ESSAYS IN MACROECONOMICS

By

Timothy Moreland

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Economics – Doctor of Philosophy

2021

ABSTRACT

ESSAYS IN MACROECONOMICS

By

Timothy Moreland

Chapter 1: Financial Consolidation and the Cyclicality of Corporate Financing

We study the impact of the concentration and complexity of the banking sector on firms' financing and investment behavior over the business cycle. We find that, after the late 1990s, while debt issuance remained procyclical for U.S. firms of all sizes, equity issuance and liquidity accumulation switched from countercyclical to procyclical for small and medium-sized publicly-traded firms. Using matched firm-bank data, we provide evidence that bank consolidation contributed to this change. We rationalize these findings in a general equilibrium business cycle model. After bank consolidation, the weakening in firms' bargaining power and relational ties with banks enhances firms' precautionary demand for liquidity and equity issuance incentives following positive shocks. The change in financing behavior increases investment and employment sensitivity to aggregate productivity shocks.

Chapter 2: Monetary Policy and Firm Heterogeneity: The Role of Leverage Since the Financial Crisis

We study how leverage determines firm-level responses to monetary policy. Using both high-frequency financial market and quarterly investment data, we find that the role of leverage in monetary transmission changed around the financial crisis of 2007-09. Firms with high leverage were less responsive to monetary policy shocks in the pre-crisis period but have become more responsive since the crisis. The higher responsiveness is driven by firms whose leverage is more dependent on long-term debt, suggesting an outsize role for monetary policy affecting long-term funding conditions since the crisis. We also find suggestive evidence for transmission through changes in monetary policy uncertainty.

Chapter 3: The International Spillover Effects of US Monetary Policy Uncertainty

An extensive literature studies the international transmission of US monetary policy surprises (shifts in expected path of the policy rate). In this paper we show that changes in uncertainty around the expected path constitute an important additional dimension of spillover effects to global bond yields. In advanced countries, it is the term premium component of yields that responds to uncertainty. We find that this can be explained by an international portfolio balance mechanism. In contrast, for emerging countries it is the expected component of yields that reacts to uncertainty. This can be rationalized from a flight to safety channel. We find heterogeneity in the country-level response to uncertainty only in emerging countries and it is driven by the degree of financial openness. Finally, equity markets in both advanced and emerging countries also respond to US monetary policy uncertainty.

Copyright by
TIMOTHY MORELAND
2021

TABLE OF CONTENTS

LIST OF TABLES vii

LIST OF FIGURES xi

CHAPTER 1 FINANCIAL CONSOLIDATION AND THE CYCLICALITY OF CORPORATE FINANCING 1
- 1.1 Introduction 1
- 1.2 Empirical Evidence 6
  - 1.2.1 Firm-Level Data 6
  - 1.2.2 Lender Data 9
- 1.3 Firm Financing over the Business Cycle 10
  - 1.3.1 Aggregate Time Series Evidence 11
  - 1.3.2 Firm-Level Evidence 12
- 1.4 Robustness 15
  - 1.4.1 Identifying the Structural Break 16
  - 1.4.2 Other Robustness Tests 16
- 1.5 The Role of Financial Consolidation 18
  - 1.5.1 Timing of Riegle-Neal Adoption 18
  - 1.5.2 Measures of Financial Consolidation 19
- 1.6 The Model 22
  - 1.6.1 Firm Technology and Financing 22
  - 1.6.2 Firm Decisions 26
  - 1.6.3 Household Decisions and General Equilibrium 28
- 1.7 Calibration and Quantitative Analysis 29
  - 1.7.1 Calibration 30
  - 1.7.2 Simulated Responses 30
- 1.8 Financial and TFP Shocks 32
- 1.9 Investment and Employment 34
- 1.10 Conclusion 36

CHAPTER 2 MONETARY POLICY AND FIRM HETEROGENEITY: THE ROLE OF LEVERAGE SINCE THE FINANCIAL CRISIS 38
- 2.1 Introduction 38
- 2.2 Data 44
  - 2.2.1 Monetary Policy Shocks 44
  - 2.2.2 Firm-Level Variables 46
- 2.3 Results 47
  - 2.3.1 Evidence from firm-level stock returns 47
  - 2.3.2 Leverage in the pre- and post-crisis samples 50
  - 2.3.3 Evidence from firm-level options data 52
  - 2.3.4 Evidence from investment data 54

2.4 Mechanism . . . 56
2.4.1 Ottonello & Winberry channels of monetary transmission . . . 57
2.4.2 Transmission through changes in long-term funding conditions . . . 62
2.4.3 Transmission through monetary policy uncertainty changes . . . 64
2.5 Robustness Checks . . . 66
2.6 Conclusion . . . 68

CHAPTER 3 THE INTERNATIONAL SPILLOVER EFFECTS OF US MONETARY POLICY UNCERTAINTY . . . 69
3.1 Introduction . . . 69
3.2 US Monetary Policy Shocks . . . 75
3.2.1 Monetary Policy Uncertainty . . . 75
3.2.2 Monetary Policy Surprise . . . 77
3.3 Data . . . 78
3.3.1 Summary Statistics . . . 79
3.4 Results . . . 80
3.4.1 Response of US asset prices to US monetary policy uncertainty . . . 80
3.4.2 Response of international bond yields to US monetary policy uncertainty . 81
3.4.3 Understanding the response . . . 87
3.4.3.1 Response in advanced countries . . . 89
3.4.3.2 Response in emerging countries . . . 92
3.4.4 Heterogeneity in response to monetary policy uncertainty . . . 94
3.4.5 Response of international equity indices to US monetary policy uncertainty 97
3.4.6 Robustness Checks . . . 98
3.5 Conclusion . . . 100

APPENDICES . . . 102
APPENDIX A SUPPLEMENTAL INFO FOR CHAPTER 1 . . . 103
APPENDIX B TABLES FOR CHAPTER 1 . . . 106
APPENDIX C FIGURES FOR CHAPTER 1 . . . 122
APPENDIX D TABLES FOR CHAPTER 2 . . . 131
APPENDIX E FIGURES FOR CHAPTER 2 . . . 145
APPENDIX F SUPPLEMENTAL INFO FOR CHAPTER 3 . . . 147
APPENDIX G TABLES FOR CHAPTER 3 . . . 149
APPENDIX H FIGURES FOR CHAPTER 3 . . . 178

BIBLIOGRAPHY . . . 188

LIST OF TABLES

Table B1: Summary statistics 106

Table B2: Cyclicality of Aggregate Financing Variables, by Size 107

Table B3: Firm-Level Cyclicality of Financing Variables 108

Table B4: State-Level Timing of Riegle-Neal Adoption 109

Table B5: Reduction in Small Firm's Bargaining Power, Syndicate Structure 110

Table B6: Reduction in Small Firm's Bargaining Power, Lender Market Power 111

Table B7: Increase in Small Firms' Lender Relationship Complexity, MBHC Status, 1999-2012 112

Table B8: Calibration 113

Table B9: Response of Financing Behavior to Positive TFP and Financial Shocks 114

Table B10: Firm-Level Cyclicality of Real Variables 115

Table B11: Robustness Tests: Firm Fixed Effect and Consistent Sample 116

Table B12: Panel Regression: Alternative Financing Variables 117

Table B13: Aggregate Financing Variables: No Filtering 118

Table B14: Effects of Consolidation by Size of Lender Pool, 1999-2012, All Lender Pool . . 119

Table B15: Panel Regression: Financing Response to Negative Shock 120

Table B16: Panel Regression: Real Response to Negative Shock 121

Table D1: Summary Statistics 131

Table D2: Response of firm-level stock returns to monetary shocks 132

Table D3: Regression of firm-level implied volatility leading up to FOMC announcement . 133

Table D4: Contemporaneous response of firm-level investment to monetary shocks 134

Table D5: Response of Bond Yield Spread to Monetary Policy Shock 134

Table D6: Response of 10 year nominal yield, real yield and term premium to monetary shocks 135

Table D7: Response of firm-level stock returns (by high/low long-term leverage) 136

Table D8: Response of firm-level stock returns to monetary policy uncertainty shocks . . . 136

Table D9: Response of Firm-Level Implied Volatility to MPU Shock 137

Table D10: Summary Statistics of Firm Characteristics 137

Table D11: Response of firm-level stock returns to monetary shocks w/ control interactions . 138

Table D12: Response of firm-level stock returns to monetary shocks: Without a time fixed effect 139

Table D13: Response of firm-level stock returns to monetary shocks (Pre. vs. Post 1SD leverage outliers removed) 140

Table D14: Robustness of baseline results to alternative measure of leverage: Debt-to-Assets 141

Table D15: Robustness of baseline results to alternative measure of leverage: 1-quarter lagged debt-to-capital 142

Table D16: Robustness of baseline results to time-sector FE 143

Table D17: Robustness of baseline results to full CRSP/Compustat sample: No firm entry/exit 144

Table G1: Summary Statistics 149

Table G2: Response of US asset prices to monetary shocks 150

Table G3: Response of international bond yields to monetary shocks 151

Table G4: Response of international bond yields to monetary and macro data news shocks . 152

Table G5: Response of expected component and term premium component of international bond yields to monetary shocks 153

Table G6: Response of exchange rates to monetary shocks 154

Table G7: Response of term premium component of international bond yields to monetary shocks (bond substitutability interaction) 154

Table G8: Response of US holdings of foreign bonds to monetary shocks 155

Table G9: Understanding the cross-country heterogeneity of asset price responses: Emerging countries 156

Table G10: Response of international equity indices to monetary shocks 157

Table G11: Response of international bond yields accounting for zero lower bound 158

Table G12: Response of forecast dispersion to monetary shocks 159

Table G13: Data coverage for sample countries 160

Table G14: Response of international bond yields to monetary shocks with QE dummy . . . 161

Table G15: Response of international bond yields to monetary shocks (Pre-crisis sample) . . 162

Table G16: Response of international asset prices to monetary shocks (Post-crisis sample) . . 163

Table G17: Response of US bond term premia to monetary policy shocks 164

Table G18: Understanding the cross-country heterogeneity of asset price responses: Advanced countries 165

Table G19: Understanding the cross-country heterogeneity of asset price responses: Emerging countries with dollar debt exposure 166

Table G20: Response of international bond yields to monetary shocks (1-day window) 167

Table G21: Response of international bond yields to monetary shocks, controlling for LIBOR-OIS spread 168

Table G22: Response of international bond yields to monetary shocks, 2 year yield as *mps* . 169

Table G23: Response of international bond yields to monetary shocks, 10 year yield as *mps* . 170

Table G24: Response of expected component and term premium component of international bond yields to monetary policy uncertainty (pre- and post-crisis samples) . 171

Table G25: Response of term premium component of international bond yields to mpu shocks (bond substitutability interaction) 172

Table G26: Response of US holdings of foreign bonds to monetary shocks (robustness) . . . 173

Table G27: Response of international bond yields to monetary shocks, controlling for target and path factor 174

Table G28: Response of international bond yields to monetary shocks (only scheduled FOMC meetings) 175

Table G29: Response of international bond yields to monetary shocks controlling for information effect 176

Table G30: Response of international bond yields to monetary shocks with country fixed-effects 177

LIST OF FIGURES

Figure C1: Concentration of US Banking Industry . . . 122

Figure C2: Time Series of Financial Variables, by Firm Size . . . 123

Figure C3: Within-Period Model Timeline . . . 124

Figure C4: IRFs of Financial Variables to Positive TFP & Financial Shocks . . . 125

Figure C5: IRFs of Capital FOC Components to Positive TFP Shock . . . 126

Figure C6: Wald Test for Structural Break in Cyclicality of Small Firm Financing . . . 127

Figure C7: Time Series of Financial & TFP Shocks . . . 128

Figure C8: IRFs of Capital FOC Components to Positive Financial Shock . . . 129

Figure C9: IRFs of Financial Variables: Alternative Household Budget Constraint . . . 130

Figure E1: Firm Leverage Plots . . . 145

Figure E2: Effects of an expansionary monetary policy shock . . . 146

Figure H1: Monetary policy uncertainty changes (*mpu*) on FOMC meeting days . . . 178

Figure H2: 10 Year Yield Response on Prominent Monetary Policy Uncertainty Dates . . . 179

Figure H3: Response of 3 month yield to monetary policy uncertainty . . . 180

Figure H4: Correlation between change in monetary policy uncertainty (*mpu*) and monetary policy surprise (*mps*) . . . 181

Figure H5: Standard deviation of international asset prices . . . 182

Figure H6: 10 Year Yield Response on Prominent Monetary Policy Uncertainty Dates . . . 183

Figure H7: Persistence of international asset price response to *mpu* . . . 184

Figure H8: Heterogeneity in response to *mpu* across countries . . . 185

Figure H9: Robustness of capital account openness interaction with mpu . . . 185

Figure H10: 2 and 10 Year Yield Response to Monetary Policy Uncertainty. Dropping One Country at a Time. 186

Figure H11: 2 and 10 Year Yield Response to Monetary Policy Uncertainty. Dropping One FOMC Date at a TIme. 187

CHAPTER 1

FINANCIAL CONSOLIDATION AND THE CYCLICALITY OF CORPORATE FINANCING

1.1 Introduction

The concentration and complexity of financial institutions can have major consequences for firms' access to finance and, ultimately, for investment and production decisions. An aspect that thus far has received limited attention is the way the structure of the financial sector influences the behavior of firms' financing over the business cycle. And yet, studying the drivers of cyclical financing patterns is critical for understanding firms' resilience to macroeconomic disturbances and the mechanisms of propagation of real and financial shocks. The goal of this paper is to investigate how changes in the degree of concentration and complexity of financial institutions shape firms' financing behavior over the business cycle. The United States provides a natural setting for our analysis. In the mid-1990s, banking regulatory reforms, especially the Riegle-Neal Interstate Banking and Branching Efficiency Act, allowed for financial institutions to engage in acquisitions and mergers across state lines. Since then, the US financial sector has seen a dramatic consolidation, with financial institutions becoming larger and more complex. Figure C1 illustrates the increase in the concentration of the US banking sector, as measured by the Herfindahl-Hirschman indices of bank loans and assets. In recent years, the share of banking assets held by the top 10 bank-holding companies has exceeded 60% (Fernholz & Koch (2016)).[1]

The literature has established three key facts about the cyclical behavior of publicly-traded firms' financing.[2] First, firms of all sizes borrow procyclically, that is, during economic expansions firms increase their debt.[3] Second, small and medium-sized firms issue equity procyclically, while

*This chapter is joint work with Raoul Minetti and Sotirios Kokas.
[1]See Berger et al. (1999) for further discussion on the implications of financial consolidation.
[2]Covas & Den Haan (2011), Jermann & Quadrini (2012), Karabarbounis et al. (2014) and Begenau & Salomao (2019) are primary examples.
[3]Unless otherwise stated, a "firm" refers to a publicly-traded US firm.

larger firms issue equity countercyclically. Third, liquidity accumulation follows the same pattern as equity issuance, with small and medium-sized firms increasing cash holdings during economic expansions and large firms increasing cash holdings during downturns. In this paper, we confirm these facts for the period 1981-2017; however, we show that the procyclical equity issuance and liquidity accumulation of small and medium-sized firms is driven by the latter half of this period. From the early 1980s to the late 1990s, in fact, equity financing and liquidity accumulation for firms of all sizes was countercyclical. After the mid-1990s banking regulatory reforms, the cyclicality of equity issuance and liquidity accumulation has changed dramatically for the firms most likely to have been impacted by the reforms: small and medium-sized firms with lower bargaining power vis-à-vis banks and that experienced an increase in the complexity of the relationships with their lending banks.

Following prior literature, we use data on US firms from the Compustat North America database to construct two types of data sets: aggregate time series and firm-level panel. We then document the cyclicality of financing during the 1981-2017 period for a sample of 16,675 firms and uncover a change in financing behavior for small and medium-sized firms in the late 1990s.[4] This change occurred earlier in US states that implemented earlier the Riegle-Neal Act, pointing to a role for the reforms that led to financial consolidation. Next, we match Compustat firms to syndicated loan data from Thomson Reuters LPCs DealScan database for the years 1987-2012. Using characteristics of lenders and loans, we provide further evidence that the US financial consolidation contributed to the change in cyclicality for small and medium-sized firms. Specifically, procyclical equity issuance and liquidity accumulation after the late 1990s is most prevalent among firms with a weaker relationship to their lenders, i.e. firms whose lenders were involved in a large merger or were acquired by a multi-bank holding company (increased size and complexity of lenders) and firms with a smaller set of available lenders (weaker firm bargaining power vis-à-vis lenders).

After uncovering evidence consistent with US financial consolidation as a driver of the changed cyclicality of small firm financing, we rationalize the empirical findings though a general equilib-

[4]In Section 1.4, we perform a Wald test to identify 1999 as the break year.

rium business cycle model with financial constraints. In the model economy, firms can borrow and issue equity to cover short-term and long-term financing needs (see, e.g., Jermann & Quadrini (2012)). Access to bank credit is constrained by imperfect enforcement of debt contracts. Access to equity markets entails equity issuance costs. We additionally allow firms to endogenously accumulate liquidity and directly bargain with their lending banks over the cost of short-term borrowing. The threat point of a firm in these negotiations is increased by holding liquidity, as this allows the firm to cover its short-term financing needs in case of withholding of bank credit.[5] Financial consolidation is then simulated in the model by weakening firms' bargaining power vis-à-vis their lending banks and strengthening banks' outside option. This financial consolidation produces cyclical financing patterns in line with those documented for small and medium-sized publicly-traded firms in the 1999-2017 period. Specifically, the documented change in cyclicality occurs in response to TFP shocks in the model, rather than shocks to firms' financial constraints. We show that this also holds true empirically.

The intuition for the theoretical results revolves around the idea that, after financial consolidation, smaller firms have stronger incentives to issue equity and accumulate precautionary liquidity following positive shocks. In particular, a firm's demand for labor can be met by accessing short-term bank credit or drawing down accumulated liquidity.[6] The firm bargains with the lender over the cost of bank credit. If a firm has high bargaining power vis-à-vis its lending bank and/or the bank has less valuable alternatives to lending to the firm, then the cost of accessing bank credit is low. When a positive TFP shock occurs, firms want to increase their labor. A firm with a low cost of accessing short-term bank credit (a "large" firm) simply increases borrowing and pays out higher profits from the positive shock to equity holders. A firm with a high cost of accessing bank credit (a "small" firm) will also desire to increase its labor; however, the lender can extract a high share of the surplus of doing so. In response, the firm will have the incentive to carry more liquidity to offset the bank's bargaining advantage. The firm finances this extra precautionary liquidity by issuing

[5]As it realistically takes time for a firm to issue equity, by assumption the firm cannot access equity at the time of bargaining with the lender; thus, the firm wants to be holding accumulated liquidity.

[6]See Lins et al. (2010) for evidence that firms substitute between cash and credit lines.

equity. As a result, both liquidity accumulation and equity issuance increase following a positive TFP shock, i.e. they behave in a procyclical manner. This pattern does not hold for a positive financial shock, as the loosening of the firm's borrowing constraint allows for a firm (regardless of bargaining power or the lender's outside option) to simply increase its debt issuance rather than its liquidity accumulation and equity issuance.

We next investigate how the changes in cyclical financing behavior prompted by financial sector consolidation affect the cyclical behavior of firms' investment and employment. Empirically, the investment and employment of small and medium-sized firms show an increased sensitivity to shocks in the post-financial sector consolidation period. By contrast, large firms' investment and employment sensitivity does not change following consolidation. In the model economy, pronounced effects of shocks on investment occur in the post-financial sector consolidation period via the financial channel illlustrated above. Specifically, firms' liquidity holdings magnify their ability to appropriate surplus when negotiating with banks, as well as increase the value of capital as collateral. The procyclical liquidity accumulation post-financial consolidation, therefore, boosts firms' returns from accumulating capital as a productive input and as collateral, increasing the sensitivity of investment to shocks.

Related literature. This paper contributes to three strands of literature. The first investigates empirically and theoretically the behavior of firm financing and liquidity accumulation over the business cycle. Covas & Den Haan (2011), Jermann & Quadrini (2012), Karabarbounis et al. (2014) and Begenau & Salomao (2019) generally find that debt issuance is procyclical in samples that begin in the early 1980s, while the cyclicality of equity issuance depends on firm size. Karabarbounis et al. (2014) show that equity issuance is procyclical for smaller firms and countercyclical for large firms. We confirm these prior studies for the baseline period of 1981-2017; however, we show that the finding of procyclical equity issuance for smaller firms is driven by the post-financial consolidation period. On the theoretical side, Covas & Den Haan (2012) and Jermann & Quadrini (2012) introduce financial frictions to generate a tradeoff between debt and equity financing over the business cycle. Unlike Covas & Den Haan (2012), this paper develops a general equilibrium model, which allows for the incorporation of employment. Further, neither of these models have a role for firm liquidity. Bacchetta et al. (2019) introduce firm liquidity holdings into a general equilibrium model in which firms pay wages using external financing or internal liquidity. Our model differs from Bacchetta et al. (2019) by allowing for bargaining between firms and their lenders. This allows for an analysis of the effects of financial consolidation on the cyclicality of firm financing.

The second strand of related literature investigates the effects of financial sector consolidation on non-financial firms. Di Patti & Gobbi (2007) show that Italian bank mergers reduced availability of credit to firms. Karceski et al. (2005) find that bank mergers in Norway lowered the equity value of publicly-traded firms that borrow from the merging banks. Carow et al. (2003) show that US bank mergers have negative equity effects for publicly-traded companies by decreasing their bargaining power vis-à-vis the merging lenders. We contribute to this literature by exploring the impact of financial consolidation on the cyclicality of firms' financing, and the consequences to the cyclical behavior of investment and employment.

Finally, we contribute to the literature on the relative importance of TFP shocks and financial shocks to the business cycle. Jermann & Quadrini (2012) find that financial shocks are an important driver of the US business cycle. In contrast, Zetlin-Jones & Shourideh (2017) and Guo (2019) suggest that financial shocks have small effects on real GDP. We find that large firms' debt issuance, equity issuance and liquidity accumulation respond to financial shocks. This was true of smaller firms as well, prior to financial consolidation, while equity issuance and liquidity accumulation are mostly driven by TFP shocks in the post-consolidation period. Through this financial channel, TFP shocks could have gained relative importance over the past two decades.

The remainder of the paper is organized as follows. Section 2 details data and variable definitions. Section 3 presents the empirical results using aggregate time series and firm-level panel data. Section 4 shows that the empirical results are robust to alternate specifications. Section 5 utilizes syndicated loan data to provide empirical evidence that financial consolidation can help explain the empirical findings. Section 6 describes the business cycle model. Section

7 simulates financial consolidation in the model. Section 8 provides empirical evidence on the relative importance of TFP shocks and financial shocks to the cyclicality of financing behavior. Section 9 presents evidence that smaller firms' investment and employment have become more sensitive to shocks in the post-financial consolidation period. Section 10 concludes. Additional results are relegated to the Online Appendix.

1.2 Empirical Evidence

This section describes the data sources we use to explain how and why firm financing behavior has changed over time. This paper uses two primary data sources: Compustat and DealScan. Compustat provides balance sheet data for publicly-traded firms. The DealScan database contains information describing the syndicated lenders for firms in the Compustat sample. We complement these primary sources with the Call Report data from the Federal Reserve Bank of Chicago for information on the bank-holding status of financial institutions and the Merger Description data from the Federal Reserve Bank of Chicago for information on the timing and characteristics of bank mergers.

1.2.1 Firm-Level Data

The 1981-2017 Compustat North America - Fundamentals Annual files include publicly-traded firms. Compustat firms account for approximately one fourth of total private sector U.S. employment; thus, they represent an economically important sample of businesses (see, e.g., Davis et al. (2006)). We are interested in the effects of consolidation among financial institutions (banks), and publicly-traded firms may not be as reliant on bank debt as private firms. However, Table B1 shows that bank debt accounts for an important share of total debt amongst Compustat firms: over 20% of total debt for the average firm in Compustat.[7] Bank debt has also been shown to play a key role in the sensitivity of Compustat firms to shocks. For example, Ippolito et al. (2018) find that

[7]We proxy for bank debt by subtracting commercial paper (CMP) from long-term debt - other (DLTO), as in Lee (2017). Alternatively, Crouzet (2020) creates a bank debt proxy by summing DLTO and notes payable (NP). Using this alternative measure would result in an even higher bank debt share for Compustat firms.

Compustat firms with a higher ratio of bank debt to assets are more sensitive to monetary policy shocks.

The relevant variables for our analysis are primarily those reported in the cash flow statement, which are not well-populated prior to 1981.[8] Firms incorporated outside of the United States are dropped from the sample. Financial firms (SIC 6000-6999), utility firms (SIC 4900-4999) and quasi-governmental firms (SIC 9000-9999) are also excluded. The latter two groups are heavily regulated, which makes their financing decisions distinct from other corporate firms. Similarly, financial firms are subject to regulations, such as capital requirements, that uniquely affect their financing behavior. As in Covas & Den Haan (2011), three additional restrictions are made. First, we remove any firm that engaged in a major merger during the 1981-2017 time period.[9] Second, we remove General Electric, General Motors, Ford and Chrysler, as these firms were heavily affected by the FASB94 accounting rule instituted in 1988. Third, we drop any firm-year observations where the accounting identity (assets = liabilities + equity) is violated by more than 10% of the firm's book value of assets. Finally, any firm-year observations with missing values for assets, liabilities, equity, debt, cash or (net) capital stock are dropped.

Creation of the primary financing variables most closely follows Eisfeldt & Muir (2016). Net debt issuance is computed as long-term debt issuance (DLTIS) minus long-term debt reduction (DLTR) plus changes in current debt (DLCCH) minus (net) interest paid (XINT).[10] Net equity issuance is the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC) minus cash dividends (DV).[11] Liquidity accumulation is defined as the

[8]Other papers in this literature also tend to begin their samples in the early 1980s, due to changes in U.S. financial markets and the general behavior of numerous economic variables, e.g. the Great Moderation. In the Online Appendix, we show that the results are virtually unchanged if we start the sample in 1984, rather than 1981.

[9]A "major merger" is defined as any merger or acquisition where sales increased by at least 50 percent afterwards (Compustat sales footnote code AB).

[10]For firms with an scf code of 1, DLCCH is subtracted. As described in Chang et al. (2014), prior to the adoption of uniform reporting rules in 1988, DLCCH that was reported on a firm's working capital statement (scf = 1) has the opposite sign as when reported on other financial statements. For firms with a data code of 4, DLCCH was assumed to be included in DLTIS, so DLCCH was set to zero.

[11]Missing values of DV are set to zero in order to avoid too many missing values for net equity issuance. We show in the Robustness section that using net sale of stock (i.e. SSTK minus PRSTKC) produces results very similar to the equity issuance measure. Thus, the results are not driven by the behavior of dividends.

change in cash and cash equivalents (CHE_t - CHE_{t-1}).[12] All variables are normalized by the lagged book value of total assets (AT). We show in the Robustness section that the results hold if we instead normalize by the lagged (net) capital stock (PPENT).

As in Covas & Den Haan (2011), firms are grouped into size bins using acyclical cutoffs of the book value of total assets. Specifically, firms are first split into size groups by the previous year's asset value. We define small firms as those with a book value of assets below the 60th percentile and large firms as those above the 60th percentile (excluding the top 10 percent of firms).[13] A (log) linear trend is then fit through these annual cutoff values and used as the new cutoff values for firm size groupings. This prevents the cutoff values themselves from being cyclical; however, the results using the original cutoff values are very similar to those with the adjusted values.

For the aggregate time series results, we follow a similar methodology as Eisfeldt & Muir (2016) and Covas & Den Haan (2011). Specifically, we sum the financing variable of interest for all firms of a size classification within a year. Then, we divide each series by the sum of the asset value for all firms of a size classification within a year to create the aggregate series by size. Finally, we HP filter the aggregate financing series to produce a stationary series.[14] The cyclical component of this HP-filtered series is then used in all correlations to remove the longer-run trends in the variables. While it has been standard to use HP filtering in this literature, Hamilton (2018) warns that HP filtering can cause spurious correlations. We show in the Robustness section that the results hold if we use either the non-HP-filtered financing series or if we filter based on the Hamilton (2018) methodology.[15] Further, the firm-level panel regressions do not use filtering and still produce results similar to those found with the HP-filtered aggregate series; thus, the results are not driven by the choice to use HP filtering.

[12] We use the balance sheet version of cash, rather than the cash flow statement version (CHECH). This is due to CHECH being unavailable prior to 1984. We show in the Robustness section that the results hold using either version of liquidity accumulation, as well as using change in cash only (CH_t - CH_{t-1}), i.e. excluding cash equivalents.

[13] See Eisfeldt & Muir (2016) for a description of how the top 10 percent of firms present measurement problems and anomalous financing behavior that makes their inclusion in the sample misleading of firm dynamics.

[14] For the baseline results, we use annual data; thus, the smoothing parameter is set to 100. For quarterly data, the smoothing parameter is set to 1600.

[15] To perform the Hamilton (2018) filtering, we use the Diallo (2018) HAMILTONFILTER Stata command. For annual data, this amounts to using the residual from regressing the variable of interest at year t on its values at year $t-2$ and $t-3$.

Splitting by firm size categories, Table B1 shows summary statistics of asset value, firm age and key financing variables for the 16,675 firms in the sample. Since all firms are publicly-traded, even "small firms" are quite large relative to the typical private firm. Still, there is a sizable discrepancy between the firm categories: the average small firm has an asset value of $71.5 million, while the average large firm has an asset value of $931 million. As expected, larger firms tend to be older. Smaller firms rely more on equity financing than larger firms and also tend to accumulate more liquidity. During the sample period 1981-2017, approximately 90% of firms fall within their modal firm size category. Put differently, firms rarely cross size bins. This suggests we can (approximately) treat firm size as a fixed firm characteristic.

1.2.2 Lender Data

We use information on syndicated loans from the Thomson Reuters LPC's DealScan database for the years 1987-2012. This database allows us to link syndicated lenders to their borrowing firms in Compustat. The syndicated loan market consists of groups of lenders that jointly loan funds to a single borrowing firm. A subset of the lenders in a syndicate are the lead arrangers. The lead arrangers agree with the firm on the key characteristics of the loan, including loan amount, collateral, and interest rate. They are also responsible for inviting the other syndicate lenders to join. The non-lead members of the syndicate ("participants") provide funds and assist in the administrative tasks (Delis et al. (2017)).

Using the DealScan database, we create a pool of lenders for each Compustat firm that matches to DealScan. Specifically, any lender that was engaged in a syndicated loan relationship with a firm in the current year, the previous 5 years or the next 5 years are classified as belonging to a firm's lender pool. Since firms do not necessarily participate in the syndicated loan market every year, using a window of ±5 years allows us to capture those banks that act as key lenders to the firm in the current period.[16] Both the lead lenders and participants interact, and contract, directly with the firm (Mugasha (1998)). This allows the lenders, including the participant lenders, to gain important

[16]The results are generally robust to using a different window length.

information about the borrowing firm through the syndicated loan agreement (Li (2017)).

After creating this lender pool, we are interested in measures of the relative power of the lenders vis-à-vis the borrowing firms. We use various proxies: the total number of lenders in a firm's pool, the share of syndicated loans provided by the lead lender(s), an indicator for a lender recently being acquired by another lender, and an indicator for a lender recently joining a multi-bank holding company. The last two indicators represent exogenous changes in the relationship between a firm and a lender. In Section 1.5, we use these proxies to present evidence that an increase in the size and complexity of the lending banks is a key driver in changing the cyclicality of small and medium-sized firms' financing behavior.

1.3 Firm Financing over the Business Cycle

In this section, we present evidence of a structural break in the financing behavior of small and medium-sized publicly-traded firms in the late 1990s. In an April 2001 speech, Federal Reserve Vice Chairman Roger Ferguson noted that "Financial consolidation has helped to create a significant number of large, and in some cases increasingly complex, financial institutions" and that "the pace of consolidation increased over time, including a noticeable acceleration in the last three years of the [1990s]" (Ferguson (2001)). A key contributor to this consolidation was the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, which applied to states at different dates between 1994 and 1997.[17] Heiney (2010) presents evidence that the banking sector consolidation of the 1990s begins to slow down after 1999. As shown in Figure C1, the concentration of the banking sector, as measured by Herfindahl-Hirschman indices of bank loans and assets, noticeably increases between the passage of Riegle-Neal in 1994 and the end of the 1990s. The other major financial reform of the 1990s, the Gramm-Leach-Bliley Act, was passed in 1999 and allowed for bank holding companies to integrate their commercial banking activities with investment banking. For the above reasons, the year 1999 serves as a natural partition for our analysis.[18]

We show that, prior to 1999, the cyclicality of debt issuance, equity issuance and liquidity

[17]See Dick (2006) for a list of state-specific dates of adoption.

[18]Additional empirical evidence for using the year 1999 is presented below in the Robustness section.

accumulation behaves similarly for smaller and larger firms. But, after 1999, the financing behavior of small and medium-sized firms becomes significantly different than larger firms. Specifically, these firms begin to issue equity and accumulate liquidity in a procyclical fashion. These results hold using both the correlations of aggregated time series data and panel regression estimates of disaggregated firm-level data. The following sections explore the potential causes of this change in cyclicality and find that the mechanisms are consistent with financial consolidation: a weakening of smaller firms' bargaining power vis-à-vis their lending banks and an increase in the complexity of their relationships with banks.

1.3.1 Aggregate Time Series Evidence

To visually illustrate the main stylized facts documented in this paper, Figure C2 plots the aggregate time series of debt issuance (Panel a) and equity issuance (Panel b) separately for "small" (asset value below the 60th percentile) and "large" firms (asset value between the 60th and 90th percentiles), as well as the cyclical component of real corporate GDP. All series are standardized to have a mean of zero and unit variance. In Panel (a), the debt issuance series for small and large firms essentially overlap each other for the entire 1980-2017 period. They also clearly comove positively with cyclical GDP, i.e. debt issuance is procyclical for both small and large firms. In Panel (b), the equity issuance series for both small and large firms positively comove throughout the first half of the sample period; however, these series negatively comove during the 2000s. In terms of cyclicality, both small and large firms negatively comove with cyclical GDP in the first half of the time period, while the equity issuance of small firms positively comoves in the latter half. The behavior of the liquidity accumulation series is quite similar to that of equity issuance. In what follows we more rigorously demonstrate that the cyclicality of small firms' equity issuance and liquidity accumulation changed in the late 1990s and uncover a role for financial consolidation in this phenomenon.

Using the aggregate series displayed in Figure C2, Table B2 presents the correlation between each of the main financing variables and the cyclical component of real corporate GDP.[19] Panel A shows the correlations for the entire 1981-2017 period.[20] As commonly found in the literature, debt issuance is strongly procyclical for firms of all sizes, while equity issuance and liquidity accumulation are procyclical for smaller firms and countercyclical for large firms. One of the insights of this paper is evident by comparing Panel B to Panel C: the commonly found procyclicality of small firms' equity issuance and liquidity accumulation is driven by the post-1999 time period (Panel C). One can see from Panel B that equity issuance and liquidity accumulation are countercyclical for smaller firms prior to 1999. In contrast, large firms behave virtually the same in both periods.

1.3.2 Firm-Level Evidence

Next, we reproduce these cyclical financing patterns using firm-level panel data, which allows for the addition of firm characteristics beyond size. Table B3 displays results from estimating a total of 24 regressions with the following 3 specifications. First, the reported coefficients are estimated by 12 regressions (2 time periods x 3 financing variables x 2 size groups) of the following specification:

$$V_{i,t} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \beta Y_t + \Gamma' Z_{i,t-1} + e_{i,t} \tag{1.1}$$

where $V_{i,t}$ is the financing variable of interest normalized by the lagged book value of assets, α_0 is a constant [21], t and t^2 capture trends in the financing variable, Y_t is the cyclical component of real corporate GDP normalized such that a unit increase in Y_t indicates moving from the lowest value of the cyclical component to the highest value during the sample period 1981-2017, $Z_{i,t-1}$ includes the lagged values of the controls, and $e_{i,t}$ is the error term. For the baseline specification, we follow Covas & Den Haan (2011) and include the following controls: firm's cash flow and Tobin's Q, where each control variable is the difference between the firm's value at $t-1$ and the respective size group's mean value at $t-1$. This normalization prevents the controls from picking up variations

[19]Following most of the literature, we use the cyclical component of HP-filtered real corporate GDP to measure the business cycle. In the Robustness section, we show that the results are robust to alternative measures.
[20]Since we HP filter the variables for the baseline results, there is potential for end-point bias. In the Online Appendix, we drop the first and last three years from the baseline sample and show that the results are nearly identical.
[21]Next we show that including a firm fixed effect produces similar results.

in aggregate economic conditions.[22] We report the β coefficient in the tables, with standard errors in parentheses clustered along both the time and firm dimensions.

