions, it is plausible to think short-run changes in prices are easier for the firm than changes in factors, especially capital subject to partial irreversibility.

However, as discussed in the section above on real options, volatility also raises the option value of waiting, therefore the inaction region gets wider which makes firms temporarily suspend their decisions (including price adjustment). The latter effect is called indirect effect in Vavra's language. Vavra (2014) indicates that in case of a persistent increase in volatility, the direct effect dominates the indirect effect, therefore during recessions more firms adjust their prices and prices get more flexible which undermines the effectiveness of any nominal changes. Figure 3.2 shows both effects in a stylized way.

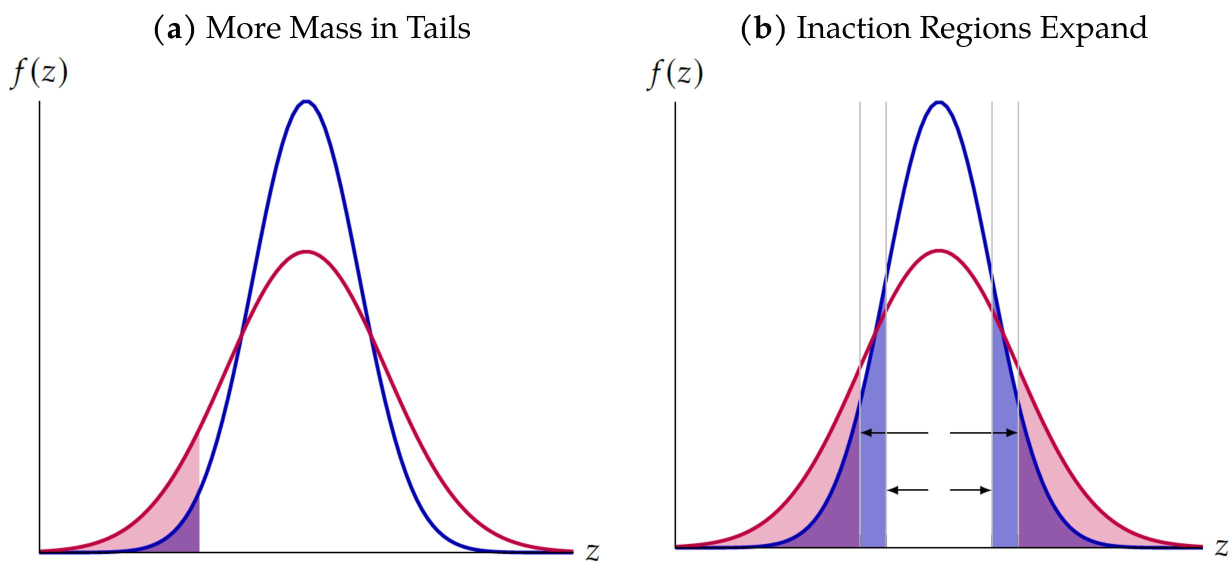
In order to explain these results, he also uses an Ss type model. First, he assumes that idiosyncratic volatility is perfectly negatively correlated with aggregate productivity (*i.e.* as the aggregate productivity increases the dispersion of idiosyncratic productivity shocks decreases). In the model, aggregate states are the aggregate nominal spending, and aggregate productivity, while the idiosyncratic states are previous period's nominal price, current period idiosyncratic productivity and the menu cost.

Firms operate as follows. In each period, after observing their own idiosyncratic productivity and a menu cost draw, and knowing its own inherited price, aggregate nominal spending, and aggregate productivity, firms decide either to change their posted nominal price or keep prices unchanged for another period. If firms decide to change price, then they pay the menu costs, enabling them to set their optimal nominal price. On the other hand, if they decide not to change their price, then they keep their inherited price.

He explains the above-mentioned empirical facts by the direct channel of second moment shocks dominating the indirect effects, in the context of price setting. Higher disper-

Figure 3.2

Direct and Indirect Effects of Second Moment Shocks



Note. Panel (a) $F(z|v_H) > F(z|v_L)$ for extreme values of z in the left tail. Panel (b) Inaction regions expand with volatility as the option value of waiting increases.

sion leads to more frequent price changes, which makes prices more flexible. Therefore, as the volatility increases, nominal shocks should have smaller real effects.

Our empirical findings state that as the dispersion of idiosyncratic productivity shocks at the sector level increases, the investment responsiveness of firms to monetary policy shocks falls. While this is consistent with the mechanism proposed by Vavra, we should differentiate our setting from his.

Firstly, Vavra (2014)'s model does not feature capital, so cannot speak directly to paths from volatility to the investment channel of monetary policy transmission, nevertheless the broader lessons of the model are informative externally: higher idiosyncratic shock volatility shifts the relative balance between real versus nominal channels of adjustment.

Secondly, he examines responses to monetary shocks as a function of dispersion pooled at the economy-wide level, while we examine dispersion at the sector level. His work focuses on variations in dispersion over time, while our work uses cross-sectional variation, comparing differences in dispersion across sectors, and the full panel variation of our dataset, using variation within sectors, moving over time.

Finally, we do not observe firms' pricing choices directly, and our labor data is at a lower frequency than needed. As such, there is not a direct mapping from his model to our data analysis, and our results only speak for capital adjustment. Nevertheless, we rely on the notion that higher shock dispersion forces more firm adjustment following monetary policy operations to be nominal (through prices) and less to be real (input quantities).

3.4 Monetary Policy Analysis

To analyse the impact of monetary policy on firm-level investment we employ a local projections specification. We regress investment at horizon h steps ahead $I_{i,t+h} = \log k_{i,t+h} - \log k_{i,t-1}$ on a constant, the monetary policy shock mps_t, firm-level controls, as well as firm and calendar-quarter seasonal effects.

Our vector of controls, $\mathbf{X}_{ist-1}$, comprises four lags of the shock and firm characteristics (age and size). Since we include firm fixed effects, we have no need f or sector effects. Sector fixed effects would be a linear combination of the firm effects. Thus we implicitly control for permanent differences in average investment behaviour across sectors. In this baseline regression, all sectors are pooled together.

$$\text{Firm Investment}_{ist+h} = c_h + \beta_h \text{mps}_t + \mathbf{X}_{ist-1}\Gamma_h + f_{hi} + \lambda_{hq} + v_{ist+h} \tag{3.10}$$

The monetary policy shock is scaled such that it induces a 25 basis points increase in the short-term interest rate (3-month Treasury bill rate), with monetary policy shocks proxied with the high frequency shock series of Miranda-Agrippino and Ricco (2017). This series proxies for the changes in policy which are separate from the endogeneous component which reacts to the state of the macroeconomy (e.g a Taylor-type rule creates a simaltaneity problem between policy and state of the economy).

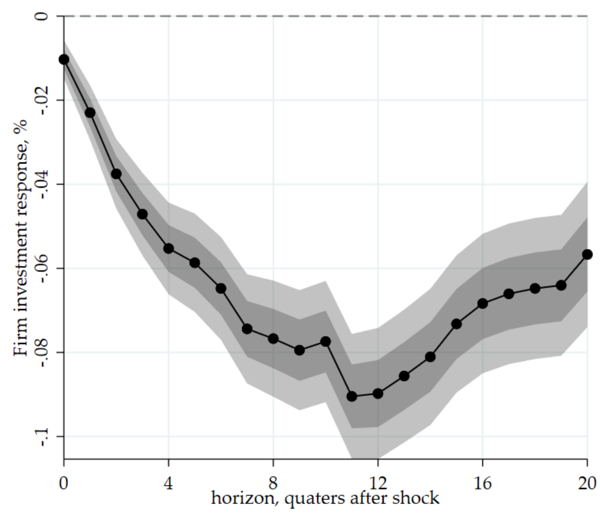
We prefer this proxy for monetary policy shocks since it does not generate the price or output puzzles of other similarly motivated proxies (Romer and Romer, 1989; Gertler and Karadi, 2015), that is to say, empirical IRFs have the signs which match with economic theory (see Appendix for aggregate IRFs to RR, GK, and MAR shocks). Standard errors are clustered on the firm-level.

Our baseline regression sample runs from 1991q2 to 2009q4, made up of approximately 20,000 firms and 600,000 firm-quarters.

Impulse Response Functions Dynamic responses to monetary policy shocks are presented as impulse response functions (IRF). The sequence of coefficients $\{\beta_{(0)}, \beta_{(1)} ... \beta_{(H)}\}$ trace out the investment response to the shock mps_t over the horizon $h \in \{0, 1, ...H\}$ after a monetary policy shock. The IRF conducts the following thought experiment: comparing two observationally similar firms over periods $\{t, t+1, ..., t+H\}$, but one is subject to an isolated, one-period unit shock, and the other is not, holding constant certain characteristics of the two firms, for example recent histories of shocks, size, and age.

$$\beta_h = E\left[\text{Investment}_{it+h}\middle|\ \text{mps}_t = 1, \mathbf{X}_{t-1}\right] - E\left[\text{Investment}_{it+h}\middle|\ \text{mps}_t = 0, \mathbf{X}_{t-1}\right] \tag{3.11}$$

Figure 3.3
Impulse Response Functions of Firm Investment (%)



NOTE. Shaded regions represent 68 and 95 percent confidence intervals respectively. Standard errors are clustered at the firm level. Vertical axis is in percent difference, horizontal axis is quarters after shock hits.

Figure (3.3) shows average investment is cut gradually, with a peak contraction of around 8-10 percent occurring around the end of the third year after impact.

3.4.1 Volatility Across Sectors and Monetary Policy

Next, we interact the monetary policy shock with volatility (time-pooled by sector). Given the exogeneity of the shock mps_t, this regression investigates the differential responses of investment to monetary policy across volatility by sector. In regression subscripts, sector s denotes the sector of firm i: $s = s(i)$.

$$\text{Investment}_{ist+h} = c_h + (\beta_h + \gamma_h \sigma_s) \cdot \text{mps}_t + \mathbf{X}_{ist-1}\Gamma_h + f_{hi} + \lambda_{hq} + v_{ist+h} \tag{3.12}$$

Controls remain unchanged from the baseline model. An estimate for γ_h with the opposite sign to β_h would suggest volatility decreases responsiveness to monetary policy shocks.

The second column of Figure (3.4) reports positive interaction coefficients along the horizon, for all three volatility measures. The first two remain statistically significant along the majority of the horizon shown. Results suggest that the investment channel of monetary policy is patterned across sectors by volatility, with sectors with higher overall volatility reacting significantly less to monetary policy shocks. Figure (3.5) uses the regression estimates to construct IRFs for firms at the tenth and ninetieth percentiles of the sectoral volatility distribution, for all three measures of volatility.

Figure(3.4) shows that firms operating in sectors with higher *average* volatility of idiosyncractic TFP shocks adjust their capital on average less than those operating is less volatile sectors in response to a monetary policy shock. This pattern of volatility dampening the investment channel of monetary policy is robust to the choice of volatility construction.

Next, we look at time varying volatility, to see how volatility dampens real reactions *within* sectors, using panel variation following sectors through time.

3.4.2 Time-varying Volatility Interactions

We recalculate volatility so that that volatility can vary across sectors and through time, $\sigma_{s,y-1}$, however variation in volatility is at the yearly not quarterly frequency due to labor input data availability only at the lower frequency. This time-varying volatility enters the regression lagged by one year $y(t)-1$ so that volatility is allowed to influence monetary policy transmission, but the measure of volatility is not contaminated by the effects monetary policy shock in period t.

$$\text{Investment}_{ist+h} = c_h + (\beta_h + \gamma_h \sigma_{s,y-1}) \cdot \text{mps}_t + \mathbf{X}_{ist-1}\Gamma_h + f_{hi} + \lambda_{hq} + v_{it+h} \tag{3.13}$$

Controls and regression structure remain otherwise the same as the baseline specification. Figure(3.6) presents IRFs to the monetary policy shock and the shock-volatility interaction coefficients.

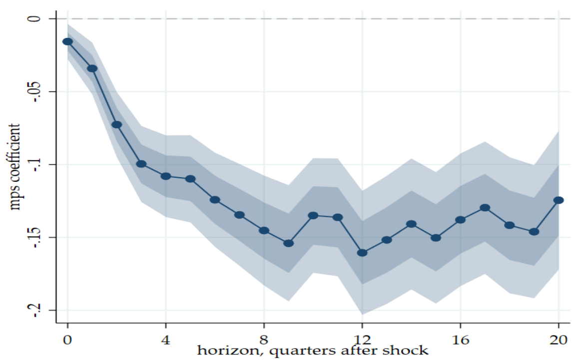
If volatility is high for a given sector when the shock hits, the implied response is significantly dampened compared to if the shock hit in a period when baseline (time t) volatility was low.

Of the three measures of TFP shock volatility, CS and OP show results consistent with a dampening effect of volatility on the investment channel of monetary policy. Volatility interaction coefficients are typically positive, if not signficant along all of the horizon, however Olley-Pakes volatility interaction coefficients reach zero at certain horizons. One

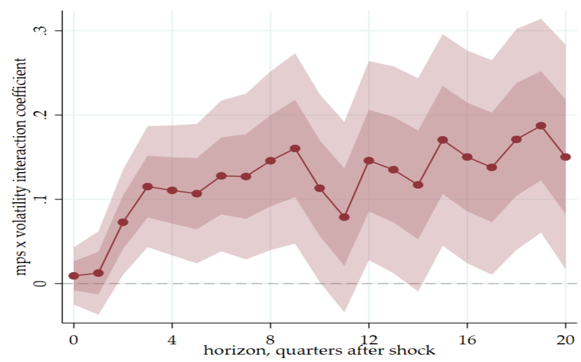
Figure 3.4

Investment Impulse Response Functions to Monetary Policy Shocks and Mps-Volatility Interactions

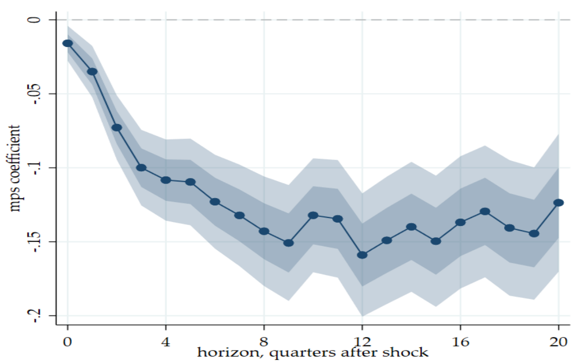
(a) **Cost Share:** Monetary Policy Shock Coefficient



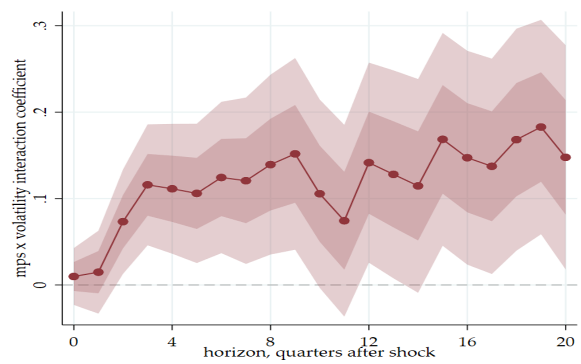
(b) **Cost Share:** MPS - Volatility Interaction Coefficient



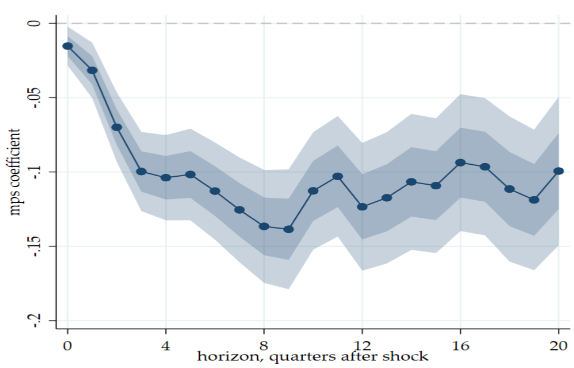
(c) **Olley Pakes:** Monetary Policy Shock Coefficient



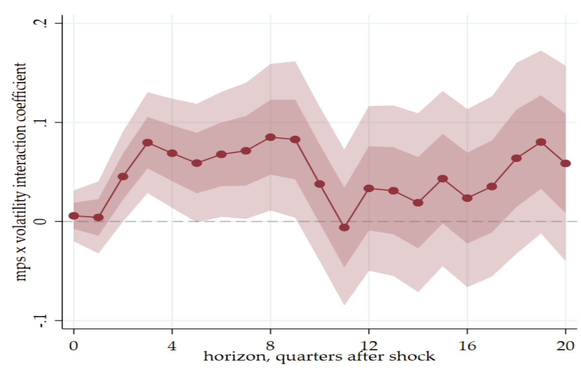
(d) **Olley Pakes:** MPS - Volatility Interaction Coefficient



(e) **GMM:** Monetary Policy Shock Coefficient



(f) **GMM:** MPS - Volatility Interaction Coefficient

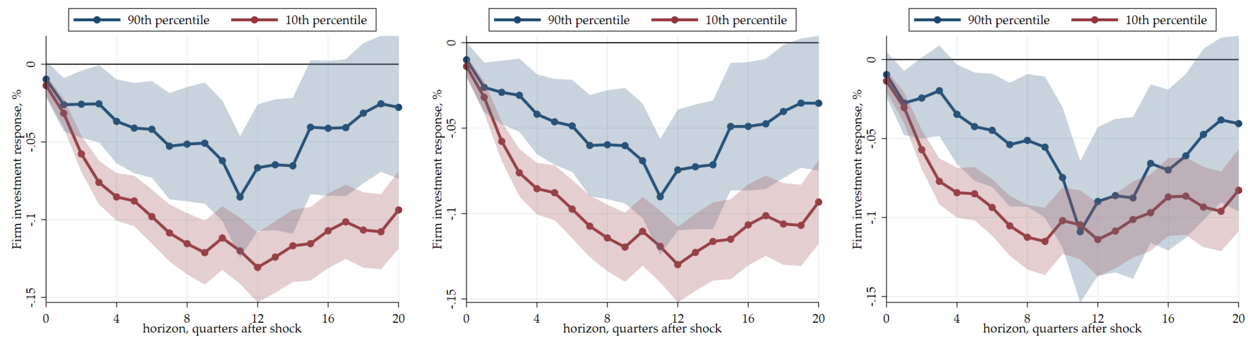


Note. Shaded regions represent 68 and 95 percent confidence intervals respectively. Standard errors are clustered at the firm level. Vertical axis is in percent difference, horizontal axis is quarters after shock hits.