Second, the reported p-values are the result of 6 regressions (2 time periods x 3 financing variables) where the 2 firm size groups are pooled:

$$V_{i,t} = \alpha_j + I(j)_{i,t}(\alpha_{1,j}t + \alpha_{2,j}t^2 + \beta_j Y_t + \Gamma'_j Z_{i,t-1}) + e_{i,t} \tag{1.2}$$

where α_j is a size group j fixed effect and $I(j)_{i,t}$ is an indicator for the size group to which firm i belongs to in year t. This indicator is interacted with all of the explanatory variables. We report the p-values of β_{large}, where $small$ is the base group. These p-values indicate whether the cyclicality of the $small$ group statistically differs from the large group.

The bold coefficients in the post-1999 period are based on the p-values from 6 regressions (3 financing variables x 2 size groups) where the 2 time periods are pooled:

$$V_{i,t} = \alpha_k + I(k)_{i,t}(\alpha_{1,k}t + \alpha_{2,k}t^2 + \beta_k Y_t + \Gamma'_k Z_{i,t-1}) + e_{i,t} \tag{1.3}$$

where α_k is a time period k fixed effect and $I(k)_{i,t}$ is an indicator for the time period to which firm i belongs to in year t. This indicator is interacted with all of the explanatory variables. We bold the coefficients in the post-1999 period to indicate a p-value below 0.05 for the coefficient $\beta_{post1999}$, where $pre1999$ is the base group. These p-values indicate whether the cyclicality of the variable of interest is statistically different in the 1999-2017 period, relative to the 1981-1998 period.

Panel A of Table B3 reports the baseline panel results. The coefficients can be interpreted as the effect on the financing variable (as a percentage of the firm's asset value) of moving from the lowest realization of the business cycle measure in the full sample period 1981-2017 to the highest realization, i.e. a positive coefficient indicates a procyclical relationship. First, note that the strength and direction of the cyclicality implied by the coefficients in Panel A qualitatively match quite closely with the aggregate correlations in Panel B and Panel C of Table B2. Thus,

[22]Using a small number of controls allows for a parsimonious model; however, it does not rule out the possibility that the estimated cyclicality by firm size is driven by omitted non-size variables. On the one hand, firm size is intended to broadly capture characteristics shared by firms of similar size. Still, in the Online Appendix we show that the firm size results hold when we allow a wider set of firm characteristics to explain cyclicality in financing variables.

while the panel regressions treat each firm observation equally, the results are quite similar to the aggregate data, where firms are weighted by their asset value. Second, the p-values in the pre-1999 period for equity issuance and liquidity accumulation are at or below 0.10, indicating statistically significant differences in the cyclicality of equity issuance between small firms and large firms. Third, as indicated by the bold coefficients in Panel A, the cyclicality of equity issuance and liquidity accumulation for small firms are significantly different in the post-1999 period than the cyclicality of small firms in the pre-1999 period. For small firms, the sign of the coefficient flips, with the magnitude of the coefficients in the post-1999 period being quite similar to the pre-1999 coefficients in absolute value. In sum, we detect large and statistically significant changes in the financing behavior of only small firms for the post-1999 period.

We can get a sense of the magnitude of changes in GDP on equity issuance by converting to a one-standard deviation change in cyclical GDP. Moving from the lowest realization of the business cycle measure in the full sample period 1981-2017 to the highest realization is approximately a 4.5 standard deviation change. Thus, dividing the post-1999 equity issuance coefficient for small firms of 11.12 by 4.5 results in a standardized coefficient of 2.5. Comparing to the simple average equity issuance for small firms of 19.1% of assets (see Table B1), this amounts to an effect equivalent to 13% of average equity issuance. Alternatively, we could compare to the average annual aggregate equity issuance for small firms of 9.85%. This amounts to an effect equivalent to 25% of average equity issuance. Changes in GDP thus appear to have an economically significant effect on firm equity issuance.

To this point, the regressions have not included a firm fixed effect; however, it could be the case that an idiosyncratic firm component is responsible for the results. We next include a firm fixed effect to control for permanent heterogeneity. Since the Compustat sample contains a substantial amount of firm entry and exit, we do not want the firm fixed effect to be endogenous. As a result, we keep only firms that have greater than 5 years of data within a subperiod. In Table B11, we report the results of estimating the baseline specification while including this firm-specific constant term. As with the baseline specification, equity issuance and liquidity accumulation are countercyclical in the pre-1999 period and significantly more procyclical in the post-1999 period.

However, since firms rarely move between the two firm size categories, the inclusion of a firm fixed effect does not exploit within-firm size variance over time. As an alternative, we next use a continuous firm size measure. Specifically, we want to answer the question, "During the post-1999 period, does equity issuance and liquidity accumulation for a firm become less procyclical as that individual firm grows?"We re-estimate the baseline panel specification with the following changes: the addition of a firm fixed effect, the use of a continuous measure of size (i.e. log of asset value) and the demeaning of the continuous size measure at the firm level. The specification is the following:[23]

$$V_{i,t} = \alpha_i + \alpha_1 t + \alpha_2 t^2 + \beta_1 (s_{it} - E_i[s_i]) Y_t + \Gamma' Z_{i,t-1} + e_{i,t} \tag{1.4}$$

where α_i is a firm i fixed effect. The variable s_{it} measures firm i's size (i.e. log of asset value) in year t and $E_i[s_i]$ is the average size of firm i in the sub-period. With this specification, the cyclicality of a firm's financing variables is identified by the variation in a firm's current size relative to that firm's average size.

In the post-1999 period, one would anticipate that a firm's equity issuance and liquidity accumulation becomes significantly less procyclical as it grows, i.e. looks more like a "large" firm. The results in Panel B of Table B3 show that this is true.[24] As well, this was clearly not true of the pre-1999 period. Given these empirical results, Section 5 will use information about firms' lenders to investigate what caused smaller firms' financing behavior to change post-1999.

1.4 Robustness

This section first presents evidence that the change in smaller firm behavior occurred around 1999, consistent with the importance of financial consolidation. Then, we show that the empirical results are robust to alternative specifications and assumptions. Specifically, we test the robustness of the main finding: equity issuance and liquidity accumulation became procyclical in the 1999-2017 period for smaller firms only.

[23]We again drop firms that appear in fewer than 6 sample years to prevent the firm fixed effect from being endogenous.

[24]The Online Appendix presents the results of using continuous size without a firm fixed effect or isolating within-firm variance. The results are consistent with the baseline categorical size findings.

1.4.1 Identifying the Structural Break

Thus far, we have used 1999 as the year where small firms experienced a structural break in their equity issuance and liquidity accumulation. Intuitively, 1999 is a natural break year, as a substantial portion of the post-reform financial consolidation had occurred by 1999. To provide evidence of the suitability of this assumption, we regress the aggregate financing variable series for small firms on the cyclical component of real corporate GDP. We then perform a Wald test for a structural break in the estimated cyclicality coefficient. In Figure C6, we plot the p-values of these Wald tests for each year from 1984-2014. Unsurprisingly, the p-values for debt issuance are never below 0.1, as there is not strong evidence for a change in the cyclicality of debt issuance. Conversely, the p-value for a structural break in equity issuance is at its lowest, below 0.1, in 1999.[25] The results for liquidity accumulation are similar, with the p-value falling below 0.1 in 1999. We conclude that 1999 is the strongest candidate for a structural break in the cyclicality estimates.[26]

1.4.2 Other Robustness Tests

One potential concern with the empirical results is that, rather than capturing the cyclicality of smaller firms, they could be capturing the cyclicality of firm entry. In other words, during an expansion, many young firms choose to go public and disproportionately issue equity. To account for this, we restrict the sample to only those firms that entered the Compustat sample prior to 1990 and were also in the sample in 2017. Despite severely restricting the sample, Table B11 shows that the results hold. Thus, the findings are not driven by firm entry or a change in the composition of the sample over time.

Next, one may prefer alternative definitions of the financing variables. Table B12 displays the results of alternative definitions for equity issuance and liquidity accumulation. We split the net equity issuance variable into its two components: net sale of stock and dividend payouts. Recall

[25]Similarly, we also rerun the baseline panel results using different break years. This method produces similar results as the Wald test, which is that the pre-1999 vs post-1999 break is the break year with the highest significance and the results weaken as the break year moves away from 1999.

[26]Given the literature discussed above that shows an increase in financial consolidation beginning in the mid-1980s, it is not surprising that there is a decreasing trend in the p-values of our Wald tests throughout much of the 1990s.

that net equity issuance is the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC) minus cash dividends (DV). Table B12 shows that the net sale of stock (i.e. excluding cash dividends) results closely match the equity issuance results. Thus, the behavior of dividend payouts does not drive the findings. The main results also qualitatively hold for three alternative definitions of liquidity accumulation. The first alternative definition uses the cash flow statement version of change in cash and cash equivalents, rather than the balance sheet version used in the baseline estimates.[27] The second alternative definition uses changes in cash only, rather than cash and cash equivalents. The third definition uses retained earnings.

While it is standard to use HP-filtering in this literature, it could be the case that the filtering of the GDP measure and/or financing variables (aggregate results only) are non-trivially impacting the results. In Table B13 we reproduce the baseline correlation results with the non-filtered financing series and the annual growth rate in real corporate GDP. The main findings are less strong, but the general pattern clearly holds. Next, we additionally show that filtering the financing series and/or GDP using the Hamilton (2018) methodology produces qualitatively similar results to the baseline estimations. Appendix Table B13 shows this for the aggregate correlation results. Overall, the results are not dependent on the choice to HP-filter the data.

Finally, we include a few additional robustness checks in the Online Appendix. First, we verify that the findings are not driven by the cyclicality or potential endogeneity of asset value. We do so with two robustness checks: normalizing the financing variables by the (net) capital stock value or by the firm's first reported asset value. Both normalizations produce results quite similar to our baseline findings. Second, we exclude all observations with any merger, rather than just firms that experienced a major merger. The results are largely unchanged to this exclusion; thus, the findings are not due to, for example, the issuance of equity during the merging process. Third, one might be concerned that small firms are more likely to be on the verge of bankruptcy, i.e. financially distressed, and that our results might then be picking up the impact of financial distress. We have already confirmed that the results are not driven by firm entry or exit. But, in the Online Appendix,

[27]The cash flow statement version is not available until 1984.

we exclude firms that are considered "financially distressed" according to the Altman Z-Score. The results remain largely unaltered.

1.5 The Role of Financial Consolidation

We study the role of financial consolidation in driving the change in small firms' financing cyclicality. We first exploit the staggered adoption of the Riegle-Neal Interstate Banking and Branching Efficiency Act and show that the change in financing cyclicality is most pronounced amongst firms headquartered in states that adopted Riegle-Neal earlier. Next, we create a pool of lenders with whom Compustat firms have a syndicated loan relationship, as detailed in Section 1.2. The characteristics of these firms' key lenders are then used to test whether a change in bargaining power and bank complexity contributed to the flip in financing cyclicality for smaller firms beginning in the late 1990s.

1.5.1 Timing of Riegle-Neal Adoption

The Riegle-Neal Interstate Banking and Branching Efficiency Act was passed in 1994, but states individually passed legislation that determined when Riegle-Neal went into effect. This led to staggered adoption during the years 1995 (14 states), 1996 (12 states) and 1997 (24 states). We test whether the year of adoption is associated with different procyclicality of equity and liquidity for smaller firms using the following specification:

$$V_{i,t} = \alpha_h + \alpha_1 t + \alpha_2 t^2 + I(h)_i \beta_h Y_t + \Gamma' Z_{i,t-1} + e_{i,t} \tag{1.5}$$

where h is the year of Riegle-Neal adoption for the state in which a firm is headquartered and $I(h)_i$ is an indicator for this year. In Table B4, we display the estimates of β_{1995}, β_{1996} and β_{1997} for smaller firms in the periods 1981-1998, 1999-2009 and 1999-2019. Panel C (1999-2019) shows that equity and liquidity are significantly less procyclical for firms headquartered in 1997 adopters. This is especially true for the first decade after reform, as seen in Panel B (1999-2009). These same trends were not apparent prior to Riegle-Neal (see Panel A: 1981-1998). These results suggest that the state-specific adoption of Riegle-Neal noticeably contributed to the change in cyclicality patterns identified above. In what follows, we use matched bank-firm information to further test the effects of financial consolidation on financing cyclicality.

1.5.2 Measures of Financial Consolidation

a. Reduction in Firms' Bargaining Power vis-à-vis Lenders

In Table B5, we re-estimate the baseline panel regression with an additional interaction term to test whether a reduction in firms' bargaining power vis-à-vis banks is associated with the documented change in cyclicality for smaller firms post-1999:

$$V_{i,t} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \beta_1 Y_t + \beta_2 X_{i,t} + \beta_3 Y_t * X_{i,t} + \Gamma' Z_{i,t-1} + e_{i,t} \tag{1.6}$$

where $Y_t * X_{i,t}$ is the interaction of our business cycle measure, Y_t, with a characteristic of the firm's lender pool, $X_{i,t}$. The main coefficient of interest is β_3, which captures the effect on the cyclicality measure, Y_t, of moving from the 25th percentile value for the characteristic of the firm's lender pool to the 75th percentile value. Since we are interested in only the interaction term, we could alternatively replace the trend variables with a year fixed effect to control for omitted aggregate variables. Doing so does not meaningfully change our estimates of β_3.

Sharpe (1990), Rajan (1992), Boot (2000) and Ongena & Smith (2001) show that a single bank can extract monopoly rents through future loans to the firm. Borrowing from multiple banks moderated such "hold-up" issues. In Panel A of Table B5, we use the total number of lenders in the created firm's lender pool as the proxy for a firm's outside options in bargaining with a lender. Here, a higher number of lenders for smaller firms in the post-1999 period is associated with a *less* procyclical equity issuance and liquidity accumulation, as well as a more procyclical debt issuance. This suggests that the cyclicality of smaller firms financing behavior moves in the direction of larger firms cyclicality when smaller firms have a larger set of lenders. By contrast, no such evidence emerges for the pre-1999 period.

Next, we proxy for the firm's outside option with the lead lender(s) average share of the total syndicated loan value for a firm. As demonstrated by Rajan (1992), the larger the share of the lead lender, the stronger the informational monopoly power of the lender vis-à-vis the firm. Thus, a high lead lender share suggests that the firm is more reliant on the lead lender for financing. As expected, in Panel B, we see that the more concentrated the syndicated loans amongst the lead lender(s), the less that small firms behave like large firms, in terms of the cyclicality of debt issuance, equity issuance and liquidity accumulation.

Importantly, the interaction coefficients for the pre-1999 period are generally insignificant and opposite of the post-1999 sign. For example, decreasing the number of lenders in post-1999 is significantly related with a more procyclical equity issuance for smaller firms; however, there is no relationship pre-1999. Table B1 shows means for key characteristics of the syndicated lenders. Our proxies have not seen substantial change from the pre to post periods. But the size/strength of the lenders in the lender pools has seen a noticeable increase, as illustrated by the average lender's share of state assets and the average lender's Lerner index.[28] Thus, for a given reduction in the number of available lenders for a firm, the effect is stronger in the post-1999 period. This suggests that financial consolidation influenced the impact of firm-bank relationships on financing behavior by increasing the intensity of the effect, i.e. a change in available lenders matters more because the lenders themselves are "stronger".

To probe this point further, we next use a proxy for the lender's market power. We re-estimate similar regressions as above; however, the interaction term now flags when a firm's lender has recently been acquired by another lender. This plausibly captures an exogenous change in the market power of a firm's lender. Panel A of Table B6 shows evidence for the full 1985-2012 period that a firm's lending bank being acquired by another bank matters, i.e. it is associated with increased procyclicality of smaller firms' equity and liquidity. While we do not find that this marginal effect of mergers is stronger in the post-1999 period, it is the case that mergers occur twice as frequently in the DealScan sample during this latter period (see Table B1). This suggests the overall contribution of mergers to smaller firms' cyclicality has become more important via the increased incidence of mergers. Additionally, one would expect that a larger merger would have a

[28]The Lerner index is the difference between the price of bank production and the marginal cost, divided by the marginal cost.

greater impact on the borrowing firms. Panel B of Table B6 presents a triple interaction between the size of the merger (i.e. the percentage increase in the original lender's asset value due to the merger), the incidence of a merger and cyclical GDP. Increasing the size of the merger in the All Lender Pool by one standard deviation leads to an additional 23.38 percentage point increase in the procyclicality of equity issuance and an additional 10.56 percentage point increase for liquidity accumulation.

We can further assess the impact of a bank merger by splitting firms into those with few outside options and those with many outside options. One would expect the impact of a bank acquisition to be greater for those firms with fewer lenders in their lender pool. In Panel C of Table B6, we split our sample into firms with a below average number of lenders ("Few Lenders") and firms with an average or above number of lenders ("Many Lenders"). As expected, firms with few lenders whose lead lender was recently acquired by another lender have significantly more procyclical equity issuance. In contrast, firms with many lenders see no effect from a lead lender acquisition. Table B14 shows qualitatively similar results for the acquisition of any lender.

b. Increased Complexity in Bank-Firm Relationships

Panel A of Table B7 repeats the same exercise with an interaction term to test whether increased distance between the firm and the lender can explain the documented changes in cyclicality. Here, the term "distance" refers both to physical distance as well as the level of complexity in the relationship between a firm and lender. First, we interact the business cycle measure with whether any of the firm's lenders has joined a multi-bank holding company (MBHC) within the past 5 years. Joining a MBHC is evidence that more of the lender's decisions are moved away from the local loan officers to far-away headquarters. Thus, the bank is less interested in (has a looser link with) the local firm.[29] Equity issuance is significantly more procyclical for those small firms who have a lender in their pool who has recently joined a MBHC. There is also a similar effect from a *lead* lender joining a MBHC.

Note that the base group, i.e. those firms without a lender who has recently joined a MBHC,

[29]Berger et al. (2005) show that larger banks tend to have shorter, more impersonal lending relationships with firms.

still includes many lenders who had previously joined a MBHC more than five years ago. Thus, this would be expected to attenuate our estimate of β_3. Still, we find a significant effect consistent with a weakening in the relationship between a firm and a lender leading to a more procyclical equity issuance.

Finally, we can further assess the impact of increased complexity by splitting firms into those with few outside options and those with many outside options. In Panel B of Table B7, we split our sample into firms with a below average number of lenders ("Few Lenders") and firms with an average or above number of lenders ("Many Lenders"). Firms with few lenders whose lead lender recently joined a MBHC have significantly more procyclical equity issuance. In contrast, firms with many lenders see no effect. Table B14 shows qualitatively similar results for any of the firm's lenders joining a MBHC.

1.6 The Model

Motivated by the empirical findings, we study a general equilibrium business cycle model with financially constrained firms. In line with the empirical setting, firms can finance short-term and long-term financing needs via borrowing or equity issuance. The model economy builds upon Covas & Den Haan (2012), Hennessy & Whited (2005) and Jermann & Quadrini (2012). Our model most closely resembles Jermann & Quadrini (2012); however, we depart in at least two key ways. First, we allow for firms to hold liquidity. This is important to investigating the comovement of debt issuance, equity issuance and liquidity accumulation. Second, we posit that firms bargain with banks over the cost of loans. This endogenizes the desire for firms to hold liquidity.

1.6.1 Firm Technology and Financing

Time is discrete and infinite (see Figure C3 for the within-period timeline of the economy). There is a $[0,1]$ continuum of firms with a production function $F(z_t, k_t, n_t) = z_t k_t^{\theta} n_t^{1-\theta}$, where z_t is stochastic aggregate productivity, k_t is the firm's capital stock, and n_t is the firm's labor. Capital evolves according to $k_{t+1} = (1-\delta)k_t + i_t$, where i_t is investment and δ denotes the depreciation rate.

Firms have access to three forms of external financing: equity issuance, intertemporal debt (bonds) and an intraperiod loan, obtained from a lender (bank). The amount of intraperiod borrowing from a bank is subject to constraints, due to enforcement problems. Firms can issue equity by decreasing their equity payout, d_t, where a negative value indicates net equity issuance. Firms that deviate from the long-run equity payout target are subject to a quadratic cost that makes the total cost of equity payouts $\varphi(d_t) = d_t + \kappa \cdot (d_t - \bar{d})^2$, where $\kappa \geq 0$ represents the friction of substituting from debt financing to equity financing and $\bar{d}$ is the long-run (steady-state) equity payout target. Intertemporal debt, b_t, has a tax advantage that makes it preferable to issuing equity. This preference of debt to equity follows the standard pecking order assumption found in models such as Jermann & Quadrini (2012) and Hennessy & Whited (2005). Specifically, firms face an effective gross interest rate of $R_t = 1 + r_t(1 - \tau)$, where r_t is the interest rate and τ is a tax subsidy. The intraperiod bank loan will be discussed in further detail below.

Firms can accumulate liquidity, a_t, and carry it between periods. Holding liquidity allows firms to cover current period operating costs and reduces the amount of external financing required. With the standard assumption of $\beta R < 1$, liquidity must provide some additional benefit that justifies the firm holding liquidity between periods rather than reducing its intertemporal debt, b_t, and associated interest payments. Firms choose to hold liquidity in this economy for two reasons: to increase their threat point in bargaining over the cost of the intraperiod bank loan and to pay for labor expenses.

Specifically, firms enter the period holding capital for use in production; however, in order to produce, they must also hire labor at the beginning of the period. If firms enter the period holding less liquidity than necessary to cover desired labor expenses, then they can pay for these labor expenses by borrowing via an intraperiod bank loan, l_t. The firm and lender bargain over repayment on the intraperiod loan, i.e. the net cost e_t per unit of loan. This reveals two benefits to a firm from carrying liquidity. First, holding liquidity reduces the size of the intraperiod loan that a firm desires, all else equal. Second, as detailed below, holding liquidity increases the value of the firm's threat point in the process of bargaining over loan repayment e_t. The effect of both is to decrease the total cost of financing labor expenses.

To make the solution of the bargaining problem tractable, the cost e_t is paid by the firm after production. Additionally, the firm has the choice to defer until the end of the period payment on a fraction $1-\nu$ of its labor expenses that are paid out of accumulated liquidity.[30] Thus, labor expenses can be written as

$$w_t n_t = l_t + \nu a_t + (1-\nu)a_t \tag{1.7}$$

where w_t is the wage rate paid to labor. The firm and lender bargain over the cost of the intraperiod loan. Instead of reaching an agreement with the lender, the firm can threaten to walk away and produce using only the labor it can afford to hire with its accumulated liquidity. This leads to the following bargaining problem:

$$\max_{e_t} \left\{ \left[F\left(z_t, k_t, \frac{l_t + a_t}{w_t}\right) - (1+e_t)l_t - F\left(z_t, k_t, \frac{a_t}{w_t}\right)\right]^{\eta} \left[(e_t - \gamma)l_t\right]^{1-\eta} \right\}$$

where η is the bargaining power of the firm and γ is the return on the lender's outside option.[31] Since the returns of the production function are diminishing in labor, a firm with higher liquidity, a_t, will produce less additional surplus from agreeing to an intraperiod loan. This means, all else equal, that the cost of the intraperiod loan will be lower for firms holding more liquidity. Solving this bargaining problem, the cost of the intraperiod loan is

$$e_t = \frac{(1-\eta)\left[z_t k_t^{\theta}\left(\left(\frac{l_t+a_t}{w_t}\right)^{1-\theta} - \left(\frac{a_t}{w_t}\right)^{1-\theta}\right) - l_t\right] + \eta\gamma l_t}{l_t} \tag{1.8}$$

The firm's intertemporal budget constraint can be written as follows:

$$(1+e_t)l_t + w_t n_t + b_t + k_{t+1} + \varphi(d_t) + a_{t+1} = (1-\delta)k_t + F(z_t, k_t, n_t) + \frac{b_{t+1}}{R_t} + a_t + l_t$$

[30]See the end of this subsection for further discussion of the ν parameter.
[31]See the end of this subsection for further discussion of the γ parameter.

Then, cancelling l_t, which is paid back within the same period as it is contracted, substituting in Equation (1.8) for $e_t l_t$, substituting in $n_t = \frac{l_t + a_t}{w_t}$ and $l_t = w_t n_t - a_t$ gives the following budget constraint:

$$\begin{aligned} &\eta(1+\gamma)w_t n_t + b_t + k_{t+1} + \varphi(d_t) + a_{t+1} \\ &\qquad = (1-\delta)k_t + \eta F(z_t, k_t, n_t) + \frac{b_{t+1}}{R_t} + \eta(1+\gamma)a_t + (1-\eta)F(z_t, k_t, \frac{a_t}{w_t}) \end{aligned} \quad (1.9)$$

Finally, since firms are able to default on their loans (i.e. the enforceability of loan obligations is imperfect), the ability for a firm to borrow is limited. Specifically, at the end of the period, the firm can choose to default on the intraperiod loan l_t. After production and paying costs $e_t l_t$, $w_t n_t - (1-\nu)a_t$, b_t, k_{t+1} and $\varphi(d_t)$, the firm is holding liquid resources equal to $l_t + a_{t+1} + (1-\nu)a_t$. By assumption, the firm can defer a portion, $(1-\nu)a_t$, of its labor costs to the end of the period. If the firm defaults, then the lender is able to recover the full value of the firm's non-liquid physical capital, k_{t+1}, with probability ξ_t and recover nothing with probability $1-\xi_t$. However, the firm is able to hide its liquid resources, $l_t + a_{t+1} + (1-\nu)a_t$. It follows that the lender's enforcement constraint is:[32]

$$\xi_t(k_{t+1} - \frac{b_{t+1}}{1+r_t}) \geq w_t n_t - \nu a_t \quad (1.10)$$

Increasing the amount of intertemporal debt, b_{t+1}, or intraperiod debt, $l_t = w_t n_t - a_t$, will tighten the enforcement constraint. Capital, k_{t+1}, serves as collateral and loosens the enforcement constraint. Note that, all else equal, holding more liquidity loosens the enforcement constraint through reducing the desired intraperiod loan amount. As in Jermann & Quadrini (2012), ξ_t, is an aggregate stochastic innovation where changes are referred to as a "financial shock".

Before solving for the firm's optimization problem, two parameters deserve additional discussion. The ν parameter governs the fraction of a_t that functionally acts as collateral. This parameter can be rationalized in at least two ways. First, it could be thought of as the lender having an enforce-

[32]See Appendix for a complete proof of the derivation of the enforcement constraint.

ment mechanism that makes the firm commit to paying a portion of wages in a timely manner. The portion of the labor costs that are not reliant on the lender can be deferred. This shares similarities with the block-bargaining assumption of Petrosky-Nadeau & Wasmer (2013) in which the firm and banker form a block to negotiate wages with workers. Alternatively, ν can be interpreted as the portion of liquidity that the lender can verify, i.e. that the firm cannot escape with in the event of default. Since the lender can recoup this fraction of liquidity in the event of default, it functionally acts as collateral.

The γ parameter governs the value of the lender's outside option in the event that the firm and lender do not agree to an intraperiod loan. Thus, it is assumed the lender can still re-invest the funds, l_t, in the event of a negotiation breakdown, but at a lower net benefit. Alternatively, we could think that the lender has some superior storage technology that returns a non-zero net benefit.

1.6.2 Firm Decisions

Since the two shocks, productivity and financial, are aggregate shocks, we can work with a representative firm model. Let V(**s**;k,b,a) be the cum-dividend value of the firm, where **s** is the aggregate states. The representative firm's optimization problem then reads:

$$V(\mathbf{s}; k, b, a) = \max_{d,n,k',b',a'} \{d + Em'V(\mathbf{s}'; k', b', a')\} \tag{1.11}$$

subject to

$$\xi(k' - \frac{b'}{1+r}) \geq wn - \nu a$$

and

$$\varphi(d) = (1-\delta)k + \eta z k^{\theta} n^{1-\theta} + \frac{b'}{R} + \eta(1+\gamma)a + (1-\eta)zk^{\theta}(\frac{a}{w})^{1-\theta} - b - k' - a' - \eta(1+\gamma)wn.$$

The first constraint is the enforcement constraint (EC) while the second constraint is the budget constraint (BC). Let λ and μ be the Lagrange multipliers on the budget constraint and enforcement constraint, respectively, and m' be a stochastic discount factor. The FOC for d gives $\lambda = \frac{1}{\varphi_d(d)}$.

Substituting this in for λ, using the envelope conditions for k, b and a and rearranging terms gives the FOCs:

a$'$:

$$Em' \cdot \left(\underbrace{\mu' \nu}_{\text{EC loosening}} + \frac{1}{\varphi_d(d')} \left(\underbrace{\eta(1+\gamma) + (1-\eta)(1-\theta) z' k'^{\theta} (\frac{a'}{w'})^{-\theta} \cdot \frac{1}{w'}}_{\text{Negotiation Benefit}} \right) \right) = \frac{1}{\varphi_d(d)} \tag{1.12}$$

Accumulating liquidity yields two benefits. First, it loosens the EC in the next period by $\mu'\nu$: the multiplier on the next-period EC times the fraction of liquidity that cannot be absconded from the lender (and thus acts as collateral). Second, accumulating liquidity also loosens the next-period BC by the next-period BC multiplier times the "negotiation benefit" terms, i.e. accumulating liquidity lowers the cost of the intraperiod loan. The cost of accumulating liquidity is a reduction in dividend payments, tightening the BC this period by $\frac{1}{\varphi_d(d)} = \lambda$.

b$'$:

$$\frac{1}{\varphi_d(d)} \cdot \frac{1}{R} = \frac{\mu\xi}{1+r} + Em' \cdot \left(\frac{1}{\varphi_d(d')} \right) \tag{1.13}$$

Intertemporal borrowing loosens the BC this period, but tightens the EC this period as well as the BC next period.

k$'$:

$$Em' \cdot \left\{ \left(\frac{1}{\varphi_d(d')} \right) \cdot (1 - \delta + \eta\theta z' k'^{\theta-1} n'^{1-\theta} + (1-\eta)\theta z' k'^{\theta-1} (\frac{a'}{w'})^{1-\theta}) \right\} + \xi\mu = \frac{1}{\varphi_d(d)} \tag{1.14}$$

Purchasing capital loosens the BC next period through liquidation, increased production and lowered cost e (through decreasing returns to scale of the production function) and loosens the EC this period as collateral. But, it tightens the BC this period.

n:

$$(1-\theta) z k^{\theta} n^{-\theta} = \frac{\varphi_d(d)\mu + \eta(1+\gamma)}{\eta} \cdot w \tag{1.15}$$

Increasing labor increases production by the marginal product of labor. On the other hand, it tightens the EC through requiring more l and tightens the BC through the wage payment and increasing the intraperiod loan cost.

1.6.3 Household Decisions and General Equilibrium

There is a continuum of identical households, who maximize expected lifetime utility. Households consume c_t and supply labor n_t to firms. Households also act as the firms' shareholders and lend to the firms by purchasing bonds b_t. Thus, households solve the following optimization problem:

$$\max_{n_t, b_{t+1}, s_{t+1}} E_0 \sum_{t=0}^{\infty} \beta^t U(c_t, n_t) \tag{1.16}$$

subject to

$$w_t n_t + b_t + s_t(d_t + p_t) = \frac{b_{t+1}}{1 + r_t} + s_{t+1} p_t + c_t + T_t,$$

where w_t is the wage rate, s_t are the equity shares, d_t are the equity payouts received from owning equity shares, p_t is the market price of shares, r_t is the interest rate, and $T_t = \frac{B_{t+1}}{1+r_t(1-\tau)} - \frac{B_{t+1}}{1+r_t}$ is the lump-sum tax that funds the tax subsidy, τ, of firms' debt.[33]

The household's FOCs for n_t, b_{t+1}, and s_{t+1}, respectively, are:

$$w_t U_c(c_t, n_t) + U_n(c_t, n_t) = 0 \tag{1.17}$$

$$U_c(c_t, n_t) - \beta(1 + r_t) E U_c(c_{t+1}, n_{t+1}) = 0 \tag{1.18}$$

$$U_c(c_t, n_t) p_t - \beta E(d_{t+1} + p_{t+1}) U_c(c_{t+1}, n_{t+1}) = 0 \tag{1.19}$$

The aggregate states $\mathbf{s}$ are productivity z, the liquidation technology ξ (capturing the tightness of the borrowing constraint), the aggregate capital K, the aggregate bonds B and the aggregate liquidity A. A general equilibrium is defined as follows:

DEFINITION 1: *A recursive competitive equilibrium is defined as a set of functions for (i) households' policies* $c^h(\mathbf{s})$, $n^h(\mathbf{s})$, *and* $b^h(\mathbf{s})$; *(ii) firms' policies* $d(\mathbf{s}; k, b)$, $n(\mathbf{s}; k, b)$, $k(\mathbf{s}; k, b)$, $b(\mathbf{s}; k, b)$, *and* $a(\mathbf{s}; k, b)$; *(iii) firms' value* $V(\mathbf{s}, k, b)$; *(iv) aggregate prices* $w(\mathbf{s})$, $r(\mathbf{s})$, *and* $m(\mathbf{s}, \mathbf{s}')$; *(v)*

[33]For simplicity, we assume in the baseline model that the bank's profits, $e_t l_t$, are immediately consumed by the bank. Alternatively, these profits could be distributed to the households as a lump-sum payment. We show in the Appendix that this does not have a meaningful impact on the results.

law of motion for the aggregate states $\mathbf{s}'=\Psi(\mathbf{s})$*, such that: households' policies satisfy conditions 1.17-1.18; (ii) firms' policies are optimal and* $V(\mathbf{s}, k, b)$ *satisfies the Bellman equation 1.11; (iii) the wage and interest rates clear the labor and bond markets and* $m(\mathbf{s}, \mathbf{s}\hat{a}') = \beta U_c(c\hat{a}', n\hat{a}')/U_c(c, n)$*; (iv) the law of motion* $\Psi(\mathbf{s})$ *is consistent with individual decisions and the stochastic processes for* z *and* ξ*.*

1.7 Calibration and Quantitative Analysis

The empirical evidence shows a stark contrast in the cyclical financing behavior of small firms in the post-financial consolidation period relative to the pre-consolidation period. The evidence suggests that firms with low bargaining power vis-à-vis their lenders and a high value for the bank's outside option (i.e. a weaker relationship between the firm and lender) are responsible for the post-consolidation behavior. Thus, in this section, we calibrate the model and then vary the corresponding parameters, η and γ.

We first set these parameters to reflect a state of the world prior to financial consolidation and widespread interstate banking: high firms' bargaining power vis-à-vis their lenders and a low value for the banks' outside option. We are going to see that in this "pre financial consolidation" world, the impulse response functions for equity issuance and liquidity accumulation are consistent with the cyclicality patterns of large firms and small firms in the pre-1999 period. However, when η and γ are varied to reflect a state of the world with financial consolidation and widespread interstate banking (i.e. low firms' bargaining power and a high value for the banks' outside option), then the impulse response functions for equity issuance and liquidity accumulation are consistent with the smaller firms in the post-1999 period. The response of debt issuance remains procyclical for all parameter values, in line with the empirical findings.

Specifically, when η and γ are set to reflect the post-1999 period with low firm bargaining power vis-à-vis their lenders and a high value for the banks' outside option, then equity issuance and liquidity accumulation increase in response to a positive shock (i.e. are procyclical). Importantly, this result depends on the type of shock. For financial shocks (i.e. shocks to ξ), equity issuance and liquidity accumulation remain countercyclical. Instead, it is the response to TFP shocks that are consistent with the empirical cyclicality results. In Section 1.8, we show evidence that TFP shocks are in fact what drive the main cyclicality findings.