Figure 3.5

TOTAL FACTOR PRODUCTIVITY BY SECTOR

(**a**) Cost Share (**b**) Olley Pakes (**c**) GMM



NOTE. Pooled TFP levels and innovations calculated according to Cost Share method. Filled diamonds mark sectoral means (left) and vertical lines mark the tenth and ninetieth percentiles respectively (right

could expect a slight deterioration of signficance/preciison of estimates in the time-varying volatility case given that volatility enters with a one year lag and only evolves annually. In the next section we try to improve estimation by using other proxies for faster moving quarterly volatility.

As in the previous regressions, we then use these coefficients to construct hypothetical IRFs at the tenth and ninetieth percentiles of the sector-year volatility distribution, shown in Figure(3.7).

Interpreting the results of the time-invariant volatility interactions and time-varying interactions jointly, it appears that only one of the possible six specifications tested in total produces results not consistent with some pattern of volatility dampening of the investment channel of monetary policy.

Cost Share and Olley Pakes measure of time-varying volatility show evidence of volatility dampening, however the effect is stronger when using the CS measure. The p90-p10 IRFs are not significantly different for the GMM measure over the full horizon. While the p90-p10 IRFs in the right panel partially overlap for the OP measure, the partial separation at shorter horizons still implies a differential in the cumulative investment responses over the full horizon.

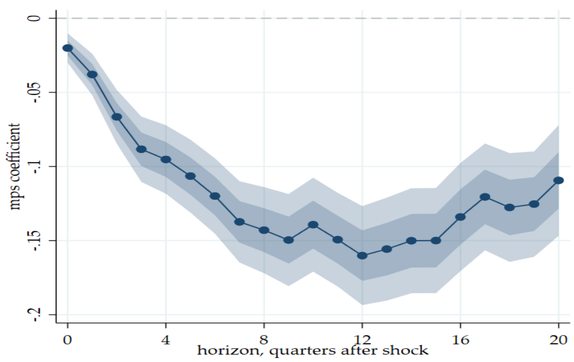
3.4.3 Firm-Level Sales Volatility and Aggregate Financial Volatility

Given that our measures of volatility are at the annual frequency and enter regressions from the previous year in order to avoid the feedback from monetary policy to volatility, we now look at a faster moving proxy for sector level volatility, following Castro et al.

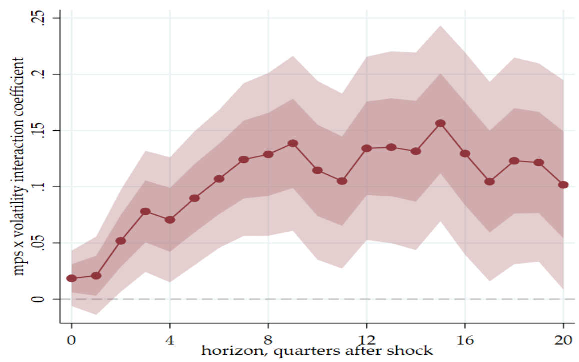
Figure 3.6

INVESTMENT IMPULSE RESPONSE FUNCTIONS TO MONETARY POLICY SHOCKS AND MPS-VOLATILITY INTERACTIONS (USING TIME-VARYING SECTORAL VOLATILITY)

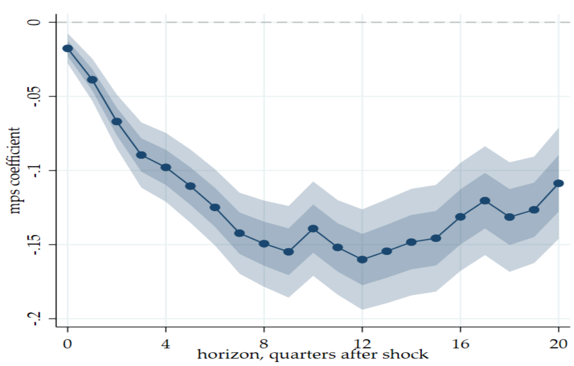
(a) **Cost Share:** Monetary Policy Shock Coefficient



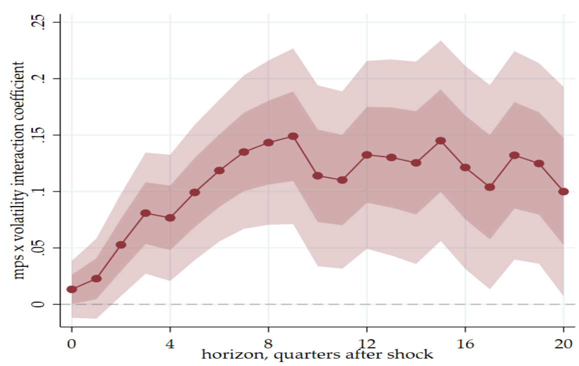
(b) **Cost Share:** MPS - Volatility Interaction Coefficient



(c) **Olley Pakes:** Monetary Policy Shock Coefficient

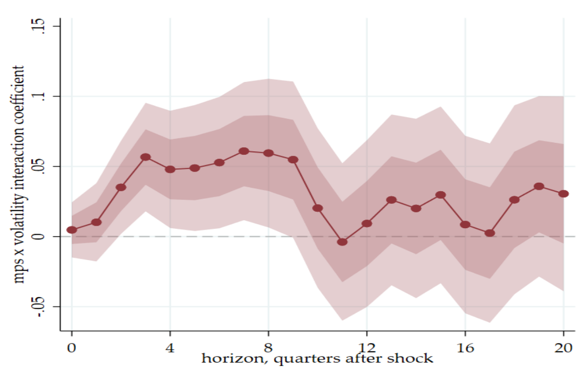


(d) **Olley Pakes:** MPS - Volatility Interaction Coefficient



(e) **GMM:** Monetary Policy Shock Coefficient

(f) **GMM:** MPS - Volatility Interaction Coefficient

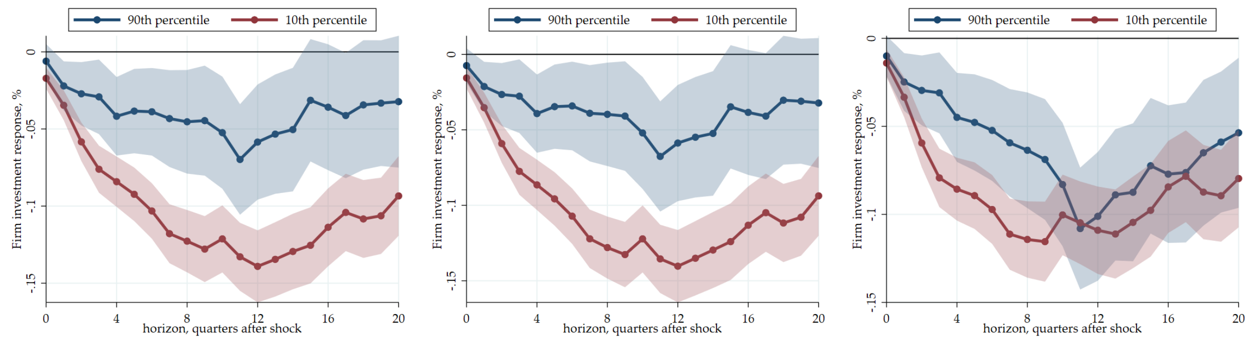


NOTE. Shaded regions represent 68 and 95 percent confidence intervals respectively. Standard errors clustered at the firm level. Vertical axis is in percent difference, horizontal axis is quarters after shock hits.

Figure 3.7

Total Factor Productivity by Sector

(**a**) Cost Share (**b**) Olley Pakes (**c**) GMM



Note. The above charts construct IRFs to a 25 basis points contractionary monetary policy shock, evaluated at the tenth and ninetieth percentile of the unconditional time-varying volatility distribution.

(2015). This measure first purges log sales of variation due to log capital, log age as well as firm and sector-quarter non-parametric trends. From this filtering regression, the squared residuals (a time-varying shock variance proxy) are then regressed in a second stage on sector-quarter effects to estimate the component of shock variance which varies systematically at the sector-quarter-level. These transformed sector-quarter effects are then interacted with the monetary policy shock, proxying for sales volatility. Alternatively we use the VIX index as a proxy for aggregate volatility (although the VIX is forward looking in nature and a better proxy for uncertainty than volatility).

$$\text{Investment}_{ist+h} = c_h + (\beta_h + \gamma_h \text{vol}_{s,t-1}) \cdot \text{mps}_t + X_{ist-1}\Gamma_h + f_{hi} + \lambda_{hq} + v_{ist+h} \tag{3.14}$$

Consistent with the results presented in previous sections, faster moving quarterly measures of volatility at the sector and aggregate level (proxied by adjusted sales volatility and the VIX) also show similar dampening patterns in the investment channel of monetary policy.

High sales growth volatility implies less dampening of the investment channel of monetary policy compared to periods when the VIX index is high, possibly due to the very skewed nature of the VIX index and the occurrence of high VIX values during a period of financial crisis.

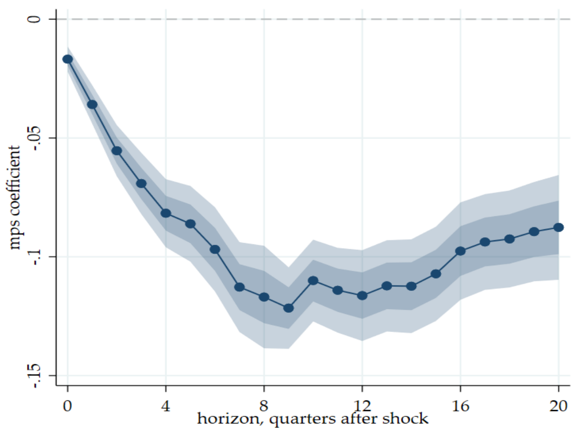
3.4.4 Full Specification

The fullest version of our regression specification is:

Figure 3.8

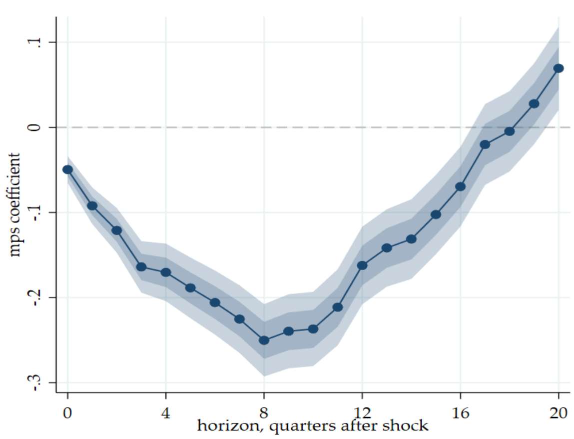
SALES GROWTH VOLATILITY AND AGGREGATE VOLATILITY INTERACTIONS

(**a**) Monetary Policy Shock Coefficients



(**b**) Sales growth volatility Interaction Coefficients

(**c**) Monetary Policy Shock Coefficients

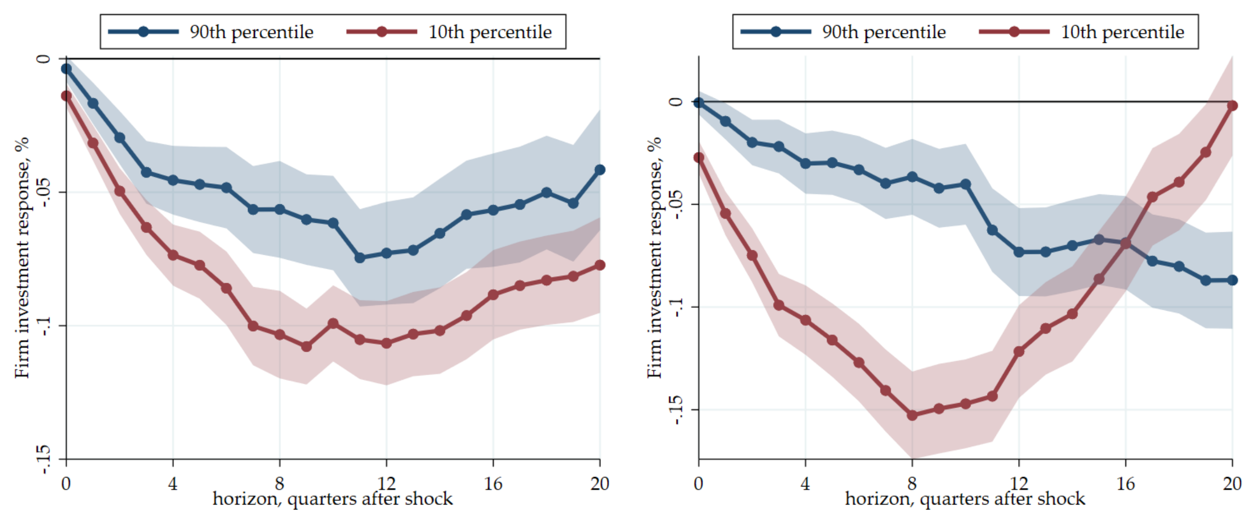


(**d**) VIX Interaction Coefficients

Figure 3.9

Heterogeneity in Investment Channel of Monetary Policy, Alternative Volatility Measures

(**a**) Sales Growth Volatility (**b**) VIX



Note. The above charts construct IRFs to a 25 basis points contractionary monetary policy shock, evaluated at the tenth and ninetieth percentile of the unconditional time-varying volatility distribution.

$$\Delta_{h+1}\log k_{i,t+h} = f_{i,h} + \lambda_{\mathbf{S1}(s),t+h} + \left(\beta_h + \beta_h^m \epsilon_t^m\right)\left[v_{s,\mathbf{y}(t)-1} - \mathbf{E}_s(v)\right] + \left(\boldsymbol{\Omega}'_h + \epsilon_t^m \boldsymbol{\Omega}^{\mathbf{m}\prime}{}_h\right)\mathbf{X}_{it-1} + u_{it+h} \tag{3.15}$$

We include both firm fixed effects to capture permanent differences in investment behaviour across firms, $f_{i,h}$ and broadly defined industry-specific time-trends, grouping sectors at the highest `SIC1` level, $\lambda_{\mathbf{S1}(s),t+h}$. The term ϵ_t^m which would otherwise enter linearly is omitted since variation in the shock is only at the time level, and is therefore completely absorbed by the time trends. Nevertheless, we can account for level shifters in the investment-monetary-policy response function, and well as control for changes in its slope. β_h controls for the direct level effect of volatility on investment, independent of monetary policy stance, while β_h^m is the parameter of interest and captures how the responsiveness of investment to monetary policy shocks changes with volatility.

Controls We include a rich vector of firm level controls, $\mathbf{X}_{it-1}$, in order to separate the level- ($\boldsymbol{\Omega}'_h$) and slope-effects ($\boldsymbol{\Omega}_h^{m\prime}$) attributable to key covariates highlighted in the literature: firms' cash-, current assets-, debt ratio, tobin's q, size, age, dividend status.

3.5 Conclusion

In this paper, we explore the interaction between idiosyncratic firm risk and the investment channel of monetary policy. We contribute new findings that show significant heterogeneity in the investment channel of monetary policy transmission depending on the dispersion of idiosyncratic TFP shocks. More concretely, comparing sectors of different levels of dispersion of idiosyncratic shocks, we find that in more volatile sectors firms respond less to monetary policy shocks. Refining our measure of volatility to be time-varying, we also find evidence that within sectors, changes in sectoral volatility through time also play a role in dampening investment responsiveness to monetary policy.

Our results are of interest to monetary policymakers, as we find evidence of a dampening mechanism that directly affects firm responsiveness to monetary policy operations. Moreover, we contribute to evidence that monetary policy might be weakened in recessions - exactly when countercyclical stabilisation policies are most needed. Our results also suggest that volatility/uncertainty shocks reduce firms responsiveness to other types of aggregate shocks and not just idiosyncratic productivity shocks.

This work suggests much more aggressive monetary measures are needed to fight recessions versus tempering booms, or opens the door to alternative stabilisation policies by the fiscal authorities.

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Appendix A

Appendix to Chapter 1

A.1 Data Appendix

In this section, I elaborate the steps taken in data process. Section A.1.1, A.1.2, and A.1.3 discusses the selection/construction of the variables of interest from Compustat, DealScan, and CRSP datasets, respectively. Section A.1.4 details the merging procedure of the datasets: Compustat, DealScan, and CRSP. Data appendix continues with the discussion of macro variables, as Section A.1.5 presents each macro time series utilized in the analyses, and Section A.1.6 elaborates the sources of the identified monetary policy shocks. Figure A.1.1 shows the comprehensive picture of the finalized data set.

A.1.1 Firm-level Data

This subsection describes the firm-level, quarterly Compustat variables used in the empirical exercises of the paper. The variable definitions and their implied role in the analyses along with the sample selection procedure closely follow standard practices in the literature (Cloyne et al., 2018; Jeenas, 2018; Ottonello and Winberry, 2020). Briefly, if a variable is defined as a ratio, it is directly used as they are in Compustat. However, if the variable is in levels, then it is deflated by the aggregate GVA deflator. Some Compustat variables are reported as cumulative values within the firm's fiscal year. To convert these variables to quarterly series, I take the first difference of these variables within each fiscal year. Furthermore, if there is only one missing observation in the data series, I estimate it by linear interpolation, however, if there is more than one missing variable in the consecutive periods, then no data imputation is involved. All Compustat variables are deseasonalized by regressing them on quarter-dummies, and using the residuals in the actual exercises. Table A.1.1 briefly presents the variable definitions and corresponding Compustat variable codes, but below I present further details about these variables.

Investment. Following the literature which works with Compustat data (Mongey and Williams, 2017; Jeenas, 2018; Ottonello and Winberry, 2020), I employ perpetual inventory method to calculate the investment variable which is defined as $\Delta\log(k_{j,t+1})$. Due to being sparsely populated, level of gross plant, property, and equipment (`PPEGTQ`) cannot be used directly. Instead for each firm, I track the earliest observation of `PPEGTQ` in Compustat and record it as the first value of $k_{j,t+1}$. Then, by consecutively adding the changes of net plant, property, and equipment (`PPENTQ`) in each period, I obtain the series $k_{j,t+1}$. Note that the variable is `PPENTQ` is well populated and reported (from the source) as the net of depreciation. However, if a firm has only one missing observation of `PPENTQ`, I estimate that missing observation by linear interpolation. If there are more than one missing observation in the consecutive periods, I do not impute the values

Leverage. I measure leverage as the ratio of total debt (`DLCQ` and `DLTTQ`) to total assets (`ATQ`).

Size. I define size as the log of total real assets (`ATQ`), deflated by the aggregate GVA deflator.

Liquidity. I measure liquidty as the ratio of cash and short-term investments (`CHEQ`) to total assets (`ATQ`).

Cash flow. I define cash flow as EBITDA `OIBDPQ` deflated by the aggregate GVA deflator.

Dividend. I calculate dividend `DVQ` by taking the first difference of `DVY` within the firm's own fiscal year. Then deflate resulting `DVQ` by the aggregate GVA deflator.

Cash receipts. Following Lian and Ma (2021), cash receipt is defined as the ratio of the sum of cash flows from operations (`OANCFQ`) plus interest and related expenses (`XINTQ`) to the firm size (`ATQ`). Here, I calculate the cash flows from operation (`OANCFQ`), by taking the first difference of `OANCFY` within the firm's own fiscal year.

Tobin's Q. Following Cloyne et al. (2018), I define Tobin's Q as the ratio of total assets at market value to the total assets. Here market value is calculated as the sum of total assets

(ATQ), market value of common shares outstanding (PRCCQxCSHOQ), and deferred taxes and investment tax credit (TXDITCQ) less common equity (CEQQ)[1].

Collateral. Following Dinlersoz et al. (2018) and Cloyne et al. (2018), collateral is defined as the ratio of the sum of net property, plant and equipment (PPENTQ), inventory (INVTQ), and receiables (RECTQ) to the total assets (ATQ).

Asset pledgeability. Following Dinlersoz et al. (2018), I define asset pledgeability as the ratio of collateralizable assets to the total assets.

Profitability. Following Dinlersoz et al. (2018), I define profitability as the ratio of net income (NIQ) to the total assets (ATQ).

Table A.1.1
COMPUSTAT VARIABLE DEFINITIONS

Variable	COMPUSTAT
Total Assets (Book Value)	ATQ
Long-term Debt (Book Value)	DLTTQ
Total Debt (Book Value)	DLCQ + DLTTQ
Leverage (Book Value)	(DLCQ + DLTTQ) / ATQ
Liquidity Ratio (Book Value)	CHEQ / ATQ
EBITDA	OIBDPQ
Interest and Related Expenses	XINTQ
Rent Expense	XRENT
Dividends	D.DVY (within year)
Acquisitions	AQCY / ATQ
Tobin's Q	(ATQ + PRCCQ x CSHOQ - CEQQ +TXDITCQ) / ATQ
Collateral (Book Value, Annual)	PPENT + INVT + RECT
Operating Cash Flow	D.OANCFY (within year)
Cash Receipts	(OANCFQ + XINTQ) / AT

Sample Selection. Before cleansing the data with the given sample selection procedure, following Ottonello and Winberry (2020), I winsorize observations at the top and bottom 0.5% of the distribution to prevent outliers contaminating the results. Then, I impose a set of sample restrictions:

[1] CSHOQ is recorded (at the source) as the actual number of shares and PRCCQ is the acutal level of share price, and therefore both variables are adjusted for stock splits. See Section A.1.3 for further details about the retroactive adjustment procedure.

1. Firms not incorporated in the United States are excluded.

2. Firms in the finance, insurance, real estate (FIRE) and public sectors are excluded.

3. Firm-quarter observations with below conditions are dropped.

   - Negative capital or assets
   - Acquisitions (constructed based on AQCY) larger than 5% of assets.
   - Investment rate is in the top and bottom 0.5% of the distribution.
   - Investment spell is shorter than 40 quarters.
   - Net current assets as a share of total assets higher than 10 or below -10.
   - Leverage higher than 10 or negative.
   - Quarterly real sales growth above 1 or below -1.
   - Negative sales or liquidity

WorldScope Following Cloyne et al. (2018), I construct firm age in two steps. First, I use the incorporation date from WorldScope (INCORPDAT), and second I check the firm's first appeareance in Compustat. Firm age is calculated by taking the earlier one between WorldScope variable and Compustat first appearance.

Furthermore, the regional dummy used in the analyses in Section A.2.3 is constructed by using the corresponding ZIP code variable in WorldScope.

A.1.2 Loan-level Data

DealScan is a detailed loan-level database. The unit observation is loan facility. Although the dataset presents information on many other aspects of the loan, in this paper I use the following variables: contract type, start date, end date, covenant type, amount, spread, and maturity. Since, this paper focuses on the firm-quarter observations, before merging DealScan with Compustat, there has to be two aggregation layers involved in the dataset. First layer is package level. Lenders may choose to bundle the loan facilities into one package or create new packages depending on the characteristics of the loan facilities. Therefore, for a given quarter, a firm may have multiple packages and each of these packages may include multiple loan facilities. Following Chava and Roberts (2008), covenant info is aggregated to firm level as follows. As covenants -most of the time- apply to all loan facilities in a package, life of the package starts with the loan with the earliest start date within the package and ends with the ending date of the most recent loan. Related, each of the loan packages firm have could be tied to a different covenant. Following Chava and Roberts (2008) and Nini et al. (2012) it is assumed that for a given quarter, tightness of these covenants are similar. Therefore, while parallel packages may have different debt covenants, such as debt-to-EBITDA, net worth, or interest payment, since the most pertinent to the analysis is the debt-to-EBITDA covenants, among multiple covenants I consider "Max. Debt-to-EBITDA" covenant.

DealScan is a wide format database. Therefore, each row in the dataset denotes a loan facility with information such as start/end date, amount, spread, maturity etc. cross section with different origination dates. Following Chava and Roberts (2008), I transform the dataset into long format with quarterly frequency (not annual). It is because firms are subject to due diligence 4 times a year and have to show their compliance with financial covenants by reporting their balance sheet/income statement details. Therefore, the it is logical to assume that restrictions apply at a quarterly frequency.

Classification. First step of categorization is the determining whether a loan is asset based or cash flow based (or neither). To do so:

- A loan is classified as asset based if
  - Backed by specific physical and other separable assets including equipment, inventory, receivable etc.
  - Specify a *"borrowing base"*,
  - Explicit statements in the notes
- A loan is classified as cash flow based
  - Backed by borrowers' **"all assets"** or **"cash and cash equivalents"**
  - Explicit statement about a lien on the entire corporate entity,
  - Entails financial covenants based on cash flow, mostly **"Max. Debt-to-EBITDA"**,

Second step is determining whether the active borrowing constraint is asset based or cash flow based for a given quarter. Following the corporate finance literature, the key feature is that terms of asset based contracts being loan specific, while the terms of cash flow based contracts are usually blanket liens. Namely, the borrowing constraint is defined as asset based ***iff*** all the packages include asset based contracts exclusively. However, it is enough to have only one cash flow-based contract to define the borrowing constraint as cash flow-based.

Sample Selection. Since the variable about financial covenants was sparsely populated before 1997, sample period starts with 1997 Q1. The ending of the sample period is restricted by the Chava-Roberts link file which is 2017 Q3.

A.1.3 Security-level Data

The Center for Research in Security Prices (CRSP) is the detailed security level dataset which is widely used in the literature. I use the variables S&P Domestic long term issuer Credit rating (`SPLTICRM`), stock price variable (`PRC`), Cumulative Factor to Adjust Prices (`CFACPR`), and S&P return (`SPRTRN`). Price variables of interest in CRSP (`PRC`) and Compustat (`PRCCQ`) are historically recorded at the source and require further treatment as they have not been retroactively adjusted for splits[2]. But fortunately, both Compustat and CRSP have dedicated split adjustment factor variables. In Compustat, this factor variable is `ADJEX` and in CRSP it is `CFACPR`. By using these variables, I retroactively adjust the stock returns for stock splits as follows. In order to retroactively adjust the historical prices for the stock split, I divide `PRC` by `CFACPR`. For instance if a stock is priced at 86.92 before the split, and 44.01 after the split, after the adjustment it becomes 43.46 and 44.01, before and after the split.

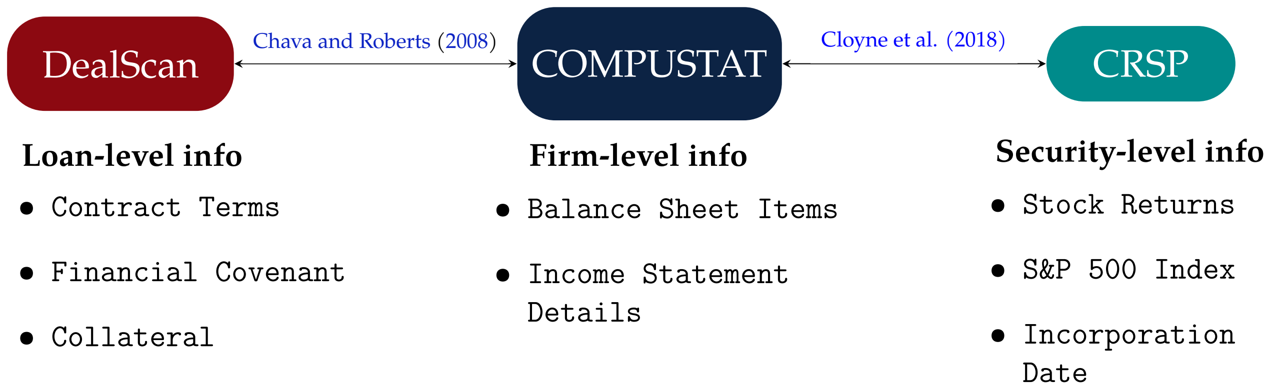
A.1.4 Dataset Construction

In this subsection I elaborate the merging procedure of Compustat, DealScan, and CRSP. Figure A.1.1 depicts the final body of the constructed dataset, along with the information about which items come from which dataset. The final version of the merged data set covers more than 60,000 firm-quarter observations for more than 1,000 distinct firms from 1997 to 2018.

Merging Compustat - DealScan. Following Chava and Roberts (2008), I merge Compustat and DealScan by utilizing the identifier link provided publicly by Michael Roberts and is available on Michael Roberts' personal website. Unfortunately, the link file is updated infrequently, and the version used in this paper is April 2018 version. Merging procedure

[2]From time to time, a company's share price can increase too much, and becomes unaffordable for some investors. This situation is detrimental to the stock's liquidity. In this case, a firm can undertake a stock split decision to increase the number of shares outstanding by spliting existing shares. This operation does not alter the underlying value of the company. Common split ratios are 2-for-1 and 3-for-1, which means that after the stock split operation an investor who owns the stock will have two or three shares, respectively, for every share held before the split.

Figure A.1.1
Dataset Construction



is inner join, namely I drop firms from Compustat that do not appear at in Dealscan data and similarly drop loan observations that if the firm cannot be found in Compustat.

Merging Compustat - CRSP. I merge Compustat - CRSP datasets to carry out the analysis in Section A.2.1. I merge Compustat with CRSP by employing the Compustat/CRSP link-table available in WRDS. The link table maps the firm identifier in CRSP (`CUSIP`) to the firm identifier of Compustat (`GVKEY`).

A.1.5 Macro Time Series Data

Macro data is obtained from the Federal Reserve Bank of St. Louis (FRED). I closely follow the definitions and interpretations of Cloyne et al. (2018), which builds upon Gertler and Karadi (2015). The GVA deflator series is `B358RG3Q086SBEA`, the Price Index for Gross Value Added (GDP: Business: Nonfarm (chain-type price index)). Aggregate business investment is `PNFI`, Private Nonresidential Fixed Investment. CPI is `CPALTT01USM661S`, Consumer Price Index: Total All Items for the United States. One-year risk free rate is `GS1`, Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity, Quoted on an Investment Basis. Three-months risk free rate is `DGS3MO`, Market Yield on U.S. Treasury Securities at 3-Month Constant Maturity, Quoted on an Investment Basis. Industrial production is `INDPRO`, Industrial Production: Total Index. GDP is `GDPC1`, Real Gross Domestic Product. Unemployment rate is `UNRATE`, Unemployment Rate. Volatility index is `VIXCLS`, CBOE Volatility Index: VIX.

A.1.6 Monetary Policy Shocks

For the baseline exercises, I use the exact FOMC meeting dates, time stamp of press release from FOMC, and daily shocks in percentage points from Gorodnichenko and Weber (2016). The data is publicly available and can be downloaded from Michael Weber's personal website. Sample period is from Feb 5, 1997 to Dec 16, 2009.

For robustness check, I use Policy News Shock from Nakamura and Steinsson (2018). Corresponding data, along with the dates are publicly available and can be downloaded from Emi Nakamura and Jon Steinsson's personal websites.

A.2 Additional Empirical Exercises

A.2.1 CAPM Regression

In order to measure the profitability (Jensen's Alpha) and return volatility (Beta), I estimate the below single factor CAPM model.

$$r_{j,t-\tau} - r_{f,t-\tau} = \alpha_j^{\tau} + \beta_j^{\tau} \left(r_{m,t-\tau} - r_{f,t-\tau} \right) + e_{j,t-\tau} \tag{A.2.1}$$

$\tau = 0, 1, \ldots, \mathrm{T}$ represents the active time horizon. Following both the literature and industry tradition, rolling regressions are estimated using a window of 36 months (*i.e.* $\mathrm{T} = 36$). $r_{j,t}$ is the stock return of firm j, $r_{m,t}$ is the $S\&P$ 500 Index and $r_{f,t}$ is the risk free rate. To carry out the analyses I merge Center for Research in Security Prices (CRSP) and Compustat databases via a Compustat/CRSP link-table, which maps the identifier in CRSP (`PERMNO`) to the identifier in Compustat (`GVKEY`). Here note that A.2.1 does not represent a panel data regression, but instead a separate time series regression is estimated for each firm j. This process yields time series for α_j (**Jensen's alpha**) and β_j (**Stock Beta**) coefficients for each firm j.

A.2.2 Differential Responses

To investigate more formally whether the differential response between high- and lowleverage firms is statistically significant, we estimate the dynamic effect of monetary policy

To provide a better comparable impulse responses with Section 1.6.2, I estimate the following regression. The resulting impulse responses are differential, and thus show the relative response of asset based borrowers compared to cash flow based borrowers.