1.7.1 Calibration

Table B8 displays the calibrated values of our main parameters. The household utility function is $U(c, n) = ln(c) + \alpha \cdot ln(1 - n)$. The disutility of work parameter α is set such that hours worked, n, equals 0.3 in steady state. The Cobb-Douglas production function of the firm has a capital share parameter θ equal to 0.36. Capital depreciates at the standard rate of δ equal to 0.025. Debt has a tax advantage over equity of τ equal to 0.35 to match the 35 percent marginal corporate income tax rate that was in place for most of our sample period. The nonfinancial business sector has an average quarterly debt to GDP ratio of 3.4 (see Jermann & Quadrini (2012)). Thus, we set the mean value of $\bar{\xi}$ to target this steady state debt to GDP ratio. Finally, the parameters that govern the properties of the TFP shock, σ_z, and the financial shock, σ_ξ, are derived from our empirical estimates of these shocks. Section 1.8 provides details on the construction of these series.

The calibrated values of the discount parameter, β, and the parameter for the value of liquidity as collateral, ν, require further attention. The product of these two parameters is key to determining the firm's desire to hold liquidity. If the desire to carry liquidity between periods is too high, then the bargaining between firms and banks over the intraperiod loan becomes unnecessary as firms can cover all wage costs with accumulated liquidity. Thus, we can produce qualitatively similar results to our baseline by increasing β and decreasing ν. For example, we can increase β from 0.9 to 0.97 and simultaneously decrease ν from 0.25 to 0.1. We detail the firm bargaining power parameter, η, and the bank outside option parameter, γ, below.

1.7.2 Simulated Responses

To evaluate the cyclical properties of the financing variables, we subject two different steady states to two types of shocks. The first steady state is the pre-financial consolidation state, which we refer to as the "stronger borrowers" state. We set the firm bargaining power parameter, η, to 0.99 and the bank outside option parameter, γ, to 0.01. The bargaining power parameter value of 0.99 approximates the case of full firm bargaining power, as found, e.g., in Jermann & Quadrini (2012) and Diamond & Rajan (2001). The bank outside option parameter of 0.01 approximates the case where the bank simply stores the intraperiod loan funds at zero net benefit in the event of no agreement with the firm. This is similar to the assumption of Diamond & Rajan (2001), for example, where a lender's only outside option is liquidation.

Table B8 shows the steady state values for select variables. Note that debt issuance and liquidity accumulation are zero in steady state. Thus, the IRFs will show the absolute (i.e. the percentage point) deviation for each financing variable. Consistent with Jermann & Quadrini (2012), the financing variables are scaled by output. Panel (a) of Figure C4 shows the impulse responses of debt issuance, equity issuance and liquidity accumulation to a one-time positive productivity (TFP) shock (ϵ_z) and a one-time positive financial shock (ϵ_ξ) from this pre-financial consolidation steady state. Debt issuance rises upon impact and equity issuance falls for both positive shocks. This is consistent with the empirical results of debt issuance being procyclical and equity issuance countercyclical in the pre-1999 period. Liquidity accumulation essentially does not respond to a shock. Given that liquidity acts as a buffer to increased bargaining costs, firms with such a high value of η do not need to respond to shocks by adjusting liquidity, as banks are anyway unable to extract a meaningful amount of surplus in the bargaining process.

In the second steady state, the post-financial consolidation steady state, we reduce the firm bargaining power parameter from 0.99 to 0.7 and increase the bank outside option parameter to 0.04. Petrosky-Nadeau & Wasmer (2013) estimates the bargaining power parameter for banks in the US economy as 0.68, but with a range from 0.37 to 0.98. This change acts to illustrate the effects of financial consolidation on smaller firms, i.e. those in which we see empirical evidence that bargaining power and the bank's outside option matter following the financial consolidation of the 1990s. In Panel (b), the "weaker borrowers" state shows the impulse responses for positive shocks to this new steady state. For the financial shock, the magnitude of the impact on equity issuance and debt issuance is smaller; however, the direction of the response remains the same as in the pre-financial consolidation steady state. In contrast, equity issuance now responds positively to a positive TFP shock, i.e. equity issuance displays a procyclical pattern upon impact. Similarly, liquidity accumulation now responds positively.

The difference in the impulse responses in the post-financial consolidation steady state, relative to the pre-financial consolidation state, can be interpreted as an enhanced incentive for firms to accumulate precautionary liquidity and, hence, to issue equity. Faced with the prospect of a relevant surplus extraction by their lending banks, firms have an increased appetite for liquidity when productivity rises. To finance this precautionary accumulation of liquidity, they issue more equity when a TFP shock hits. A positive financial shock, by contrast, relaxes the access to external financing. This reduces the need for precautionary liquidity. We now discuss empirical evidence for the importance of small firms' response to TFP shocks in explaining the change in the cyclicality of equity issuance and liquidity accumulation.

1.8 Financial and TFP Shocks

As shown in the previous section, the change in the cyclicality of equity issuance and liquidity accumulation occurs only in response to TFP shocks in the model economy. This yields a testable implication: we can re-estimate the baseline panel regressions, replacing the cyclical component of real corporate GDP with measures of TFP and financial shocks. To be consistent with the model, we would expect that the procyclicality of equity issuance and liquidity accumulation for small firms is due to TFP shocks, rather than financial shocks, during the post-1999 period.

To create the baseline measures of TFP and financial shocks, we follow the methodology of Jermann & Quadrini (2012) and extend their series through 2017. First, to create a time series of productivity shocks, we compute the Solow residuals of the production function:

$$\hat{z}_t = \hat{y}_t - \theta \hat{k}_t - (1 - \theta)\hat{n}_t \tag{1.20}$$

where the hat represents the log-deviation from the deterministic trend. The output variable, y_t, is real GDP from the National Income and Product Accounts. The capital variable, k_t, is from the

Flow of Funds Accounts. The labor variable, n_t is the total private aggregate weekly hours from the Current Employment Statistics survey.

Next, we create the financial shock series using the (binding) enforcement constraint from Jermann & Quadrini (2012):[34]

$$\xi_t\left(k_{t+1} - \frac{b_{t+1}}{1 + r_t}\right) = y_t \tag{1.21}$$

The financial variable ξ_t is then computed as the residual. The debt variable is from the Flow of Funds Accounts.

Finally, as in Jermann & Quadrini (2012), we compute the shocks to z and ξ using the following autoregressive system:

$$\begin{pmatrix} \hat{z}_{t+1} \\ \hat{\xi}_{t+1} \end{pmatrix} = \mathbf{A}\begin{pmatrix} \hat{z}_t \\ \hat{\xi}_t \end{pmatrix} + \begin{pmatrix} \epsilon_{z,t+1} \\ \epsilon_{\xi,t+1} \end{pmatrix} \tag{1.22}$$

Figure C7 plots the estimated series of TFP shocks ($\epsilon_{z,t+1}$) and financial shocks ($\epsilon_{\xi,t+1}$), as well as the cyclical GDP measure. All series have been standardized to have a mean of zero and unit variance to more easily evaluate the comovement of each measure.

After having computed TFP and financial shocks, we replace the cyclical component of real corporate GDP in the baseline empirical panel specification with the one-year lagged value of these shocks. Since the firm financing data is reported at the annual level, the contemporaneous shock value contains information for a shock that occurs (at least partially) after the financing decision. Using the lagged shock avoids this issue. The results are displayed in Table B9 for both large firms and smaller firms, split by the pre-1999 and post-1999 periods. In the pre-1999 period, the results across firm size are quite similar: a positive financial shock (i.e. a loosening of the financial constraint) is associated with an increase in debt issuance, a decrease in equity issuance and a decrease in liquidity accumulation. As it becomes easier to borrow, both large and small firms shift toward issuing debt and away from issuing equity and accumulating liquidity. This aligns with the earlier cyclicality results and the standard pecking order theory. Interestingly, TFP shocks are insignificant for both firm sizes and all financing variables in the pre-1999 period.

[34] We recognize that this enforcement constraint differs from the one used in our model. To generate financial shocks comparable to the literature, we used this more common enforcement constraint.

In the post-1999 period (i.e. following financial consolidation), the financing behavior of large firms remains qualitatively unchanged; however, smaller firms see a dramatic change. While debt issuance remains closely related to positive financial shocks, the relationship between financial shocks and equity issuance/liquidity accumulation becomes statistically insignificant. Positive TFP shocks are now significantly associated with an increase in both equity issuance and liquidity accumulation. Thus, both the type of shock and the sign of the relationship with the relevant shock have changed for smaller firms in the post-1999 period. This matches the change observed for the cyclicality of equity issuance and liquidity accumulation in the latter period. The importance of TFP shocks is also consistent with the impulse response functions above, in which a change in cyclicality for equity issuance and liquidity accumulation occurred for TFP shocks and not for financial shocks.

Finally, we can compare the magnitude of the equity issuance response in our model to the empirical estimates. In the model, equity issuance for weak borrowers increases by 2% over the first four quarters following a positive TFP shock (an increase of 0.35 from the steady state value of 17.3%). Empirically, we estimate in Table B9 that small firms' annual equity issuance increases by 2.43 percentage points in response to a positive TFP shock. This is an increase of 9% relative to the post-1999 average of 26% for small firms' equity issuance. Thus, the model explains approximately two-ninths, or 22%, of the equity issuance response to TFP shocks in the post-1999 period.

1.9 Investment and Employment

To this point, we have documented a significant change in the cyclicality of equity issuance and liquidity accumulation for smaller firms. We have additionally uncovered both empirical and theoretical evidence that consolidation among lenders contribute to explaining these changes. In this section, we investigate the implications for the investment and employment behavior of smaller publicly-traded firms over the business cycle.

As seen in equation 1.14, the first order condition for capital, there are three main mechanisms by which a TFP shock impacts a firm's demand for capital: a "Surplus Appropriation Channel",

$\eta\theta z' k'^{\theta-1} n'^{1-\theta}$; a "Financial Channel", $(1-\eta)\theta z' k'^{\theta-1}(\frac{a'}{w'})^{1-\theta}$; and a "Collateral Channel", $\xi\mu$. First, increased productivity leads to higher output. The lender will want to extract this surplus during the bargaining phase; the firm's bargaining power, η, determines how much of the surplus the firm can keep. The more surplus the firm can keep, the higher its demand for capital. Second, as noted, the liquidity holdings of the firm are used as the threat point in bargaining with the lender, as they can be used to hire labor. This benefit of liquidity has a complementary effect with the capital stock. Thus, capital provides a larger benefit through this financial channel for firms with more accumulated liquidity. Third, capital benefits the firm as collateral in the enforcement constraint.

Figure C5 shows the IRFs for each of these three components (Surplus Appropriation, Financial, Collateral) in response to a positive TFP shock.[35] Capital increases more for the stronger borrowers than for the weaker borrowers via the Surplus Appropriation mechanism. This reflects the fact that the higher bargaining power of stronger borrowers limits the lender's ability to appropriate the surplus of additional capital. The main difference between stronger and weaker borrowers is the Financial Channel response. For stronger borrowers, their bargaining power is so high that they do not have an incentive to increase their threat point. The opposite is true for weaker borrowers. Thus, the channel most closely related to financial consolidation increases the sensitivity of the weaker borrowers. That is, the changing cyclicality in corporate financing results in higher investment sensitivity. Interestingly, the Collateral Channel shows minimal difference between the two types of borrowers. Next, we investigate empirically whether financial consolidation indeed resulted in higher sensitivity for smaller firms.

Given the evidence presented above on the cyclicality of firm financing, we would expect smaller firms to reduce equity issuance and liquidity accumulation in response to a negative shock, but only during the post-1999 period. Table B15 shows the change in the financing variables of interest in the face of a negative shock, i.e. the years with negative growth in the cyclical component of HP-filtered real corporate GDP (1982, 1986, 1989-1993, 2001-2003, 2007-2009, and 2016).[36]

[35]Figure C8 shows the same IRFs for a positive financial shock.

[36]In the Online Appendix, we try three alternative definitions of a negative shock. First, we use an indicator that is instead set to 1 in years with negative real corporate GDP growth. Second, we use an indicator that is set to 1 in years that overlap with the NBER dating of a recession. Third, we use a discrete variable that measures the number

As expected, small firms see a large decline in equity issuance and liquidity accumulation during years with negative growth (relative to positive growth years) and, as seen in Panel B, this holds true during the post-1999 period only.

Next, in Table B16 we repeat the above exercise with change in investment and log change in employment replacing the financing variables. For both firm sizes, investment and employment fall in years with negative economic growth for each subperiod. However, as revealed by the p-values, it is only the small firms that see a significant increase in responsiveness from the pre-1999 to the post-1999 period. Alternatively, we can substitute in investment and employment measures for our financing variables in the baseline panel specification to estimate the overall cyclicality. As seen in Table B10, it is again only small firms that experience a significant difference from pre-1999 to post-1999. This suggests that the change in the cyclicality of financing for smaller firms may also have resulted in increased sensitivity of investment and employment.

To further isolate the Financial Channel, we also split small firms by their liquidity position leading into the post-1999 period. Specifically, "low liquidity position" firms are those small firms with a cash-to-asset ratio in 1996-1998 that was at or below the median. "High liquidity position" are those small firms with a cash-to-asset ratio in 1996-1998 above the median. In the terminology of our model, firms with high liquidity position should have a higher threat point. Small firms with a low liquidity position are in a weaker position to counter the effects of financial consolidation; thus, they should be more sensitive in the post-1999 period. Panel B of Table B10 provides evidence that this was the case. Firms with a low liquidity position prior to 1999 showed a greater increase in the sensitivity of investment and employment after 1999. This again points to financial consolidation resulting in higher investment sensitivity for those firms most affected.

1.10 Conclusion

In recent decades, an intense debate has developed on the consequences of financial sector consolidation. This paper contributes by identifying an important effect of financial consolidation

of quarters in a year that overlap with the NBER dating of a recession. All three of these definitions of a negative shock produce similar results to Table B15.

on the corporate sector, in the form of a structural change in firms' financing behavior over the business cycle. We find that due to the weakened bargaining power vis-à-vis their lending banks and a fraying of the relationships between firms and banks, small and medium-sized publicly-traded firms began to issue equity and accumulate precautionary liquidity during expansions. This behavior starkly contrasts with the countercyclical equity and liquidity behavior of larger publicly-traded firms and reflects the attempt of small and medium-sized firms to offset their weakened position vis-à-vis larger and more complex financial institutions. The change in cyclical financing behavior appears to also have far-reaching consequences for firms' investment and labor hiring decisions. The empirical evidence presented in the paper shows that small and medium-sized firms' investment and employment became significantly more sensitive to negative shocks.

The paper leaves relevant questions open for future research. For example, equity issuance and hoarding of precautionary liquidity can entail relevant costs for firms. Thus, it becomes important to evaluate the welfare implications of the altered financing patterns. Further, as noted, private firms are likely to be even more exposed than small publicly listed firms to financial consolidation, as they lack access to stock markets as a form of financing alternative to bank lending. In this sense, the results of this analysis may constitute a lower bound of the actual effects of financial consolidation through cyclical financing patterns. We leave these and other relevant issues to further research.

CHAPTER 2

MONETARY POLICY AND FIRM HETEROGENEITY: THE ROLE OF LEVERAGE SINCE THE FINANCIAL CRISIS

2.1 Introduction

Since the federal funds rate hit the zero lower bound at the beginning of the financial crisis, the Federal Reserve has relied more on unconventional policy tools like forward guidance and quantitative easing. In this paper we explore how the monetary transmission mechanism may have changed since the crisis, with a focus on the role of heterogeneity in firms' financing conditions. While the importance of the balance sheet of firms for the monetary transmission mechanism has long been established, recent work has highlighted the role of firm-level heterogeneity.[1] However, this literature on firm-level financial heterogeneity has typically focused on the pre-crisis period to study the transmission of conventional monetary policy actions.[2] Our main contribution is to show that the role of financing conditions in determining the firm-level response to monetary shocks has *reversed* in the post-crisis sample.

We document this result with three complementary empirical approaches using both high frequency financial market and quarterly real activity data for non-financial firms. For all approaches, we construct monetary policy shocks using high frequency data from futures and Treasury bond markets. Our preferred measure of monetary policy shocks combines unexpected changes in the federal funds target with the change in the 10 year Treasury yield in a narrow window around FOMC announcements. This allows us to parsimoniously capture both conventional and unconventional monetary policy actions.[3]

*This chapter is joint work with Aeimit Lakdawala.

[1]For an early survey of the importance of the credit channel of monetary policy, see Bernanke & Gertler (1995). For recent work on firm-level heterogeneity see Ottonello & Winberry (2018), Jeenas (2018) and Ozdagli (2018).

[2]A notable exception is the paper of Wu (2018), which we discuss below.

[3]This approach is especially important in the post-crisis sample where the federal funds rate is mostly stuck at the zero lower bound. But we also show that using one single policy indicator for both the pre- and post-crisis samples (e.g. the change in the 2 year Treasury rate) confirms our results.

For our first approach, we combine firm-level characteristics with high frequency data on stock prices. Using leverage as the measure of the firm's financial position we find that before the financial crisis of 2007-09, stock prices of firms with higher leverage respond *less* to monetary policy shocks on FOMC announcement days. However, this pattern is reversed after the crisis: in the post-crisis sample firms with higher leverage respond *more* to monetary shocks. The panel data allows us to control for a variety of firm level variables including a firm fixed effect to account for any permanent features at the firm level. More importantly, since we are interested in the interaction of leverage and monetary shocks, with time fixed effects we can also control for any aggregate factors that could be changing over time.

Given that monetary policy shocks are not predictable, these results have no implications for the *expected direction* of the movement in the stock price of firms with higher (or lower) leverage on FOMC announcement days. However, there is a direct implication for the *expected volatility* of the stock price. Specifically, we should expect that firms with high leverage will be less volatile on FOMC announcement days in the pre-crisis sample. Moreover, this relationship should flip with the crisis making high leverage firms more volatile on announcement days in the post-crisis sample. Our second approach involves testing this hypothesis by using high frequency firm-level options data. These options data allow us to construct a measure of expected volatility for each firm. We analyze these firm-level expected volatility measures on the day before the FOMC announcement and confirm the reversal in the relationship between leverage and monetary policy announcements since the financial crisis. Markets expected high leverage firms to be less volatile on FOMC announcement days in the pre-crisis sample but more volatile since then.

Our third approach involves using firm-level investment data. Since this measure of real activity is only available quarterly, we aggregate our monetary policy shock measure up to the quarterly level. At this quarterly frequency, there are several factors that could affect firm-level investment other than monetary policy.[4] Nevertheless, these quarterly results confirm the pattern

[4]Since we use an exogenous measure of monetary shocks and time-fixed effects we are not worried about endogeneity but rather about the loss of precision as a smaller fraction of the firm-level dependent variable will be driven by monetary policy here relative to the high frequency specification.

of increasing responsiveness of firms with higher leverage since the financial crisis. There is an ongoing discussion in the literature regarding the longer-run response of investment to monetary policy shocks, see Ottonello & Winberry (2018) and Jeenas (2018). The relatively shorter sample of data since the crisis makes it difficult to do inference on comparing long-run responses in the pre- and post-crisis samples, so in this paper we focus on the contemporaneous response. Our findings for the contemporaneous response of investment in the pre-crisis sample are consistent with both these papers.

Our results hold across a variety of robustness checks, including using alternative measures of leverage, expanding our baseline sample from firms in the S&P 500 to a broader set of firms in the CRSP/Compustat dataset, dropping unscheduled FOMC meetings, using time-by-sector fixed effects and including financial firms in our sample. A natural question is whether our results are driven by the changing behavior of leverage since the crisis. We document that average leverage has only slightly increased since the crisis and that the cross-sectional distribution of leverage is similar in the two samples. Moreover, we show that most firms have not moved around much in the leverage distribution since the crisis and that excluding firms that did move around a lot does not affect our results.

In the next part of the paper we shed light on the mechanism driving our empirical results. There is a growing literature on the transmission of monetary policy and heterogeneity in firm balance sheets. But, as mentioned above, this literature has focused on the pre-crisis period. We start by placing our pre-crisis results in the context of the leading heterogenous firm model of Ottonello & Winberry (2018), which builds on the work of Khan et al. (2016). Within this model, we then discuss potential channels that can rationalize our post-crisis results and provide supporting empirical evidence.

In the Ottonello & Winberry (2018) model there are competing forces affecting how high vs. low leverage firms respond to an expansionary monetary policy shock. The marginal cost curve of a high leverage firm is steeper making it less responsive to monetary policy induced shifts of the marginal benefit curve. However, the expansionary monetary policy shock flattens out the marginal cost curve more because of an increase in the value of collateral and cash flows, making high leverage firms more responsive. In a pre-crisis calibration, Ottonello & Winberry (2018) find that the former effect dominates, implying results that are consistent with our pre-crisis findings. We argue that to reverse this result in the post-crisis sample, an expansionary monetary policy shock must flatten the marginal cost curve substantially more for high leverage firms. A direct testable implication of this hypothesis is that credit spreads for high leverage firms should fall more (relative to low leverage firms) in the post-crisis sample. We provide evidence of this channel by using the credit spread between firms rated BAA relative to those rated AAA. Consistent with the hypothesis, the BAA-AAA spread falls more (in response to an expansionary monetary policy shock) in the post-crisis sample.[5]

Why is it that monetary policy actions flatten the marginal cost curve more and thus compress the yield spread between high leverage and low leverage firms more in the post-crisis sample? Our hypothesis is that longer-term interest rates, and thus firms that are more dependent on long-term funding, have become more sensitive to monetary policy actions in the post-crisis sample. We first document that the nominal and real 10 year Treasury yields respond significantly more to monetary policy shocks in the post-crisis sample. Next, we test if this increased sensitivity is spilling over into long-term funding conditions and contributing to our baseline results. To do this we separate a firm's leverage into two components, one depending on long-term debt and the other on short-term debt. We find that the increased responsiveness since the crisis is largely driven by firms that have a larger share of long-term debt in their leverage. This is consistent with the results of Foley-Fisher et al. (2016) who find that firms that are more dependent on long-term debt responded more to the Federal Reserve's Maturity Extension Program implemented in 2011 and 2012. However, our results suggest that this increased responsiveness to monetary policy is a feature prevalent throughout the post-crisis sample rather than just in response to specific large scale asset purchase episodes.

We also provide some suggestive evidence for the role of another monetary transmission channel,

[5]This result is broadly consistent with the findings of Gilchrist & Zakrajšek (2013) that borrowing costs of riskier firms reacted substantially more to quantitative easing announcements in the post-crisis sample.

namely through changes in uncertainty about future policy decisions. In recent empirical work, Kroencke et al. (2018), Bauer et al. (2019) and Bundick et al. (2017b) find that monetary policy uncertainty shocks are likely drivers of term-premium on long rates and general risk-premium in the financial markets. Moreover, Bauer et al. (2019) find that monetary transmission to financial markets through uncertainty has strengthened in the post-crisis sample. We use their uncertainty measure of the changes in the standard deviation of the expected future policy rate, as constructed using high-frequency options data around FOMC announcements. We find that monetary policy uncertainty shocks induce a similar reversal in the sign of the relationship between the firm-level response and leverage. Specifically, in response to uncertainty shocks firms with high-leverage respond less in the pre-crisis sample but more in the post-crisis sample.

Related Literature: Our paper is related to three strands of the literature. The first one identifies firm-level characteristics, particularly financial constraints such as leverage, that are associated with a heterogenous stock market response to monetary policy shocks. Both Ehrmann & Fratzscher (2004) and Ottonello & Winberry (2018) find that financial constraints affect the strength of a firm's response to monetary policy. Consistent with our results, they find evidence that stock prices for firms with high leverage are relatively less responsive to monetary shocks in the pre-crisis period. Ozdagli (2018) finds that firms that have higher information frictions are less responsive while Ippolito et al. (2018) find that more financially constrained firms have a stronger response to monetary policy.[6] While most of the literature focuses on the period prior to the financial crisis, Wu (2018) analyses stock price responsiveness to monetary policy during the 2008-2012 period. Consistent with our results, he finds that firms with higher leverage were more responsive to monetary policy during this period. Our contribution is to highlight the changing relationship between leverage and stock price response since the financial crisis. We also confirm this changing relationship using both high-frequency options data and quarterly firm-level investment data. Finally, we interpret our findings through a structural model and provide evidence of the mechanism working through long-term funding conditions and monetary policy uncertainty

[6]Ippolito et al. (2018) find increased sensitivity using a measure of leverage that only includes bank debt.

changes.

Our paper also adds to the growing literature on the heterogenous effects of unconventional monetary policy since the crisis. In addition to the Foley-Fisher et al. (2016) paper discussed above, there is some recent work analyzing the heterogenous impact of European Central Bank's (ECB) unconventional policies. Grosse-Rueschkamp et al. (2019) study the effect of ECB's corporate sector purchase program on firm's capital structure, while Daetz et al. (2018) investigate the impact of the ECB's longer-term refinancing operations on corporate investment.

Finally, our paper is related to the literature that explores heterogenous responses of real economic activity to changes in monetary policy. Gertler & Gilchrist (1994), an early influential paper in this literature, notes that sales at small manufacturing firms decrease disproportionately relative to larger manufacturing firms after Romer and Romer tight money dates.[7] They provide evidence that small firms are a proxy for financial constraints, as smaller firms seem to have more difficulty acquiring credit when monetary policy becomes contractionary. More recent papers explicitly attempt to control for financial constraints. Ottonello & Winberry (2018) find that investment spending at firms with higher leverage is less responsive to monetary policy shocks in the quarter of a monetary shock. Dedola & Lippi (2005) show that output of industries in the U.S. and four other OECD countries with higher leverage is less responsive between 4 and 12 quarters after a monetary policy shock. In contrast to those two papers, Jeenas (2019) and Jeenas (2018) find that sales and investment of higher leverage firms are more responsive to monetary policy shocks after approximately 8 quarters. We provide evidence that the contemporaneous effect on higher leverage firms has become larger following the financial crisis. Cloyne et al. (2018) stress the importance of firm age for the investment response to monetary shocks with younger firms being the most responsive. In our analysis the combination of firm- and time-fixed effects effectively control for age and imply that firm age is not driving the changing relationship between leverage and monetary transmission.

The rest of the paper is organized as follows. In the next section we outline the data sources

[7]A related literature uses business cycle contractions as the type of shock under investigation rather than monetary shocks, e.g. Kudlyak & Sanchez (2016), Crouzet et al. (2017), Kalemli-Ozcan et al. (2018) and Bustamante (2018).

and data variables used in our empirical analysis. Section 2.3 presents the results from our three main empirical strategies using stock price, options and investment data. Next, in Section 2.4 we shed some light on the mechanism driving our results. Section 2.5 provides a variety of robustness checks and Section 2.6 concludes.

2.2 Data

This paper uses the daily firm share prices from the CRSP/Compustat Merged Security Daily dataset for July 1991 to December 2017 and firm characteristics from the 1991:Q3 to 2017:Q4 CRSP/Compustat Merged Fundamentals Quarterly dataset. We combine this firm-level data with measures of monetary policy shocks that occur on FOMC meeting days. Additionally, we merge a subsample of the firms in the CRSP/Compustat Merged dataset with a dataset of firm-level implied volatility from OptionMetrics. This section further describes these three data sources.

2.2.1 Monetary Policy Shocks

To construct our measure of monetary policy shocks, we combine data from fed funds futures and Treasury bond markets. In the high-frequency monetary policy literature, the most common method to construct shocks involves looking at the change in futures contracts around FOMC announcements, where the underlying asset is the fed funds rate. The early work of Kuttner (2001) and Bernanke & Kuttner (2005) used changes in the current month's futures contract. This measure captures any unexpected changes to the target for the fed funds rate. However, in more recent years, the Federal Reserve has been using alternative unconventional policy tools, including large scale asset purchases (quantitative easing) and forward guidance. FOMC announcements that provide information about these unconventional policy actions are not well captured by this measure. This issue has been especially relevant since the fed funds rate hit the zero lower bound in late 2008. Thus we also use the change in longer-term Treasury yields around FOMC announcements to supplement the Kuttner (2001) measure. Specifically, our monetary policy shock ϵ_t^m is defined as

$$\epsilon_t^m = P_{t+\delta_+} - P_{t-\delta_-} \tag{2.1}$$

where t is the time of the FOMC announcement, P_t is either the implied fed funds rate from the price of the current month's fed funds futures contract or on-the-run Treasury yields, $t + \delta_+$ and $t - \delta_-$ represent 20 minutes after the FOMC announcement and 10 minutes before the FOMC announcement, respectively. For our baseline measure (labeled MP Shock) we combine the change in the current month's futures contract[8] (labeled FFR Shock) and the 10 year Treasury yield by taking the first principal component of these two measures. The idea is to parsimoniously capture both conventional and unconventional monetary policy actions in one tool.[9] Since the scale of this shock is arbitrary, we rescale it to have a unit effect on the 2 year yield. We also present our baseline regressions including both the FFR Shock and the change in the 10 year yield as separate measures of monetary policy shocks.[10] Finally, we also use a single monetary policy indicator in both the samples: the change in the 2 year Treasury yield as recommended by Hanson & Stein (2015a). We find that the main results are robust to the choice of monetary policy shock; however, for simplicity, we most frequently report results based on the MP Shock, i.e. the first principal component of changes in the current month's fed funds futures contract and the on-the-run 10-year Treasury yield.

Table D1 shows the summary statistics for the monetary policy shock measures for a pre-crisis sample (July 1991 to June 2008) and a post-crisis sample (August 2009 to December 2017). The effect of the zero lower bound is clearly apparent. The standard deviation of the FFR Shock measure falls substantially from 9 basis points in the pre-crisis sample to 1 basis point in the post-crisis sample. Even for the two year shock measure the standard deviation falls from 6.5 basis points to 3.5 basis points, reflecting the effective lower bound on Treasury yields starting in late 2011 as reported by Swanson & Williams (2014). However the standard deviation of the 10 year shock

[8] Since fed funds futures contracts are based on the average rate for a month, the change in the implied rate needs to be adjusted by $\tau(t) = \frac{\tau_m^n(t)}{\tau_m^n(t) - \tau_m^d(t)}$ where $\tau_m^n(t)$ is the number of days in the month of the announcement and $\tau_m^d(t)$ is the day of the month the announcement occurred

[9] We perform this principal component analysis separately for the pre-crisis and post-crisis periods. The first principal component explains 84% of the variation in these two rates during the pre-crisis sample and 90% of the variation in these two rates during the post-crisis sample.

[10] Since the 10-year rate is a function of shorter-term rates, we first regress it on the short-term rate and use the residuals as the orthogonalized measure of the 10-year rate.

measure is roughly similar in the pre- and post-crisis samples, motivating our reliance on this measure to effectively capture monetary policy shocks in the post-crisis period.

2.2.2 Firm-Level Variables

We use the CRSP/Compustat Merged Fundamentals Quarterly sample beginning in 1991:Q3, as this is the first year where we have a complete record of our monetary policy shock measures. For the baseline results we use the firms in the S&P 500 index and, as is common in the literature, we exclude financial firms (SIC 6000-6999). In the Online Appendix we include robustness checks expanding the sample to all firms in the CRSP/Compustat dataset and also another check including financial firms in our sample. Our primary measure of interest from Compustat is the firm's leverage ratio. The baseline results use the ratio of debt-to-capital, measured as the sum of debt in current liabilities (Compustat item: DLCQ) and long-term debt (DLTTQ) over the sum of debt in current liabilities, long-term debt and stockholder's equity (SEQQ). We also confirm our results (relegated to the Online Appendix) using an alternative measure of leverage: debt-to-assets (using the book value of assets (ATQ)). Table D1 displays the summary statistics for these definitions of leverage measured as the 4-quarter rolling average at the firm level.

Additionally, we create several control variables using these quarterly data: year-over-year real sales growth, firm size as measured by the log of the book value of assets, price-to-cost margin, receivables-minus-payables to sales, depreciation to assets, firm age, the log of quarterly market capitalization and the ratio of current assets to total assets. Including these controls are intended to capture important characteristics of the firm that could be correlated with both firm leverage and firm performance. Table D10 in the appendix displays summary statistics of these measures, dividing the sample into firms with above and below average leverage. The construction of these variables follows standard methods in the literature; however, we include these details in the Online Appendix.[11]

[11] In Section 2.3.4 we investigate the impact of monetary policy shocks on firms' quarterly investment. The construction of this investment variable is also detailed in the Online Appendix.

We also use daily stock returns and implied volatility measures at the firm level. We use the daily return of a firm's share price on the day of an FOMC meeting, measured as the log difference between the closing share price on the day of the FOMC meeting and the closing share price on the day prior to the FOMC meeting. The implied volatility measures are computed using firm-level options data from OptionMetrics. The methodology used to do this calculation closely follows the one used for implied volatility of the S&P 500 index, i.e. the VIX. This daily data is available from January 1996 to December 2017. To ensure sufficient liquidity in the market for options, we make two restrictions to our implied volatility sample. First, we use implied volatility measures for options set to expire in greater than 3 months. Second, we use the 100 most-liquid firms, i.e. the 100 firms with the highest number of days with available data in our sample period. Summary statistics for both these variables are also presented in Table D1.

2.3 Results

This section presents the main results illustrating how leverage affects the firm-level response to monetary shocks and how that relationship has changed since the financial crisis. First we document this changing effect using high frequency data on stock prices. Next, we use firm-level options data to show that financial market participants have been aware of this changing responsiveness. Finally, we use quarterly data on firm investment and show that a similar pattern emerges.

2.3.1 Evidence from firm-level stock returns

We first examine how leverage determines the stock price response to monetary policy shocks. In our baseline results we will consider a pre-crisis sample ranging from July 1991 to June 2008 and a post-crisis sample from August 2009 to November 2017. We are thus leaving out the crisis period as categorized by July 2008 to July 2009. These dates are commonly used in the literature due to turbulence in the financial markets and the presence of some asset pricing anomalies, see for example Nakamura & Steinsson (2018).[12]

[12]In the Online Appendix we show that our results are robust to including the financial crisis dates in the "post-crisis" sample.

Our baseline regression takes the following general form

$$s_{i,t} = \alpha_i + \alpha_t + \beta l_{i,t-1}\epsilon_t^m + \delta l_{i,t-1} + \Gamma' Z_{i,t-1} + e_{i,t} \tag{2.2}$$

where $s_{i,t}$ is the (daily) return on firm i's share price on FOMC meeting day t,[13] α_i is a firm i fixed effect, α_t is an FOMC meeting day t fixed effect (i.e. a dummy for each time period), $l_{i,t-1}$ is firm i's average leverage (measured as debt-to-capital) for the four quarters preceding the quarter of the FOMC announcement, ϵ_t^m is the monetary policy shock, and $Z_{i,t-1}$ is a vector of firm-level controls (lagged by a quarter). The monetary policy shock ϵ_t^m is not included separately as a regressor because it is subsumed by the time fixed effect. $Z_{i,t-1}$ includes the following firm-level financial measures as controls: real sales growth, the log of the book value of assets, the price-to-cost margin, receivables-minus-payables to sales, depreciation to assets, firm age, the log of quarterly market capitalization and the ratio of current assets to total assets.[14] Since the firm-level characteristics are measured at the quarterly level, the leverage ratio and the firm-level controls are lagged to ensure they are predetermined at the time of the FOMC announcement. We also include a dummy for the fiscal quarter, to account for differences across firms due to different positions in their fiscal year. The firm fixed effect accounts for permanent characteristics of the change in firm i's stock price that are not captured by our controls. The time fixed effect accounts for aggregate shocks common to all the firms on the day of the FOMC announcement. The standard errors reported in the parentheses are calculated using two-way clustering along the time and firm dimensions.[15]

We multiply the monetary policy shock measure by negative one so that an increase in ϵ_t^m corresponds to an expansionary shock. The key parameter in the above specification is β, which captures how the responsiveness of a firm's share price to a monetary policy shock changes based on a firm's leverage ratio. We standardize leverage to be mean zero and unit variance, so β can be interpreted as the additional change in a firm's daily stock price in response to a unit expansionary monetary shock by moving from an average level of leverage to one standard deviation above the

[13] $s_{i,t} = ln(p_{i,t}) - ln(p_{i,t-1})$ where the stock price p is measured at the end of the day.

[14] In the Table D11 we show that our results are robust to interacting these controls, as well as the firm's sector, with the monetary policy shock.

[15] Our results are robust to using Driscoll-Kraay standard errors instead of two-way clustering.

average leverage. In standardizing leverage we use the full sample mean and standard deviation of leverage across all firms.

Table D2 presents the results for firms in the S&P 500 for pre- and post-crisis samples for the three different monetary policy shock measures. Columns 1a and 1b show the results for our first measure (labeled MP shock), which is the first principal component of the change in the current month's fed funds futures contract and the change in the on-the-run 10 year yield. The interaction coefficient of MP shock and leverage (β) is *negative* and significant in the pre-crisis sample but *positive* and significant in the post-crisis sample. Since we use time fixed effects, we cannot estimate the stand-alone effect of the monetary policy shock on firm-level stock returns from this specification. However, we show in Table D12 that the sign is as expected and implies that a 100 basis point expansionary monetary policy shock leads to an over 6% increase in stock prices.[16] This means that the interaction coefficient of MP shock and leverage shows that firms with higher leverage were *less* responsive to monetary shocks before the crisis and have become *more* responsive since the crisis. Specifically, for a firm that has leverage one standard deviation above the mean, its stock price *falls* by 5.5% more (relative to a firm that has average leverage) in the pre-crisis sample but *increases* by 2.2% more in the post-crisis sample. To formally test that the pre- and post-crisis responses are statistically significantly different from each other we run a specification with triple interactions ($D_t^{post} * \epsilon_t^m * l_{i,t-1}$) where D_t^{post} is a dummy for the post-crisis sample. The lower panel of Table D2 shows that the coefficient on this triple-interaction is positive and statistically significant implying that firms with higher leverage have become significantly *more* responsive to monetary shocks in the post-crisis, relative to the pre-crisis.

Columns 2a and 2b show the results where we include both the change in the current month's fed funds futures contract (FFR shock) and the change in the on-the-run 10 year yield as monetary shocks.[17] In the pre-crisis sample firms with higher leverage are less responsive to a FFR shock while the 10 year shock response is essentially the same for firms regardless of leverage. In the

[16] Recall that the MP shock measure has been scaled to have a unit (100 basis point) effect on the 2 year Treasury yield.

[17] Since the 10 year yield is mechanically a function of the short rate, we first orthogonalize the 10 year yield change with respect to the FFR shock. In other words, we first regress the change in the on-the-run 10 year yield on the FFR shock and use the residual from this regression as our monetary shock measure (labeled "10 yr shock").

post-crisis sample this relationship changes and the FFR shock has an identical effect for firms across the leverage spectrum whereas firms with higher leverage are now responding more to the 10 year shock. The heterogenous effects of monetary policy worked directly through fed funds rate target changes in the pre-crisis sample but in the post-crisis sample worked through the changes in the 10 year rate. This is not surprising given that the fed funds rate was stuck at the zero lower bound for most of the post-crisis sample and in this period the Federal Reserve used unconventional measures like forward guidance and quantitative easing. This result also highlights the convenience of our MP shock measure that parsimoniously captures the joint effect of the FFR shock and the 10 year shock in one variable. Thus we will use the MP shock for most of the results shown below.

Finally, Table D2 shows the results when we use only a single rate as the monetary policy indicator. Columns 3a and 3b show the results using the change in the on-the-run 2 year Treasury yield as the monetary policy shock (labeled “2 yr shock") for both samples. These results confirm the reversal in the relationship. Firms with higher leverage were less responsive to monetary policy shocks in the pre-crisis sample but more responsive in the post-crisis sample. The bottom panel also shows the triple interaction specification using the 2 year rate as the monetary policy indicator. Consistent with the earlier results, this interaction coefficient is positive and statistically significant.

In Section 2.5 below we conduct a battery of robustness checks. These include using a different leverage measure (debt-to-assets), expanding our S&P 500 sample to all non-financial firms in the CRSP/Compustat dataset, including the crisis dates in the sample, excluding unscheduled FOMC meetings from the sample, using time-by-sector fixed effects, narrowing our panel to firms without any entry or exit from the sample and including financial firms. First, we document some empirical patterns in our baseline leverage measure to show that our results are not being driven by any sudden change in the behavior of leverage since the crisis.

2.3.2 Leverage in the pre- and post-crisis samples

The results of differential responsiveness in the pre- versus post-crisis samples raise some natural questions about the behavior of leverage in the two samples. Has average leverage changed since the crisis? How does the cross-sectional distribution of leverage compare across the two samples? Has there been any "churning" of firms from low leverage in one sample to high-leverage in the other sample? Importantly, do these patterns play a role in driving the results? In this section we tackle these issues in order.

First, from Table D1 we can see that leverage is on average only slightly higher in the post-crisis sample. For example our baseline measure of leverage, debt-to-capital, has a mean of 0.41 in the post-crisis sample relative to a mean of 0.38 in the pre-crisis sample.[18] Similarly the standard deviation of leverage is also roughly the same across the two samples. Figure E1 shows the distribution of leverage in the two samples where we have taken the firm-specific average for each sample. The grey shaded bars show the histogram for the pre-crisis sample while the red transparent bars show the post-crisis histogram. While there is a little more mass toward the right in the post-crisis sample (and a little more toward the left in the pre-crisis sample), the distribution is quite similar in the two samples. In our baseline results presented in Section 2.3.1 we standardized our leverage measure by using the full sample mean and standard deviation of leverage. We have also tried using the pre-crisis mean and standard deviation to standardize our leverage measure. These results are presented in the Online Appendix. As one would expect with the patterns from Table D1 and Figure E1 we find these results are very similar to our baseline results.

We further investigate whether firms have moved around in the distribution in the two samples. Given the stability of the leverage distribution in the two samples, it is still possible that our results are driven by i) less-sensitive firms that had high-leverage in the pre-crisis sample but switched to having lower leverage in the post-crisis sample and ii) more-sensitive firms with low leverage in the pre-crisis sample but switched to having higher leverage in the post-crisis sample. To this end, Figure E1 displays a scatter plot of the firm-specific average leverage in the post-crisis sample versus the average in the pre-crisis sample. If firms' leverage across the two samples is similar, we should expect the points in the scatter plot to cluster around the 45 degree line. Figure E1 does in fact show this pattern. We also investigate whether our results are driven by the firms that did

[18]The fact that leverage is increasing a little on average for all firms in the post-crisis sample is not a concern because our results are driven by how firm response is different across the leverage distribution.

change their leverage noticeably, i.e. the ones that are not close to the 45 degree line. In the Table D13, we present our baseline results excluding firms which lie more than 1 standard deviation away from the 45 degree line. The table confirms that our baseline stock market results are robust to excluding these outliers. This suggests that movement of firms across the leverage distribution does not explain the difference in transmission of monetary policy through firm leverage following the financial crisis.

Next, we show this pattern of high leverage being related to less responsiveness before the financial crisis and more responsiveness afterwards is also evident using firm-level options data.

2.3.3 Evidence from firm-level options data

Given that monetary policy shocks are not predictable, our results from Section 2.3.1 have no implications for the *expected direction* of the movement in the stock price of firms with higher (or lower) leverage on FOMC announcement days. However, there is a direct implication for the *expected volatility* of the stock price of firms with higher (or lower) leverage. Specifically, we should expect that in the pre-crisis period high leverage firms should be less volatile on FOMC announcement days but more volatile in the post-crisis sample. In this section, using options data we indeed find strong evidence for this pattern.

We construct firm-level measures of expected volatility using options data from the OptionMetrics dataset. The methodology used to do this calculation closely follows the one used for implied volatility of the S&P 500 index, i.e. the VIX. Specifically, for each firm we use the implied volatility of the expected stock return, based on firm-level options prices. To assure the options in our sample are sufficiently liquid, we restrict the sample to those options set to expire in one quarter or longer. Even with this restriction, on any given trading day there exist many firms with missing implied volatility data. Thus, for the following specification, we will use the the most recent day (within the previous three trading days) in which an S&P 500 firm has a non-missing value for its implied volatility.[19]

[19]Our results are very similar if we instead choose not to impute any of the missing implied volatility data

Using this implied volatility measure we explore whether the interrelation between firm-level expected volatility, leverage and FOMC announcements has changed in a way that is consistent with our earlier results. Specifically we run the following regression

$$ivol_{i,t-1} = \alpha_i + \alpha_t + \delta l_{i,t} + \beta l_{i,t-1} D_t^{post} + \Gamma Z_{i,t-1} + e_{i,t} \tag{2.3}$$

where for an FOMC meeting occurring on day t, $ivol_{i,t-1}$ is the level of implied volatility for firm i on the day before the FOMC meeting, $l_{i,t-1}$ is average leverage (debt-to-capital) for firm i for the four quarters preceding the quarter of the FOMC announcement, D_t^{post} is a dummy that is set to 1 for the post-crisis sample of August 2009 to December 2017, $Z_{i,t-1}$ contains a variety of firm-level controls,[20] α_i is a firm fixed effect and α_t is a time-fixed effect. The combination of the firm- and time-fixed effect allows us to control for factors that are firm specific (but fixed over time) and aggregate patterns that affect the level of the firm-specific implied volatility measure. Due to the data availability of options data, our sample runs from January 1996 to December 2017.

The estimates are presented in Table D3 with two-way clustered standard errors along the firm and time dimension. Column 1 does not include any firm-level controls, while column 2 adds the full list of firm-specific controls listed above. For both columns, the coefficient on leverage (δ) is negative and significant: In the pre-crisis sample firms with higher leverage had lower levels of expected volatility on the day before the FOMC announcement. But the coefficient on the interaction of leverage and the post-crisis dummy (β) is positive and significant: Relative to the pre-crisis sample, leverage is more positively associated with implied volatility in the post-crisis sample. In the post-crisis sample, expected volatility is roughly one-quarter of a standard deviation higher for a firm that has leverage one standard deviation above the mean. Moreover, the size of the total effect in the post-crisis sample ($\delta + \beta$) is positive and significant, as shown by p-values in the table. This means that as measured on the day before the FOMC announcement, high leverage firms were expected to be *less* volatile in the pre-crisis sample but *more* volatile in the post-crisis sample.

[20]The controls include the same as those in our baseline stock market regression, as well as the firm-level stock price on the trading day prior to the FOMC day.

The results from Table D3 are also robust to using the alternative measures of leverage (debt-to-assets and debt-to-equity), putting in time-sector fixed effects, excluding unscheduled FOMC meetings from the sample, including the crisis dates in the post-crisis period or including financial firms in the sample. These results are discussed in Section 2.5.

In summary, the firm-level options data confirm the reversal in the relationship between leverage and monetary policy announcements since the financial crisis. Moreover, our options-based variable is measuring *expected* volatility as captured on the day before the FOMC announcement. The change in the sign of the relationship between this expected volatility and leverage implies that participants in the financial markets have internalized the change in relationship since the crisis that we estimated with stock returns in Section 2.3.1. Next, we provide evidence for this changing relationship using firm-level investment data.

2.3.4 Evidence from investment data

In this section we corroborate the evidence from the stock market using firm-level variables on economic activity from Compustat. Specifically we explore the response among S&P 500 firms of firm-level investment and sales to monetary policy shocks. We focus in the main text on the investment response, relegating our sales growth results to the Online Appendix. Our baseline empirical specification is the following:

$$\Delta ln(y_{it}) = \alpha_i + \alpha_t + \sum_{n \in N} \beta_{1,n} l_{i,t-n-1} \epsilon^m_{t-n} + \beta_{2,n} l_{i,t-n-1} \epsilon^m_{t-n} D^{post}_{t-n} + \Gamma' Z_{i,t-1} + e_{it} \qquad (2.4)$$

where y_{it} is the value of either firm i's real sales revenue or capital stock in quarter t, α_i is a firm i fixed effect, α_t is a quarter t fixed effect, l_{it} is firm i's leverage ratio, ϵ^m_t is the sum of all high-frequency monetary policy shocks that occur in quarter t, D^{post}_t is an indicator for the post-crisis period, $Z_{i,t-1}$ is a vector of firm-level controls (lagged by one quarter) and e_{it} is the residual.[21]

[21] $Z_{i,t-1}$ also contains each of the n lags of the firm's leverage ratio and the respective interactions with the lagged post-crisis dummy. As with the stock market specification, the monetary policy shock ϵ^m_t is subsumed by the time fixed effect. The same is true of the post-crisis dummy and its interaction with the monetary policy shock.

For the specification with investment as the dependent variable, $N = [0, 12]$. Due to the strong seasonality of sales data, $N = \{0, 4, 8, 12\}$ for the specification with sales growth as the dependent variable.

The key parameters in the above specification are $\beta_{1,0}$ and $\beta_{2,0}$, which estimate how the responsiveness of the real variable, y_{it}, to a contemporaneous quarterly monetary policy shock differs based on a firm's leverage ratio in the pre-crisis and post-crisis, respectively. Since we standardize l_{it} to be mean zero and unit variance, these parameters can be interpreted as the additional increase in a firm's quarterly sales or investment in response to an expansionary monetary shock by moving from an average leverage ratio to one standard deviation above the average leverage ratio. As in the results discussed above, we multiply the monetary policy shock measure by negative one so that an increase in ϵ_t^m corresponds to an expansionary shock.

We control for factors in $Z_{i,t-1}$ that could potentially affect both a firm's leverage ratio and the quarterly growth in the firm's sales or capital stock. For regressions with investment as the dependent variable, $Z_{i,t-1}$ includes the log of the book value of assets, the ratio of current assets to total assets, the ratio of sales revenue to the (net) capital stock and the year-over-year real sales growth. These controls are intended to capture the size of the firm and its liquidity/cash flow, both of which should increase a firm's ability to finance investment expenditures. For regressions with sales growth as the dependent variable, $Z_{i,t-1}$ includes the log of the book value of assets and the ratio of current assets to total assets. Since the monetary policy shocks occur throughout the quarter and the firm-level variables are measured at the quarterly level, leverage and the controls are lagged to ensure they are predetermined at the time of the monetary policy shocks. We also include a dummy for the fiscal quarter in all specifications, to account for differences across firms due to different positions in their fiscal year. This is particularly important for sales, which displays a strong seasonal trend based on fiscal quarter. Since we are using panel data, we are able to include firm and time fixed effects. The firm fixed effect accounts for permanent characteristics of changes in firm i's sales or capital stock that are not captured by our controls. The time fixed effect accounts for aggregate shocks common to all the firms in quarter t. The standard errors reported in the parentheses are calculated using two-way clustering along the time and firm dimensions. Finally, to ensure that the firm fixed effect is not endogenous, we only keep firms in the sample that have at least 40 observations with non-missing sales or investment data in either the pre- or post-crisis sample.

Table D4 shows the contemporaneous response of investment with the results for sales provided in the Online Appendix. These results are consistent with the pattern emerging from the stock price and implied volatility results. In the pre-crisis sample, the interaction between the monetary policy shock and leverage is negative and significant, while the interaction is positive and significant in the post-crisis sample. Our finding that investment is less responsive to a contemporaneous monetary policy shock in the pre-crisis period matches the main finding of Ottonello & Winberry (2018).[22] Specifically, during the pre-crisis period, a firm with leverage one standard deviation above average experiences an increase in investment 3.71% *less* than a firm with average leverage during the quarter in which an expansionary monetary policy shock occurs. In the post-crisis period, a high-leverage firm would experience an increase in investment 7.86% *more* than a firm with average leverage.

In section 2.5 below we discuss further robustness checks of these results, including using time-sector fixed effects, adding more controls and expanding the sample beyond S&P 500 firms. Before detailing these tests, we now turn to a discussion of potential mechanisms behind the empirical findings we have presented up to this point.

2.4 Mechanism

We began by showing that there has been a change in the relationship between firm leverage and monetary transmission. Specifically, using both high frequency stock market data and quarterly

[22] Jeenas (2018) finds that higher leverage firms become more responsive than lower leverage firms several quarters after a monetary policy shock in the pre-crisis period. In contrast, Ottonello & Winberry (2018) do not find a differential effect by leverage beyond the contemporaneous quarter. Ottonello & Winberry (2018) contains a lengthy discussion of the methodological differences between these two papers. Due to limited amount of data in the post-crisis sample, it is difficult to discern any statistically significant differences in the long-term response between the pre- and post-crisis samples. We find that the clearest change from the pre- to the post-crisis occurs in the contemporaneous sensitivity of investment due to differences in firm leverage. Thus we choose to focus on these results here.

economic activity variables we showed that high leverage firms were less responsive in the pre-crisis sample but more responsive in the post-crisis sample. In this section we shed some light on the mechanism underlying the change in this relationship.

In the post-crisis sample, with the fed funds rate stuck at the zero lower bound, the Federal Reserve has leaned more on unconventional monetary policy actions like large scale asset purchases and forward guidance. While there is a large literature on the channels of unconventional policy transmission, there is very little work that studies the heterogeneous transmission through the balance sheets of non-financial firms. In this section we start with the recent heterogeneous firm general equilibrium model of Ottonello & Winberry (2018) (OW hereafter) who study the transmission of conventional monetary policy (in the pre-crisis sample) through firm balance sheets. Within this framework, we discuss a channel that can rationalize our post-crisis findings and provide supporting empirical evidence for it. Next, we dig deeper to understand this channel and show that long rates have become more sensitive to monetary policy shocks in the post-crisis sample. Thus a monetary policy induced change in long rates could have outsize spillover effects on financing conditions for firms who rely more on longer term funding. Consistent with this story, we find that our baseline results are driven by firms whose leverage is more dependent on long-term debt. Finally, we provide some suggestive evidence for an additional channel of monetary transmission to firm balance sheets since the crisis, namely through changes in uncertainty about future monetary policy decisions.

2.4.1 Ottonello & Winberry channels of monetary transmission

The canonical theoretical framework to understand the transmission of monetary policy through firm balance sheets is the financial accelerator model of Bernanke et al. (1999). The essential feature of the models in this vein is the existence of some financial friction in the borrower-lender relationship. For our purposes, the key question is what this framework implies for the heterogenous firm response to monetary policy. In the literature, the theoretical predictions of how firm balance sheet characteristics affect monetary transmission are ambiguous. Bernanke et al. (1999) did extend their baseline model to a heterogenous (two-firm) case. With their preferred calibration they find that firms that have a larger external finance premium respond more strongly to monetary policy shocks. Building on the work of Khan et al. (2016), OW extend the Bernanke et al. (1999) framework to allow for a richer structure of heterogeneity (including firm-specific productivity and capital quality shocks) and firm default. Contrary to Bernanke et al. (1999), they find that firms with higher leverage are less responsive to monetary policy. Moreover, they confirm their results using an empirical analysis for the pre-crisis sample. These OW results are consistent with our empirical results shown above for the pre-crisis sample. If we start with the OW model as our baseline model for the pre-crisis sample, is it possible to explain our post-crisis results in this framework? Below we summarize their model in brief and layout the key mechanisms from their model to understand this issue.

The OW model has firms that can invest in capital by borrowing or using internal funds and generates default in equilibrium. They embed this heterogeneous firm setup into a standard New Keynesian sticky-price framework to study the effects of monetary policy. To understand the relevant mechanism of monetary transmission, we reproduce a key first-order condition from their model. For a given level of productivity (z), the first order condition for the optimal choice of a firm's investment (k') and borrowing (b') is given by[23]

$$\left(q_t - \varepsilon_{R,k'}\left(z, k', b'\right)\frac{b'}{k'}\right)\frac{R_t^{\mathrm{sp}}\left(z, k', b'\right)}{1-\varepsilon_{R,b'}\left(z, k', b'\right)} = \frac{1}{R_t}\mathbb{E}_t\left[\mathrm{MRPK}_{t+1}\left(z', k'\right)\right]$$

The left hand side represents the marginal cost of capital and is a product of two terms. The first one is the price of capital net of the elasticity of the lender's rate schedule with respect to investment ($\varepsilon_{R,k'}\left(z, k', b'\right)$). An extra unit of investment costs q_t but it adds to the firm's collateral

[23]We have omitted two terms that capture the marginal benefit of investment from this first order condition. The first one is $\frac{1}{R_t}\frac{\mathrm{Cov}_t\left(\mathrm{MRPK}_{t+1}\left(z',k'\right),1+\lambda_{t+1}\left(z',k',b'\right)\right)}{\mathbb{E}_t\left[1+\lambda_{t+1}\left(z',k',b'\right)\right]}$ which is the covariance between the return to capital and the firm's shadow value of resources. The second one is given by $\frac{1}{R_t}v_t^0\left(\underline{z}_{t+1}\left(k', b'\right)\right)g\left(\underline{z}\left(k', b'\right)\right)\left(\frac{\partial \underline{z}_{t+1}\left(k',b'\right)}{\partial k'} - \frac{\partial \underline{z}_{t+1}\left(k',b'\right)}{\partial b'}\right)$ and captures how more investment affects a firm's default probability. OW find that these two terms do not play a major role and we have thus omitted them for convenience.

and thus lowers the interest rate charged by lenders. The second term is how borrowing costs change with investment. $R_t^{sp}(z, k', b')$ is the firm-specific rate $R_t(z, k', b')$ (relative to the risk-free rate R_t). This is scaled by one minus the elasticity of the debt price schedule $(1 - \varepsilon_{R,b'}(z, k', b'))$ with respect to borrowing, which captures the idea that an increase in borrowing makes the firm riskier and thus makes lenders charge a higher premium. Graphically (as can be seen in Figure E2), the marginal cost schedule (as a function of capital accumulation) is flat for low levels of capital as the firm has enough cash on hand to not be perceived as risky. After a certain cutoff point, the marginal cost curve slopes upward as the higher level of borrowing required to fund the capital increases the riskiness of firms. The right hand side represents the marginal revenue product of capital discounted by the risk-free rate. Graphically, the marginal benefit schedule is represented by a standard downward sloping curve due to diminishing returns to capital.

What is the effect of an expansionary monetary policy shock in this framework? By lowering the risk-free rate, an expansionary shock lowers the discount rate and thus shifts the marginal benefit curve up and to the right.[24] An expansionary shock has three effects on the marginal cost curve. First, it shifts up the curve because an increase in the demand for investment leads to an increase in the price of capital. Next, this shock extends the flat part of the marginal cost curve because it increases the firm's cash on hand and decreases the amount the firm needs to borrow to finance a given amount of investment. Finally, it flattens the upward sloping part of the curve because the firm's collateral is worth more and thus reduces the loss to the lender in case of default. These can be seen in Figure E2.

How do firms with high and low leverage react differently to monetary policy shocks? In this framework there are competing channels which make it theoretically ambiguous whether a high or low leverage firm will respond more. For a high-leverage firm, the upward sloping part of the marginal cost curve is steeper and thus this will make it less responsive to monetary policy induced shifts of the marginal benefit curve. On the other hand, a high leverage firm's marginal cost curve will flatten more in response to an expansionary monetary shock, making it more responsive. In

[24] There are also general equilibrium effects due to changes in the price of output, capital and wages which in the OW calibration further shift out the marginal benefit curve.

the OW calibration they find that the former effect dominates and thus a high leverage firm is less responsive to monetary policy shocks. This case is highlighted in the top row of Figure E2. So how can we explain our results of higher sensitivity for high leverage firms in the post-crisis sample using this framework?

Theoretically, there are three possible ways in which this can happen. In the post-crisis sample we would need that i)the marginal benefit curve shifts more for high leverage firms in response to a monetary shock or ii)the slope of the marginal cost curve is more flat (on average, not in response to monetary shocks) for high leverage firms (relative to low leverage firms) or iii) the slope of the marginal cost curve flattens more in response to a monetary shock for high leverage firms and that this increased flattening is enough to outweigh the relative steepness of high leverage firms.

We argue that the first two explanations are less plausible and provide evidence that the third explanation is likely at play. Regarding the first explanation, the shift of the marginal benefit curve is driven by changes in the discount rate. It is unlikely that discount rates for high leverage firms respond differentially in the post-crisis samples.[25] The second explanation would require that in the post-crisis sample high leverage firms are perceived to be less risky than low-leverage firms. In other words, the credit spread charged by lenders (relative to the risk-free rate) to high leverage firms would increase less as these firms take on more borrowing. First, recall that in FigureE1 above we have shown that a firm's leverage position is fairly stable across the two samples. Moreover, Figure E1 shows that the correlation of leverage with measures of firm riskiness are stable across the pre- and post-crisis samples. This rules out the unlikely scenario that our results are being driven by the high leverage firms somehow becoming less risky in the post-crisis sample.

This leaves us with the third explanation. This requires that an expansionary monetary policy shock would flatten the marginal cost curve of high leverage firms more (relative to low leverage firms). Additionally this increased flattening would have to be large enough to overcome the relative steepness of the marginal cost curve for high leverage firms. From the first-order condition above, the marginal cost curve flattening more would imply that the credit spread charged by the lender

[25]There are also general equilibrium effects that work through the price of output goods, capital and wages but these are also unlikely to respond differentially for high leverage firms in the post-crisis sample.

(relative to the risk-free rate) to a high leverage firm falls more (relative to a low leverage firm) in response to an expansionary monetary shock. We can see this readily from the bottom row of Figure E2. This figure shows in the post-crisis sample that even though the slope of a high leverage firm is unconditionally steeper than a low leverage firm, it flattens more in response to an expansionary monetary shock to make the desired change in investment higher for high leverage firms.

This explanation provides a simple testable implication: the credit spread (relative to the risk-free rate) of high leverage firms should fall more in response to an expansionary monetary shock in the post-crisis sample. While we do not have access to high-frequency firm-level bond yields, we use bond indices that group together firms with similar risk profiles. Specifically, we use the Moody's bond yields index on firms rated AAA and those rated BAA.[26] Recall that Figure E1 showed that there is a negative and significant correlation between leverage and credit rating in both the pre- and post-crisis samples. Our hypothesis then is that the spread between the BAA yield and risk free rate falls more in the post-crisis sample relative to the spread between the AAA yield and the risk-free rate. Or alternatively, the BAA-AAA yield spread should fall more in the post-crisis sample. We test the hypothesis using the following regression

$$\Delta ln(y_t) = \alpha_0 + \alpha_1 D_t^{post} + \delta \varepsilon_t^m + \beta D_t^{post} \varepsilon_t^m + e_{it} \tag{2.5}$$

where y_t is the Moody's BAA-AAA bond yield spread, D_t^{post} is a dummy for the post-crisis period and ε_t^m is the monetary policy shock. The results presented in Table D5 show that indeed this is the case. In the pre-crisis sample, this bond spread response to monetary policy is small and not statistically significant. However, in the post-crisis sample the bond spread response is negative and significant at the 10% level. In response to an expansionary monetary policy shock that lowers the two year rate by 1%, the BAA-AAA bond spread falls 20% more in the post-crisis sample. We interpret this as suggestive evidence that monetary policy shocks are flattening the marginal cost curve more for firms with higher leverage in the post-crisis sample, thus driving their increased responsiveness. Overall, this result is consistent with the work of Gilchrist & Zakrajšek (2013) who

[26]Over 70% of the firms in our sample are rated BAA or higher.

find using credit default swap data that QE announcements reduced the cost of insuring against default risk more for higher risk firms.

2.4.2 Transmission through changes in long-term funding conditions

Why is it that monetary policy actions flatten the marginal cost more and thus compress the yield spread between high leverage and low leverage firms more in the post-crisis sample? The explanation that we pursue in this subsection relies on the fact that long rates have become more sensitive to monetary policy in the post-crisis sample and thus monetary shocks can potentially affect financing conditions more for firms that rely on long-term funding.

It is well established in the literature that monetary policy has substantial effects on long-term rates. Gürkaynak et al. (2005) showed this for nominal rates and more recently Hanson & Stein (2015a) showed this even for real rates. We first document that both nominal and real long-term rates (and term premium estimates commonly used in the literature) have become more sensitive to monetary policy shocks in the post-crisis sample.

In Table D6 we regress the (daily) change in the 10 year nominal yield, the 10 year real yield and the term premium of the 10 year nominal yield on the monetary policy shock. The nominal yields are from Gürkaynak et al. (2007), the real yields from Gürkaynak et al. (2010) and the term premium estimates are from Kim & Wright (2005). The table shows our baseline measure (MP shock) in Panel A and the 2 year shock in Panel B. An expansionary 2 year shock lowers all three: nominal yield, real yield and the term premium of the 10 year bond. Importantly, the fall in these three variables is substantially larger in the post-crisis sample.[27] The difference between the pre- and post-crisis coefficients is also statistically significant for the real yield and term premium response. In response to a 100 basis point reduction in the 2 year rate, the real yield (term premium) falls by 33 (21) basis points in the pre-crisis sample but by 101 (63) basis points in the post-crisis sample. Thus the real yield and the term premium on the 10 year Treasury bond are three times as sensitive to monetary policy shocks in the post-crisis sample relative to the pre-crisis sample.

[27]These results are consistent with the pattern documented in Hanson et al. (2017).

Recall that our baseline measure combines the fed funds rate target shocks with the 10 year shocks; thus, it is not straightforward to interpret the regressions reported in Panel A. But, we include them for completeness and moreover these results confirm the findings from the 2 year rate regressions.

These results suggest that monetary policy may be having an outsize effect on long-term funding conditions in the post-crisis sample. This could translate into a bigger effect on firms that are more reliant on long-term funding, for example through the “gap-filling" framework outlined in Greenwood et al. (2010). Foley-Fisher et al. (2016) find some supporting evidence of this channel by studying the Federal Reserve’s Maturity Extension Program (MEP) in 2011 and 2012. They find that MEP had disproportionate effects on firms that had more long-term debt. The relevant question for us is whether firms whose leverage is driven more by long-term debt are driving our results regarding the changing relationship since the crisis. To test this mechanism we focus on a long-term component of our overall leverage measure. Our baseline leverage measure (debt-to-capital) is defined as leverage = $\frac{\text{debt}}{\text{debt + equity}}$. We now define LT leverage = $\frac{\text{LT debt}}{\text{debt + equity}}$ where LT debt is defined as all debt maturing in more than one year. We separate firms as having high LT leverage (top two-thirds of the LT leverage distribution) and low LT leverage (bottom third of the LT leverage distribution). Then we run our baseline regressions separately for these two groups in the pre- and post-crisis samples.

The results are presented in Table D7. The first two columns (1a and 1b) show the baseline regressions for the firms classified as “High LT leverage" and the next two columns (2a and 2b) show them for the “Low LT Leverage" firms. For the high LT leverage firms, we get the same flip in the sign of the interaction coefficient as the baseline results, with a negative and significant coefficient in the pre-crisis sample but a positive and significant coefficient in the post-crisis sample. For the low LT leverage firms, the coefficient is negative and significant in the pre-crisis sample but insignificant and essentially zero in the post-crisis sample. Thus, in the post-crisis sample, our baseline results of high leverage firms being more responsive to monetary policy shocks is driven by firms whose leverage is more dependent on long-term debt. This is consistent with the interpretation that in the post-crisis sample monetary policy affects firms that are more exposed to funding using long-term instruments. Moreover, these results are consistent with the work of Foley-Fisher et al. (2016) who studied the MEP program. We have run our results dropping the two MEP related FOMC meetings in 2011 and 2012 and find that they are essentially identical to those reported in Table D7. Thus our results indicate that the phenomenon of monetary policy having a bigger effect on firms that are more exposed to long-term debt has been true more generally of Federal Reserve policy since the crisis and not just specific to the MEP.

2.4.3 Transmission through monetary policy uncertainty changes

In the previous subsection we provided some evidence that firms with leverage more dependent on long-term debt were more responsive to monetary policy shocks in the post-crisis sample. Here we explore another channel through which monetary policy actions since the crisis could have had heterogenous effects, namely the uncertainty channel.

There is a growing literature that highlights the role of changes in policy uncertainty as a channel of monetary transmission.[28] Moreover, Bauer et al. (2019) and Kroencke et al. (2018) highlight the growing importance of this uncertainty channel in the post-crisis sample. To investigate the role of this channel we use the high-frequency market-based measure of monetary policy uncertainty developed by Bauer et al. (2019). They use options on Eurodollar futures to get a model-free estimate of the standard deviation of the expected interest rate at horizons of 0.5 year, 1 year, 1.5 years and 2 years. We construct a single series by taking the first principal component of these four measures.[29] We will use the (daily) change in this principal component measure on FOMC days as the monetary policy uncertainty shock (labeled “MPU shock").

First, we explore the effect of this monetary policy uncertainty measure on firm-level stock returns and whether high leverage firms respond differentially. We estimate the following regression

$$s_{i,t} = \alpha_i + \alpha_t + \beta l_{i,t-1}\epsilon_t^{mpu} + \delta l_{i,t-1} + \Gamma' Z_{i,t-1} + e_{i,t} \tag{2.6}$$

[28]See the recent work of Creal & Wu (2017), Husted et al. (2017), Bauer et al. (2019), Kroencke et al. (2018) and Bundick et al. (2017b)

[29]The estimates for the 1.5 year and 2 year horizons are not available for the entirety of our sample. Thus, we perform separate principal component analyses on three subsamples, partitioned by the number of measures available.

where we have replaced the monetary policy shock from our baseline specification in Equation 2.2 with the MPU shock (ϵ_t^{mpu}). Because of the limited availability of the uncertainty measure, our sample starts in January 1994. The MPU shock is scaled so that a positive number reflects a lowering of uncertainty ("an expansionary shock"). Table D8 shows the regression results for the pre- and post-crisis sample. In the pre-crisis sample the interaction coefficient of leverage and MPU shock is negative but small in magnitude and statistically insignificant: in the pre-crisis sample, leverage did not play a role in firms' stock price response to uncertainty shocks. However, this coefficient is positive and statistically significant in the post-crisis sample: in the post-crisis sample firms with higher leverage are more responsive to monetary policy uncertainty shocks.[30]

We also find some additional evidence for the heterogenous effects of the monetary policy uncertainty shocks using firm-level implied volatility constructed from options data. We find that the change in the expected volatility of firm-level stock returns responds significantly to monetary uncertainty shocks. Moreover, this transmission is stronger for high leverage firms in the post-crisis sample. Specifically, we estimate the following regression

$$\Delta ivol_{i,t} = \alpha_i + \alpha_t + \beta_1 l_{i,t-1}\epsilon_t^{mpu} + \beta_2 D_t^{post} l_{i,t-1}\epsilon_t^{mpu} + \delta l_{i,t-1} + \Gamma' Z_{i,t-1} + e_{i,t} \tag{2.7}$$

where $\Delta ivol_{i,t}$ is the (daily) change in firm-level implied volatility on FOMC days, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, $l_{i,t-1}$ is leverage, ϵ_t^{mpu} is the monetary policy uncertainty shock, D_t^{post} is a dummy for the post-crisis period and $Z_{i,t-1}$ is a vector of firm-level controls containing the firm's share price change, real sales growth, size, price-to-cost margin, receivables-minus-payables to sales, depreciation to assets, age, log(market cap), current assets to total assets and an indicator for current fiscal quarter. Table D9 shows that β_1 is positive and significant. Since the baseline effect of a reduction in uncertainty is to reduce expected volatility, a positive β_1 implies that expected volatility fell less on FOMC days in response to reduced uncertainty for firms with high leverage in the pre-crisis sample. In other words, in the pre-crisis sample an FOMC announcement that lowered uncertainty would translate into a smaller reduction in expected future

[30]One issue with this uncertainty measure is that it is only available at a daily frequency. Since our monetary policy shock is constructed at a higher frequency, it is not straightforward to compare the relative contribution of our baseline monetary policy shocks versus the monetary policy uncertainty shocks.

volatility for a firm with high leverage. But the estimate of β_2 is negative and significant. This suggests that this relationship changes after the crisis. In the post-crisis sample, the response of a firm with high leverage to uncertainty shocks is more negative, i.e. high leverage firms are more responsive to reductions in uncertainty.

2.5 Robustness Checks

We start by documenting the robustness of our three different empirical approaches to using an alternative definition of leverage: debt-to-assets. Debt-to-assets is widely used in the literature to measure firm leverage, e.g. Whited & Wu (2006) find that Compustat firms with a higher debt-to-assets ratio are more financially constrained. Table D14 shows that these results using debt-to-assets confirm the baseline results. Our baseline results use the four-quarter moving average of debt-to-capital[31]; however, one could be concerned that this smooths out meaningful, higher-frequency variations in leverage. In Table D15, we show that our results are robust to using the one-quarter lagged version of our leverage measure.

Next, we tackle the concern that our results may be driven by different sectors being more or less responsive to monetary policy shocks. To account for this we include a sector by FOMC day fixed effect, rather than just an FOMC day fixed effect. In Table D16, we show that the significance and magnitude of our baseline results are not meaningfully affected.