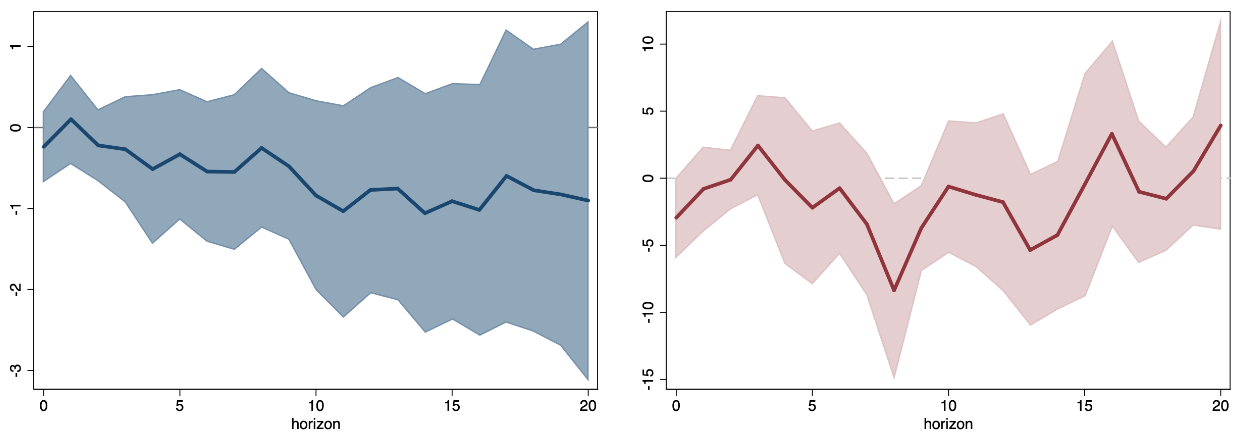
$$y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \gamma^h \mathcal{I}_{j,t-1}^{Asset} \epsilon_t^m + \sum_{p=1}^{P_Z} \Gamma_p \mathbf{Z}_{j,t-p} + \sum_{p=1}^{P_X} \Gamma_p \mathbf{X}_{t-p} + e_{j,t+h} \tag{A.2.2}$$

$\mathcal{I}_{j,t-1}^{Asset}$ is the dummy variable that equals 1 when the firm j holds an asset based borrowing contract in time $t-1$. γ_h is the coefficient of interest which captures the effect of monetary policy shock on the dependent variable for asset-based borrowers relative to cash flow-based borrowers. h denotes the horizon, with $h = 0, 1, 2, ..., H$.

Figure A.2.1

RELATIVE IMPULSE RESPONSES

(**a**) Investment (**b**) Borrowing



NOTE. Relative impulse responses for the investment and borrowing following a 25 bps increase in 3-month T-bill rate. The responses are estimated with the local projection specification given by (A.2.2). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

A.2.3 Robustness of the Baseline Results

In order to show the robustness of the baseline results, I carry out additional set of empirical exercises presented below.

Spread. Anderson and Cesa-Bianchi (2020) stresses the role of credit spread on the firm level investment. The mechanism in their setup is that firms having higher credit spread response cut their investment and borrowing more, therefore responds more to a monetary policy surprise. Therefore, the baseline results in Figure 1.1, could be driven by spread responses regardless of the underlying borrowing method. To address this concern, I run the same setup as in (1.1), with the dependent variable being the spread (Dealscan variable *AllInDrawn*).

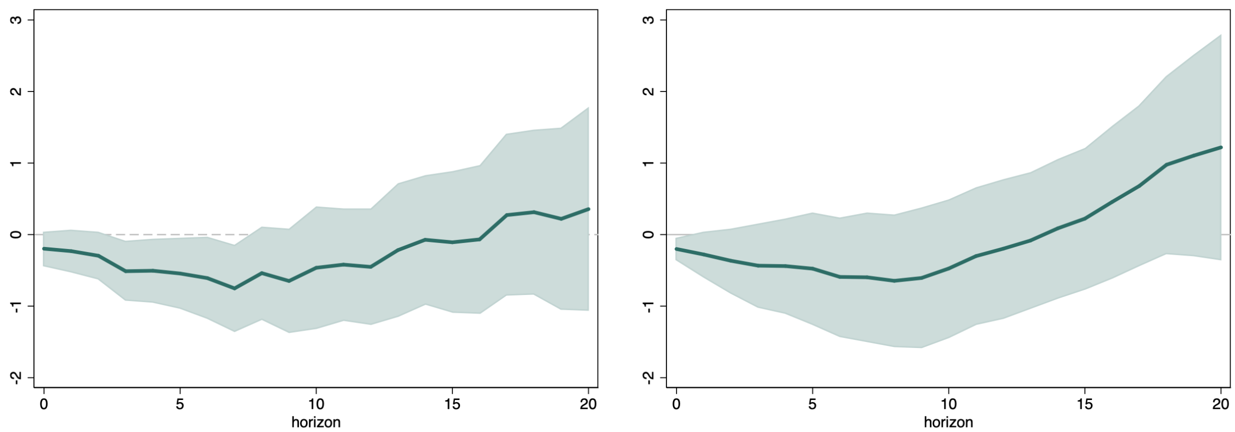
Figure A.2.2 reports the results obtained. The point estimates among subgroups are almost identical, therefore the baseline results in Figure 1.1 cannot be driven by the response of credit spread.

Figure A.2.2

Impulse Responses: Spread

Asset-based vs. Cash flow-based

(**a**) **Spread:** Asset Based (**b**) **Spread:** Cash-flow Based



Note. Average impulse response functions for the spread following a 25 bps increase in 3-month T-bill rate. The responses are classified into asset-based and cash flow-based borrowers and estimated with the local projection specification given by (1.5) with the dependent variable being the spread (Dealscan variable *AllInDrawn*). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

Regional heterogeneity. As documented by Chaney, Sraer, and Thesmar (2012), the value of real estate has considerable impact on firm-level activity through the collateral channel. Further, Bahaj, Pinter, Foulis, and Surico (2019) show that regional heterogeneity plays role in the response of property prices to monetary policy. These two studies suggest that the results depicted in Section 1.2.4 may simply reflect that some firms reside in areas where real estate prices are more responsive to monetary policy than others. To address this concern, I run a variant of (1.5) and include regional dummies as shown below

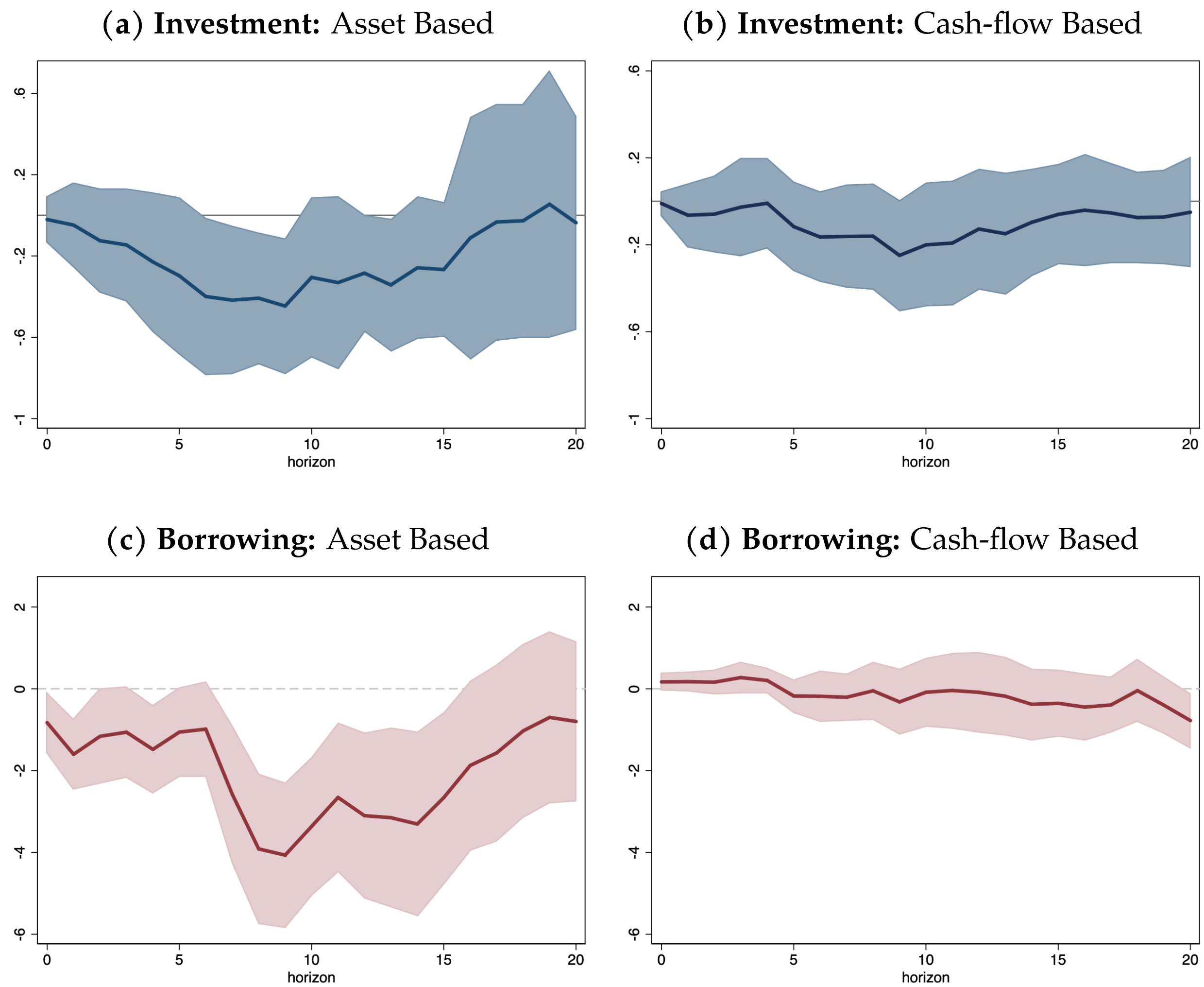
$$y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \gamma_{l,s}^h + \beta_1^h \left(\epsilon_t^m \mathcal{I}_{j,t-1}^{Asset}\right) + \beta_2^h \left(\epsilon_t^m \mathcal{I}_{j,t-1}^{Cash}\right) + \sum_{p=1}^{P_Z} \Gamma_p \mathbf{Z}_{j,t-p} + \sum_{p=1}^{P_X} \Gamma_p \mathbf{X}_{t-p} + e_{j,t+h}. \tag{A.2.3}$$

$\gamma_{l,s}^h$ is the regional dummy equals 1 for firms that operate in the region l in the quarter-year s and 0 otherwise. Figure A.2.3 depicts that estimated responses are similar to Figure 1.1 and still statistically significant.

Figure A.2.3

IMPULSE RESPONSES: REGIONAL HETEROGENEITY

ASSET-BASED VS. CASH FLOW-BASED



NOTE. Average impulse response functions for the investment and borrowing following a 25 bps increase in 3-month T-bill rate. The responses are classified into asset-based and cash flow-based borrowers and estimated with the local projection specification given by (A.2.3). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

External finance dependence. As originally proposed by Rajan and Zingales (1998), in order to fund their investment expenditures, some firms could be inherently more dependent on the financial sector. This dependence could arise from the sector's frequent investment requirements or simply from the strong link between banks and the firm. Following Rajan and Zingales (1998), I construct a proxy for the external finance dependence as presented below.[3]

$$ExFin = \frac{\text{Capital Expenditures} - \text{Cash Flow from Operations}}{\text{Capital Expenditures}} \tag{A.2.4}$$

To address this concern, I switch to the " double-sorting" strategy and interact the coefficient of borrowing method with the external finance dependence coefficient. That is, I estimate the following specification

$$\begin{gathered} y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \sum_{x \in \{\chi\}} \beta_x^h \left(\epsilon_t^m \mathcal{I}_{j,t-1}^x \right) + \\ \textstyle\sum_{p=1}^{P_Z} \Gamma_p \mathbf{Z}_{j,t-p} + \sum_{p=1}^{P_X} \Gamma_p \mathbf{X}_{t-p} + e_{j,t+h}. \end{gathered} \tag{A.2.5}$$

Figure A.2.4 and A.2.5 presents the results for firms of which their external finance dependence is below and above median, respectively. Even after double sorting, the results remain unchanged.

[3]Here Rajan and Zingales (1998) stresses that as being large and publicly traded, most Compustat firms face the least frictions in accessing finance. Thus the amount of external finance used by these Compustat firms is likely to be a good proxy of their demand for external finance.

Figure A.2.4

IMPULSE RESPONSES: ***LOW*** EXTERNAL FINANCE DEPENDENCE

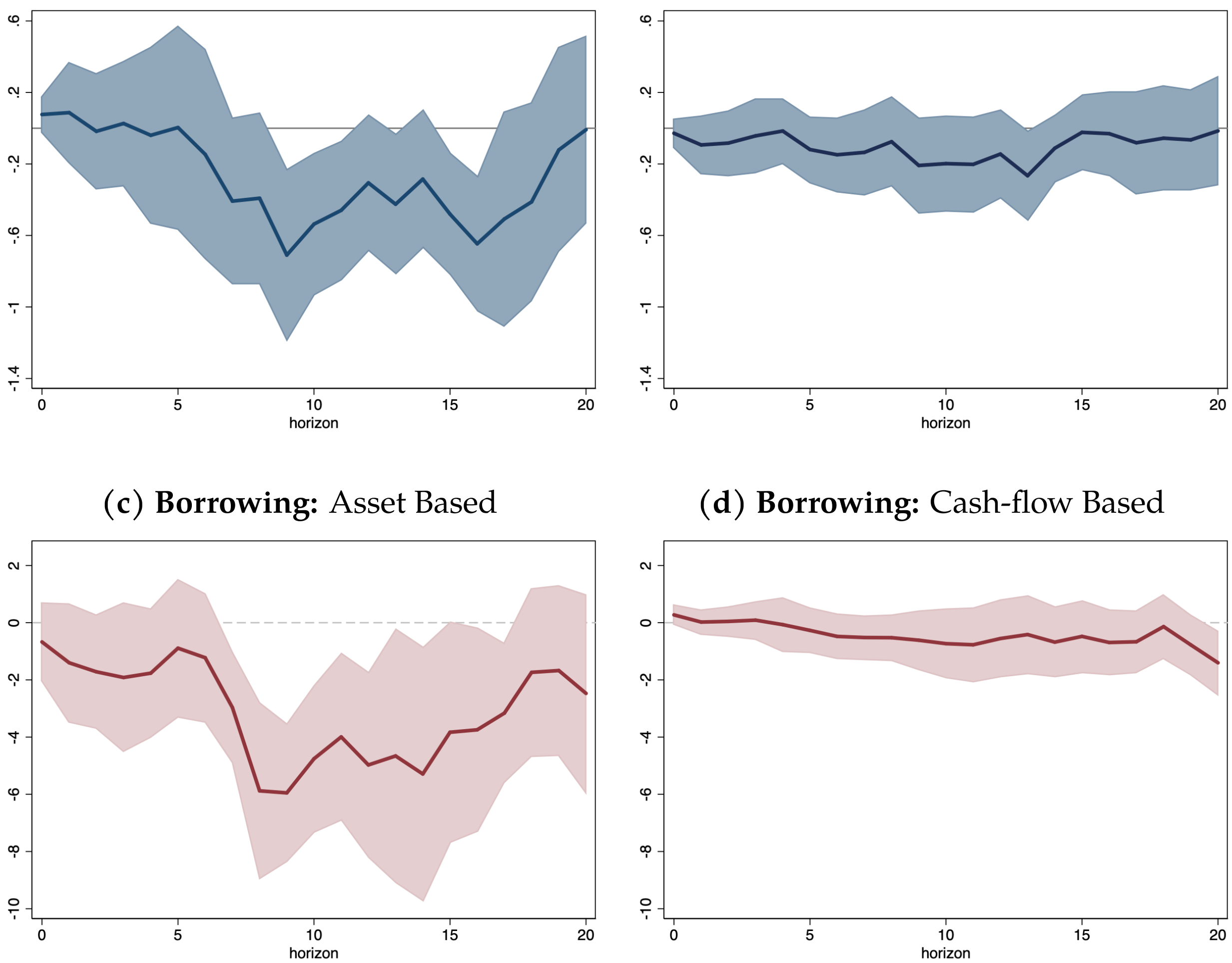
ASSET-BASED VS. CASH FLOW-BASED

(a) **Investment:** Asset Based

(b) **Investment:** Cash-flow Based

(c) **Borrowing:** Asset Based

(d) **Borrowing:** Cash-flow Based

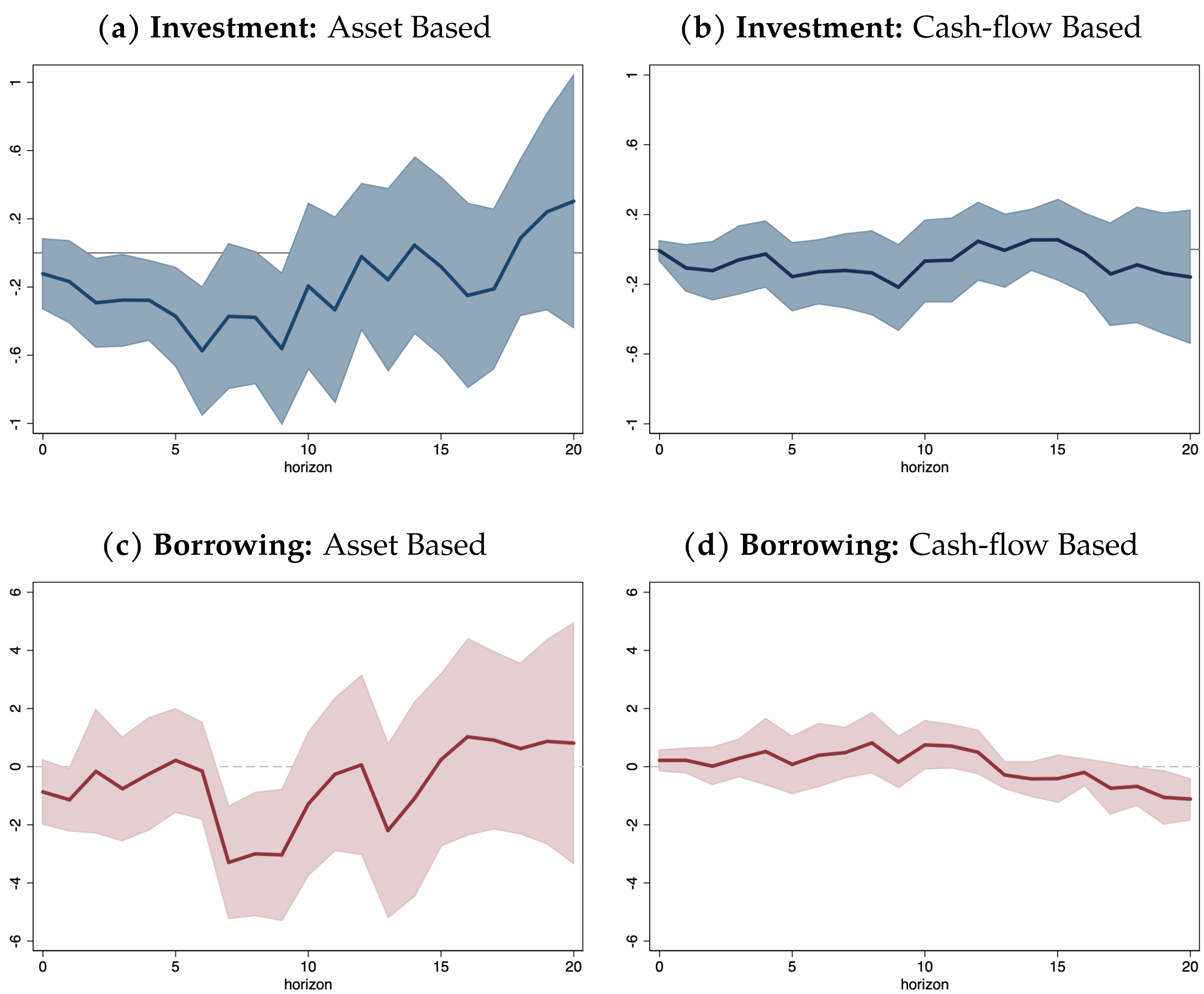


NOTE. Average impulse response functions for the investment and borrowing following a 25 bps increase in 3-month T-bill rate. The responses are classified into 4 groups: asset-based/low dependence, asset-based/high dependence, and cash flow-based/low dependence, cash flow-based/high dependence. The impulse responses are estimated with the local projection specification given by (A.2.4). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

Figure A.2.5

IMPULSE RESPONSES: ***HIGH*** EXTERNAL FINANCE DEPENDENCE

ASSET-BASED VS. CASH FLOW-BASED



NOTE. Average impulse response functions for the investment and borrowing following a 25 bps increase in 3-month T-bill rate. The responses are classified into 4 groups: asset-based/low dependence, asset-based/high dependence, and cash flow-based/low dependence, cash flow-based/high dependence. The impulse responses are estimated with the local projection specification given by (A.2.4). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

Figure A.2.6

Impulse Responses: Nakamura and Steinsson (2018) Shocks

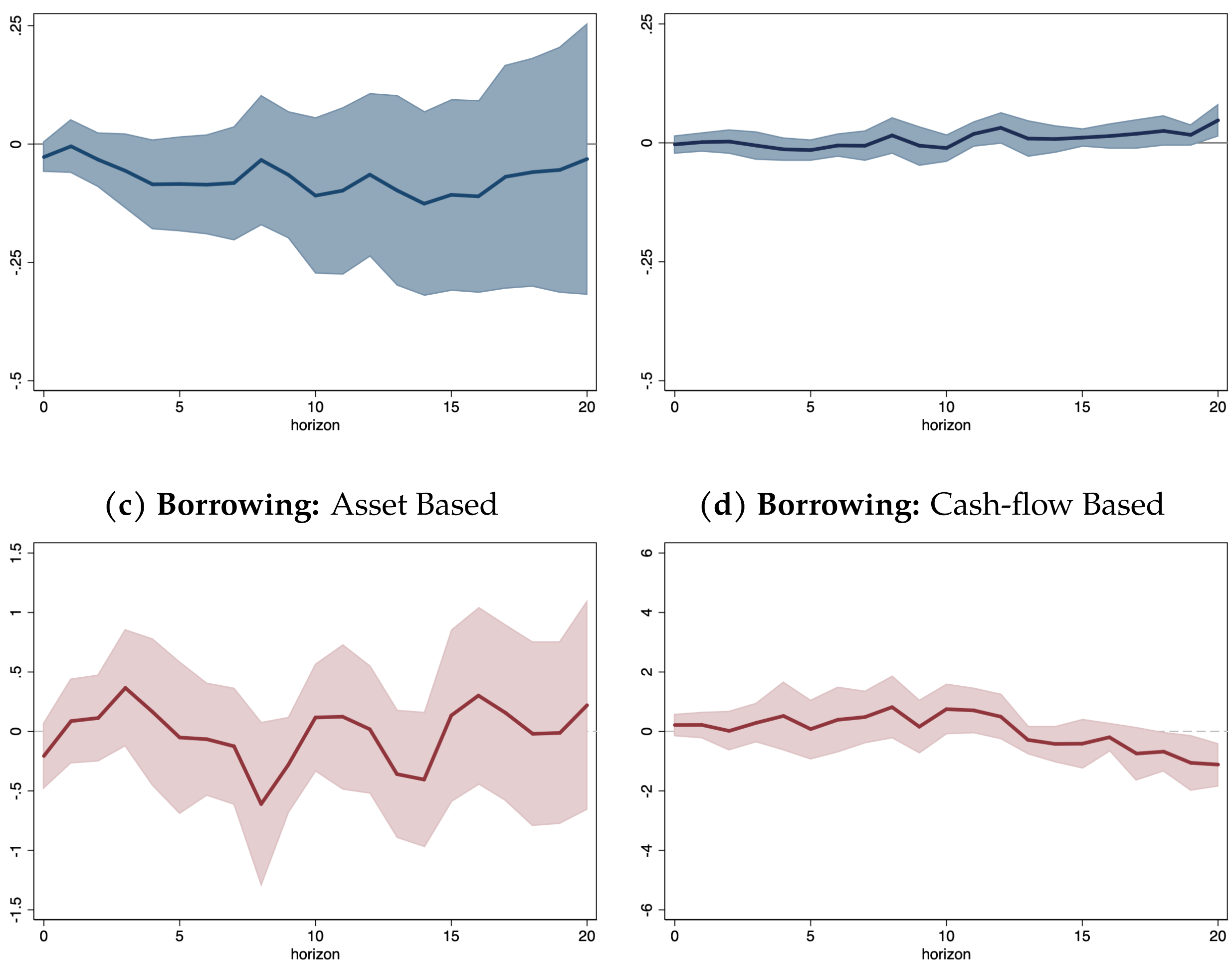
Asset-based vs. Cash flow-based

(a) **Investment:** Asset Based

(b) **Investment:** Cash-flow Based

(c) **Borrowing:** Asset Based

(d) **Borrowing:** Cash-flow Based



Note. Average impulse response functions for the investment and borrowing following a 25 bps increase in 3-month T-bill rate. The impulse responses are estimated with the local projection specification given by (1.5). Monetary policy shock is interacted with indicator variable based on the firm borrowing status. The shaded areas display 90 percent confidence intervals. Standard errors are clustered two-way clustered at firm and quarter.

A.3 Model Appendix

A.3.1 Discussion of Key Assumptions

The following discusses the implications of and rationale behind some of the key modeling assumptions made.

No spread difference between contract types. I employ a simplifying assumption that there is no difference in their spreads between asset based and cash flow based contracts.[4] Empirically, it is obvious that such a spread exits between corporate borrowing rate and risk free policy rates, however from the modeling perspective, as long as there is no spread difference between asset based and cash flow based contracts, model's implications would not have changed, if I had included spread over risk-free rate.

To be able to assume no spread difference between asset based and cash flow based contract types, three conditions must be satisfied. First, empirically the difference between the *level* of spreads has to be small enough. As can be seen from Table 1.1, at the mean the difference between these two borrowing types is only 0.37 pp, and thus we can accept that this condition is satisfied. Second, the loan maturities have to be close to each other. Otherwise these contracts would have been exposed to different duration risk. Table 1.1 depicts that at the median maturity of both types exactly equal each other (60 months). Third, the *response* of spread to a common monetary policy shock must be similar. Figure A.2.2 shows that indeed in terms of point estimates the responses are similar and both asset based and cash flow based borrowers experience similar fluctuations in relevant borrowin rates. Since these three conditions are satisfied, I could assume no spread difference among contract types.

Exogenous exit of firms. A common curse in the macrofinance models is that in the model economy, firms accumulate capital and thus become financially unconstrained very quickly. However, the focus of the paper is to understand how debt contracts and financial constraints shape the monetary policy transmission to firm level borrowing and investment decisions. Therefore, in order to prevent firms from accumulating enough capital that firms do not face a binding borrowing limit forever. This is forestalled by imposing stochastic exogenous exit in the model. Since exiting firms are replaced by entrants which

[4] By introducing endogenous default mechanism, one can introduce endogenous spread in two aspects: *i*) between the borrowing rate and risk free rates, *ii*) between the borrowing rates of asset based and cash flow based contract holders. Although interesting, this extension is irrelevant to the core mechanism of the paper (*i.e.* asset price channel of monetary policy transmission).

are small by definition, it takes time for new entrants to reach their optimal scale due to the existence of financial frictions.

Non-negative dividends. It is common in the macro finance literature to assume that firms do not raise equity to fund their investment expenditures. First, this assumption is convenient in the sense that it allows for a leaner computational process. Second, the assumption is also backed by empirical studies such that new equity issuance occurs very infrequently and it is lumpy due to its costly nature (Altınkılıç and Hansen, 2000; Bazdresch, 2013).

Pass-through financial intermediary. Following the literature (Jeenas, 2018; Ottonello and Winberry, 2020), I model the financial intermediary as pass-through. It is because the purpose of this paper to explain/interpret firm behavior regarding their debt contract choice and its interaction with a monetary policy surprise. Therefore mechanisms like relationship lending (*i.e.* lenders behave differently to the borrowers they already know) or search friction in the credit markets (*i.e.* borrowers search for a suitable source of funding among lenders and there is nonzero probability of failure to do so) are abstracted from this model. Although interesting, the concept of financial intermediary with such self interests is beyond the scope of this paper.

Aggregate capital adjustment cost. The main point of the quantitative section is to illustrate the main mechanism behind why asset based borrowers are more responsive to monetary policy shocks. As discussed rigorously above it is the collateral channel through asset price fluctations. Therefore, to induce time varying capital price within the model economy, I incorporate separate aggregate capital producer firms subject to convex capital adjustment costs. In a nutshell, by this method, model is able to include financial accelerator mechanism (Bernanke et al., 1999).

A.3.2 Derivations

Some selected derivations along with further details about the model is provided in this subsection.

Capital Good Producer. Capital good producers operate in a perfectly competitive market, thus take the capital price q_t as given. These firms buy the existing capital stock, K_t and also purchase I_t units of final good to produce next period's capital stock, K_{t+1}. Capital good producer solves the below problem.[5]

$$\max_{I_t} \quad q_t K_{t+1} - q_t(1-\delta)K_t - I_t \tag{A.3.1}$$

subject to the production function

$$\Phi\left(\frac{I_t}{K_t}\right) = \frac{\hat{\delta}^{1/\phi}}{1-1/\phi}\left(\frac{I_t}{K_t}\right)^{1-1/\phi} - \frac{\hat{\delta}}{\phi-1} \tag{A.3.2}$$

and the capital adjustment cost

$$K_{t+1} = \Phi\left(\frac{I_t}{K_t}\right) K_t \tag{A.3.3}$$

Above profit maximization problem yields the relative price of capital as

$$q_t = \frac{1}{\Phi'\left(\frac{I_t}{K_t}\right)} = \left(\frac{I_t/K_t}{\hat{\delta}}\right)^{1/\phi} \tag{A.3.4}$$

A.3.3 Equilibrium Definition

A recursive equilibrium in this economy, given prices $\left\{\rho, r^D, r^B, w, p, q\right\}$, the borrowing constraint rules, operating cost, initial distribution $\mu_0(z, nw)$ of firms over idiosyncratic states, set of value functions $\left\{v_t(a,\eta), v_t(z,nw), v_t^{Asset}(z,nw), v_t^{Cash}(z,nw), v_I(B,D)\right\}$ and allocations $\{c, l, a', \eta'(z', nw'), B', D', k', b', l'\}$ such that:

1) Production firms. Given the borrowing constraint rules and operating cost $\{\Phi\}$ and prices $\{p, q, \mathcal{Q}, w\}$; allocation $\{k', b', l\}$; the value function $\{v_t(z,nw)\}$ solves production firm's problem governed by (1.10) - (1.16)

2) Financial Intermediary. (1.19) holds and financial intermediary earns zero profits. Also, intermediary's lending operations are solely funded through deposits it receive, *i.e.* $B' = D'$;

3) Household. Given prices $\{r, w, \rho\}$, value function $\{V(a,\eta)\}$ and allocation $\{c, l, a', \eta'(z, k', b')\}$ solves the household's problem governed by (1.24), (1.25). And it satisfies (1.26) and the intratemporal optimality condition $w = \psi c$;

[5]Note that, since capital good producers have to buy the entire aggregate capital stock, only choice variable for these firms is how much final good to use to produce new aggregate capital stock.

4) Stationary distribution. Stationary distribution of firms

$$\mu(z, nw) = \mu'(z, nw) \tag{A.3.5}$$

5) Labor market clearing. Labor market clears.

$$l = \int_{\mathbf{S}} l\mu(z, nw)\, d(z, nw) \tag{A.3.6}$$

6) Equity market clearing. The equity market clears.

$$\eta(z, k', b') = 1 \quad \text{for each firm } (z, k', b') \in \mathbf{S} \tag{A.3.7}$$

7) Debt market clearing. The debt market clears.

$$B' = \int_{\mathbf{S}} b'\mu(z, nw)\, d(z, nw) \tag{A.3.8}$$

8) Deposit market clearing. The deposit market clears.

$$D' = a' \tag{A.3.9}$$

9) Goods market clearing. The goods market clear by Walras Law.

$$\begin{aligned} C + &\int_{\mathbf{S}} k'\mu(z, nw)\, d(z, nw) + \int_{\mathbf{S}} \Phi\mu(z, nw)\, d(z, nw) + \int_{\mathbf{S}} k_0\mu(z, nw)\, d(z, nw) \\ = &\int_{\mathbf{S}} zk^{\theta}l^{\nu}\mu(z, nw)\, d(z, nw) + (1-\delta)\int_{\mathbf{S}} k\mu(z, nw)\, d(z, nw) \end{aligned} \tag{A.3.10}$$

A.4 Quantitative Tightening as a Model Exercise

Quantitative tightening is conducted by the monetary authority, which affects the capital price q_t through a reduced form formula (A.4.1). Modeling QT shock (A.4.1) is not far from the actual channels that QT transmits. Krishnamurthy and Vissing-Jorgensen (2013) indicates that QE mostly transmits through the effect of large-scale purchases on asset prices, and the channel through long-term bond yields is generally ineffective. Therefore, although this is a reduced form approach to modeling quantitative tightening, it may still provide insights into how quantitative tightening transmits to firm-level investment and borrowing through the borrowing constraints.

The steady-state capital price is pinned down as $q_{SS} = 1$.

$$q_t = q_{SS} + \varepsilon_t^q \quad \text{where } \varepsilon_t^q \sim N\left(0, \sigma_q^2\right) \tag{A.4.1}$$

$\varepsilon_t^{\mathrm{q}}$ is the unconventional monetary policy shock (*i.e.* unexpected asset purchases by the central bank). Similar to the conventional monetary experiment, I assume that the economy is initially in steady state and unexpectedly receives a $\varepsilon_{t=0}^{\mathrm{q}} = -0.25$ percent innovation to the reduced form rule which reverts to 0 according to $\varepsilon_{t+1}^{\mathrm{q}} = \rho_{\mathrm{q}}\varepsilon_{\mathrm{q}}$ with $\rho_{\mathrm{q}} = 0.5$. Given the price path, I compute the perfect foresight transition path of the economy as it converges back to steady state.