As a further robustness check, we expand our sample beyond S&P 500 firms. One main difference between the S&P 500 sample and a full CRSP/Compustat sample is that firms in the expanded sample enter and exit much more frequently, as well as have more missing data values. To limit the effects of changes in sample composition amongst the full CRSP/Compustat sample, we keep only those firms that are present in our entire sample period. These results are displayed in Table D17. We see that our baseline results are robust to broadening our sample to include more than just S&P 500 firms.[32]

[31] To be consistent with Ottonello & Winberry (2018), our baseline investment table uses the one-quarter lagged debt-to-capital ratio. We show in the Online Appendix, as well as Table D16, that our investment results become stronger in terms of magnitude and significance when using the four-quarter moving average of the debt-to-capital ratio.

[32] Due to the limited availability of expected volatility data for firms outside the S&P 500, we include only our stock

The Online Appendix contains several more robustness checks. First, we present the results when we include the crisis dates in the post-crisis sample. The coefficients show that including the financial crisis dates does not materially change the results. Second, we show that our stock market results are not driven by a change in the composition of the sample between the pre-crisis and post-crisis periods. In the Online Appendix we rerun our baseline stock market specification, limiting the sample to only those firms with non-missing data for all 221 FOMC days in our sample. Despite losing approximately 75% of our sample to this restriction, the results qualitatively match our baseline results: higher leverage firms are less responsive in the pre-crisis period and more responsive in the post-crisis period. This shows that our main results are not caused by certain firms entering or exiting the sample, e.g. firms that did not survive the financial crisis.

FOMC meetings that are unscheduled can have effects on financial markets that are different from regularly scheduled meetings as the unscheduled meetings typically occur in times of economic turmoil. The unscheduled meetings are also instances in which the Federal Reserve is more likely to release information about economic fundamentals, see for example Lakdawala & Schaffer (2019a). Thus we want to make sure that our results are not driven by these unscheduled meetings. This issue only arises in the pre-crisis sample which has 16 unscheduled meetings, while our post-crisis sample has none. The Online Appendix shows the regression results excluding the unscheduled meetings. These results are quite similar to the baseline case. There may still be a concern that even on regularly scheduled FOMC meetings the high frequency monetary policy shocks contain a substantial information component. To address this concern we use forecast data (following the approach in Lakdawala (forthcoming)) to cleanse the monetary policy shock of any information effects. These results, also shown in the Online Appendix, confirm that our baseline results are not driven by this issue. Finally, we show in the Online Appendix that including financial firms in our sample does not affect our results.

market and investment results.

2.6 Conclusion

In this paper we add to the growing empirical literature on monetary policy and firm-level heterogeneity. Using both high frequency data from the stock market and lower frequency investment data we show that the role of leverage in transmitting monetary policy shocks has changed since the financial crisis. Before the financial crisis a firm with higher than average leverage was less responsive to monetary policy shocks. However, after the financial crisis this relationship has reversed so that firms with higher leverage are now more responsive to monetary policy shocks. We interpret our pre-crisis results through a structural model and provide suggestive evidence for a mechanism that can rationalize our post-crisis results. Since the crisis, long rates have become more sensitive to monetary policy shocks suggesting increased sensitivity of long-term funding conditions to monetary policy. Consistent with this story, we show that our baseline results of increased responsiveness since the crisis are driven by firms whose leverage is more dependent on long-term debt. Finally, we also provide some suggestive evidence that monetary transmission related to leverage works in part through an uncertainty channel, where FOMC announcements change the market's perceived uncertainty about future policy actions.

Our results have potentially important implications for the aggregate effects of monetary policy. Focusing on the pre-crisis sample, Ottonello & Winberry (2018) find that monetary policy is less effective in the aggregate when there is a bigger share of riskier firms in the economy. Our estimates from the post-crisis sample indicate that this relationship has reversed in the last decade. This suggests two important avenues for future research. First developing general equilibrium models with firm heterogeneity that also allow a role for unconventional monetary policy will help us understand the aggregate transmission of monetary policy since the crisis. Second, we think that further exploring empirical strategies to tease out the state-dependent effects of monetary policy based on firm balance sheets is a promising area for future research.

CHAPTER 3

THE INTERNATIONAL SPILLOVER EFFECTS OF US MONETARY POLICY UNCERTAINTY

3.1 Introduction

Recent work has highlighted the phenomenon of the global financial cycle and the crucial driving role of US monetary policy (Miranda-Agrippino & Rey (2015), Jordà et al. (2019)). The literature has documented a variety of transmission channels through which Federal Reserve actions affect international financial markets. However, most of the focus in the literature has been on transmission through changes in the level of the Federal Reserve's policy rate (i.e. first moment changes).[1] In this paper we show that changes in uncertainty around the level of the policy rate (i.e. second moment changes) constitute an important *additional* dimension through which Federal Reserve decisions transmit to international financial markets.

The importance of uncertainty as an additional dimension of FOMC announcements is readily seen from the Aug 2011 FOMC meeting. At this meeting the FOMC introduced explicit calendar-based forward guidance for the first time by saying that rates will be low until "...mid-2013". Commonly used measures of the first-moment monetary policy shocks (e.g. changes in futures rates up to 1 year ahead) did not move much in response to the announcement but the market-perceived uncertainty fell substantially. In this paper we conduct a systematic evaluation of how such FOMC-induced changes in uncertainty transmit to international financial markets.

To perform this analysis, we use an event-study framework around FOMC meetings with bond yield data for a panel of 31 advanced and emerging countries.[2] Our measure of monetary policy uncertainty is the recent one developed by Bauer et al. (2019). This measure relies on high frequency

*This chapter is joint work with Aeimit Lakdawala and Matthew Schaffer.

[1]Albagli et al. (2019), Gilchrist et al. (2019) and Curcuru et al. (2018) are some recent examples from this literature. There are also numerous papers that study the transmission of unconventional monetary policy actions and we discuss how our work relates to that literature below.

[2]While the primary focus is the response of global bond yields, we also show that global equity markets react considerably to monetary policy uncertainty.

options data to calculate the market's perceived uncertainty; the conditional, risk-neutral 1 year ahead standard deviation of changes in the Federal Reserve's policy rate. We find that an increase in this market-based uncertainty raises bond yields in both advanced and emerging countries. This effect is over and above the effect of surprise changes in the expected policy rate, which is the most widely used measure of monetary shocks. In other words, uncertainty matters even after controlling for first moment shocks. While the average effect is moderate, we document that the international spillover through monetary policy uncertainty is larger when the Federal Reserve made deliberate changes to its forward guidance language in the FOMC statement. This suggests that by changing its communication about the uncertainty of its future actions, the Federal Reserve has an additional policy tool through which it can affect international financial conditions.[3]

What is the channel through which changes in US monetary policy uncertainty affect international bond yields? We find that there is a key difference in the mechanism through which monetary policy uncertainty is transmitted to yields in advanced versus emerging countries. In advanced countries, the response works through an international portfolio balance channel whereas for emerging countries it is related to a flight to safety channel. We perform a variety of analyses to better understand the differential transmission mechanisms.

First, we note that a standard asset pricing framework implies that the excess return of a long-term bond is a function of its conditional volatility (among other things). A change in the market's perceived uncertainty about future short rates is a clear signal about long-term bonds' conditional volatility. Thus an increase in uncertainty would imply that investors should demand a greater premium for holding long-term bonds. We document that changes in monetary policy uncertainty do indeed affect US bond yields through risk/term premia. This result is consistent with the recent work of Bundick et al. (2017a) and Bauer et al. (2019).

Next, we decompose changes in international bond yields into an expected (or risk-neutral) component and a term premium component. This is done using the methodology of Joslin et al.

[3]From a structural perspective, monetary policy uncertainty shocks can arise from variance of the residual of a policy rule or from uncertainty about the reaction function part of the policy rule. See Appendix Section F.0.1 for a detailed discussion.

(2011) and applying the bias correction of Bauer et al. (2012). Interestingly, we find that US monetary policy uncertainty affects bond yields in advanced countries only through the response of the term premium whereas the emerging country response is entirely due to changes in the expected component.

Taking up the advanced country response first, we show that the effect of monetary policy uncertainty on term premia in these countries works through changes in the term premium on the US 10 year Treasury bond.[4] Thus, the transmission channel runs from monetary policy uncertainty to US term premia and eventually to advanced country term premia. This mechanism is consistent with recent theoretical work on the so-called international portfolio balance channel, for example see Alpanda & Kabaca (2019). In this framework investors view bonds in different countries as imperfect substitutes for each other and this creates a link for changes in bond term premia in one country to affect those in another.[5] A key implication from this framework is that the size of this spillover should directly depend on the degree of substitutability between the countries' bonds. We provide a test of this hypothesis by constructing an empirical measure of the degree of substitutability between the bonds of a foreign country with the US. This measure is similar to the recent work of de los Rios & Shamloo (2017) and related to the older idea of Frankel (1982). As expected, we find that bonds of advanced countries are viewed as more substitutable with the US. Importantly, and consistent with the theoretical framework, we find that the term premium response to uncertainty in a given country is larger if its bonds are more substitutable with the US.

These results also shed light on the driving force behind some recent empirical work in the literature on the international spillover of US financial markets. Two recent papers (Mehrotra et al. (2019) and Curcuru et al. (2018)) find that changes in US term premia have a stronger effect on yields in advanced countries relative to emerging countries, consistent with our results. Our

[4]Specifically, in a regression of advanced country term premia on uncertainty, the coefficient on uncertainty is positive and significant. But when we control for the US 10 year term premium in this regression, the coefficient on uncertainty essentially goes to zero.

[5]The theoretical papers in this field do not explicitly focus on monetary policy uncertainty as the originating source for the transmission. However, the transmission mechanism is relevant as long as there is an effect through term premia. For example, Alpanda & Kabaca (2019) focus on the role of quantitative easing in driving term premia, while we are interpreting this effect coming from changes in monetary policy uncertainty.

work highlights that an important source of this transmission through term premia is driven by FOMC-induced changes in uncertainty.

US monetary policy uncertainty transmission to emerging countries works through a different channel than the one we highlighted for advanced countries. Changes in monetary policy uncertainty show up not in the term premium component of emerging country bonds, but rather the expected component. In other words, after an increase in uncertainty, markets expect that interest rates in emerging countries will rise. Using a local projections framework we confirm that the market reaction is correct; short rates in emerging countries do indeed rise and are higher a year after the shock. This response in emerging countries is tied to a flight to safety channel whereby an increase in uncertainty makes investors pull capital out of countries that are perceived to be risky. Using the Treasury's TIC monthly capital flows, we show that net holdings of emerging country (but not of advanced country) bonds decrease in response to monetary policy uncertainty shocks. Overall these results are consistent with the recent idea that capital flows in emerging countries are quite risk-sensitive (Kalemli-Ozcan (2019)).

The recent work of Rey (2013) suggests that the classic Mundell-Fleming "trilemma" may have morphed into a "dilemma", whereby flexible exchange rates do not insulate countries from financial spillovers unless there are additional restrictions on capital mobility. Kalemli-Ozcan (2019) argues that for emerging countries this is not quite the case, at least in response to first moment US monetary shocks. We find that the emerging country response to US monetary uncertainty is not related to the exchange rate regime, but rather to that country's financial openness. Specifically, the higher is the Chinn & Ito (2006) index of capital account openness, the larger is that country's response to uncertainty. We also investigate more broadly if there is heterogeneity across countries in their responsiveness to monetary policy uncertainty following the methodology of Iacoviello & Navarro (2019). For advanced countries, we do not find evidence of this. The usual country characteristics that are used in the literature to explain cross-country differences do not matter for reaction to monetary policy uncertainty.[6] For emerging countries we see somewhat more heterogeneity across

[6] Our baseline variables include financial depth, exchange rate regime, trade openness, capital account openness and the short-term interest rate differential with the US. We also attempted specifications using trade with the US and

countries but do not find much other than financial openness that can explain the responsiveness of yields.[7]

There are differences in the advanced and emerging country yield response over time. The advanced country response is relatively stable over our full sample from January 1995 to June 2019. But for emerging country bonds the responsiveness to monetary policy uncertainty is only prevalent in the period since the financial crisis. This suggests that in more recent years not only has the interconnectedness of global financial markets increased but shocks originating in one country are now being transmitted through new channels. These results highlight the need for exploring and incorporating these uncertainty-based transmission mechanisms in theoretical open economy macroeconomic models.

We also investigate the impact of US monetary policy uncertainty on international stock prices. An increase in US monetary policy uncertainty leads to a reduction in stock prices in both advanced and emerging countries, but only in the period since the financial crisis.[8] For both advanced and emerging countries, stock markets respond more to uncertainty in the post-crisis sample.

For long term yields and equity prices in both advanced and emerging countries, the size of the response to monetary policy uncertainty is larger than the response to the conventional first moment policy surprises.[9] Moreover, accounting for changes in the second moment is important even if one is only interested in the first moment effect of international spillovers. Leaving out changes in monetary policy uncertainty in the event-study regression biases the estimated effect of monetary policy surprises. This is because there is a positive correlation between changes in the first and second moment. Our estimates suggest that omitting uncertainty can lead to overstating the effects of monetary policy surprises by up to 50%.[10] Moreover, we document substantial increases in R^2

dollar debt exposure.

[7]Consistent with our results, Bowman et al. (2015) find that financial vulnerability (including capital account openness) is one of the main determinants of yield responses.

[8]This result confirms a general pattern that is consistent with the investigation of Indian stock markets carried out in Lakdawala (2018), where they attribute the increased responsiveness to the growing role of foreign institutional investors in domestic equity markets.

[9]For shorter maturity yields, relative to the first moment policy surprise, the uncertainty effect is somewhat smaller in advanced countries and roughly the same size in emerging countries.

[10]Our uncertainty measure is a risk-neutral measure and thus (as we explain below) the 50% estimate may be better viewed as an upper bound.

when adding uncertainty to the event-study regressions. Thus we argue that leaving out monetary policy uncertainty gives an incomplete picture of the transmission of Federal Reserve actions to international financial markets.

Our paper builds on the work of Bauer et al. (2019) that develops the measure of monetary policy uncertainty used in our paper. The main focus in Bauer et al. (2019) is on exploring how uncertainty is related to forward guidance language used by the FOMC and its transmission to domestic financial markets in the US. In this paper we focus on the international transmission of changes in uncertainty to bond and stock markets in a large set of advanced and emerging countries.

There is also a substantial literature that focuses on the international effects of unconventional Federal Reserve actions, e.g. see Anaya et al. (2017), Bhattarai et al. (2015), Bowman et al. (2015), Neely (2015), Fratzscher et al. (2018), and Kolasa & Wesołowski (2020). We show that the transmission of uncertainty is not altered on FOMC meeting dates with notable quantitative easing announcements. There is a view that attributes quantitative easing announcements as working through a signal about the future expected path of the policy rate, the so-called signalling channel (Bauer & Rudebusch (2014) and Bauer & Neely (2014)). Our results suggest that signals about the uncertainty around future rates are an additional and largely unexplored dimension of unconventional monetary policy transmission.

In addition to the literature that studies the effects of US monetary policy on asset prices (e.g. Albagli et al. (2019), Gilchrist et al. (2019), Curcuru et al. (2018), Ehrmann et al. (2011) and Hausman & Wongswan (2011)), there is also a large literature exploring the effects on capital flows (e.g. Kalemli-Ozcan (2019), Dahlhaus & Vasishtha (2014), Chari et al. (2020)). But this literature estimates the effect of changes in the *level* of the Federal Reserve's policy rate. We extend this literature to consider the international spillovers of changes in US monetary policy *uncertainty*.

While there is also a growing literature studying the international spillover effects of overall US uncertainty (see for example Bhattarai et al. (2019) and Carrière-Swallow & Céspedes (2013)), few papers have explored the international transmission of monetary policy specific uncertainty. On the empirical front, Lakdawala (2018) shows that the effect of US monetary policy uncertainty on the Indian stock market has grown since the financial crisis. Gupta et al. (2020) study uncertainty spillovers between a sample of nine advanced countries using the measure of Istrefi & Mouabbi (2018), which primarily captures disagreement among professional forecasters. A related theoretical work is Ghironi & Ozhan (2019), which investigates the impact of shocks to the variance of the domestic country's policy rate. Our emerging country results are broadly consistent with their framework.

3.2 US Monetary Policy Shocks

An increasingly common approach in the literature to measure US monetary policy shocks is to use changes in futures rates around FOMC announcements.[11] This measure is a first moment shock that captures surprise changes to the expected path of the FOMC's policy rate. The main contribution of this paper is to show that a second moment shock (i.e surprise changes to the uncertainty around the expected path of the FOMC's policy rate) also has substantial spillover to international financial markets. In Appendix Section F.0.1 we frame monetary policy uncertainty through the lens of a simple structural monetary policy rule. There we show that monetary policy uncertainty can come from variance of the residual in the monetary policy rule and also uncertainty about the reaction function part of the policy rule. Next, we detail the construction of this shock from option prices and provide a discussion of how prominent changes in our measure are related to specific changes in the forward guidance language used by the FOMC. While the focus will be on the transmission of this uncertainty measure, we also include the traditional first moment shock because, as we discuss below, the two measures are correlated.[12]

3.2.1 Monetary Policy Uncertainty

To construct the monetary policy uncertainty (*mpu*) measure, we use the methodology of Bauer et al. (2019). The object of interest is the standard deviation of the federal funds rate τ-periods ahead

[11] For example see the early work of Kuttner (2001). For more recent work see Nakamura & Steinsson (2018).

[12] We view our approach of separately studying the second moment shock transmission as complimentary to the large literature that studies the overall effect of both conventional and unconventional monetary policy actions.

conditional on the current information at time t, i.e. $\sqrt{Var(FFR_{t+\tau}|\mathcal{I}_t)}$. The methodology provides a model-free estimate of the risk-neutral conditional standard deviation, given prices of futures and options at time t. Our baseline measure will set τ to 12 months to measure the uncertainty about the 1 year ahead rate. The change in this measure is calculated in a two-day window around the FOMC announcement. We scale our measure to have unit standard deviation.

We refer the reader to Appendix Section F.0.2 for the details of the construction of the uncertainty measure. Here we provide a brief discussion of the relevant empirical properties and also what drives the big changes in our measure. Figure H1 plots our baseline measure: the change in the standard deviation of the 1 year ahead expected rate in a two day window around the FOMC announcement. We label this measure *mpu* in the regression analysis that follows. On average, our measure declines on FOMC days: the average is -0.49 standard deviations (2 basis points) and is statistically significant with a p-value less than 0.01. In other words, the FOMC announcement leads to a resolution of uncertainty on average. But there is also a fair amount of variation across individual FOMC dates, with some large declines and even some large increases.

Importantly, there is typically a direct relation between a specific change in the forward guidance language used by the Federal Reserve and changes in our measure. To aid in interpretation, the figure labels the three biggest falls and three biggest increases and provides a snippet from the FOMC statement or related market coverage that helps understand these episodes. For example, the biggest fall in our sample is in December 2008, where the FOMC cut rates to reach the zero lower bound. But in addition to this rate cut, there was explicit forward guidance language ("... warrant exceptionally low levels of the federal funds rate for some time") that signaled to the market that low rates were here to stay. The second biggest fall is in August 2011. Prior to this meeting, the FOMC statement contained a phrase that rates would be kept low *"...for an extended period"*. At the August meeting, the FOMC explicitly changed the language to signal that rates would be kept low *"at least through mid-2013"*, the start of so-called "calendar-based forward guidance". Markets clearly interpreted this as a sign that rates would indeed stay low and revised downwards their uncertainty about future rates. Another date labeled on the figure is January 29,

2004. At this meeting there was a change in the language to "*can be patient in removing its policy accommodation*" from the previous statement which said "*accommodation can be maintained for a considerable period*". The market interpreted this as increasing uncertainty about when rates would eventually increase.

In Section 3.4.2 below we discuss that changes in uncertainty are positively correlated with first-moment surprises. But the biggest changes in uncertainty do not always coincide with surprises about the policy path, and vice versa. For example, among the four announcements with the largest changes in uncertainty, two of them (in October 2008 and December 2008) also led to substantial first-moment surprises, whereas the other two (in August 2011 and November 1998) caused only modest ones. Moreover, we find that our measure of uncertainty (but not the first-moment shock) is positively correlated with changes in the dispersion of survey forecasts. In Table G12, we show this using data from the Survey of Professional Forecasters (SPF) and the Summary of Economic Projections (SEP).

Overall, our narrative evidence suggests that Fed communication has important effects on perceived monetary policy uncertainty and that these changes in uncertainty are often a separate dimension of the Fed's policy actions. We will systematically evaluate how these changes in market-perceived uncertainty about the future rate caused by FOMC announcements is transmitted to international financial markets and document that they indeed constitute an important additional dimension of FOMC actions.

3.2.2 Monetary Policy Surprise

As mentioned above, we also consider the well-known measure of a first moment monetary policy shock. This is because surprises to the expected path of policy rates (i.e. mps) are positively correlated with changes in uncertainty about future rates (mpu), as can be seen in Figure H4. Thus to isolate the effect of monetary transmission through changes in the second moment we need to control for changes in the first moment. We do that in our analysis by using the following first moment measure, labeled *mps* or MP Surprise. This shock is calculated as the change in the futures price in a window around the FOMC meeting. Let e_t represent the monetary shock and ε represent the length of the window, then $e_t^{(h)} = p_t^{(h)} - p_{t-\varepsilon}^{(h)}$ where $p_t^{(h)}$ is the price of a futures contract at time t that matures in $t + h$. As with *mpu* our baseline measure uses a two-day window. We use four Eurodollar futures contracts, expiring 1 quarter ahead (ED1) to 4 quarters ahead (ED4).[13] Taken together, the four contracts contain rich information about the short and medium term path of expected interest rates. To summarize this information in a parsimonious way we perform a principal component analysis. The first principal component of the 4 futures price changes explains more than 90% of the total variation across all the contracts. We therefore use this first principal component as one of our measures of monetary policy shocks. This is essentially identical to the measure used in Nakamura & Steinsson (2018). Since the scale of this principal component is arbitrary, we normalize our measure to have a one standard deviation effect on the 1 year ahead rate.

One issue worth noting for both measures of monetary policy shocks is that the underlying interest rate for Eurodollar futures is the three month LIBOR rate. LIBOR typically trades at a spread over the federal funds rate; thus, our monetary shock measures capture not only changes in the first and second moments of the future policy rate but also changes owing to the time-varying spread. The difference between LIBOR and the fed funds rate is best measured by the LIBOR-OIS spread. Other than the period around the financial crisis of 2007-2009, this spread has been low, and crucially, stable. Moreover, as we discuss in the section on robustness checks below (Section 3.4.6) the results are unchanged when we control for this spread in the regression analysis.

3.3 Data

Next, we describe the data used to measure the international spillover of US monetary policy. Our primary outcome measures are international asset prices: 2 year and 10 year government bond yields, equity prices and exchange rates vis-à-vis the US. We collected this data from Bloomberg for 28 advanced countries and 16 emerging market countries between January 1995 and June 2019,

[13]In Section 3.4.6 we show that our results are robust to using longer-horizon measures of *mps*.

where available. The data availability varies by country.[14] Table G13 details the data coverage for our international asset price data and the classification of countries. We will focus on two day changes around FOMC announcements. We use two day changes to allow for all international asset markets to respond to US monetary policy shocks.[15] The two day change is calculated as the difference between the closing price one day after and one day before an FOMC announcement. Some markets are open when FOMC announcements are made while others are not. We account for these country-specific timing differences when calculating the two day changes. Below, we also show that our results are robust to using a narrower one day window.

For constructing both of our US monetary policy shocks, we use daily Eurodollar futures data and daily Eurodollar options data which are from the Chicago Mercantile Exchange. For US data, the treasury yields are zero-coupon yields from Bloomberg and the S&P 500 return is from Yahoo Finance.

3.3.1 Summary Statistics

Table G1 reports summary statistics for the key variables of interest. Panel (a) contains our measures of monetary policy surprise and monetary policy uncertainty. The full sample includes 204 FOMC announcements from January 1995 to June 2019.[16] To aid in interpreting the regressions coefficients, we normalize the two monetary policy shocks in the following way. The monetary policy uncertainty measure is standardized to have unit standard deviation. Since the monetary policy surprise measure is calculated using a principal component analysis, its scale is arbitrary; thus, we normalize it to have an effect on the 1 year ahead futures rate equal to one standard deviation. Panel (b) presents summary statistics for exchange rate return, stock return, and changes

[14] We have data on exchange rate and stock prices for 28 advanced countries and 16 emerging countries. For government yields we have data for 22 advanced countries and 8 emerging countries.

[15] This is consistent with the recent literature that uses two-day changes (Albagli et al. (2019) and Hanson & Stein (2015b)) and is based on the idea that since FOMC meetings happen at 2:15 pm, using daily changes does not give markets enough time to react before close.

[16] We exclude the 9/17/2001 announcement following the 9/11 terrorist attacks and the 5/2/2018 announcement due to a lack of asset data availability. The 10/8/2008 announcement is excluded because many other central banks took joint action on that date, making it impossible to isolate the effect of US monetary policy. The 5/22/2013 “taper tantrum" episode is excluded as well, as it was driven by a speech by the Chairman rather than an FOMC announcement.

in 2 and 10 year government bond yields for the advanced and emerging countries in our sample, calculated in a two day window around FOMC announcements.

3.4 Results

In this section we present the main results that show the spillover effects from changes in US monetary policy uncertainty to international asset prices. To establish a benchmark, we first document the response of US asset prices to monetary policy uncertainty changes. In Section 3.4.2 we present our main results for international bond yields, followed by an investigation of the mechanism behind our baseline results in Section 3.4.3. Next, we provide a discussion of the heterogeneity in the country-level responses in Section 3.4.4. This is followed by results on the response of international equity markets in Section 3.4.5 and we conclude with robustness checks in Section 3.4.6.

3.4.1 Response of US asset prices to US monetary policy uncertainty

We study the response of 2 and 10 year Treasury bond yields and the S&P 500 return. The two monetary policy shocks detailed in Section 3.2 are i) monetary policy surprise (mps_t) which measures surprise changes in the expected path of the policy rate and ii) monetary policy uncertainty (mpu_t) which measures surprise changes in the uncertainty around the expected path, both for the 1 year horizon. As mentioned above, both measures have been scaled to reflect a one standard deviation effect. For each asset, we calculate the change in a two-day window, labeled (y_t). We estimate the following regression equation:

$$y_t = \alpha_0 + \alpha_1 mps_t + \alpha_2 mpu_t + \varepsilon_t \tag{3.1}$$

The results are presented in Table G2 with heteroskedasticity-robust standard errors in parentheses. The top panel shows the results for the full sample that runs from January 1995 to June 2019. The middle panel shows a pre-crisis sample from January 1995 to November 2007 and the bottom panel shows the post-crisis sample from December 2007 to June 2019. The first row shows the well-known effect of monetary policy surprises on US financial markets. A contractionary surprise lowers stock prices and raises both 2 and 10 year yields.[17] Results for the two samples are quite similar with somewhat smaller effects in the post-crisis sample.

The second row shows the response to monetary policy uncertainty shocks. An increase in monetary policy uncertainty lowers stock prices and raises long-term bond yields, but not short-term yields. For the full sample, the response of the 10 year yield is significant (at the 1% level) but the stock market and 2 year yield responses are not. Qualitatively, the effects of an increase in uncertainty have similar effects to a contractionary monetary policy surprise. In terms of magnitude, the response to a one standard deviation increase in *mpu* is about half the size of *mps* for stocks and 10 year yields. For example the 10 year yield increases by 4 basis points (0.3 standard deviations) in response to a one standard deviation increase in *mpu*. Finally, the effect of *mpu* strengthens in the post-crisis sample. In the pre-crisis sample *mpu* only has a statistically significant effect on 10 year yields. But in the post-crisis sample, stock returns and 10 year yields respond significantly to *mpu*, with a rise in the size of the effect as well. These results of the additional effect of *mpu* on US financial markets are consistent with those documented in Bauer et al. (2019). We now turn our attention to the main focus of this paper: the spillover effects of *mpu* to international financial markets.

3.4.2 Response of international bond yields to US monetary policy uncertainty

The common event-study approach in the literature involves regressing an asset price on the monetary policy shock measure in the event window. For studying the international spillover this would translate to the following panel regression

$$y_{i,t} = \delta_0 + \delta_1 mps_t + v_{i,t} \tag{3.2}$$

where $y_{i,t}$ is the two-day change in asset price of country i on date t, with the monetary shock measured by the so-called monetary policy surprise measure (*mps*) in a window around the FOMC announcement. *mps* typically measures surprise changes in the expected path of the policy rate.

[17]The response of the stock price to *mps* is smaller and less significant than Bernanke & Kuttner (2005). This result in the more recent sample is due to our use of daily futures data as also noted by Lakdawala & Schaffer (2019b).

The main goal of this paper is to evaluate the response to changes in monetary policy uncertainty. To do this we augment the above specification by adding *mpu*, which measures surprise changes in the uncertainty around the expected path. The regression takes the following specification[18]

$$y_{i,t} = \beta_0 + \beta_1 mps_t + \beta_2 mpu_t + \varepsilon_{i,t} \tag{3.3}$$

where $y_{i,t}$ is the two-day change in the 2 or 10 year bond yield around the FOMC meeting on day t for country i. As discussed in Section 3.2, both monetary shock measures are calculated for a 1 year horizon and have been scaled to reflect a one standard deviation effect. We also standardize the international bond yields to have unit standard deviation within each country.[19] Since our variables are measured within a relatively tight window around FOMC days, we make the assumption that the FOMC announcement is the primary driver of asset prices in this window. This assumption is commonly used in the event-study literature. While our baseline window is a two-day window following Hanson & Stein (2015b) and Albagli et al. (2019), we show in Section 3.4.6 below that our results are robust to using a one-day window.

For our main specification we separate the countries into two groups: advanced and emerging market countries.[20] Table G3 reports the regression coefficients with the advanced country results in the top panel and emerging country results in the bottom panel. Standard errors reported in parentheses are two-way clustered along the country and time dimension. In column (1) we estimate Equation 3.2 with only *mps* as the regressor to document that monetary policy surprises have a statistically significant and economically meaningful impact on international yields in both advanced and emerging countries. A contractionary monetary policy suprise in the US raises bond yields around the world. This result is well established in the literature for both advanced and emerging countries, e.g. see Hausman & Wongswan (2011), Gilchrist et al. (2019) and Albagli et al. (2019).

[18] As we discuss in the section on robustness checks (Section 3.4.6), adding country fixed effects to this baseline specification does not change our results.

[19] This is done because there is substantial heterogeneity in the standard deviation of yield changes across countries in our sample. This can be seen in Figure H5.

[20] We have yield data for 22 advanced and 8 emerging countries. See Table G13 for details on the sample countries.

The second column in each panel adds *mpu* to the regression and shows our first set of main results. For both advanced and emerging countries, the *mpu* shock has a statistically and economically significant effect on 2 and 10 year bond yields. An increase in monetary policy uncertainty raises global bond yields even after controlling for the conventionally used first-moment shock (i.e. *mps*). This effect is bigger for 10 year yields compared to 2 year yields and is also bigger for advanced countries relative to emerging countries. A one standard deviation increase in *mpu* raises 10 year yields in advanced (emerging) countries by .264 (.171) standard deviations.[21] At the long end of the yield curve, *mpu* has a bigger effect than *mps*, while at the shorter end the *mps* effect is larger. Additionally, for advanced countries, an increase in monetary policy uncertainty raises 10 year yields by roughly twice as much as 2 year yields, but for emerging countries the response of 2 and 10 year yields is essentially the same.

While the average effect of *mpu* on international bond yields is moderate, we show that this can amount to a substantially larger role for *mpu* in driving bond yields on days with big changes in *mpu*. Moreover, the effect of *mpu* dwarfs the *mps* effect on these days. As we discussed in Section 3.2.1, the big changes in *mpu* occur when the Federal Reserve willfully chose to make notable changes to the forward guidance language used in the FOMC statement. To study the yield response on these "prominent" dates, we isolate the ten FOMC dates with the largest increase in *mpu* and the ten FOMC dates with the largest decrease in *mpu*. We then average the total change in 10 year bond yields on these dates and compare to the average predicted component due to *mpu* and that due to *mps*, based on the coefficients estimated in Equation 3.3.[22] Figure H2 plots this separately for advanced and emerging countries. For advanced countries, the white bar shows that yields fall (or rise) by about one standard deviation (8 basis points) on these dates. *mpu* (gray bar) accounts for nearly half of this change on days with large increases in *mpu* and nearly all of the change on days with large decreases. In contrast, *mps* (black bar) accounts for less than one quarter. For emerging countries, the pattern is similar: *mpu* accounts for a lion's share of the change in bond yields on these 20 dates. From the 15 basis point fall in emerging yields, roughly three-quarters is due to

[21]This amounts to a 2 basis point rise in advanced and 3 basis point rise in emerging countries.
[22]In Figure H6 we show numbers for each of the 20 FOMC meetings individually.

mpu. Thus, Federal Reserve actions that affect the market's perceived uncertainty about future rates can have substantial effects on global yields. The implication is that the Federal Reserve has an additional tool in its arsenal to affect international financial conditions, one which has scarcely received any attention in the literature.

To contextualize the magnitude of the *mpu* spillover, we estimate the effects of "news shocks" around major US macroeconomic data releases.[23] Table G4 shows that retail sales shocks have a statistically significant effect on advanced country 2 and 10 year yields, and that CPI shocks have a significant impact on 2 year yields. Importantly, the yield response is much larger for the monetary policy shocks, as a one standard deviation change in *mpu* has an effect on international bond yields that is at least one order of magnitude higher than the effect of news shocks. Furthermore, the table also shows that none of the news shocks have a statistically significant effect on emerging country yields. These results highlight the unique impact of US monetary shocks on international yields.

We also check if the effect of *mpu* on international asset prices is driven by specific announcements about large scale asset purchases (quantitative easing or QE). Table G14 shows the baseline regression from Equation 3.3 where we have added a QE dummy along with its interaction with *mps* and *mpu*. The QE dates are taken from Fawley et al. (2013). The results show that yields in advanced countries do not respond differently to *mpu* on these dates and there is some weak evidence that the effects of *mpu* are stronger for 10 year yields in emerging countries. More importantly, the baseline effect of *mpu* on yields on non-QE dates stays roughly the same in terms of economic size and statistical significance. There is a debate in the literature on whether QE transmits through the signaling channel (Bauer & Rudebusch (2014)). Our results suggest that QE can also transmit through an "uncertainty signalling channel", whereby signals about uncertainty regarding future rates have an effect on financial markets. In Section 3.4.6 we also show that excluding the zero lower bound period does not materially affect our results.

[23]We collect data on five news announcements in the US: employment, GDP, CPI, PPI, and retail sales. For each news release, the surprise component, or "shock", is calculated as the difference between the actual released number and the consensus forecast from Action Economics/Money Market Services. For the employment report, we use non-farm payrolls, for CPI and PPI we use headline inflation, retail sales are the total sales including automobiles and GDP is the advance GDP release. We scale the news shocks to have unit standard deviation so that the size of the coefficient can be directly compared to the *mpu* coefficient.

Next, in Section 3.4.3 below we investigate the mechanisms driving the international yield response to monetary policy uncertainty, including differences across countries and across maturities. But first, we document that there have been some important changes over time in the transmission of *mpu* to international asset prices, especially for the emerging countries.

Table G15 and Table G16 report estimates for the baseline specification from Equation 3.3, splitting the full sample into a pre-crisis sample that runs from January 1995 to November 2007 and a post-crisis sample from December 2007 to June 2019. For our split sample results, we perform the standardization of our variables based on the split sample standard deviations. For advanced countries, the yield response is roughly similar across the samples, with a slightly larger response of the 10 year yield in the post-crisis sample. For emerging countries, however, a different picture emerges. The significant response of emerging yields to *mpu* in the full sample is driven entirely by the post-crisis sample. Specifically, the yield response is insignificant and essentially zero in the pre-crisis sample but larger in magnitude and strongly significant in the post-crisis sample. We discuss below in Section 3.4.4 that this can partially be explained by the average increase in capital account openness in emerging countries over the full sample.