To observe the model's internal dynamics via these borrowing constraints while keeping the comparability to the Section 1.6, I estimate a variant local projection specification (A.4.2) on the simulated data. Regressions yield the coefficients of interest γ_1^h and γ_2^h which capture the impulse response to a QT shock.

$$y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \delta_t + \gamma_1^h\left(\epsilon_t^q \mathcal{I}_{j,t-1}^{Asset}\right) + \gamma_2^h\left(\epsilon_t^q \mathcal{I}_{j,t-1}^{Cash}\right) + \sum_{p=1}^{P_Z} \Gamma_p \mathbf{Z}_{j,t-p} + e_{j,t+h} \tag{A.4.2}$$

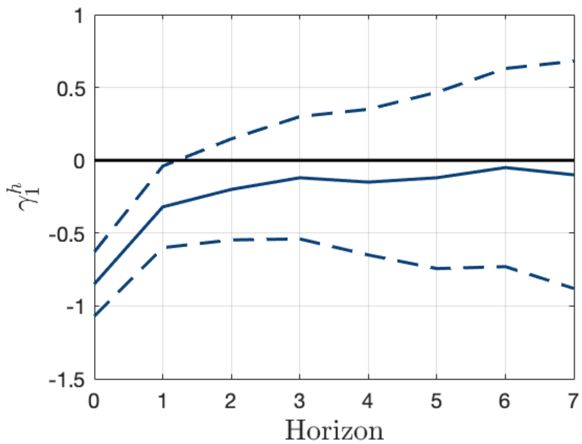
$h = 0, 1, ..., H$ represents the time horizon where $H = 10$ quarters. $y_{j,t+h}$ is the dependent variable of interest at horizon h: investment and borrowing. α_j^h is the firm fixed effect, ϵ_t^q is the quarterly QT shock. $\mathcal{I}_{j,t-1}^{Asset} = 1$ when firm j use asset-based borrowing practices in the prior quarter of the QT shock (otherwise zero) and $\mathcal{I}_{j,t-1}^{Cash} = 1$ when firm j use cash flow based borrowing practices in the quarter that precedes the QT surprise (otherwise zero). Baseline specification also controls for a variety of idiosyncratic factors and also includes time fixed effect, δ_t to control for the aggregate factors.

Figure A.4.1 depicts the impulse responses estimated using (A.4.2) and the dashed lines denote the 90 percent confidence intervals. The top row, Panel (A) and Panel (B),

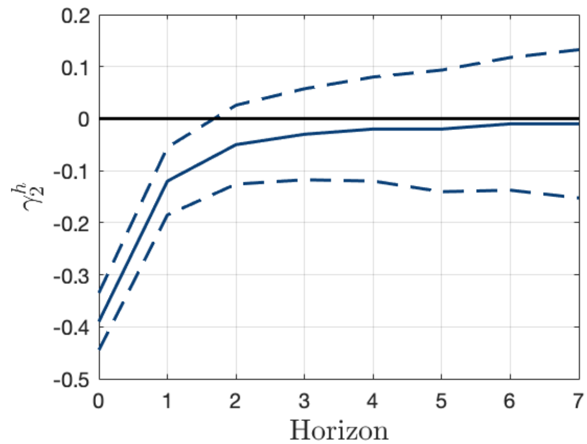
Figure A.4.1

IMPULSE RESPONSES TO A QUANTITATIVE TIGHTENING SHOCK:
ASSET-BASED VS. CASH FLOW-BASED

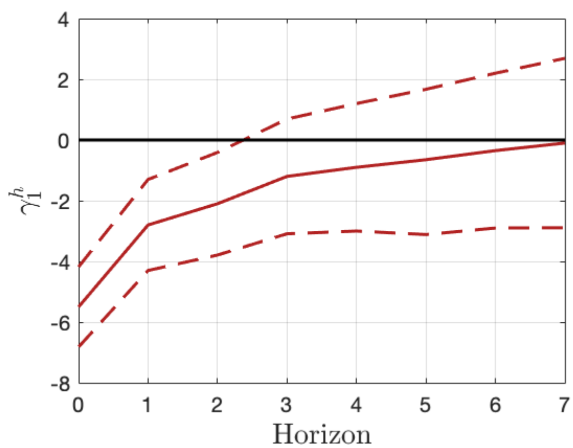
(a) **Investment:** Asset Based



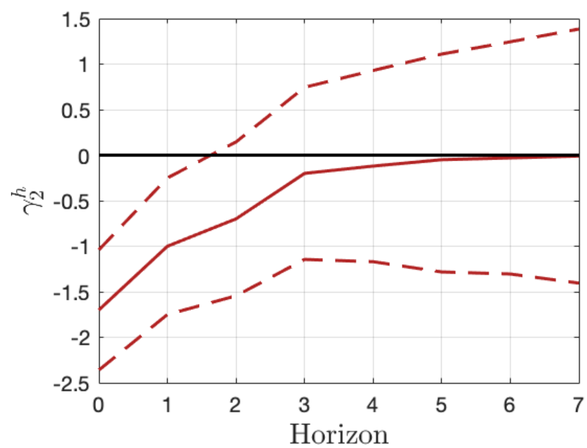
(b) **Investment:** Cash-flow Based



(c) **Borrowing:** Asset Based



(d) **Borrowing:** Cash-flow Based



NOTE. Average impulse response functions for the investment and borrowing to a quantitative tightening shock. The responses are estimated with (A.4.2). Quantitative tightening shock is interacted with indicator variable based on the firm borrowing status. The dashed lines display 90 percent confidence intervals.

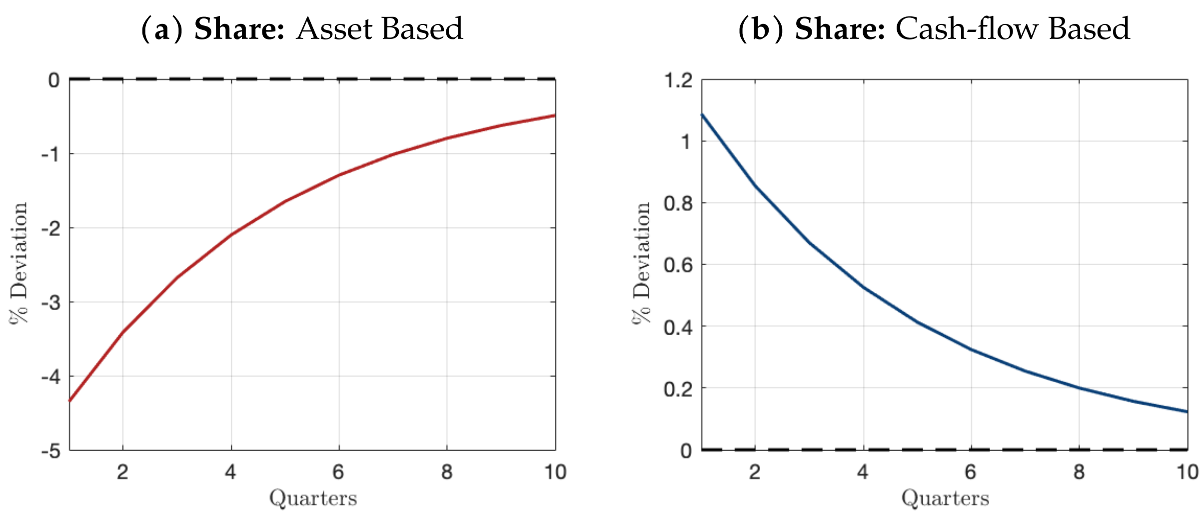
show that asset-based borrowers' peak investment response is almost double that of cash flow-based borrowers. The bottom row, Panel (C) and Panel (D), show that the borrowing response resembles the investment response, as the magnitude is three times larger for asset-based borrowers (at their peak).

The underlying mechanism also works through the response of borrowing constraints to a change in asset prices. Lower asset prices mean lower collateral value, which leads to tighter borrowing constraints for asset-based borrowers. Since such a channel is not operative on the cash flow-based contracts, we see the heterogeneous transmission of QT shock to the firm-level investment. As for the QE shock, since the effect of a QE shock is symmetric to a QT shock, given that asset-based borrowing firms are affected by changes in asset prices in a straightforward manner, QE programs directly lift the financial situation of these particularly fragile firms.

Figure A.4.2

RESPONSE OF SHARES TO A QT SHOCK

ASSET-BASED VS. CASH FLOW-BASED



NOTE. Aggregate impulse response functions for the shares of contracts following a quantitative tightening shock. The shock is applied as an unexpected innovation to the rule (A.4.1). The shock series starts with $\epsilon_t^q = 0.0025$ and continue as $\epsilon_{t+1}^q = 0.5 * \epsilon_t^q$. The responses are computed as the perfect foresight transition path.

Figure A.4.2 shows that firms respond to a QT shock by switching from asset-based contracts to cash flow-based contracts. This behavior is in line with the finding in Section 1.6.3 that the borrowing constraint of asset-based contracts is affected more severely by asset price fluctuations than cash flow-based borrowers. The main mechanism is that to avoid the tightening borrowing constraints, firms with asset-based contracts switch to cash flow-based debt contracts if they are able to do so.[6] One final note about switching behavior is that compared to 1.6, in Figure A.4.2 the impulse response is more persistent.

A.5 Discussion About Debt Contracts

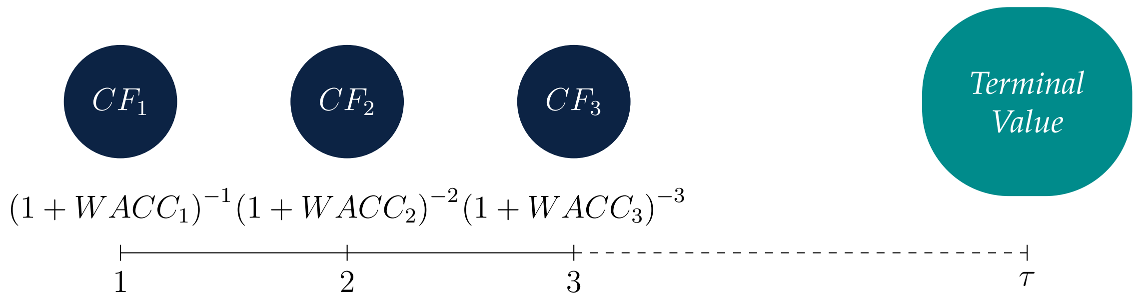
A.5.1 Valuation Methods

There are two main approaches in business valuation: absolute valuation and relative valuation. Absolute valuation, also called as intrinsic valuation, employs discounted cash flow (DCF) analysis to evaluate a firm's financial worth. DCF method determines a firm's intrinsic value by using its projected cash flows. Figure A.5.1 depicts a diagram summarizing the DCF analysis. However, using the absolute value analysis poses some challenges such as accurately forecasting cash flows, predicting accurate growth rates, and evaluating appropriate discount rates. First, forecasting the exact cash flow values is nearly impossible given the idiosyncratic and aggregate disturbances firm faces. Second, not only cash flow values but also an appropriate discount rate (i.e. weighted average cost of capital) needs to be forecasted with complete certainty. Third, as can be seen from Figure A.5.1, the largest chunk that needs to be forecasted is the terminal value. More elaborately, all of the DCF analysis assume that each firm reaches a stable path in their lifecycle in which exhibits a constant growth rate, cash flow and discount rate. The analyst also has to assume the length of time period until its terminal value. Although there are methods to estimate these values from firm's balance sheet and income statement, these estimations are still far from being absolute. Therefore, it is difficult for borrower and lender to agree on any of these estimations given the very sensitive nature of the analysis. The caveats of this approach makes it controversial while forming the contracts.

Given the contractibility issues of absolute valuation, borrowers and lenders employ a much more practical approach. Relative valuation is a business valuation approach in which a firm's value is assessed by using some measures of the firm's competitors or industry peers. In order to evaluate the firm of interest, analysts and investors compare the ratios such as value-to-EBITDA, price-to-earnings, market capitalization etc. to other similar firms. Nevertheless, absolute valuation via DCF method is also used by analysts to support the relative valuation. Therefore one can think of these two approaches as complements rather than substitutes.

[6]Similar to the mechanism in Section 1.6.2, the limited commitment of debt dampens the number of switching firms. Since financial intermediary ensures repayment in every state of tomorrow, most firms do not find it optimal to switch their contracts.

Figure A.5.1
DCF Analysis



Note. This figure summarizes the discounted cash flow analysis. $WACC_t$ stands for weighted average cost of capital in period t. Terminal value is defined as $TV = \frac{CF}{WACC-g}$ where CF is the constant cash flow value, WACC is the constant weighted average cost of capital, and g is the constant growth rate of the firm.

Sectoral Heterogeneity. Some sectors exhibit strong preference in one of the debt contract types. Lian and Ma (2021) indicates that firms in the airline industry constitute good example as they predominantly employ asset-based borrowing due to having substantial amounts of standardized, transferable assets such as aircrafts and hangars. Having higher amounts of pledgeable assets makes asset based borrowing ideal for the firms in airline sector. By presenting impact of aircraft collateral and fire sale mechanism in this industry, Pulvino (1998),Benmelech and Bergman (2009) and Benmelech and Bergman (2011) also emphasize the dominance of asset based borrowing in airline sector.

On the other extreme, firms operating in services and technology (*e.g.* software) sectors mostly rely on cash flow based lending. In these sectors, firms mostly operate using intangible capital rather than tangible capital. Therefore these firms do not have enough tangible assets to pledge as collateral, so they rely on cash flow-based lending. One caveat for this group is that if these firms are low on productivity, then they cannot generate enough cash flows, leading to tighter borrowing constraints (Giglio and Severo, 2012).

Loan vs Bond. Kahan and Tuckman (1993) states that compared to terms of corporate bond issuance, loan agreements more aggressively dictate terms and thus impose strict limits to the firm's actions (mostly borrowing). Verde (1999) compares firms' choice of debt instruments and finds that borrowing via bonds generally comes with looser restrictions. Furthermore, Billett, King, and Mauer (2007) suggests that only 5% of bond indentures dictates restriction on firm. However, even though bonds do not contain such limits on firm's actions, they are still bounded by the loan covenants as a loan covenant limits firm's total debt, regardless the underlying source of the debt (*i.e.* bond issuance or loans).

The underlying reasons behind why firms borrow via loans and comply with the stricter covenants: (*i*) loans are faster way to borrow, (*ii*) bond issuance are subject to considerable amount of transaction costs, (*iii*) credit rating agencies charge significant amount to grade the issued bonds (sometimes this cost is high enough that some firms opt for issuing un-graded bonds which are significantly cheaper than their graded counterparts), *iv*) if a firm is rated as "below investment grade" then the premium they are obliged to pay is relatively larger.

Appendix B

Appendix to Chapter 2

B.1 Appendix

B.1.1 Idiosyncratic Demand Shocks

In the presence of idiosyncratic demand shocks, consider a consumption aggregator of $c = (\sum_i \alpha_i c_i^{\gamma})^{\frac{1}{\gamma}}$ with $\gamma \equiv \frac{\varepsilon-1}{\varepsilon}$. In this specification, α_i is a weight on good i as not all goods are weighted equally in utility. Relative demands are given by

$$\frac{c_i}{c_j} = \left(\frac{\alpha_j p_i}{\alpha_i p_j}\right)^{-\sigma}$$

where $\sigma = \frac{1}{\gamma-1}$. Define $\tilde{P} = (\sum_i \tilde{p}_i^{1-\sigma}\alpha_i)^{1/(1-\sigma)}$, so that

$$c_j = (\frac{\tilde{p}_j}{\tilde{P}})^{-\sigma}\frac{M}{\tilde{P}} = \alpha_j^{\sigma}(\frac{p_j}{\tilde{P}})^{-\sigma}\frac{M}{\tilde{P}}. \tag{B.1.1}$$

Here M is nominal spending and $\tilde{p}_j \equiv \frac{p_j}{\alpha_j}$.

We introduce relative demand shocks through this specification. For a given distribution of weights, there is nothing stochastic about the household problem with respect to tastes. That is, the young agent of generation t has fixed preferences of consumption goods when they are old. So the household problem specified in the main text remains, with the modified aggregator.

But, from the perspective of a seller, the model introduces uncertainty in that *ex ante* the seller does not know the taste shock pertaining to the particular good of that seller. This allows uncertainty in demand to exist from the perspective of a seller but not the consumer. The uncertain demand can impact the *ex ante* price as well as the *ex post* decision to adjust and, conditional on adjustment, the *ex post* price.

This specification leads to two types of shocks. First, there are seller specific realizations of demand shocks, denoted α, which directly impact revenues. Second there are variations in the distribution of α are studied through mean preserving spreads, denoted $disp_D$.

B.1.2 Generalized Definition of SREE

Here the definition of a stationary rational expectations equilibrium is generalized to include shocks to the distribution of plant-level productivity through μ_Q and $disp_Q$ as well as shocks to idiosyncratic demand, α and the distribution of the demand shocks, $disp_D$. Let $S = (x, \mu_Q, disp_Q, disp_D)$ be the aggregate state and $s = (z, \alpha, F)$ be the idiosyncratic state.[1] As earlier, M is the previous money stock and thus is known at the time prices are chosen *ex ante*.

A SREE is a set of price functions $(\bar{p}(M), \tilde{p}(M,S,s), P(M,S))$, value functions $(W^n(M,S,s), W^a(M,S,$ and a critical value of the price adjustment cost, $F^*(M,S,s)$ satisfying: (i) individual optimization by young price setters and old consumers, (ii) market clearing and (iii) consistency of beliefs and expectations for all states. These conditions can be written:

- $\bar{p}(M)$ solves the *ex ante* pricing problem given the state dependent price index $P(M,S)$;

$$\bar{p}(M) = argmax_p E_{S,s,S'} \left\{ V\left(\frac{R\left(M; p, \alpha; P(M,S), x\right) x'}{P(Mx, S')}\right) - g\left(\frac{d(M; p, \alpha; P(M,S), x)}{\mu_Q z}\right)\right\} \tag{B.1.2}$$

  for all M.

- $\tilde{p}(M,S,s)$ solves the *ex post* pricing problem:

$$\tilde{p}(M,S,s) = argmax_p E_{S'} \left\{ V\left(\frac{R(M; p, \alpha; P(M,S), x)x'}{P(Mx, S')}\right)\right\} - g\left(\frac{d(M; p, \alpha; P(M,S), x)}{\mu_Q z}\right). \tag{B.1.3}$$

  given $P(M,S)$, for all (M,S,s);

- At the critical adjustment cost, $F^*(M,S,s)$, the seller is just indifferent between adjusting and not:

$$F^*(M,S,s) \equiv W^n(M,S,s) - W^a(M,S,s)$$

[1] So here the notation is different from that in the text to be more explicit about aggregate and idiosyncratic variables.

for all (M, S, s), with $W^a(M, S, s)$ given by:

$$W^a(M, S, s) = E_{S'}\left\{V\left(\frac{R(M; \tilde{p}(M, S, s), \alpha; P(M, S), x)x'}{P(Mx, S')}\right)\right\} - g\left(\frac{d(M; \tilde{p}(M, S, s), \alpha; P(M, S), x)}{\mu_Q z}\right), \tag{B.1.4}$$

and $W^n(M, S, s)$ given by

$$W^n(M, S, s) = E_{S'}\left\{V\left(\frac{R(M; \bar{p}(M), \alpha; P(M, S), x)x'}{P(Mx, S')}\right)\right\} - g\left(\frac{d(M; \bar{p}(M), \alpha; P(M, S), x)}{\mu_Q z}\right). \tag{B.1.5}$$

- $P(M, S)$ is the aggregate price index in state (M, S) given by:

$$P(M, S) = [E_s(1 - \Omega(F^*(M, S, s)))\bar{p}(M)^{1-\varepsilon} + E_s(\Omega(F^*(M, S, s))\tilde{p}(M, S, s)^{1-\varepsilon})]^{\frac{1}{1-\varepsilon}} \tag{B.1.6}$$

where $d(M; \bar{p}(M), \alpha; P(M, S), x) = \alpha^{\varepsilon}\left(\frac{\bar{p}(M)}{P(M,S)}\right)^{-\varepsilon} Y$ and $d\left(M; \tilde{p}(M, S, s), \alpha; P(M, S), x\right) = \alpha^{\varepsilon}\left(\frac{\tilde{p}(M,S,s)}{P(M,S)}\right)^{-\varepsilon} Y$. Here $Y = \frac{Mx}{P(M,S)}$ is the equilibrium determined real value of money holdings.

B.1.3 SREE: Linear Quadratic

For the case of linear quadratic preferences, the SREE defined in section 2.2.3 becomes a set of functions $\{\bar{p}(M), \tilde{p}\left(M; z, \alpha; x, \mu_Q\right), F^*\left(M; z, \alpha; x, disp_Q, disp_D, \mu_Q\right), P\left(M; x, disp_Q, disp_D, \mu_Q\right)\}$ such that:

- $\bar{p}(M)$ solves the *ex ante* pricing problem given the state dependent price index $P\left(M; x, disp_Q, disp_D,\right.$

$$\hat{\varepsilon}\,\bar{p}(M)\,E_{\alpha;x,x',disp_Q',disp_D',\mu_Q'}\left[\frac{x'}{P\left(Mx; x', disp_Q', disp_D', \mu_Q'\right)} d(M; \bar{p}(M), \alpha; x)\right] = E_{z,\alpha;x,\mu_Q}\left[\frac{d(M; \bar{p}(M), \alpha; x)}{\mu_Q z}\right]^2. \tag{B.1.7}$$

- $\tilde{p}\left(M; z, \alpha; x, \mu_Q\right)$ solves the *ex post* pricing problem given the state dependent price index $P\left(M; x, disp_Q, disp_D, \mu_Q\right)$;

$$\hat{\varepsilon}\,\tilde{p}\left(M;z,\alpha;x,\mu_Q\right)\;E_{x',disp_Q',disp_D',\mu_Q'}\left[\frac{x'}{P\left(Mx;x',disp_Q',disp_D',\mu_Q'\right)}\right]=\frac{d\left(M;\tilde{p}\left(M;z,\alpha;x,\mu_Q\right),\alpha;x\right)}{{\mu_Q}^2z^2}. \tag{B.1.8}$$

- At the critical adjustment cost $F^*\left(M;z,\alpha;x,\mu_Q\right)$, the seller is just indifferent between adjusting and not:

  $F^*\left(M;z,\alpha;x,\mu_Q\right)=W^a\left(M;z,\alpha;x,\mu_Q\right)-W^n\left(M;z,\alpha;x,\mu_Q\right)$

- $P\left(M;x,disp_Q,disp_D,\mu_Q\right)$ is the aggregate price function in state $\left(M;x,disp_Q,disp_D,\mu_Q\right)$ given by:

$$P\left(M;x,disp_Q,disp_D,\mu_Q\right)=$$
$$\left[E_{z,\alpha}(1-\Omega(F^*(M;z,\alpha;x,\mu_Q)))\bar{p}(M)^{(1-\epsilon)}+E_{z,\alpha}\Omega(F^*(M;z,\alpha;x,\mu_Q))\tilde{p}(M;z,\alpha;x,\mu_Q)^{(1-\epsilon)}\right]^{\frac{1}{1-\epsilon}} \tag{B.1.9}$$

Throughout, $d(M;\bar{p}(M),\alpha;P\left(M;x,disp_Q,disp_D,\mu_Q\right),x)=\alpha^\varepsilon\left(\frac{\bar{p}(M)}{P\left(M;x,disp_Q,disp_D,\mu_Q\right)}\right)^{-\varepsilon}Y$ and $d(M;\tilde{p}\left(M;z,\alpha;P\left(M;x,disp_Q,disp_D,\mu_Q\right)x,\mu_Q\right),\alpha;x)=\alpha^\varepsilon\left(\frac{\tilde{p}\left(M;z,\alpha;x,\mu_Q\right)}{P\left(M;x,disp_Q,disp_D,\mu_Q\right)}\right)^{-\varepsilon}Y$. Here, note that $Y=\frac{Mx}{P\left(M;x,disp_Q,disp_D,\mu_Q\right)}$ is the real output and thus real spending.

B.1.4 Quantitative Approach

In this section, we first briefly present simulation details, and continue with the idiosyncratic and aggregate shocks, then explain how we carry out the menu cost parameterization used in the analyses. Section concludes with the computational algorithm.

Simulation Details

Simulating the shcks In the model, agents live for two period, and price setting problem takes place only in their first period. Therefore, given the one period nature of price setting, there is no gain to specify and impose a full fledged Markov transition matrix. Instead, after creating a Markov process for each shock by using Rouwenhorst method, we extract the stationary distribution for these shocks.

Simulating the economy Model period is monthly. In the model economy, we have $10,000$ firms and the economy runs for 200 periods. We keep the number of firms high enough that each shock in the state space is received by considerable amount of firms. Therefore we ensure that results are not affected by random assignment of shocks.

Shocks

Idiosyncratic shocks In the algorithm, idiosyncratic productivity shocks have unit mean and standard deviation denoted by σ_z. Likewise, idiosyncratic demand shocks have mean of 1 and standard deviation, σ_d as well. Both of these shocks have lognormal distribution.. The standard deviations, σ_z and σ_d, are governed by the $disp_Q$ and $disp_D$ shocks. If these shocks are not active, then these standard deviations are equal to the values presented in Table 2.2, which are calibrated to match the data moments.

$disp_Q$ **Shock** When imposed, the spread of idiosyncratic productivity distribution itself becomes a stochastic process. $disp_Q$ shocks change the dispersion of idiosyncratic productivity shocks for everyone, therefore is an aggregate shock. When $disp_Q$ shocks applied, agents *ex ante* do not know whether they are going to draw their idiosyncratic productivity from a wider or a narrower distribution. However, in the ex post world, after realization of shocks in the economy, $disp_Q$ dictates the standard deviation of idiosyncratic shock distribution for everyone in the economy.

The $disp_Q$ shocks have a lognormal distribution. There are 11 points in the $disp_Q$ grid. The ratio of 9th value to 3rd value is 3.94. It is 4.1 in Bloom et al. (2018).

$disp_D$ **Shock** Similar to the $disp_Q$ shocks, $disp_D$ shocks govern the dispersion of the idiosyncratic demand shock distribution. $disp_D$ shocks have a lognormal distribution.

The mean value of $disp_D$ shock is pinned down by calibration and it is a small number. The grid for $disp_D$ ranges from 0 to 0.011, and the mean value comes from calibration.

x **Shock** Monetary shocks are uniformly distributed in the range of $\pm\%15$.

μ_Q **Shock** μ_Q shocks moves the mean value of idiosyncratic productivity shock distribution, and similar to $disp_Q$ shock, in the *ex post* world, realization of μ_Q shocks moves the mean of the idiosyncratic productivity shock distribution. μ_Q shocks have log normal distribution. Similar to the x shock case, the highest and lowest values of μ_Q distribution yield $\pm\%15$ range.

Combined μ_Q and $disp_Q$ Shock To impose perfectly negatively correlated combined shocks of $disp_Q$ and μ_Q, as in Vavra (2014) we associate the highest state of $disp_Q$ with the lowest state of μ_Q; the second highest state of $disp_Q$ with the second lowest state of μ_Q, than the third and *so on…*

Menu Costs

Firms are heterogeneous due to the realization of firm-specific price adjustment costs. Furthermore, firm heterogeneity stems not only from the realizations of menu costs, but we also impose another form of heterogeneity in the distribution of menu costs. A small fraction ψ of firms face zero price adjustment cost and thus have perfectly flexible prices. The remaining fraction $1-\psi$ draws from a nondegenerate distribution of adjustment cost. Figure B.1.1 exhibits the shape of menu cost distribution.

The menu cost distribution follows Dotsey and Wolman (2019), using a tangent function given by:

$$G(F) = \frac{1}{\omega}\left\{\tan(\frac{F-\kappa_2}{\kappa_1}) + \nu \cdot \pi\right\} \tag{B.1.10}$$

with

$$\kappa_1 = \frac{\bar{F}}{[\tan^{-1}(\omega-\nu\cdot\pi)+\tan^{-1}(\nu\cdot\pi)]}; \qquad \kappa_2 = \tan^{-1}(\nu\cdot\pi)\cdot\kappa_1. \tag{B.1.11}$$

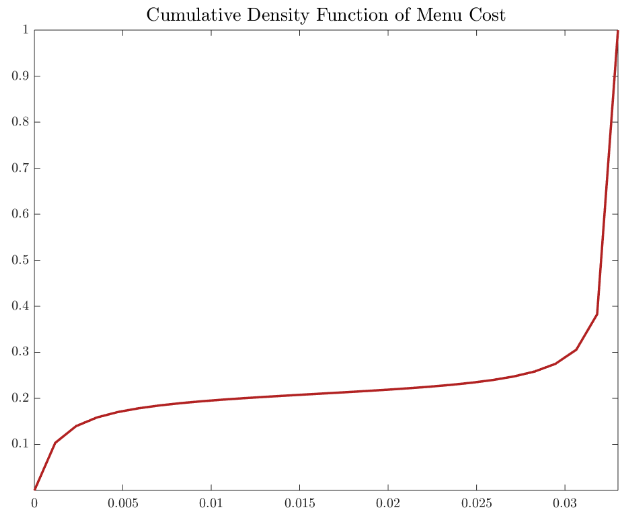
The upper bound on the fixed cost, $\bar{F}$, controls the extent of price stickiness. As $\bar{F}$ increases, higher values for menu cost is now available, making the adjustment harder. The curvature parameters (ω, ν), are chosen so that $G(F)$ is monotonically increasing. As noted above, ψ governs the fraction of flexible-price firms, and thus increasing this value leads to a larger number of small price changes and a higher overall frequency of price adjustment. Corresponding values can be found in Table 2.1.

Computational Algorithm

This section discusses how the SREE is computed. For the price setting component of the SREE, all of the state variables are exogenous except for the aggregate price level, $P(M,S)$.[2] In contrast, the aggregate price level is an equilibrium object, and is therefore calculated from the choices of the sellers, as in (B.1.9). Thus the focus of the solution approach is to find the equilibrium aggregate price function, $P(M,S)$ through the firm's individual price choices. For expositional purposes, we continue with the (S,s) notation as in Appendix B.1.2, that is we define $S = (x, \mu_Q, disp_Q, disp_D)$ as the aggregate state space and

[2]See Appendix B.1.3 for the full definition of SREE in this linear quadratic setting.

Figure B.1.1
Menu Cost Distribution



Note: This figure shows the non-degenerate distribution of price adjustment costs.

$s = (z, \alpha, F)$ as the idiosyncratic state space. The solution algorithm involves direct solution of the nonlinear system of equations which are the first order conditions derived from firm's *ex ante* and *ex post* problems. Directly solving the equations speed up the computation process and allow us adding more state variables to the model much easier than traditional methods like value function iteration. In what follows, we briefly summarize solution algorithm.

Step 1 Start with an initial guess of the aggregate price function, $P^{(0)}(M, S)$.

Step 2 Calculate the new implied aggregate price function, $P^{(1)}(M, S)$, by solving the system. Specifically,

i. Solve the nonlinear system governed by (B.1.2) - (B.1.6). Note that (B.1.3) is not an independent equation *per se*, but a set of equations for each point in the state space. Solution to the system yields *ex ante* price, $\bar{p}(M)$ and *ex post* price set, $\tilde{p}(M, S, s)$.

ii. Using the *ex ante* price, $\bar{p}(M)$ and *ex post* price set $\tilde{p}(M, S, s)$, for each point in the state space, calculate the values of adjustment $W^a(M, S, s)$ and non-adjustment $W^n(M, S, s)$, given by (B.1.4) and (B.1.5) respectively.

iii. Compare the values of adjustment $W^a(M, S, s)$ and non-adjustment $W^n(M, S, s)$ for each point in the state space, and store the maximum value of each case and also record whether adjustment or non-adjustment yield this maximum value.

iv. Given the decision about price adjustment, pick the corresponding price (*ex ante* or *ex post*) and construct the realized price matrix for each point in the state space.

v. Given the probability of occurrences of each idiosyncratic state, calculate the new aggregate price matrix, $P^{(1)}(M, S)$ for each point in the **aggregate** state space.

Step 3 If the distance between $P^{(0)}(M, S)$ and $P^{(1)}(M, S)$ is within the error tolerance band, the aggregate price function converges yielding the price policy functions. If not, return to Step 1, update the guess of aggregate price function, *i.e.* $P^{(0)}(M, S) = P^{(1)}(M, S)$. Keep iterating until the aggregate price function converges.

Note that there is no approximation involved in the solution algorithm. The approach simply solves a system of equations to find a SREE. So unlike an approach based upon Krusell and Smith (1998), there are no moments *per se* used to characterize an equilibrium.

Appendix C

Appendix to Chapter 3

C.1 Sample Descriptive Statistics

Table C.1.1
Firm Characteristics

	1960s	1970s	1980s	1990s	2000s	2010s	Total
Sales Revenue (M USD, 2015 prices)	1576.1	1193.2	1198.3	1341.2	2228.7	3553.4	1748.8
Employees (thousands)	11.21	6.995	5.621	5.391	7.308	10.50	6.999
Capital Stock (M USD)	643.6	452.9	503.7	515.5	771.3	1264.4	652.1
Value Added per Worker (000 USD)	51.80	80.32	121.9	120.4	139.0	173.1	120.9
Observations	8555	37183	43044	49169	40651	25696	204298

Table C.1.2
Sectoral Sample Shares

SIC group	1960s	1970s	1980s	1990s	2000s	2010s	Total
1. Agriculutre, Forestry, Fishing	0.432	0.514	0.541	0.431	0.389	0.436	0.462
2. Mining	3.133	4.446	6.654	4.676	4.482	6.273	5.148
3. Construction	0.245	1.181	1.052	0.744	0.563	0.630	0.817
4. Manufacturing	67.38	56.51	48.59	45.83	45.76	46.34	49.31
5. Transportation*	6.148	5.535	6.368	6.034	6.384	5.468	6.017
6. Wholesale Trade	3.682	5.295	5.209	4.424	3.461	3.020	4.349
7. Retail Trade	9.912	9.472	7.866	8.326	7.242	7.266	8.155
8. Services	5.552	9.609	13.35	18.14	20.28	18.73	15.55
9. Miscellaneous	3.518	7.436	10.37	11.39	11.44	11.84	10.19
Observations	8555	37183	43044	49169	40651	25696	204298

$*$ Transportation, Communications, Electric, Gas, and Sanitary Services.

Real variables are deflated by the GDP deflator and normalized to 2015 dollars. Shares are unweighted, representing raw counts.