We also investigate the dynamic response of bond yields using a local projection framework (Jordà (2005)). These results are presented in Figure H7. While 2 and 10 year yields remain elevated in both advanced and emerging countries after the monetary policy uncertainty shock, the standard errors get large after around a month. This makes sense as there is more background noise (i.e. other events that drive yields) as the horizon gets longer. Thus, in this paper we focus on the precisely estimated higher frequency impact.

Table G3 also shows that accounting for *mpu* is crucial in assessing the transmission of FOMC actions to international bond yields, even if one is only interested in the conventional monetary policy surprises (*mps*). Leaving out *mpu* biases both the coefficient estimate of the yield response to *mps* and the unconditional mean, as can be seen by comparing the *mps* coefficient and the intercept in columns (1) and (2). This can be easily understood from a basic omitted variable analysis. Column (1) estimates the specification from Equation 3.2 with *mpu* being the omitted variable. The key point is that *mps* (i.e. surprises to the expected path of policy rates) is positively correlated with *mpu* (i.e. changes in uncertainty about future rates). We document this correlation in Figure H4. This correlation results in an upward bias because the sign of the correlation between the dependent variable and *mpu* is the same as that between *mps* and *mpu* (both correlations are positive, as can be seen from the table). The table shows that leaving out *mpu* overstates the *mps* effect by roughly 50%.[24]

In addition to biasing the coefficient on *mps*, omitting *mpu* also affects the estimate of the intercept. Estimates of the intercept term from column (1) are negative and significant for both yields and both sets of countries. This systematic average decline is at odds with the assumptions of the event-study framework where changes in asset prices around FOMC meeting should be unpredictable. However, once we add *mpu* to the regression, the intercept term becomes effectively zero and statistically insignificant. This is driven by an average decline in *mpu* documented in Figure H1. Thus leaving out *mpu* means that the average fall in *mpu* is soaked up in the intercept, making it turn negative.[25]

Yet another way to see the importance of accounting for uncertainty changes is by comparing the R^2 in the two columns. There is a substantial increase in R^2 with the addition of *mpu*, especially at the longer end of the yield curve. For example the R^2 for emerging country 10 year yields increases from 0.036 to 0.06.

Thus our results suggest that the literature on the spillover effects has likely *overestimated* the effect coming purely through monetary policy surprises (first-moment shocks) while *under-estimating* the total effects of US monetary policy actions which also work substantially through second-moment (or uncertainty) changes.

[24]Since *mpu* is a risk-neutral measure it captures both the quantity and price of uncertainty. If *mps* shocks drive risk-aversion (or risk compensation) in financial markets including option prices and *mpu*, our methodology of controlling for *mpu* would be under-estimating the true *mps* effect. On the other hand it seems reasonable to expect that uncertainty or *mpu* shocks (and not *mps* shocks) are more likely to affect risk-aversion. Since estimating the risk-aversion response is out of the scope of this paper, we caution the reader here and recommend viewing the 50% estimate as an upper bound. Regardless, this issue is not crucial for interpreting the effects of *mpu* since we always control for *mps* when reporting estimates of *mpu*.

[25]To make this clear, consider decomposing mpu_t into a constant and time-varying term, $mpu_t = \mu_{mpu} + \varepsilon_{t,mpu}$. If the true model is Equation 3.3 but *mpu* is omitted from the regression, then the residual will soak up $\beta_2 * \varepsilon_{t,mpu}$ and the intercept will soak up the term $\beta_2 * \mu_{mpu}$ which is negative since $\beta_2 > 0$ and $\mu_{mpu} < 0$.

3.4.3 Understanding the response

What explains the response of international bond yields to changes in US monetary policy uncertainty? In this section, we provide evidence that an international portfolio balance channel is primarily responsible for transmission to advanced countries whereas a flight to safety channel is likely driving the emerging country response.

We start by discussing the mechanism through which *mpu* affects bond yields domestically in the US. There is a clear risk-based explanation for the transmission mechanism. Standard asset pricing theory implies that expected excess returns depend on the negative covariance of returns with the stochastic discount factor. One factor driving this covariance is the uncertainty about future returns, as can be seen by rewriting the covariance in terms of the correlation and the standard deviations:

$$
\begin{aligned}
E_t R_{t+1} - R_t^f &= \frac{Cov_t(-M_{t+1}, R_{t+1})}{E_t M_{t+1}} \\
&= \frac{Corr_t(-M_{t+1}, R_{t+1})}{E_t M_{t+1}} \sigma_t(M_{t+1}) \sigma_t(R_{t+1})
\end{aligned}
$$

Since changes in *mpu* are a clear signal about the conditional volatility of bond returns ($\sigma_t(R_{t+1})$), then higher short-rate uncertainty should raise term/risk premia.In earlier work, Bauer et al. (2019) and Bundick et al. (2017a) show that changes in *mpu* do indeed transmit to US bond yields through changes in term premia. In Table G17 we document this effect using the different term premium estimates of Joslin et al. (2011), Adrian et al. (2013) and Kim & Wright (2005). For all three measures, the table shows that an increase in uncertainty raises term premia on US bond yields.[26]

Next, we study whether *mpu* affects the term premia even in global yields. We apply the methodology of Joslin et al. (2011) to carry out the decomposition into an expected component and term premium component.[27] Table G5 shows the results where we use the same specification

[26] While our results about the role of uncertainty for term premia are evident, we cannot rule out that the uncertainty about the stochastic discount factor or the correlation between future returns and the stochastic discount factor could also be important.

[27] Since we have only zero-coupon yield data from Bloomberg, it is not straightforward for us to implement the alternative procedures in the literature, for example the measure of Adrian et al. (2013).

from Equation 3.1 now separately using the expected component and term premium component as the dependent variables.[28]

For advanced country yields, the response to *mpu* is entirely due to the response of the term premium with no response of the expected component. However, for emerging country yields, this pattern is reversed. The response to *mpu* is not driven through the term premium but rather through changes in the expected component. In other words, in response to changes in monetary policy uncertainty, the market does not expect that central banks of advanced countries will respond by changing their own policy rates; however, they do expect that central banks of emerging countries will. Moreover, markets react in a way that suggest their perception of the term premium for holding advanced country bonds has changed but not for emerging country bonds.

Since we are studying the response of bonds denominated in local currencies, we might expect movement in the exchange rate to be playing a role. Table G6 shows the response of the exchange rate to *mps* and *mpu* for our full sample. The exchange rates are in units of foreign currency per US dollar and thus an increase represents a depreciation of the foreign currency relative to the US dollar. As documented in the literature a contractionary *mps* leads to an appreciation of the U.S dollar relative to both advanced and emerging countries (e.g. see Hausman & Wongswan (2011)). However, we again note that including *mpu* in the regression lowers the estimated effect of *mps*. More importantly, we notice that an increase in *mpu* depreciates currencies of emerging countries but not those of advanced countries. The advanced country response is consistent with the results of Gilchrist et al. (2019) who find a substantial effect of US monetary policy on dollar-denominated sovereign bonds. They label this channel the “financial spillover" channel. In the next section, we provide a more detailed discussion and evidence for understanding the specifics of the *mpu* spillover to advanced countries. For emerging countries, we document below that this result is consistent with the recent framework of Rey (2013), where even exchange rates being “flexible" does not insulate the country from the financial spillover. However, we show countries with more capital account restrictions respond less. This discussion is presented in Section 3.4.3.2.

[28]Note that while *mps* and a constant are included in the regression, the coefficients are left out for space considerations.

3.4.3.1 Response in advanced countries

Why does the bond term premium of advanced countries (but not emerging ones) respond to *mpu*? We provide evidence for an international portfolio balance channel whereby *mpu* transmits through changes in the term premium on US bonds to term premia of foreign country bonds; but only for the bonds of countries that are considered substitutes for US bonds.

We first show that *mpu* transmission to term premia in advanced countries is driven primarily through the effect of *mpu* on *US* bond term premia. To do this we take the specification reported in Panel (a) of Table G5 (i.e. our baseline regression from Equation 3.3 but with the term premium as the dependent variable) and control for the change in the term premium on the US 10 year bond. Then we compare the coefficient on *mpu* from this specification (reported in Panel (b) of Table G5) to one without the US 10 year term premium (reported in Panel (a)). If there is no change in the *mpu* coefficient from Panel (a) to (b), then we can conclude that none of the *mpu* effect is working through US term premium changes. On the other hand, if the coefficient goes to zero, then we can conclude that the *mpu* effect is working through US term premium changes. The table shows that controlling for the US term premium has a significant effect on the term premium response to *mpu*, but only for advanced countries. Specifically, the *mpu* coefficients that govern the term premium response of emerging countries are essentially unchanged: they remain close to zero and statistically insignificant. But for advanced countries, the *mpu* coefficient of the 10 year term premium response, which was substantial (0.24) and strongly significant, drops to close to zero (0.07) and is not statistically significant. The same pattern holds for the 2 year term premium response. This is suggestive evidence that changes in monetary policy uncertainty that drive term premia in US bonds also transmit to term premia in international bonds as well, although only in advanced countries.

Why do term premia in advanced countries respond to *mpu*-driven changes in the US term premium but term premia of emerging countries do not? There is not much theoretical work in the literature on the spillover effects through US monetary policy uncertainty.[29] The theoretical

[29] There is some recent work on the spillover of overall US uncertainty, see for example Bhattarai et al. (2019). But

paper closest to our empirical work that explicitly studies this topic is the recent work of Ghironi & Ozhan (2019). However, in their paper they study only the spillover of monetary policy uncertainty to emerging countries and allow the international trade of short-term securities only. Thus there is no clear implication from their model for the differential response of long-term yields in emerging versus advanced countries. However there is a much larger literature that studies the spillover of US unconventional monetary policy, see Bhattarai & Neely (2016) for a recent survey. A common theme in this literature is that US unconventional monetary policy affects the term premium on US bond yields and also has effects on international bond yields. More specifically, the recent DSGE model of Alpanda & Kabaca (2019) that features an international portofolio balance channel is especially relevant for understanding our empirical results. They take the portfolio balance channel that features imperfect substitutability between bonds of different maturities and extend it to have imperfect substitutability between domestic and foreign bonds. A prediction from this framework is that term premium changes in the US should affect term premia in foreign countries based on how substitutable the foreign country's bonds are with the US. Specifically, a higher elasticity of substitution for a given country will mean a larger response of that country's term premium. We now provide evidence that this is indeed the channel through which *mpu* has international spillover effects.

If the long-term bonds of two countries are highly substitutable, this implies the bonds share similar degrees of risk and generally belong to the same class of securities. Perceived risk and the demand for a class of securities are two main determinants of a bond's term premium; thus, the term premium of two highly substitutable bonds should positively comove.[30] Accordingly, we construct a simple measure of the substitutability of bonds by calculating the correlation between the 10 year bond term premium of each country in our sample and the US on all *non-FOMC* days between January 1995 and June 2019. Our measure is essentially identical to the method of de los Rios & Shamloo (2017) and is comparable to the empirical test of Frankel (1982). After calculating

this work does not try to isolate the effect of monetary policy uncertainty.

[30]The models of Kabaca (2016) and Alpanda & Kabaca (2019) generate the feature that high substitutability between domestic and foreign bonds results in strong positive comovement between domestic and foreign term premia. See Bernanke (2015) for further discussion of the term premium and the factors that move it.

the correlation between the 10 year term premium for country i and the US, we scale our measure to lie between 0 and 1, i.e. we add 1 to each correlation and divide by 2.[31] Our specification is as follows

$$y_{i,t} = \kappa_0 + \kappa_1 mps_t + \kappa_2 mpu_t + \kappa_3 mps_t * bondsub_i + \kappa_4 mpu_t * bondsub_i + \varepsilon_{i,t} \tag{3.4}$$

Since the substitutability measure is scaled to lie between 0 and 1, the coefficient on the *mpu* interaction term can be interpreted as the marginal effect of an *mpu* shock on the 10 year term premium of a country with perfect substitutability (i.e. correlation= 1), relative to a country with the least substitutability (correlation= −1). Table G7 displays the *mpu* coefficients (κ_2 and κ_4) for all countries pooled together, only advanced countries and only emerging countries. For the pooled sample, the coefficient on the interaction term is positive and significant. This implies that it is indeed the case that countries whose bonds are more substitutable with US bonds on non-FOMC days also display a larger term premium response to changes in US monetary policy uncertainty on FOMC days. We see the same pattern when we restrict the regression to the advanced country sample but not when we do that for emerging countries. Advanced countries whose bonds are more substitutable with US bonds are also more sensitive to *mpu* shocks. We have also plotted the distribution of our bond substitutability measures. As expected, the bonds of advanced countries have noticeably higher substitutability with US bonds than do emerging market countries. The figure is omitted for space considerations.

To summarize, the response of advanced country bond yields to *mpu* is driven by an international portfolio balance channel with the high degree of substitutability between advanced country bonds with the US being the crucial factor. Next, we turn to why emerging country bonds also respond significantly to *mpu*.

[31] For robustness, we also calculate the bond substitutability measure using non-FOMC days between January 1995 and the FOMC meeting on day t. Online Table G25 shows the results for this alterrnative bond substitutability measure. Our results are also robust to using changes in the 10 year term premium (rather than levels) to compute the correlations and alternatively using a logistic transformation or by using a non-linear specification, e.g. binning by quantiles.

3.4.3.2 Response in emerging countries

In the previous section we discussed the international portfolio balance channel to understand the response of advanced country yields to mpu. But what explains the transmission of mpu through the expected component of bond yields for emerging markets? In this section we provide evidence on the response of capital flows in emerging countries that is consistent with a flight to safety channel.

We use data from the Treasury International Capital (TIC) reporting system, following the methodologies of Bertaut & Tryon (2007) and Bertaut & Judson (2014). Bertaut & Tryon (2007) construct a monthly measure of US holdings of foreign securities by combining annual TIC survey data with monthly TIC S flow data. Bertaut & Judson (2014) improve upon the measure by incorporating monthly TIC SLT holdings data, which becomes available in December 2011. We use the Bertaut & Tryon (2007) measure from 1995 to 2011 and the Bertaut & Judson (2014) measure from 2012-2018.[32]

This data only measures holdings by US residents of foreign assets; thus, our analysis is limited and we cannot observe the response of non-US investors to the monetary shocks. Another important caveat is that the TIC data are available at a monthly frequency and thus our regression specification is not as clean as the higher frequency specification used in the rest of the analysis. Nevertheless, we believe the data provides some interesting evidence.

We study the response of US holdings of foreign bonds to mps and mpu together with the interaction of the difference in the 3 month interest rates of the foreign country and the US (labeled $idiff$)

$$y_{i,t} = \gamma_0 + \gamma_1 mps_t + \gamma_2 mpu_t + \gamma_3 mps_t * idiff_{i,t} + \gamma_4 mpu_t * idiff_{i,t} + \varepsilon_{i,t} \tag{3.5}$$

The sample runs from 1995 to 2018 for a total of 187 FOMC meetings and excludes the financial crisis period from December 2007 to June 2009.[33]

[32] The data can be accessed here: https://www.federalreserve.gov/econres/ifdp/2014.htm. See Bertaut & Tryon (2007) and Bertaut & Judson (2014) for details.

[33] The literature has documented a large and abnormal reduction in international capital flows during the Great Recession, and in crisis periods generally. See, for example, Milesi-Ferretti & Tille (2011) and Broner et al. (2013).

Table G8 shows that for emerging countries an increase in *mpu* leads to a reduction in bond holdings. Moreover, the interaction coefficient between *mpu* and the interest rate differential is negative and significant. This means that more capital flows out of emerging countries which have a higher interest rate differential with the US (consistent with the results in Ahmed & Zlate (2014)). Table G26 confirms this result holds when including time fixed effects in the specification. Overall, these results are consistent with a flight to safety/quality channel where investors are pulling money out of countries that are perceived to be riskier than the US. These results are consistent with Bhattarai et al. (2019) who use a VAR framework and also find a flight to safety response of emerging countries to an increase in US uncertainty. They use VIX to capture a broader measure of US uncertainty. However as discussed in Bauer et al. (2019), *mpu* drives a substantial amount of variation in the VIX on FOMC meeting days, which is the sample that we focus on here. Thus our results are pointing to the role of US monetary policy specific uncertainty in driving this result.

In addition to the mechanism described above, there is a testable implication of the emerging country expected component response to changes in *mpu*. In response to an increase in monetary policy uncertainty, financial markets are expecting interest rates to rise in the future in emerging countries but not in advanced countries. Assuming that the markets are not systematically wrong, we can check to see if short rates do indeed move in the expected direction. We test this implication using the local projections framework outlined in Section 3.4.2 to map out the dynamic response of 3 month bond yields.

Results from this exercise are presented in Figure H3 with confidence intervals that use Driscoll-Kraay standard errors. Short rates in emerging markets do indeed move in the direction markets expect, as the 3 month yield is significantly higher for most of the time in the one and a half years after the *mpu* shock.[34] In contrast, the 3 month yield shows essentially no change a year after the *mpu* shock in advanced countries. Thus, it appears markets are correctly expecting short rates to respond to US monetary policy uncertainty in emerging countries, but not in advanced. These results reinforce that uncertainty is transmitted to advanced and emerging bond yields through

[34]For example, after a year short rates are 0.15 standard deviations or 3.8 basis points higher.

fundamentally different mechanisms.

We also find that the emerging market response to *mpu* is suggestive of the framework put forth by Rey (2013). As shown above in Table G6, exchange rates of emerging countries depreciate in response to a contractionary *mpu* shock. From a Mundell-Fleming perspective, a flexible exchange rate should be enough to shield a country to financial spillovers from the US. Rey (2013) suggests that this would only be the case if there are additional restrictions on capital mobility. In the next section we show that it is indeed the case that emerging countries whose capital account is more unrestricted are the ones that respond more to *mpu*.

3.4.4 Heterogeneity in response to monetary policy uncertainty

In this section, we explore potential country characteristics that are associated with the sensitivity to US monetary policy uncertainty transmission. Specifically, we test for differences in the response of asset prices conditional on country characteristics.

To establish noticeable heterogeneity in asset price responses to *mpu* shocks, we first plot the country-specific estimated coefficients on *mpu* for the full sample period. Figure H8 displays the results for 2 and 10 year bond yields. Across both advanced and emerging countries, we see a mix of statistically significant and statistically insignificant responses. Within the two country groups, the most positive responses are significantly different than the least positive responses. This points toward a meaningful amount of heterogeneity that can potentially be explained, beyond the advanced versus emerging distinction.

We attempt to explain this heterogeneity by using time-varying country characteristics. Using time-varying, rather than fixed, country characteristics allows us to use both within-country and between-country variation in our identification. Our baseline observables include financial depth, exchange rate regime, trade openness and the change in the 3 month interest rate differential with the US on an FOMC day. For emerging market countries, we also include capital account openness.[35] Financial depth is the value of credit provided to the private sector, as a percentage

[35]The capital accounts of advanced countries are almost exclusively the maximum degree of openness. Thus, virtually

of GDP. Exchange rate regime is defined as in Ilzetzki et al. (2019), where the categories are a flexible exchange rate, a partial peg and a fixed regime. Trade openness is the sum of total exports and imports divided by GDP. Capital account openness is defined as in Chinn & Ito (2006), with a higher value indicating greater openness (i.e. fewer capital controls).

Using this set of observables, our methodology most closely follows that of Iacoviello & Navarro (2019) by recursively orthogonalizing the regressors. Let $v \in V$ be our set of time-varying country characteristics for either the advanced country sample or the emerging market country sample. We estimate the following equation:

$$y_{i,t} = \alpha + \beta_1 mps_t + \beta_2 mpu_t + \sum_{v \in V} \gamma_1^v (e_{i,t}^v mps_t)^{\perp} + \sum_{v \in V} \gamma_2^v (e_{i,t}^v mpu_t)^{\perp} + \epsilon_{i,t} \tag{3.6}$$

where $e_{i,t}^v$ is the annual exposure index of variable v for country i on FOMC day t. The interaction terms $(e_{i,t}^v mps_t)^{\perp}$ and $(e_{i,t}^v mpu_t)^{\perp}$ are such that the β_1 and β_2 coefficients measure the response to an *mps* and *mpu* shock, respectively, when the exposure indices are at their 25th percentile values. The γ_1^v and γ_2^v coefficients capture the marginal response to an *mps* and *mpu* shock, respectively, when the exposure index $e_{i,t}^v$ is at its 75th percentile value.[36]

Following Iacoviello & Navarro (2019), the orthogonalized interaction terms are constructed in the following manner. First, each exposure variable, v, is standardized, i.e. we subtract the sample mean and divide by the sample standard deviation, to make the scale of the exposure indices more comparable. Second, we perform a logistic transformation of the standardized exposure variables to collapse the variables to a unit interval. Third, we scale the transformed exposure variables to the distance between the 25th and 75th percentiles i.e. we subtract the 25th percentile value and divide by the difference between the 75th and 25th percentile values. At this stage, we now have our exposure indices, $e_{i,t}^v$. Next, we multiply our exposure indices by each of the shocks to calculate our interaction terms: $(e_{i,t}^v mps_t)$ and $(e_{i,t}^v mpu_t)$. For the final step, we recursively orthogonalize each of the interaction terms, starting with the *mps* interaction within each interaction term pairing. In other

no variation exists to explain the heterogeneity in response and we exclude capital account openness as an observable variables for advanced countries.

[36]The 25th and 75th percentile values are calculated for the pooled (i.e. combined advanced and emerging) sample. For exchange rate regime, this is equivalent to moving from a floating regime to a fixed regime.

words, the interaction of the first exposure variable (v_1) and mps are orthogonalized with respect to mps_t and mpu_t, while the interaction of v_1 and mpu are orthogonalized with respect to mps_t, mpu_t and the interaction of v_1 with mps_t. Then, $(e_{i,t}^{v2} mps_t)$ is orthogonalized with respect to mps, mpu and both of the orthogonalized v_1 interaction terms, while $(e_{i,t}^{v2} mpu_t)$ is orthogonalized with respect to mps, mpu, both of the orthogonalized v_1 interaction terms and $(e_{i,t}^{v2} mps_t)^{\perp}$. This continues for all subsequent exposure variables. In the following tables, the variables are orthogonalized with respect to those that appear above them, e.g. foreign exchange regime is orthogonalized with respect to financial depth and capital account openness in Table G9.

The above procedure has at least two advantages. First, the orthogonalization addresses the within-country correlation between the different characteristics. Without orthogonalizing, this collinearity would impact the precision of our estimates.[37] Second, since the orthogonalization is recursive, each additional characteristic's coefficient can be clearly interpreted as a marginal effect after controlling for the previous characteristics. In theory, our choice of variable ordering could affect the results. We show below that our main results are robust to the ordering of orthogonalization.

Focusing on the yield responses for emerging market countries, Table G9 shows that a more open capital account significantly explains differences in both 2 year and 10 year yield responses.[38] Specifically, a country at the 75th percentile of capital account openness experiences an additional 0.12 standard deviation (0.088 standard deviation) increase in the 2 year yield (10 year yield) in response to a US monetary policy uncertainty shock, relative to a country at the 25th percentile value of capital account openness. The relationship between emerging country capital account openness and responsiveness to US monetary policy uncertainty is consistent with the results of Bowman et al. (2015) for US monetary policy surprises.[39] As in Bowman et al. (2015), countries with a greater degree of capital account openness are more sensitive to US monetary policy changes.

[37]Note, however, that our results are robust to orthogonalization.

[38]Table G18 contains the results for advanced countries. It shows that the change in the 3 month interest rate differential with the US on an FOMC day is the only observable that significantly explains heterogeneity (2 year yield response only).

[39]Bowman et al. (2015) use monthly changes in 10 year US sovereign yields to identify monetary policy surprises and monthly changes in emerging 10 year sovereign yields as the response variable of interest.

Other than capital account openness, a country's exposure to dollar-denominated debt also appears to matter for yield responses (see Table G19).[40] The 10 year yield for countries with a larger share of debt denominated in US dollars responds more sensitively to *mpu* shocks. Since an increase in US monetary policy uncertainty is expected to appreciate the dollar, this increases the real value of dollar-denominated debt and, thus, the likelihood of binding borrowing constraints.

Recursively orthogonalizing our variables allows us to estimate the marginal contribution of each exposure variable, *after we have controlled for any exposure variables that enter the regression first*. As a result, the ordering of the variables can theoretically impact the results. In practice, our main results are generally unaffected by the choice of variable ordering. The significance of capital account openness for the 2 year yield results does not depend on the ordering of the orthogonalization. For the 10 year yield results, financial depth must enter the regression prior to capital account openness, but otherwise the ordering of the variables does not matter.[41]

3.4.5 Response of international equity indices to US monetary policy uncertainty

In this section we investigate the effects of *mpu* on international stock markets. We use the same specification from Equation 3.3 with the 2-day return in the international equity indices as the dependent variable. Table G10 shows the result for the full sample, pre-crisis sample ending in November 2007 and a post-crisis sample starting in December 2007.

An increase in *mpu* leads to a fall in stock prices in both advanced and emerging countries. For emerging countries the pattern is similar to the bond yield response: no effect in the pre-crisis sample but a strong and significant effect in the post-crisis sample. A one standard deviation increase in *mpu* reduces stock prices by 0.65%. The advanced country response also follows this sub-sample pattern, with essentially zero effect in the pre-crisis sample and a 0.37% fall in the post-crisis

[40] Dollar debt exposure is the value of dollar-denominated debt as a % of GDP. Dollar debt exposure data is available only through 2012 and the measure is significant for 10 year yields only; thus, we did not include dollar debt exposure in our baseline table.

[41] Figure H9 displays the coefficient for the capital account openness interaction with mpu for all 24 unique variable orderings with financial depth listed first. Note that the magnitude and statistical significance of capital account openness generally become stronger as capital account openness is orthogonalized with respect to more variables, i.e. enters the regression later.

sample.[42] Thus, the spillover of US monetary policy uncertainty to international equity markets appears to largely be a post-crisis phenomenon. This result generalizes the pattern documented in Lakdawala (2018) for Indian stock markets. We also tried to explain the heterogeneity in the country-level response of equity markets using the country characteristics described above but did not find anything significant. A potential channel could be the growing role of foreign institutional investors in domestic equity markets as discussed in Lakdawala (2018) for Indian stock markets. We leave this topic for future research.

As with the bond yield results, we see a similar pattern in the effect of *mps* after accounting for *mpu*. Focusing on the post-crisis sample, after including *mpu* in the regression, the response of stock prices to *mpu* falls by about one-third in advanced countries and about one-half in emerging countries. Moreover, accounting for *mpu* in the regression leads to roughly a doubling of the R^2 for both advanced and emerging countries. This again highlights the importance of *mpu* even if one is only interested in the transmission of US monetary policy through first-moment shocks.

3.4.6 Robustness Checks

We conduct a variety of robustness checks for the results presented above. First, we show that our results are not driven by the zero lower bound (ZLB) period from December 2008 to December 2015. Table G11 shows that results from the non-ZLB sample are very similar to the full sample results. Next, we re-estimate equation 3.3 with the asset price changes and monetary shock measures calculated over a one day window, rather than the two day window used in the baseline results. Estimates using this narrower window are presented in Table G20 and show that overall the results are essentially unchanged.

Since the construction of our measure of monetary policy uncertainty relies on Eurodollar futures where the underlying interest rate is the LIBOR rate and not the Fed's main policy tool (federal funds rate), we want to make sure that instability in this spread is not driving our results. The best way to measure this spread is using the LIBOR-OIS spread. To this end, we re-estimate

[42]Recall that advanced country bond yields responded to *mpu* both in pre- and post-crisis samples.

our baseline estimates from Equation 3.3 but also control for changes in this LIBOR-OIS spread. The sample begins in December 2001 when LIBOR-OIS data is available. The estimates in Table G21 show that our results are robust to this particular concern.

In this paper we have highlighted that, in addition to first-moment effects of *mps*, there is a role of *mpu* through which US monetary policy can affect international markets. In Tables G22 and G23 we show that our results are robust to using longer-term measures of *mps*: changes in the 2 and 10 year Treasury yields, respectively. In earlier work, Gürkaynak et al. (2005) show that two separate factors better characterize the first-moment shocks (a target and a path factor), while we just use the first principal component (i.e. only one factor) to construct our *mps* measure. In Online Table G27 we show that controlling for these two factors does not change the effect of *mpu* on international asset prices.

One concern with the FOMC day event-study approach is the issue of unscheduled FOMC meetings. These are meetings outside the regular FOMC calendar and are typically responses to unusual circumstances in the economy. In Online Table G28 we show that our results are robust to excluding these unscheduled meetings. Another common concern is whether the results are affected by the so-called “information effect" where the Federal Reserve signals its private information about the underlying economic fundamentals. In Online Table G29 we control for this by cleansing the monetary shocks using the methodology used by Campbell et al. (2012) and Lakdawala & Schaffer (2019b). The results show that information effects are not playing a role in driving the transmission of *mpu* to international bond yields.

In the baseline specification we do not include country fixed effects. In Online Table G30 we present results including it and find that the results are essentially unchanged. Finally, we explore the sensitivity of our results to outliers across both countries and FOMC dates. Figures H10 and H11 plot coefficients and confidence intervals from the baseline specification while removing one country and one FOMC date at a time, respectively. The coefficients and confidence intervals remain similar regardless of which countries or dates are removed from the sample, eliminating the concern that the results are driven by extreme observations.

3.5 Conclusion

How does US monetary policy spillover to international financial markets? A common approach in the literature is to use an event-study framework and first-moment shocks (i.e. unexpected changes in the expected path of the policy rate) to study this question. In this paper we argue that this typical approach is not sufficient to capture the complete breadth of the international transmission of US monetary policy actions. We show that changes in uncertainty around the Federal Reserve's expected policy path have important consequences for global bond and equity markets. Moreover, omitting uncertainty from event-study regressions could lead to over-estimation of the first moment effect, since changes in first and second moments are positively correlated.

An increase in the market perceived uncertainty raises bond yields and lowers equity prices in both advanced and emerging countries. However, the transmission works through different channels. The yield response in advanced countries is driven by changes in term premia and we provide evidence for an international portfolio balance channel whereby bonds of countries that are considered to be more substitutable vis-à-vis the US respond more to uncertainty. For emerging countries, the yield response is driven by changes in the expected (or risk-neutral) component. Using capital flows data we show that uncertainty changes affect capital outflows in a manner consistent with a flight to safety channel. Moreover, for emerging countries the responsiveness to uncertainty is closely related to the country's financial openness.

Our results have implications for the design of monetary policy. We show that the uncertainty spillover is substantially larger when the FOMC deliberately made changes to the forward guidance language about future policy decisions. This suggests that the FOMC has an additional tool for influencing international financial conditions, namely by influencing the market's perceived uncertainty about the future path of the short rate. Moreover, in an environment where interest rates are more likely to be constrained by the zero lower bound, changing uncertainty will likely take on increasing importance in the FOMC's toolkit.

Our work raises some natural questions that are worth exploring. We find that the transmission of US monetary policy uncertainty has gotten stronger since the financial crisis, especially for emerging countries. There is some evidence that an increase in financial openness in emerging countries has played a role in the higher responsiveness, but a more detailed analysis is warranted. While we focus on the high-frequency response of financial markets, evaluating the spillover effects of US monetary policy on lower frequency macroeconomic variables in advanced and emerging countries appears to be a fruitful area for future research.

APPENDICES

APPENDIX A

SUPPLEMENTAL INFO FOR CHAPTER 1

Proof of Enforcement Constraint

The following proof of equation 1.10 follows the logic of Jermann & Quadrini (2012). After they produce, sell output $F(z_t, k_t, n_t)$ and pay expenses, firms can then opt to default on their intraperiod loan and renegotiate it. Thus, at the time of the default decision, firms are holding liabilities equal to $l_t + \frac{b_{t+1}}{1+r_t}$. Since all other expenses have been paid at this point, firms are holding liquidity exactly equal to $l_t + a_{t+1} + (1 - \nu)a_t$, i.e. enough liquidity to pay the intraperiod loan, carry accumulated liquidity to the next period and the amount of deferred labor expenses. Firms are also holding non-liquid assets equal to k_{t+1}, i.e. the physical capital. As in Jermann & Quadrini (2012), liquid assets can be hidden from the lender; thus, the lender can only recoup physical capital.

In the event of default, the lender seizes the firm's non-liquid assets and can liquidate them for $\xi_t * k_{t+1}$. After the firm has decided to default, ξ_t is then revealed as either 0 or 1. Thus, the lender will be able to either recoup the entire value of the physical capital or nothing.

If the firm decides to default, then the firm and lender enter a renegotiation process. For simplicity, we assume that the firm has full bargaining power in the renegotiation, as changing the bargaining power assumption for the renegotiation is equivalent to changing the value of ξ_t. Thus, the formulation of the enforcement constraint (equation 1.10) is unaffected by this assumption. We now consider the two extreme cases of ξ_t.

Case I: Lender recoups entire value of physical capital ($\xi = 1$)

In renegotiation, the firm must pay lender the amount $k_{t+1} - \frac{b_{t+1}}{1+r_t}$ and promise to repay $\frac{b_{t+1}}{1+r_t}$ next period. This is the amount that makes the lender indifferent between liquidating the firm and keeping the firm in operation. As discussed in the main text, in the event of default, the firm does not have to pay back the intraperiod loan or its deferred labor costs. Thus, the ex-post value of defaulting for the firm is:

$$Em_{t+1}V_{t+1} - k_{t+1} + \frac{b_{t+1}}{1+r_t}. + l_t + (1-\nu)a_t \tag{A.1}$$

Case II: Lender recoups nothing ($\xi = 0$)

In the event of $\xi_t = 0$, the lender will not want to liquidate the firm, as it cannot recoup anything of value. The lender will simply choose to wait until next period when the firm will repay $\frac{b_{t+1}}{1+r_t}$. Thus, the ex-post value of defaulting for the firm is:

$$Em_{t+1}V_{t+1}. + l_t + (1-\nu)a_t \tag{A.2}$$

Since ξ_t is not revealed at the time l_t is contracted, the expected value of default for the firm is:

$$Em_{t+1}V_{t+1}. + l_t + (1-\nu)a_t - \xi_t(k_{t+1} + \frac{b_{t+1}}{1+r_t}) \tag{A.3}$$

In order for the lender to agree to intraperiod loan l_t, the firm's value of not defaulting ($Em_{t+1}V_{t+1}$) must be at least as high as the value of default:

$$Em_{t+1}V_{t+1} \geq .Em_{t+1}V_{t+1}. + l_t + (1-\nu)a_t - \xi_t(k_{t+1} + \frac{b_{t+1}}{1+r_t}) \tag{A.4}$$

Thus, we get our enforcement constraint:

$$\xi_t(k_{t+1} + \frac{b_{t+1}}{1+r_t}) \geq l_t + (1-\nu)a_t = w_t n_t - \nu a_t \tag{A.5}$$

Alternative Household Budget Constraint

As mentioned above, we assume in the baseline model that the bank's profits, $e_t l_t$, are immediately consumed by the bank. Here, we distribute these profits to the households as a lump-sum payment and show that the results are essentially unchanged.

The household budget constraint now becomes

$$e_t l_t + w_t n_t + b_t + s_t(d_t + p_t) = \frac{b_{t+1}}{1 + r_t} + s_{t+1} p_t + c_t + T_t,$$

where the bank's profits, $e_t l_t$, have been added to the constraint. The rest of the budget constraint remains the same.

Substituting in Equation (1.8) for $e_t l_t$, $n_t = \frac{l_t + a_t}{w_t}$ and $l_t = w_t n_t - a_t$ gives the new household FOC for n_t:

$$((1 + \gamma)\eta w_t + (1 - \theta)(1 - \eta) z_t k_t^{\theta} n_t^{-\theta}) U_c(c_t, n_t) + U_n(c_t, n_t) = 0$$

The household's labor decision now influences household consumption via its effect on the bargaining problem between the firm and bank, i.e. the total surplus generated from agreement on the loan. The corresponding impulse response functions for our two steady states are shown in Figure C9. The results closely match the baseline IRFs.