Table C.1.3
SIC 2-digit Industry Shares

	Sales	%	Employment	%	Obs	%
A. Agriculture, Forestry, & Fishing						
Agricultural Production – Crops	1215.05	0.90	8.69	1.65	569	0.28
Agricultural Production – Livestock	120.71	0.09	0.38	0.07	172	0.08
Agricultural Services	191.43	0.14	2.26	0.43	123	0.06
Forestry	163.53	0.12	1.17	0.22	60	0.03
Fishing, Hunting, & Trapping	73.26	0.05	0.64	0.12	19	0.01
B: Mining						
Metal, Mining	579.02	0.43	2.03	0.39	1034	0.51
Coal Mining	1010.40	0.75	3.13	0.60	496	0.24
Oil & Gas Extraction	1261.38	0.93	1.93	0.37	8563	4.19
Nonmetallic Minerals, Except Fuels	694.76	0.51	2.60	0.49	425	0.21
C: Construction						
General Building Contractors	1107.47	0.82	1.78	0.34	1670	0.82
Heavy Construction, Except Building	1624.05	1.20	5.86	1.11	668	0.33
Special Trade Contractors	534.29	0.40	2.80	0.53	554	0.27
D: Manufacturing						
Food & Kindred Products	2682.37	1.99	10.30	1.96	5887	2.88
Tobacco Products	7844.94	5.81	18.78	3.57	229	0.11
Textile Mill Products	706.30	0.52	5.74	1.09	2018	0.99
Apparel & Other Textile Products	606.85	0.45	4.57	0.87	2721	1.33
Lumber & Wood Products	783.64	0.58	3.08	0.59	1656	0.81
Furniture & Fixtures	747.59	0.55	5.04	0.96	1609	0.79
Paper & Allied Products	2471.95	1.83	10.07	1.91	2376	1.16
Printing & Publishing	562.18	0.42	3.33	0.63	2918	1.43
Chemical & Allied Products	1386.12	1.03	4.43	0.84	16194	7.93
Petroleum & Coal Products	21957.81	16.28	19.47	3.70	1392	0.68
Rubber & Miscellaneous Plastics Products	1094.96	0.81	5.66	1.08	3023	1.48
Leather & Leather Products	535.25	0.40	3.45	0.66	864	0.42
Stone, Clay, & Glass Products	775.17	0.57	4.19	0.80	1989	0.97
Primary Metal Industries	1635.36	1.21	6.99	1.33	3558	1.74
Fabricated Metal Products	627.13	0.46	3.31	0.63	4602	2.25
Industrial Machinery & Equipment	1175.72	0.87	5.16	0.98	13529	6.62
Electronic & Other Electric Equipment	755.81	0.56	3.59	0.68	15931	7.80
Transportation Equipment	6053.56	4.49	22.74	4.32	5299	2.59
Instruments & Related Products	422.89	0.31	2.21	0.42	12518	6.13
Miscellaneous Manufacturing Industries	388.33	0.29	2.23	0.42	2418	1.18
E: Transportation & Public Utilities						
Railroad Transportation	4528.24	3.36	19.96	3.79	810	0.40
Local & Interurban Passenger Transit	1001.35	0.74	12.26	2.33	93	0.05
Trucking & Warehousing	2612.07	1.94	22.18	4.22	1820	0.89
Water Transportation	540.78	0.40	1.76	0.33	578	0.28
Transportation by Air	4065.98	3.01	17.93	3.41	1865	0.91
Pipelines, Except Natural Gas	1259.07	0.93	0.64	0.12	64	0.03
Transportation Services	943.04	0.70	3.34	0.64	648	0.32
Communications	3804.95	2.82	14.31	2.72	6414	3.14
F. Wholesale Trade						
Wholesale Trade – Durable Goods	1017.75	0.75	2.02	0.38	5638	2.76
Wholesale Trade – Nondurable Goods	3230.12	2.39	4.98	0.95	3246	1.59
G. Retail Trade						
Building Materials & Gardening Supplies	4219.42	3.13	18.40	3.50	680	0.33
General Merchandise Stores	9467.74	7.02	54.27	10.31	2346	1.15
Food Stores	4916.18	3.64	23.65	4.50	2185	1.07
Automative Dealers & Service Stations	2552.24	1.89	8.63	1.64	677	0.33
Apparel & Accessory Stores	1750.13	1.30	14.69	2.79	2204	1.08
Furniture & Homefurnishings Stores	1643.07	1.22	7.61	1.45	1123	0.55
Eating & Drinking Places	883.17	0.65	16.99	3.23	3595	1.76
Miscellaneous Retail	2245.13	1.66	8.41	1.60	3851	1.88
H: Finance and Real Estate						
Depository Institutions	1776.85	1.32	5.23	0.99	305	0.15
Nondepository Institutions	2411.58	1.79	4.42	0.84	3066	1.50
Security & Commodity Brokers	2715.88	2.01	3.49	0.66	2832	1.39
Insurance Carriers	4267.08	3.16	5.82	1.11	3706	1.81
Insurance Agents, Brokers, & Service	648.34	0.48	3.41	0.65	796	0.39
Real Estate	180.61	0.13	1.08	0.21	3222	1.58
Holding & Other Investment Offices	345.97	0.26	1.91	0.36	3122	1.53
I. Services						
Hotels & Other Lodging Places	606.86	0.45	8.64	1.64	1291	0.63
Personal Services	599.17	0.44	9.46	1.80	639	0.31
Business Services	790.16	0.59	6.08	1.16	18205	8.91
Auto Repair, Services, & Parking	1518.50	1.13	8.19	1.56	546	0.27
Miscellaneous Repair Services	126.40	0.09	0.70	0.13	73	0.04
Motion Pictures	679.96	0.50	3.68	0.70	1439	0.70
Amusement & Recreation Services	473.73	0.35	4.34	0.83	2398	1.17
Health Services	779.30	0.58	7.28	1.38	2864	1.40
Legal Services	155.08	0.11	0.34	0.06	26	0.01
Educational Services	418.35	0.31	3.12	0.59	696	0.34
Social Services	249.15	0.18	6.10	1.16	238	0.12
Museums, Botanical, Zoological Gardens	37.23	0.03	0.50	0.09	11	0.01
Engineering & Management Services	374.39	0.28	2.32	0.44	3339	1.63
Services, Not Elsewhere Classified	12.98	0.01	0.02	0.00	6	0.00
Non-Classifiable Establishments	3274.80	2.43	10.34	1.97	2557	1.25

C.2 Total Factor Productivity

Table C.2.1
TFPR in logs, Cost Share approach

SIC	Obs	mean	sd	p25	p50	p75	$\frac{p75}{p25}$	$\frac{p90}{p10}$	$\frac{p95}{p05}$	$\frac{p99}{p01}$	Skewness	Kurtosis
1	570	4.43	1.04	3.80	4.28	5.17	1.36	1.69	1.95	4.44	-0.28	4.85
2	6264	4.77	1.13	4.24	4.81	5.43	1.28	1.70	2.16	7.39	-1.08	7.47
3	971	5.73	0.95	5.11	5.87	6.45	1.26	1.55	1.78	2.19	-0.53	3.24
4	58254	4.55	0.90	4.23	4.59	4.99	1.18	1.45	1.81	5.63	-1.74	12.88
5	7053	4.19	0.73	3.77	4.09	4.48	1.19	1.45	1.66	2.80	0.28	9.81
6	4915	5.52	0.95	4.94	5.48	6.04	1.22	1.51	1.73	2.51	0.34	5.47
7	10570	4.42	0.72	4.03	4.45	4.82	1.20	1.54	1.72	2.16	0.19	4.42
8	18021	4.42	1.00	3.89	4.50	4.98	1.28	1.69	2.07	4.49	-0.58	7.27
9	11937	5.12	1.15	4.46	5.12	5.86	1.31	1.68	2.05	4.25	-0.34	6.14
Total	118555	4.62	0.98	4.15	4.61	5.11	1.23	1.60	1.95	4.61	-0.68	8.64

Table C.2.2
TFPR Innovations based on Cost Share approach

SIC	Obs	mean	sd	p25	p50	p75	$p_{75} - p_{25}$	$p_{90} - p_{10}$	$p_{95} - p_{05}$	$p_{99} - p_{01}$	skewness	kurtosis
1	453	0.00	0.38	-0.14	0.00	0.16	0.30	0.71	1.06	2.19	-1.98	25.81
2	4908	0.00	0.46	-0.17	0.01	0.18	0.35	0.82	1.24	2.63	-0.99	19.08
3	804	0.00	0.30	-0.16	0.00	0.16	0.32	0.63	0.87	1.63	-0.53	9.59
4	48197	0.00	0.38	-0.09	0.00	0.10	0.19	0.51	0.85	2.29	-1.24	41.21
5	5773	0.00	0.22	-0.06	0.00	0.07	0.13	0.30	0.50	1.28	0.17	65.57
6	3936	0.00	0.24	-0.08	0.00	0.09	0.17	0.40	0.61	1.28	-0.37	41.24
7	8912	0.00	0.16	-0.05	0.00	0.06	0.11	0.26	0.38	0.82	-5.23	167.07
8	13427	0.00	0.36	-0.10	0.01	0.11	0.21	0.53	0.87	2.07	-2.39	56.02
9	9523	0.00	0.39	-0.12	0.00	0.13	0.25	0.62	0.98	2.34	-1.03	26.69
Total	95933	0.00	0.35	-0.09	0.00	0.10	0.19	0.49	0.82	2.09	-1.43	43.99

C.3 Alternative Monetary Policy Shocks

The figure below compares monthly aggregate responses to three distinct monetary policy shock series. The first, RR (Romer and Romer, 1989) identifies periods in which policy was tightened in a plausibly exogeneous way by examining FOMC meeting minutes, the so-called "narrative identification". GK (Gertler and Karadi, 2015) creates a proxy for structural monetary policy shocks by examining the reaction of Fed Funds Futures to policy announcement events within a tight window, the "high frequency" identification. The final series, MAR (Miranda-Agrippino and Ricco, 2017) accounts for the fact that the central bank's and agents' information sets are not identical, so policy changes induce direct effects, as well as signaling effects - agents learn more about the state of the economy from the central banks policy choices.

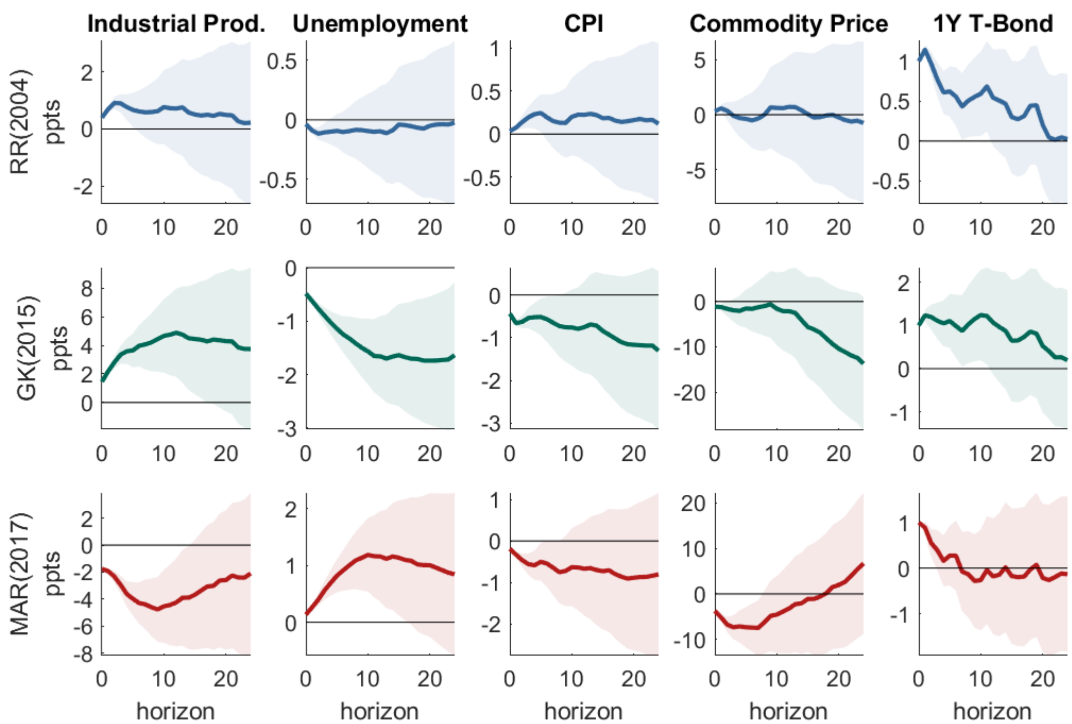


Figure C.3.1

Comparison of monetary policy shock series 1979m1 to 2014m12

The above figure shows that only the MAR shock series induces changes in the macroeconomy consistent with economic theory, i.e. jointly depresses economic activity in the decline in industrial production, and increase in the unemployment rate, a deflationary reaction of consumer prices and commodity prices, and the shock only induces a very short-lived response from short-term interest rates. The RR shocks present what might be dubbed output and price puzzles, and the decay of the response to the 1 year treasury bill rate is much slower. GK shocks conversely present problematic responses of output and unemployment, while prices seem to conform more to what one would expect.

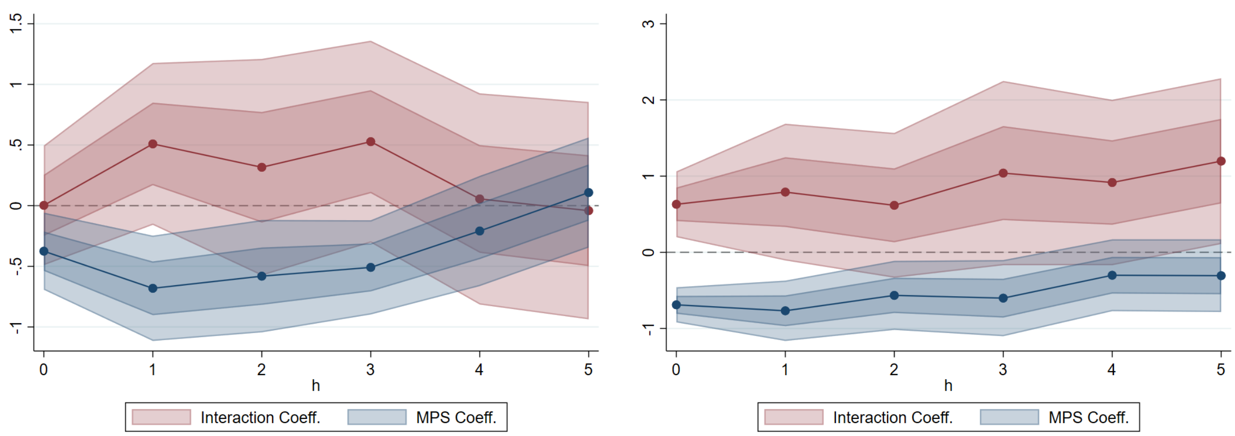
C.4 Annualized Monetary Policy Shocks

In our baseline analysis we use the higher frequency quarterly Compustat dataset. However this means we cannot examine employment responses. Below we switch to annual data, and aggregate the monetary policy shocks within a calendar year. Responses remain qualitatively similar, even if not always statistically significant. This is rationalized with a substantial loss of observations due to time aggregation.

Figure C.4.1

INVESTMENT AND HIRING RESPONSE TO MONETARY POLICY SHOCK, ANNUAL RESPONSES, FIXED VOLATILITY INTERACTION

(**a**) Investment (**b**) Hiring



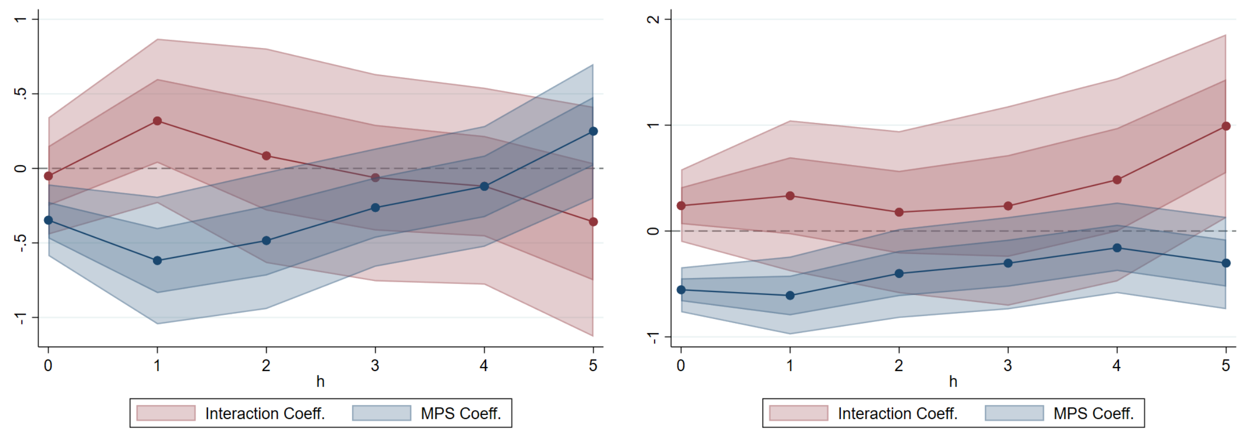
NOTE. Average response of investment and employment at horizon h (in years) to a 100 bpts monetary policy shock.

We see a slower hump-shaped IRF profile for investment, while employment reacts most on impact. In both factors sectoral volatility of TFPR innovations dampens the reaction to monetary policy shocks given the MPS an volatility interaction coefficients have opposite signs over most of the horizon.

Figure C.4.2

INVESTMENT AND HIRING RESPONSE TO MONETARY POLICY SHOCK, ANNUAL RESPONSES, TIME-VARYING VOLATILITY INTERACTION

(**a**) Investment (**b**) Hiring



NOTE. Average response of investment and employment at horizon h (in years) to a 100 bpts monetary policy shock.