APPENDIX B

TABLES FOR CHAPTER 1

Table B1: Summary statistics

Panel A: Compustat	Small Firms		Large Firms	
	mean	std. dev.	mean	std. dev.
Assets (2012 $'s, millions)	71.5	112.1	931.0	961.0
Age (years)	10.8	9.4	17.2	13.1
Debt Issuance (% of assets)	0.7	21.9	0.4	15.8
Equity Issuance (% of assets)	19.1	59.8	-0.2	11.3
Liquidity Accumulation (% of assets)	5.9	37.0	1.1	11.7
Debt-to-Assets Ratio	31.4	50.3	33.9	31.5
Bank Debt (% of total debt)	18.6	32.0	27.6	33.6
# of Firms	13,158		3,517	

Panel B: DealScan & Call Report	All Lender Pool		Lead Lender Pool	
	Pre-1999	Post-1999	Pre-1999	Post-1999
Lerner Index	0.476	0.535	0.476	0.536
Share of State Banking Assets	0.129	0.230	0.129	0.252
Number of Lenders	2.425	3.374		
Recently Joined MBHC	0.181	0.122	0.185	0.119
Recently Acquired	0.040	0.080	0.041	0.080
Lead Year Share			0.892	0.792

Panel A displays summary statistics for the book value of assets, firm age and the key financing variables. The sample period is 1981-2017. Small firms are those with a book value of assets below the 60th percentile in a given year. Large firms are those between the 60th percentile and 90th percentile. Panel B displays means for characteristics of the lenders in the All Lender Pool and Lead Lender Pool. The sample period is 1985-2012.

Table B2: Cyclicality of Aggregate Financing Variables, by Size

Panel A: 1981-2017

Size categories	Debt Iss	Equity Iss	Liq. Accum.
Small Firms	0.495***	0.276*	0.180
Large Firms	0.622***	-0.430***	-0.276*
All Firms	0.588***	-0.086	-0.038

Panel B: 1981-1998

Size categories	Debt Iss	Equity Iss	Liq. Accum.
Small Firms	0.556**	-0.487**	-0.367
Large Firms	0.691***	-0.557**	-0.262
All Firms	0.648***	-0.484**	-0.323

Panel C: 1999-2017

Size categories	Debt Iss	Equity Iss	Liq. Accum.
Small Firms	0.575**	0.509**	0.336
Large Firms	0.653***	-0.414*	-0.307
All Firms	0.647***	0.110	0.061

This table displays the correlations between the cyclical component of HP-filtered annual real corporate GDP and the three financing variables. The financing variables are the cyclical component of the respective HP-filtered series, aggregated by the indicated firm size categories and normalized by the lagged book value of assets. Small firms are those with book value of assets below the 60th percentile in a given year. Large firms are those between the 60th percentile and 90th percentile. "All firms" are the pooled sample of small and large firms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B3: Firm-Level Cyclicality of Financing Variables

Panel A: Baseline Specification

	1981-1998			1999-2017		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
Small Firms	6.41***	-10.74***	-8.61***	4.04***	**11.12****	**3.56**
	(1.631)	(3.569)	(2.964)	(0.898)	**(3.942)**	**(3.464)**
Large Firms	8.80***	-2.92**	-2.51**	6.08***	-1.42**	-1.12
	(1.436)	(1.195)	(1.158)	(1.323)	(0.592)	(1.081)
SF Observations	36,981	40,616	40,616	33,899	39,363	39,363
LF Observations	18,891	20,874	20,874	17,375	19,698	19,698
		p-values			p-values	
$H_0 : small = large$	0.040	0.006	0.009	0.179	0.003	0.108

Panel B: With-In Firm Variance in Continuous Size Measure

	1981-1998			1999-2017		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
Cyclical GDP	6.59***	-6.52**	-3.47	4.61***	6.95***	2.95
	(1.430)	(2.312)	(2.257)	(0.629)	(2.377)	(2.392)
Cyclical GDP x Size	0.35	8.32***	6.29***	1.51*	-8.62***	-4.20**
	(0.919)	(2.435)	(1.659)	(0.847)	(2.288)	(1.501)
Observations	44,680	49,118	49,118	41,634	47,965	47,965
					p-values	
$H_0 : Interaction\ in\ Pre_{1999} = Post_{1999}$				0.927	0.000	0.000

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on the cyclical component of HP-filtered annual real corporate GDP, normalized so that a unit increase in GDP indicates moving from the lowest realization to the highest realization during the sample period 1981-2017. Controls include the firm's cash flow and Tobin's Q. Each coefficient is the estimate from a separate regression for each firm size x subperiod sample. Post-1999 estimates in bold indicate the hypothesis $H_0 : \beta_j^{pre} = \beta_j^{post}$, where $j \in \{small, large\}$, is rejected at the 5% level. In Panel B, the GDP measure is interacted with a continuous measure of a firm's book value of assets (Size). A firm-specific fixed effect is included and all variables are demeaned by firm. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B4: State-Level Timing of Riegle-Neal Adoption

Panel A: 1981-1998

	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	5.30***	-11.75***	-9.63**
	(1.648)	(3.563)	(3.324)
$adopt_{1996}$ x GDP	2.50	-1.23	-0.24
	(1.776)	(2.497)	(1.750)
$adopt_{1997}$ x GDP	1.01	4.25	4.34***
	(1.122)	(2.871)	(1.274)
Observations	36,537	40,117	40,117

Panel B: 1999-2009

	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	5.08***	11.89*	6.46
	(0.554)	(5.502)	(5.377)
$adopt_{1996}$ x GDP	-1.54*	0.48	-2.16*
	(0.722)	(3.359)	(1.101)
$adopt_{1997}$ x GDP	-0.76	-7.91***	-6.75**
	(0.974)	(2.458)	(2.498)
Observations	21,913	25,763	25,763

Panel C: 1999-2019

	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	4.86***	12.44***	5.17
	(0.829)	(4.230)	(3.907)
$adopt_{1996}$ x GDP	-1.11	-0.93	-1.12
	(0.949)	(2.274)	(1.328)
$adopt_{1997}$ x GDP	-1.56	-6.02*	-4.33*
	(1.156)	(2.996)	(2.301)
Observations	32,697	38,005	38,005

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on the cyclical component of HP-filtered annual real corporate GDP, normalized so that a unit increase in GDP indicates moving from the lowest realization to the highest realization during the sample period 1981-2017. This GDP measure is interacted with an indicator for the year of state-level Riegle-Neal adoption. Controls include the firm's cash flow and Tobin's Q. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B5: Reduction in Small Firm's Bargaining Power, Syndicate Structure

Panel A: Number of Lenders

	1985-1998			1999-2012		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	0.99	-8.41	0.85	6.35***	16.35*	3.25
	(8.228)	(8.204)	(7.076)	(1.204)	(9.169)	(3.680)
NumLenders x GDP	2.57**	-0.09	0.96	2.62***	-2.16*	-1.38**
	(0.858)	(1.245)	(0.650)	(0.530)	(1.028)	(0.582)
Observations	9,386	10,420	10,420	9,186	10,761	10,761
R^2	0.047	0.064	0.014	0.031	0.026	0.005

Panel B: Lead Lender Share

	1985-1998			1999-2012		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	4.40	-8.38	4.64	10.95***	10.59	0.47
	(8.145)	(8.011)	(7.051)	(1.242)	(7.454)	(3.028)
LeadShare x GDP	-3.64*	-0.61	-5.48	-4.96***	7.27**	2.91*
	(1.973)	(4.017)	(3.279)	(1.083)	(2.505)	(1.565)
Observations	9,334	10,356	10,356	9,015	10,572	10,572
R^2	0.039	0.062	0.015	0.025	0.029	0.005

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on GDP (i.e. the cyclical component of HP-filtered real corporate GDP) and an interaction with the number of lenders in the "All Lender Pool" (Panel A) or the percentage of a firm's total syndicated loans contributed by the lead lender(s) (Panel B) during the 1985-1998 and 1999-2012 period. Controls include the firm's cash flow and Tobin's Q. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B6: Reduction in Small Firm's Bargaining Power, Lender Market Power

Panel A: Bank Merger, 1985-2012

	All Lender Pool			Lead Lender Pool		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	6.76***	7.28**	0.04	6.66***	7.00*	-0.01
	(2.238)	(3.419)	(1.500)	(2.145)	(3.443)	(1.485)
Acquired x GDP	0.26	9.60**	7.00**	0.24	7.36**	6.44*
	(2.724)	(3.821)	(3.354)	(3.451)	(3.559)	(3.234)
Observations	18,572	21,181	21,181	18,349	20,928	20,928
R^2	0.007	0.020	0.004	0.007	0.020	0.004

Panel B: Size of Merger, 1999-2012

	All Lender Pool			Lead Lender Pool		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	8.99***	13.66	1.24	8.93***	13.16	1.12
	(1.242)	(8.311)	(3.279)	(1.274)	(8.326)	(3.267)
Acquired x GDP	1.25	5.06	6.53	0.88	3.50	5.36
	(2.506)	(3.551)	(3.982)	(2.034)	(3.667)	(3.699)
Size x Acquired x GDP	-3.23	23.38***	10.56***	-11.07	20.65**	11.41**
	(5.799)	(4.974)	(3.372)	(10.322)	(9.529)	(3.984)
Observations	9,091	10,654	10,654	8,892	10,435	10,435
R^2	0.017	0.024	0.004	0.016	0.024	0.004

Panel C: By Size of Lender Pool, 1999-2012

	Few Lenders			Many Lenders		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	6.53***	18.29	3.39	12.89***	4.15	-2.00
	(1.233)	(11.464)	(4.565)	(2.893)	(2.839)	(1.834)
Acquired x GDP	1.75	8.13**	6.59	-5.34	-10.40	0.44
	(3.222)	(3.676)	(4.223)	(4.886)	(7.914)	(3.750)
Observations	5,641	6,631	6,631	3,374	3,941	3,941
R^2	0.010	0.033	0.006	0.033	0.007	0.004

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on cyclical GDP and an interaction with a flag for a lender in a firm's "All Lender Pool" or "Lead Lender Pool" being acquired by another lender during the previous five years. Firms with few (many) lenders are those with a below-average (above-average) number of lenders in their "All Lender Pool". *Size* is the percentage increase in the bank due to the merger. Controls include the firm's cash flow and Tobin's Q. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B7: Increase in Small Firms' Lender Relationship Complexity, MBHC Status, 1999-2012

Panel A: Baseline Specification

	All Lender Pool			Lead Lender Pool		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	9.63***	12.13	0.64	9.55***	12.07	0.71
	(1.144)	(7.925)	(3.089)	(1.233)	(7.999)	(3.093)
JoinMBHC x GDP	-4.32*	16.85**	9.31	-5.26**	12.67*	8.03
	(2.196)	(7.124)	(5.471)	(1.788)	(6.039)	(5.123)
Observations	9,186	10,761	10,761	9,015	10,572	10,572
R^2	0.016	0.025	0.005	0.017	0.025	0.005

Panel B: By Size of Lender Pool

	Few Lenders			Many Lenders		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	7.11***	16.93	2.79	13.26***	3.96	-2.10
	(1.299)	(10.929)	(4.266)	(2.834)	(2.875)	(1.957)
JoinMBHC x GDP	-4.09*	17.58**	9.64	-7.57	-5.99	1.44
	(1.895)	(6.745)	(5.923)	(5.211)	(6.152)	(4.725)
Observations	5,641	6,631	6,631	3,374	3,941	3,941
R^2	0.010	0.034	0.007	0.033	0.007	0.005

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on GDP (i.e. the cyclical component of HP-filtered real corporate GDP) and an interaction with an indicator for a lender in the "All Lender Pool" or the "Lead Lender Pool" that joined a multi-bank holding company in the previous 5 years during the 1999-2012 period. Firms with few lenders are those with a below-average number of lenders in their "All Lender Pool" and firms with many lenders are those with an average or above number of lenders. Controls include the firm's cash flow and Tobin's Q. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B8: Calibration

Discount Factor	$\beta = 0.9$
Disutility of Work	$\alpha = 1.53$
Tax Advantage	$\tau = 0.35$
Production Technology	$\theta = 0.36$
Depreciation Rate	$\delta = 0.025$
Payout cost parameter	$\kappa = 0.05$
Standard deviation: productivity shock	$\sigma_z = 0.006$
Standard deviation: financial shock	$\sigma_\xi = 0.0087$
Value of liquidity as collateral	$\nu = 0.25$
Matrix for the shocks process	$\begin{pmatrix} 0.9736, -0.0287 \\ 0.1509, 0.9363 \end{pmatrix}$

Steady State Values

	Strong Relationship	Weak Relationship
Equity payout, d	0.076	0.108
Liquidity, a	0.001	0.308
Cost of intraperiod loan, e	0.017	0.080
Debt, b	1.745	1.739
Equity Issuance to output, ei/y	-0.121	-0.173
Debt issuance to output, di/y	0.000	0.000
Liquidity accumulation to output, la/y	0.000	0.000
Labor, n	0.300	0.300
Capital, k	2.337	2.316

This table displays the baseline parameter values and steady state values of the general equilibrium business cycle model.

Table B9: Response of Financing Behavior to Positive TFP and Financial Shocks

Panel (a): Small Firms

	Debt Iss.		Equity Iss.		Liq. Accum.	
	Pre-1999	Post-1999	Pre-1999	Post-1999	Pre-1999	Post-1999
TFP Shock$_{t-1}$	-0.45	0.07	0.42	2.43**	0.20	1.85**
	(0.305)	(0.197)	(1.021)	(1.057)	(0.928)	(0.737)
Financial Shock$_{t-1}$	1.05***	1.14***	-2.08***	0.93	-1.50**	-0.21
	(0.289)	(0.264)	(0.629)	(1.919)	(0.649)	(1.549)
Observations	30,520	33,899	33,780	39,363	33,780	39,363
R^2	0.012	0.005	0.081	0.010	0.021	0.008

Panel (b): Large Firms

	Debt Iss.		Equity Iss.		Liq. Accum.	
	Pre-1999	Post-1999	Pre-1999	Post-1999	Pre-1999	Post-1999
TFP Shock$_{t-1}$	-0.10	0.02	0.12	0.11	0.37	0.03
	(0.294)	(0.314)	(0.314)	(0.103)	(0.233)	(0.203)
Financial Shock$_{t-1}$	1.20***	1.83***	-0.60**	-0.50**	-0.59**	-0.35
	(0.339)	(0.526)	(0.275)	(0.183)	(0.270)	(0.357)
Observations	14,406	17,375	15,994	19,698	15,994	19,698
R^2	0.026	0.015	0.003	0.022	0.031	0.008

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on the lagged annual value of the TFP shock and financial shock. The shocks are standardized to mean zero and unit variance. Controls include the firm's cash flow and Tobin's Q. Panel (a) is the sample of small firms and Panel (b) the sample of large firms. Small firms are those with book value of assets below the 60th percentile in a given year. Large firms are those between the 60th percentile and 90th percentile. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B10: Firm-Level Cyclicality of Real Variables

Panel A: Baseline Specification

	1981-1998		1999-2017	
	Investment	Employment	Investment	Employment
Small Firms	-1.35	-1.86	2.53***	12.49***
	-0.886	-3.692	-0.753	-3.344
Large Firms	0.94	9.53**	2.26**	10.34***
	-1.006	-4.42	-0.943	-3.273
SF Observations	39,893	38,235	39,129	37,331
LF Observations	20,473	20,272	19,579	19,211

	p-values	
$H_0 : small_{pre} = small_{post}$	0.002	0.006
$H_0 : large_{pre} = large_{post}$	0.338	0.883

Panel B: By Liquidity Position, Small Firms 1981-2017

	Low Liquidity Position		High Liquidity Position	
	Investment	Employment	Investment	Employment
GDP	-2.55***	-7.32*	-1.02	2.83
	0.004	0.065	0.301	0.452
D_t^{post}	5.05***	16.83***	3.26***	8.72
	0.000	0.001	0.007	0.119
SF Observations	25,918	24,973	24,700	23,988
LF Observations	0.007	0.014	0.011	0.029

This table displays the estimates of regressing change in investment (as a % of assets) and percentage change in employment on the cyclical component of HP-filtered annual real corporate GDP, normalized so that a unit increase in GDP indicates moving from the lowest realization to the highest realization during the sample period 1981-2017. Controls include the firm's cash flow and Tobin's Q. D_t^{post} is an indicator for the years 1999-2017. Each coefficient is the estimate from a separate regression for each firm size x subperiod sample. In Panel B, Liquidity Position is determined by the median cash-to-assets ratio for the years 1996-1998. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B11: Robustness Tests: Firm Fixed Effect and Consistent Sample

Panel A: Firm Fixed Effect	1981-1998			1999-2017		
	DI	EI	LA	DI	EI	LA
Small Firms	5.36***	-11.37***	-6.56**	4.10***	**6.13**	**2.40**
	(1.398)	(3.413)	(2.981)	(0.692)	**(3.649)**	**(3.270)**
Large Firms	7.40***	-4.61***	-2.59**	6.43***	-1.57**	-1.35
	(1.264)	(0.957)	(1.052)	(1.079)	(0.550)	(1.063)
SF Observations	29,709	32,516	32,516	27,873	32,488	32,488
LF Observations	16,195	17,932	17,932	15,590	17,698	17,698

Panel B: Consistent Sample	1981-1998			1999-2017		
	DI	EI	LA	DI	EI	LA
Small Firms	4.04*	-3.65	-8.56**	4.17**	**17.51****	**7.04**
	(2.134)	(3.397)	(3.106)	(1.550)	**(7.879)**	**(4.989)**
Large Firms	4.90***	-3.09***	-2.01	5.30***	-2.78***	-2.66**
	(1.631)	(0.980)	(1.310)	(0.871)	(0.570)	(1.122)
SF Observations	3,364	3,677	3,677	4,051	4,627	4,627
LF Observations	2,943	3,227	3,227	3,603	4,042	4,042

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on the cyclical component of HP-filtered annual real corporate GDP, normalized so that a unit increase in GDP indicates moving from the lowest realization to the highest realization during the sample period 1981-2017. In Panel A, a firm-specific fixed effect is included. In Panel B, the sample includes only those firms that entered the Compustat sample prior to 1990 and also appeared in the sample in 2017. Controls include the firm's cash flow and Tobin's Q. Each coefficient is the estimate from a separate regression for each firm size x subperiod sample. 1999-2017 estimates in bold indicate the hypothesis $H_0 : \beta_j^{pre} = \beta_j^{post}$, where $j \in \{small, large\}$, is rejected at the 5% level. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B12: Panel Regression: Alternative Financing Variables

Panel A: 1981-1998

	Net Sale of Stock	Alt. Liq. Accum.	Cash	Ret. Earnings
Small Firms	-10.82***	-4.63*	-1.74	-9.37***
	(3.564)	(2.575)	(2.278)	(1.737)
Large Firms	-2.96**	-1.40	0.95	-0.89
	(1.147)	(1.227)	(1.304)	(1.535)
SF Observations	40,616	35,736	35,818	40,616
LF Observations	20,874	17,153	17,246	20,874
	p-values			
$H_0 : small = large$	0.006	0.083	0.087	0.001

Panel B: 1999-2017

	Net Sale of Stock	Alt. Liq. Accum.	Cash	Ret. Earnings
Small Firms	**11.23****	**2.94**	2.29	-3.10
	(3.968)	**(2.331)**	(2.268)	(3.291)
Large Firms	-0.96	0.15	-0.15	1.62
	(0.600)	(0.567)	(0.664)	(2.063)
SF Observations	39,363	39,350	39,237	39,363
LF Observations	19,698	19,696	19,510	19,698
	p-values			
$H_0 : small = large$	0.004	0.190	0.235	0.192

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on the cyclical component of HP-filtered annual real corporate GDP, normalized so that a unit increase in GDP indicates moving from the lowest realization to the highest realization during the sample period 1981-2017. Controls include the firm's cash flow and Tobin's Q. Each coefficient is the estimate from a separate regression for each firm size x subperiod sample. Panel B estimates in bold indicate the hypothesis $H_0 : \beta_j^{pre} = \beta_j^{post}$, where $j \in \{small, large\}$, is rejected at the 5% level. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B13: Aggregate Financing Variables: No Filtering

	No Filtering 1981-2017			Hamilton Filtering 1981-2017		
Size categories	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
Small Firms	0.537***	0.332**	0.260	0.625***	0.404**	0.328*
Large Firms	0.431***	0.098	-0.161	0.602***	-0.233	-0.160
All Firms	0.578***	0.279*	0.191	0.636***	0.140	0.141

	1981-1998			1981-1998		
Size categories	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
Small Firms	0.575**	0.210	0.020	0.840***	-0.008	0.022
Large Firms	0.503**	-0.004	-0.199	0.820***	-0.476*	-0.128
All Firms	0.652***	0.320	0.069	0.838***	-0.226	0.008

	1999-2017			1999-2017		
Size categories	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
Small Firms	0.638***	0.461**	0.461**	0.639***	0.529**	0.454*
Large Firms	0.554**	-0.075	-0.091	0.664***	-0.299	-0.147
All Firms	0.641***	0.174	0.260	0.690***	0.194	0.199

The left column of this table displays the correlations between the annual growth rate in real corporate GDP and the three (non-HP-filtered) financing variables. The right column displays the correlations between the cyclical component of Hamilton (2018)-filtered annual real corporate GDP and the three financing variables. The financing variables are aggregated by the indicated firm size categories and normalized by the lagged book value of assets. Small firms are those with book value of assets below the 60th percentile in a given year. Large firms are those between the 60th percentile and 90th percentile. "All firms" are the pooled sample of small and large firms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B14: Effects of Consolidation by Size of Lender Pool, 1999-2012, All Lender Pool

	Few Lenders			Many Lenders		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	7.00***	19.39	3.69	12.50***	3.60	-2.31
	(1.203)	(11.488)	(4.587)	(3.308)	(2.718)	(1.843)
Acquired x GDP	1.52	6.15	6.05	-5.06	-7.19	0.93
	(3.294)	(3.664)	(4.104)	(8.910)	(8.455)	(4.120)
Observations	5,761	6,763	6,763	3,425	3,998	3,998
R^2	0.010	0.033	0.006	0.037	0.007	0.006

	Few Lenders			Many Lenders		
	Debt Iss.	Equity Iss.	Liq. Accum.	Debt Iss.	Equity Iss.	Liq. Accum.
GDP	7.52***	17.96	3.03	12.94***	2.62	-2.39
	(1.276)	(10.944)	(4.281)	(2.893)	(2.745)	(2.096)
JoinMBHC x GDP	-3.59	17.25**	10.12	-6.34	5.23	1.62
	(2.053)	(7.267)	(6.023)	(8.459)	(7.559)	(7.917)
Observations	5,761	6,763	6,763	3,425	3,998	3,998
R^2	0.011	0.034	0.007	0.032	0.006	0.006

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on GDP (i.e. the cyclical component of HP-filtered real corporate GDP) and an interaction with an indicator for a lender in the "All Lender Pool" that was acquired by another lender during the previous five years (Panel A) or that joined a multi-bank holding company in the previous 5 years (Panel B). Firms with few lenders are those with a below-average number of lenders in their "All Lender Pool" and firms with many lenders are those with an average or above number of lenders. Controls include the firm's cash flow and Tobin's Q. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B15: Panel Regression: Financing Response to Negative Shock

Panel A: 1981-1998

	Debt Iss.	Equity Iss.	Liq. Accum.
Small Firms	-2.56***	-0.58	0.89
	(0.634)	(1.505)	(1.150)
Large Firms	-1.59*	-0.12	0.55
	(0.822)	(0.484)	(0.481)
SF Observations	36,981	40,616	40,616
LF Observations	18,891	20,874	20,874
		p-values	
$H_0 : small = large$	0.007	0.678	0.659

Panel B: 1999-2017

	Debt Iss.	Equity Iss.	Liq. Accum.
Small Firms	-1.74***	**-7.02*****	**-4.92****
	(0.487)	**(2.236)**	**(1.800)**
Large Firms	-1.63*	0.14	-0.39
	(0.937)	(0.340)	(0.475)
SF Observations	33,899	39,363	39,363
LF Observations	17,375	19,698	19,698
		p-values	
$H_0 : small = large$	0.864	0.004	0.008

This table displays the estimates of regressing the financing variable of interest (as a percentage of firm asset value) on an indicator for a "negative shock", i.e. a year with negative growth in the cyclical component of HP-filtered real corporate GDP during the sample period 1981-2017. Years with a "negative shock" are 1982, 1986, 1989-1993, 2001-2003, 2007-2009, and 2016. Controls include the firm's cash flow and Tobin's Q. Each coefficient estimate comes from running a separate regression on the firm size x subperiod sample. Panel B estimates in bold indicate the hypothesis $H_0 : \beta_j^{pre} = \beta_j^{post}$, where $j \in \{small, large\}$, is rejected at the 5% level. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B16: Panel Regression: Real Response to Negative Shock

Panel A: 1981-1998

	Investment	Employment
Small Firms	-0.38	-4.10***
	(0.422)	(1.197)
Large Firms	-0.86**	-5.67***
	(0.359)	(1.325)
SF Observations	39,893	38,235
LF Observations	20,473	20,272

Panel B: 1999-2017

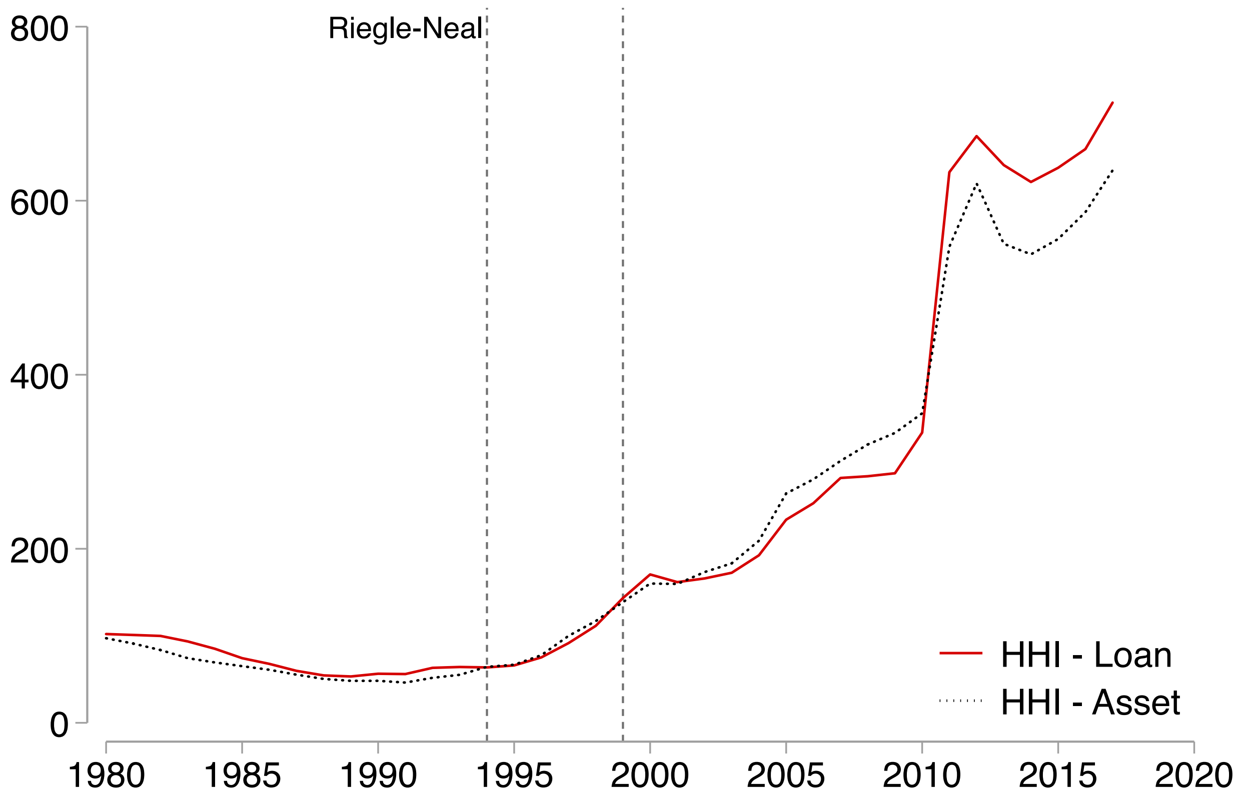
	Investment	Employment
Small Firms	-1.48***	-7.95***
	(0.330)	(1.711)
Large Firms	-1.25***	-6.75***
	(0.349)	(1.448)
SF Observations	39,129	37,331
LF Observations	19,579	19,211
	p-values	
$H_0 : small_{pre} = small_{post}$	0.045	0.070
$H_0 : large_{pre} = large_{post}$	0.437	0.580

This table displays the estimates of regressing change in investment (as a % of assets) and percentage change in employment on an indicator for a "negative shock", i.e. a year with negative growth in the cyclical component of HP-filtered real corporate GDP during the sample period 1981-2017. Years with a "negative shock" are 1982, 1986, 1989-1993, 2001-2003, 2007-2009, and 2016. Controls include the firm's cash flow and Tobin's Q. Each coefficient estimate comes from running a separate regression on the firm size x subperiod sample. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

APPENDIX C

FIGURES FOR CHAPTER 1

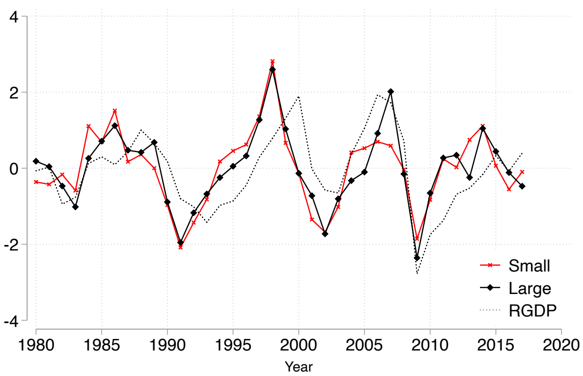
Figure C1: Concentration of US Banking Industry



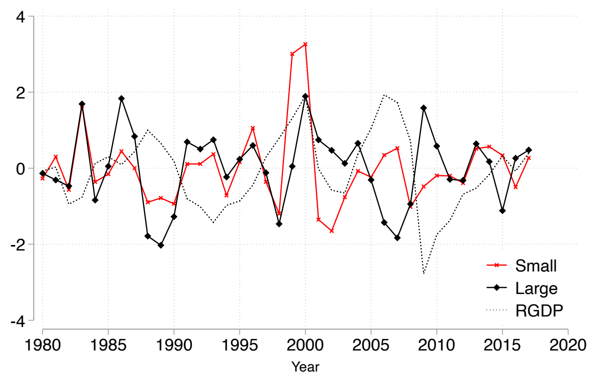
This figure plots the national Herfindahl-Hirschman index for total loans and total assets in the commercial banking sector during the period 1986-2017. Authors' calculations using FR Y-9C data.

Figure C2: Time Series of Financial Variables, by Firm Size

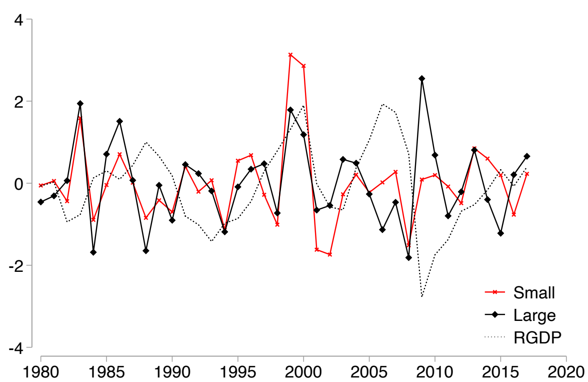
(a) Debt Issuance and Cyclical GDP



(b) Equity Issuance and Cyclical GDP



(c) Liquidity Accumulation and Cyclical GDP



This figure plots the aggregate annual series of debt issuance (Panel a), equity issuance (Panel b) and liquidity accumulation (Panel C) for small firms and large firms during the period 1980-2017. RGDP (dotted line) is the cyclical component of HP-filtered annual real corporate GDP. Small firms are those with a book value of assets below the 60th percentile in a given year. Large firms are those between the 60th percentile and 90th percentile. All series are standardized to have a mean of zero and unit variance.

Figure C3: Within-Period Model Timeline

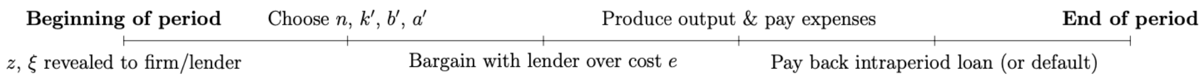
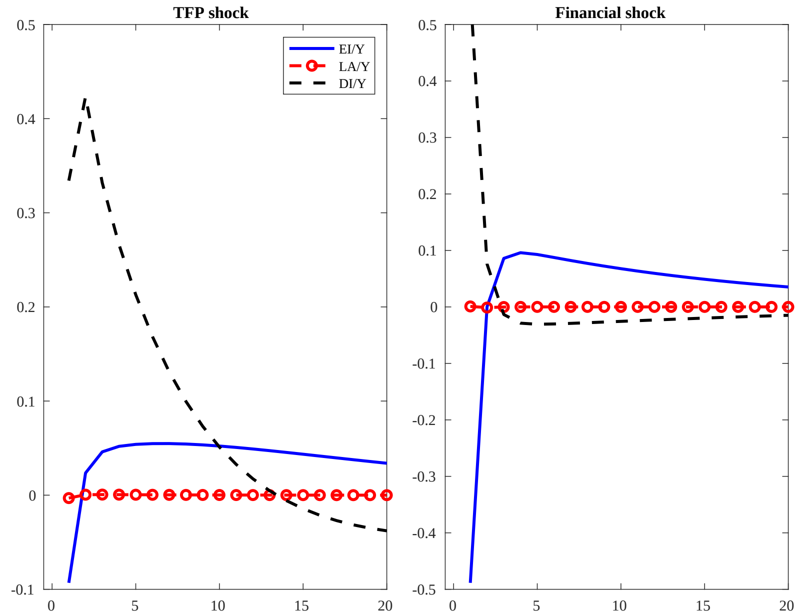
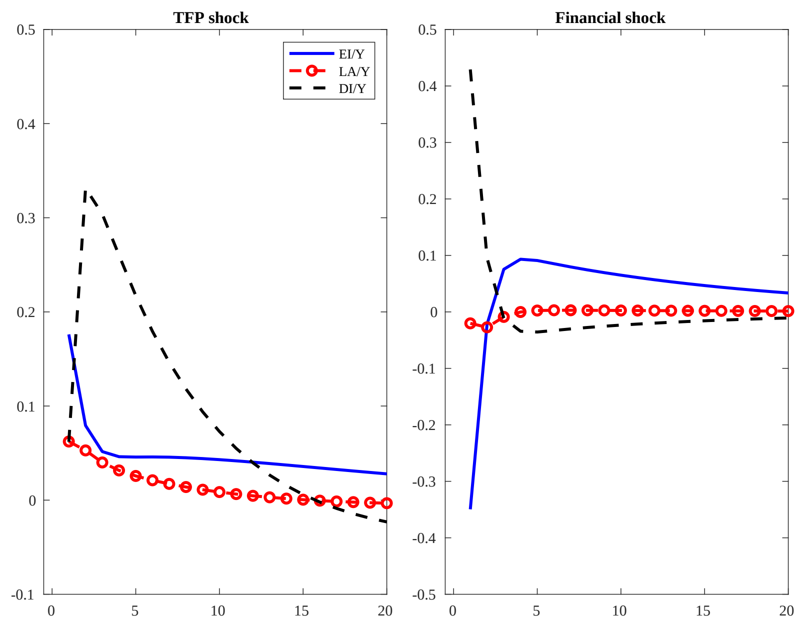


Figure C4: IRFs of Financial Variables to Positive TFP & Financial Shocks

(a) Stronger Borrowers: High Bargaining Power / Low Bank Outside Option

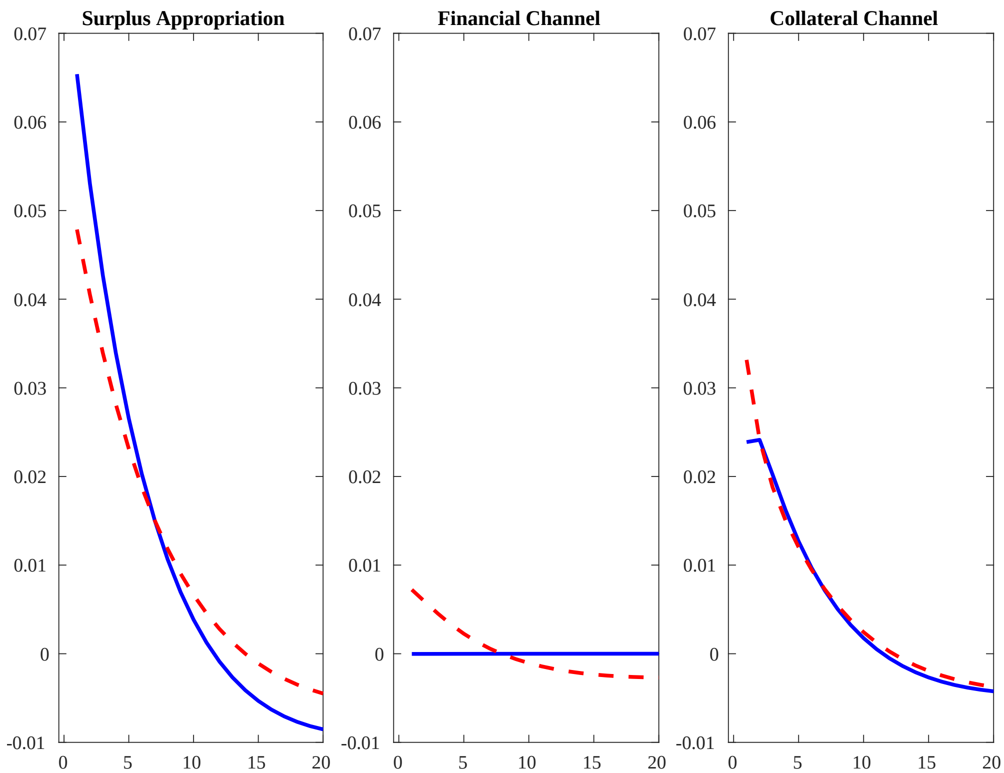


(b) Weaker Borrowers: Low Bargaining Power / High Bank Outside Option



This figure plots the impulse responses of equity issuance (EI), liquidity accumulation (LA) and debt issuance (DI) for a one standard deviation positive TFP shock (left column) and financial shock (right column). Panel (a) shows the impulse response when the firm bargaining power parameter is set high and bank outside option is set low. Panel (b) shows the opposite. The y-axis is percent deviation from the steady state value for the ratio of the financing variable to output.

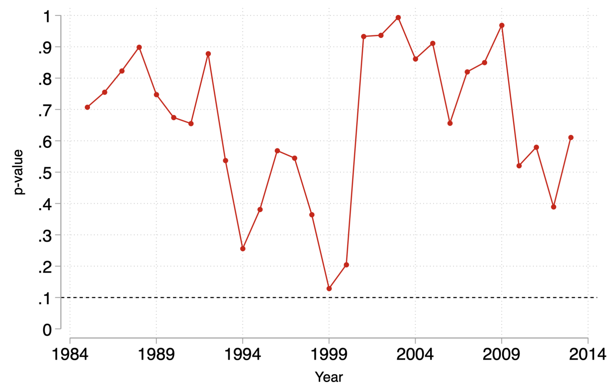
Figure C5: IRFs of Capital FOC Components to Positive TFP Shock



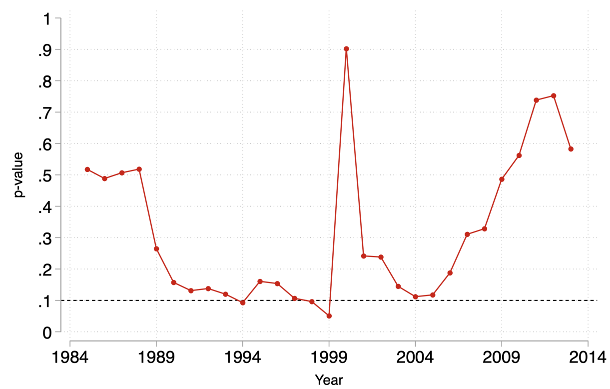
This figure plots the responses of strong borrowers (blue) and weak borrowers (red, dashed) to a one standard deviation positive TFP shock. The y-axis is absolute deviation from the steady state value.

Figure C6: Wald Test for Structural Break in Cyclicality of Small Firm Financing

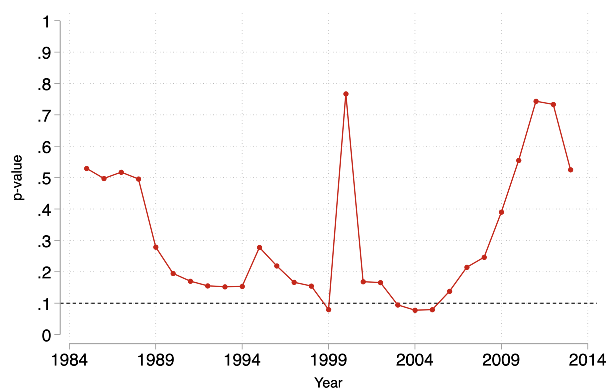
(a) Debt Issuance



(b) Equity Issuance



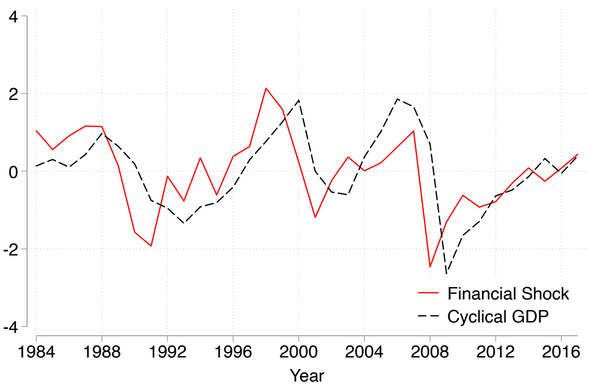
(c) Liquidity Accumulation



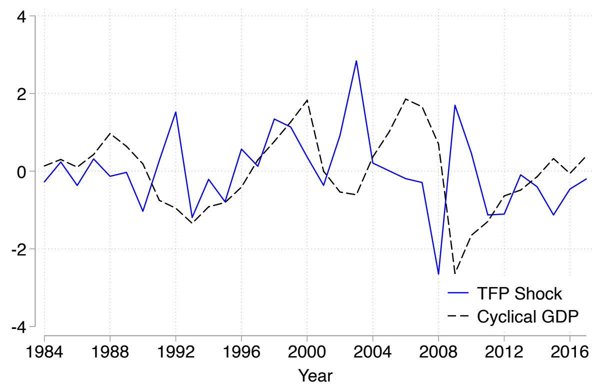
This figure plots the p-values of a Wald test to check for a structural break in the corresponding year reported on the x-axis. Variables for debt issuance (Panel a), equity issuance (Panel b) and liquidity accumulation (Panel c) are the aggregate series for small firms. Small firms are those with book value of assets below the 60th percentile in a given year. The black horizontal line indicates a p-value of 0.1.

Figure C7: Time Series of Financial & TFP Shocks

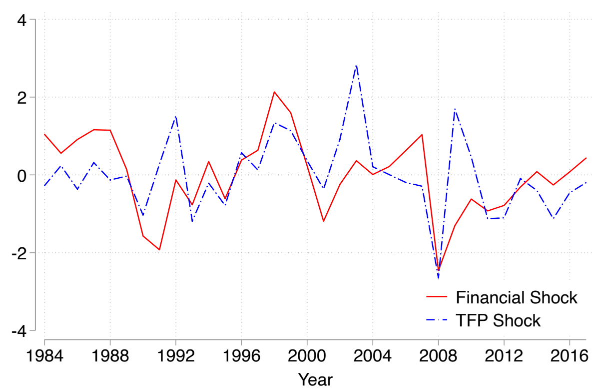
(a) Financial Shock & Cyclical GDP



(b) TFP Shock & Cyclical GDP

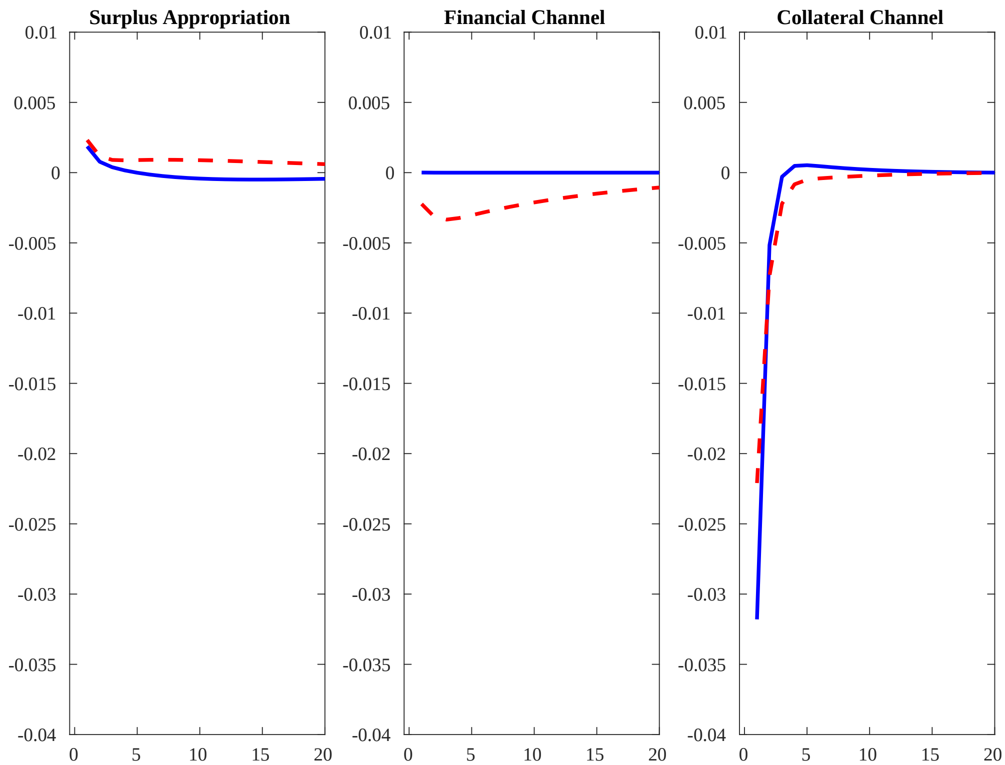


(c) Financial Shock & TFP Shock



This figure plots the model-implied annual series of the financial shocks and TFP shocks during the period 1984-2017. The dotted line in Panel (a) and Panel (b) is the cyclical component of HP-filtered annual real corporate GDP. Small firms are those with a book value of assets below the 60th percentile in a given year. Large firms are those between the 60th percentile and 90th percentile. All series are standardized to have a mean of zero and unit variance.

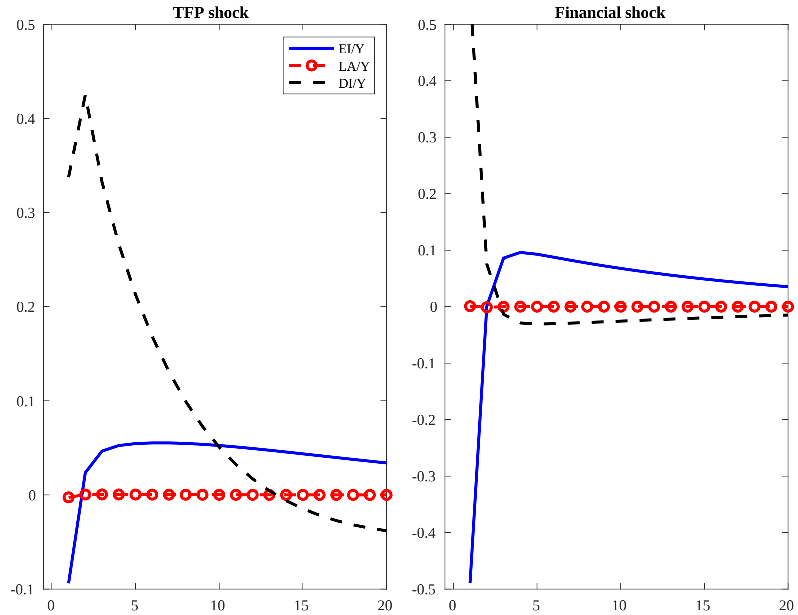
Figure C8: IRFs of Capital FOC Components to Positive Financial Shock



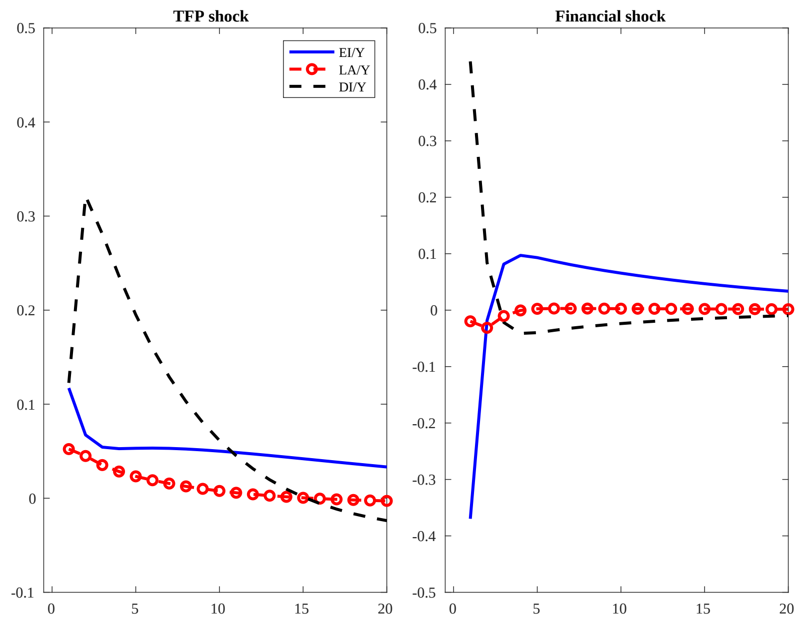
This figure plots the responses of strong borrowers (blue) and weak borrowers (red, dashed) to a one standard deviation positive financial shock. The y-axis is absolute deviation from the steady state value.

Figure C9: IRFs of Financial Variables: Alternative Household Budget Constraint

(a) Stronger Borrowers: High Bargaining Power / Low Bank Outside Option



(b) Weaker Borrowers: Low Bargaining Power / High Bank Outside Option



This figure plots the impulse responses of equity issuance (EI), liquidity accumulation (LA) and debt issuance (DI) for a one standard deviation positive TFP shock (left column) and financial shock (right column). Panel (a) shows the impulse response when the firm bargaining power parameter is set high and bank outside option is set low. Panel (b) shows the opposite. The y-axis is percent deviation from the steady state value for the ratio of the financing variable to output.

APPENDIX D

TABLES FOR CHAPTER 2

Table D1: Summary Statistics

	Pre-Crisis		Post-Crisis	
	mean	std. dev.	mean	std. dev.
Stock return	0.240	3.001	0.162	1.935
Leverage (Debt-to-Capital)	0.381	0.216	0.414	0.231
Leverage (Debt-to-Assets)	0.251	0.149	0.276	0.162
Leverage (Debt-to-Equity)	0.985	3.846	1.208	3.538
Implied volatility	34.799	14.378	27.846	9.453
MP shock	-0.007	0.035	-0.002	0.023
FFR shock	-0.020	0.094	-0.003	0.012
10 year shock	0.001	0.040	-0.002	0.035
2 year shock	-0.007	0.065	-0.006	0.035

The table shows summary statistics for stock returns, leverage measures, monetary policy shocks and implied volatility. Stock returns and implied volatility are measured daily at the firm level. Leverage is measured quarterly at the firm level. The monetary policy shocks are measured within a 30-minute window around an FOMC announcement. Sample is non-financial firms in S&P 500 on date of FOMC announcement. Pre-crisis is Jul-1991 to Jun-2008 and post-crisis is Aug-2009 to Dec-2017.

Table D2: Response of firm-level stock returns to monetary shocks

Panel A:	(1a) Pre-Crisis	(1b) Post-Crisis	(2a) Pre-Crisis	(2b) Post-Crisis	(3a) Pre-Crisis	(3b) Post-Crisis
Leverage (Debt-to-Capital)	0.006	0.009	0.006	0.011	-0.026	0.006
	(0.039)	(0.026)	(0.039)	(0.027)	(0.038)	(0.025)
MP shock x Leverage	-5.466*	2.223***				
	(3.186)	(0.573)				
FFR shock x Leverage			-2.050*	-0.368		
			(1.187)	(1.382)		
10 yr shock x Leverage			0.265	1.470***		
			(1.203)	(0.368)		
2 yr shock x Leverage					-1.205	0.915**
					(0.848)	(0.366)
Observations	48,143	24,584	48,143	24,584	48,143	24,584
R^2	0.181	0.341	0.181	0.341	0.177	0.341
Firm controls	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes

Panel B:	Full Sample	Full Sample
D_t^{post} x MP shock x Leverage (Debt-to-Capital)	7.706**	
	(3.269)	
D_t^{post} x 2 yr shock x Leverage (Debt-to-Capital)		2.107**
		(0.929)
Observations	72,733	72,733
R^2	0.206	0.203
Firm controls	yes	yes
Firm FE	yes	yes
Time FE	yes	yes

Panel A shows results from estimating $s_{i,t} = \alpha_i + \alpha_t + \beta l_{i,t-1}\epsilon_t^m + \delta l_{i,t-1} + \Gamma' Z_{i,t-1} + e_{i,t}$, where $s_{i,t}$ is firm-level daily stock return, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, $l_{i,t-1}$ is four-quarter moving average leverage normalized to have mean 0 and variance 1, ϵ_t^m is the monetary policy shock and $Z_{i,t-1}$ is a vector of firm-level controls. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Panel B shows results for
$s_{i,t} = \alpha_i + \alpha_t + \beta_1 l_{i,t-1}\epsilon_t^m + \beta_2 l_{i,t-1}\epsilon_t^m D_t^{post} + \delta_1 l_{i,t-1} + \delta_2 l_{i,t-1} D_t^{post} + \Gamma' Z_{i,t-1} + e_{i,t}$ where D_t^{post} is an indicator for the post-crisis period. Sample is non-financial firms in S&P 500 on date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D3: Regression of firm-level implied volatility leading up to FOMC announcement

	(1)	(2)
Leverage	-1.02**	-0.75*
	(0.442)	(0.414)
Post-Crisis x Leverage	2.30***	1.81***
	(0.403)	(0.370)
Observations	47,131	42,635
R^2	0.759	0.786
Firm FE	yes	yes
Time FE	yes	yes
Firm controls	no	yes

Null Hypothesis	p-value	
leverage + post x leverage = 0	0.001	0.003

Results from estimating $ivol_{i,t-1} = \alpha_i + \alpha_t + \delta l_{i,t} + \beta l_{i,t-1} D_t^{post} + \Gamma Z_{i,t-1} + e_{i,t}$, where $ivol_{i,t-1}$ is firm-level implied volatility on the day before the FOMC announcement, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, $l_{i,t-1}$ is four-quarter moving average leverage normalized to have mean 0 and variance 1, D_t^{post} is an indicator for the post-crisis period and $Z_{i,t-1}$ is the baseline vector of firm-level controls including firm-level stock price at close of prior trading day. Pre-crisis is Jan-1996 to Jun-2008 (108 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in S&P 500 on date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D4: Contemporaneous response of firm-level investment to monetary shocks

	Investment
MP shock$_t$ x Leverage$_{t-1}$	-3.71**
	(1.596)
D_t^{post} x MP shock$_t$ x Leverage$_{t-1}$	7.86***
	(2.885)
Observations	19,755
R^2	0.146
Firm controls	yes
Firm FE	yes
Time FE	yes

Results from estimating
$\Delta ln(y_{it}) = \alpha_i + \alpha_t + \sum_{n \in N} \beta_{1n} l_{i,t-n-1} \epsilon_{t-n}^m + \beta_{2n} l_{i,t-n-1} \epsilon_{t-n}^m D_{t-n}^{post} + \Gamma' Z_{i,t-1} + e_{it}$, where y_{it} is value of firm i's capital stock in quarter t, α_i is a firm i fixed effect, α_t is a quarter t fixed effect, l_{it} is one-quarter lagged leverage normalized to have mean 0 and variance 1, ϵ_t^m is the sum of all high-frequency monetary policy shocks that occur in quarter t, D_t^{post} is an indicator for the post-crisis period, $N = [0, 12]$ and Z_{it-1} is a vector of firm-level controls. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Sample is non-financial S&P 500 firms with at least 40 quarters of data in the pre-crisis or post-crisis sample for the dependent variable. Pre-crisis is 1991:Q3 to 2008:Q2 and post-crisis is 2009:Q3 to 2017:Q4. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D5: Response of Bond Yield Spread to Monetary Policy Shock

	BAA - AAA spread
MP Shock	1.034
	(4.447)
Post-Crisis x MP Shock	-20.414*
	(12.211)
Observations	221
R^2	0.021

Results from estimating $\Delta ln(y_t) = \alpha_0 + \alpha_1 D_t^{post} + \delta \epsilon_t^m + \beta D_t^{post} \epsilon_t^m + e_{it}$, where y_{it} is BAA-AAA bond yield spread, D_t^{post} is a dummy for the post-crisis period and ϵ_t^m is the monetary policy shock. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D6: Response of 10 year nominal yield, real yield and term premium to monetary shocks

Panel A:	10 year nominal		10 year real		10 year term premium	
	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis
MP Shock	-0.19	-1.77***	-0.40**	-1.89***	0.12	-1.45***
	(0.228)	(0.319)	(0.157)	(0.415)	(0.168)	(0.323)
Observations	153	68	83	68	153	68
R^2	0.012	0.311	0.104	0.352	0.010	0.309
Null Hypothesis	p-value		p-value		p-value	
D_t^{post} x MP shock = 0	0.000		0.001		0.000	

Panel B:	10 year nominal		10 year real		10 year term premium	
	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis
2 yr shock	-0.42***	-0.71***	-0.33***	-1.01***	-0.21***	-0.63***
	(0.077)	(0.244)	(0.066)	(0.216)	(0.051)	(0.203)
Observations	153	68	83	68	153	68
R^2	0.205	0.121	0.226	0.248	0.103	0.142
Null Hypothesis	p-value		p-value		p-value	
D_t^{post} x 2 yr shock = 0	0.268		0.003		0.044	

Results from estimating $\Delta y_t = \alpha_0 + \beta\epsilon_t^m + e_{it}$, where y_t is (daily) change in the 10 year nominal rate, 10-year real rate, or the Kim & Wright 10 year term premium estimate and ϵ_t^m is the monetary policy shock. The monetary policy shock is normalized so that a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). The 10-year real rate is not available prior to 1999. The p-values for each panel are for a full sample estimation of the interaction coefficient $D_t^{post} * \epsilon_t^m$, where D_t^{post} is a dummy for the post-crisis period. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D7: Response of firm-level stock returns (by high/low long-term leverage)

	High LT Leverage		Low LT Leverage	
	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis
	(1a)	(1b)	(2a)	(2b)
MP shock x Leverage	-2.738*	1.826**	-12.611*	0.245
	(1.475)	(0.867)	(6.444)	(1.668)
Observations	32,238	18,817	15,901	5,766
R^2	0.183	0.350	0.231	0.342
Firm controls	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes

Results from estimating $s_{i,t} = \alpha_i + \alpha_t + \beta l_{i,t-1}\epsilon_t^m + \delta l_{i,t-1} + \Gamma' Z_{i,t-1} + e_{i,t}$ separately for firms classified as "High (Low) LT Leverage" that are in the top two-thirds (bottom third) of the long-term (LT) leverage distribution, where $s_{i,t}$ is firm-level daily stock return, α_i is a firm fixed-effect, α_t is a time fixed-effect, $l_{i,t-1}$ is four-quarter moving average leverage normalized to have mean 0 and variance 1, ϵ_t^m is the monetary policy shock and $Z_{i,t-1}$ is a vector of firm-level controls. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in S&P 500 on date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D8: Response of firm-level stock returns to monetary policy uncertainty shocks

	Pre-Crisis	Post-Crisis
MPU Shock x Leverage	-0.117	0.852*
	(0.897)	(0.438)
Observations	39,684	24,584
R^2	0.187	0.341
Firm controls	yes	yes
Firm FE	yes	yes
Time FE	yes	yes

Results from estimating $s_{i,t} = \alpha_i + \alpha_t + \beta l_{i,t-1}\epsilon_t^{mpu} + \delta l_{i,t-1} + \Gamma' Z_{i,t-1} + e_{i,t}$, where $s_{i,t}$ is the firm-level daily stock return, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, $l_{i,t-1}$ is 4-quarter moving average leverage normalized to have mean 0 and variance 1, ϵ_t^{mpu} is monetary policy uncertainty shock (positive value means a decrease in uncertainty) and $Z_{i,t-1}$ is a vector of firm-level controls. Pre-crisis is Feb-1994 to Jun-2008 (125 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in S&P 500 on date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D9: Response of Firm-Level Implied Volatility to MPU Shock

	Full Sample
MPU Shock x Leverage	1.01**
	(0.398)
Post-Crisis x MPU Shock x Leverage	-1.15***
	(0.331)
Observations	9,965
R^2	0.367
Firm FE	yes
Time FE	yes
Firm controls	yes

Result from estimating $\Delta ivol_{i,t} = \alpha_i + \alpha_t + \beta_1 l_{i,t-1}\epsilon_t^{mpu} + \beta_2 D_t^{post} l_{i,t-1}\epsilon_t^{mpu} + \delta l_{it-1} + \Gamma' Z_{i,t-1} + e_{i,t}$, where $ivol_{it}$ is the firm-level implied volatility, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, l_{it-1} is 4-quarter moving average leverage normalized to have mean 0 and variance 1, ϵ_t^{mpu} is monetary policy uncertainty shock (positive value means a decrease in uncertainty)and Z_{it-1} is a vector of firm-level controls. Pre-crisis is Jan-1996 to Jun-2008 (108 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is Liquid 100 non-financial firms. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D10: Summary Statistics of Firm Characteristics

	Low Leverage		High Leverage	
	mean	std. dev.	mean	std. dev.
Leverage (Debt-to-Capital)	0.211	0.120	0.562	0.146
Firm age	31.52	14.18	37.62	13.03
Book value of assets ($, millions)	15,577	36,128	21,613	47,465
Market capitalization ($, millions)	24,623	51,290	18,898	37,891
Real sales growth (%, YoY)	4.424	21.029	2.010	21.858
Price-to-cost margin	0.439	0.246	0.353	0.221
Receivables-minus-payables to sales	0.268	0.368	0.245	0.677
Depreciation to assets	0.012	0.007	0.011	0.006
Current assets to total assets	0.451	0.185	0.298	0.172

The table shows summary statistics for the firm-level controls. The sample is divided into firms below (“Low Leverage") and firms above (“High Leverage") the sample mean debt-to-capital ratio. All variables are measured quarterly at the firm level. Sample is non-financial firms in the S&P 500 between Jul-1991 and Dec-2017, excluding the financial crisis dates of Jul-2008 to Jul-2009.

Table D11: Response of firm-level stock returns to monetary shocks w/ control interactions

	(1a) Pre-Crisis	(1b) Post-Crisis
MP shock x Leverage	-3.665**	1.001**
	(1.786)	(0.437)
MP shock x Current to total assets	13.676*	-4.722
	(8.058)	(4.593)
MP shock x Real sales growth	0.004	0.021
	(0.044)	(0.064)
MP shock x Firm size	2.792	0.776
	(1.769)	(1.668)
MP shock x Price-to-cost margin	5.369	2.314
	(6.225)	(4.384)
MP shock x Rec-minus-Pay to sales	0.488	-1.669**
	(1.040)	(0.769)
MP shock x Depreciation-to-Assets	176.975	-62.448
	(177.487)	(122.824)
MP shock x Firm age	-0.236	0.055
	(0.181)	(0.050)
MP shock x Market capitalization	-2.217	-1.204
	(1.636)	(2.068)
MP shock x 1st fiscal quarter	-3.209	2.206
	(4.643)	(1.719)
MP shock x 2nd fiscal quarter	-0.595	-0.291
	(2.199)	(2.362)
MP shock x 3rd fiscal quarter	1.993	-1.774
	(3.344)	(2.794)
Observations	47,872	24,516
R-squared	0.184	0.343
Firm controls	yes	yes
Firm FE	yes	yes
Time FE	yes	yes

Results from estimating $s_{it} = \alpha_i + \alpha_t + \beta l_{it-1}\epsilon_t^m + \delta l_{it-1} + \Gamma' Z_{it-1} + e_{it}$, where s_{it} is firm-level daily stock return, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, l_{it-1} is four-quarter moving average leverage normalized to have mean 0 and variance 1, ϵ_t^m is the monetary policy shock and Z_{it-1} is a vector of the baseline firm-level controls and firm's sector (and their interactions with the MP shock). The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in S&P 500 on date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D12: Response of firm-level stock returns to monetary shocks: Without a time fixed effect

	(1)	(2)	(3)
MP shock	6.943*		
	(3.912)		
Post-Crisis x MP shock	-0.829		
	(7.333)		
FFR shock		2.369	
		(1.990)	
10 yr shock		5.936***	
		(2.144)	
Post-Crisis x FFR shock		6.896	
		(10.656)	
Post-Crisis x 10 yr shock		-2.636	
		(4.593)	
2 yr shock			6.639***
			(2.243)
Post-Crisis x 2 yr shock			7.483
			(5.373)
Observations	76,599	76,599	76,599
R^2	0.021	0.027	0.038
Firm controls	yes	yes	yes
Firm FE	yes	yes	yes
Time FE	no	no	no

Results from estimating $s_{it} = \alpha_i + \beta\epsilon_t^m + \delta\epsilon_t^m D_t^{post} + \Gamma' Z_{it-1} + e_{it}$, where s_{it} is firm-level daily stock return, α_i is a firm fixed-effect, ϵ_t^m is the monetary policy shock, D_t^{post} is an indicator for the post-crisis period and Z_{it-1} is a vector of firm-level controls. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Sample is Jul-1991 to Dec-2017 with post-crisis sample of Aug-2009 to Dec-2017. Sample is non-financial firms in S&P 500 on the date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D13: Response of firm-level stock returns to monetary shocks (Pre. vs. Post 1SD leverage outliers removed)

	(1a) Pre-Crisis	(1b) Post-Crisis	(2a) Pre-Crisis	(2b) Post-Crisis	(3a) Pre-Crisis	(3b) Post-Crisis
Leverage (Debt-to-Capital)	0.015	0.001	0.015	0.001	-0.022	-0.013
	(0.047)	(0.051)	(0.048)	(0.052)	(0.051)	(0.052)
MP shock x Leverage	-5.709*	4.428***				
	(3.365)	(1.010)				
FFR shock x Leverage			-2.170*	0.462		
			(1.232)	(1.078)		
10 yr shock x Leverage			-0.683	2.855***		
			(1.241)	(0.658)		
2 yr shock x Leverage					-1.625	2.254***
					(0.999)	(0.599)
Observations	22,731	13,699	22,731	13,699	22,731	13,699
R-squared	0.205	0.382	0.205	0.382	0.202	0.381
Firm controls	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes

Results from estimating $s_{it} = \alpha_i + \alpha_t + \beta l_{it-1}\epsilon_t^m + \delta l_{it-1} + \Gamma' Z_{it-1} + e_{it}$, where s_{it} is firm-level daily stock return, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, l_{it-1} is four-quarter moving average leverage normalized to have mean 0 and variance 1, ϵ_t^m is the monetary policy shock and Z_{it-1} is a vector of firm-level controls. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in S&P 500 on date of FOMC announcement. We exclude 111 firms with a change in leverage from pre-crisis to post-crisis greater than 1 standard deviation and 485 firms without an observation in either the pre- or post-crisis sample. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D14: Robustness of baseline results to alternative measure of leverage: Debt-to-Assets

	(1a)	(1b)	(2)	(3)
	Firm Share Price		Expected Volatility	Investment
	Pre-Crisis	Post-Crisis	Pre & Post	Pre & Post
Leverage (Debt-to-Assets)	0.004	-0.009	-0.94**	-5.59*
	(0.034)	(0.026)	(0.412)	(3.014)
MP shock x Leverage	-4.732*	2.159***		-12.94***
	(2.850)	(0.542)		(4.315)
D_t^{post} x Leverage			1.87***	1.97
			(0.365)	(4.710)
D_t^{post} x MP shock x Leverage				25.26***
				(6.701)
Observations	48,169	24,594	42,655	19,441
R^2	0.180	0.341	0.786	0.147
Firm controls	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes

Columns (1a) and (1b) are the results from estimating $s_{it} = \alpha_i + \alpha_t + \beta l_{it-1}\epsilon_t^m + \delta l_{it-1} + \Gamma' Z_{it-1} + e_{it}$, where s_{it} is firm-level daily stock return, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, l_{it-1} is four-quarter moving average debt-to-assets normalized to have mean 0 and variance 1 , ϵ_t^m is the monetary policy shock and Z_{it-1} is a vector of firm-level controls. Column (2) is the result from estimating $ivol_{i,t-1} = \alpha_i + \alpha_t + \delta l_{i,t} + \beta l_{i,t-1} D_t^{post} + \Gamma Z_{i,t-1} + e_{i,t}$. Column (3) is the result from estimating $\Delta ln(y_{it}) = \alpha_i + \alpha_t + \sum_{n \in N} \beta_{1n} l_{i,t-n-1}\epsilon_{t-n}^m + \beta_{2n} l_{i,t-n-1}\epsilon_{t-n}^m D_{t-n}^{post} + \Gamma' Z_{i,t-1} + e_{it}$, where y_{it} is the value of firm i's capital stock in quarter t. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. The pre-crisis sample is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in S&P 500 on date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D15: Robustness of baseline results to alternative measure of leverage: 1-quarter lagged debt-to-capital

	(1a)	(1b)	(2)	(3)
	Firm Share Price		Expected Volatility	Investment
	Pre-Crisis	Post-Crisis	Pre & Post	Pre & Post
Leverage (Debt-to-Capital)	0.014	0.012	-0.58	0.88*
	(0.040)	(0.029)	(0.385)	(0.483)
MP shock x Leverage	-4.990	2.127***		-3.78**
	(3.058)	(0.599)		(1.601)
D_t^{post} x Leverage			1.75***	-1.02
			(0.362)	(0.656)
D_t^{post} x MP shock x Leverage				7.12**
				(2.804)
Observations	48,895	24,928	43,255	18,488
R^2	0.181	0.341	0.786	0.160
Firm controls	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes

Columns (1a) and (1b) are the results from estimating $s_{it} = \alpha_i + \alpha_t + \beta l_{it-1}\epsilon_t^m + \delta l_{it-1} + \Gamma' Z_{it-1} + e_{it}$, where s_{it} is the firm-level daily stock return, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, l_{it-1} is one-quarter lagged leverage normalized to have mean 0 and variance 1, ϵ_t^m is the monetary policy shock and Z_{it-1} is a vector of firm-level controls. Column (2) is the result from estimating $ivol_{i,t-1} = \alpha_i + \alpha_t + \delta l_{i,t} + \beta l_{i,t-1} D_t^{post} + \Gamma Z_{i,t-1} + e_{i,t}$. Column (3) is the result from estimating $\Delta ln(y_{it}) = \alpha_i + \alpha_j t + \sum_{n \in N} \beta_{1n} l_{i,t-n-1}\epsilon_{t-n}^m + \beta_{2n} l_{i,t-n-1}\epsilon_{t-n}^m D_{t-n}^{post} + \Gamma' Z_{i,t-1} + e_{it}$, where y_{it} is the value of firm i's capital stock in quarter t. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in S&P 500 on date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D16: Robustness of baseline results to time-sector FE

	(1a) Firm Share Price Pre-Crisis	(1b) Firm Share Price Post-Crisis	(2) Expected Volatility Pre & Post	(3) Investment Pre & Post
Leverage (Debt-to-Capital)	0.001	0.007	-0.58	-2.08*
	(0.037)	(0.027)	(0.408)	(1.114)
MP shock x Leverage	-4.628*	1.461***		-3.94**
	(2.762)	(0.549)		(1.718)
D_t^{post} x Leverage			1.90***	2.97
			(0.368)	(2.616)
D_t^{post} x MP shock x Leverage				7.02**
				(3.212)
Observations	47,737	24,450	42,468	19,323
R^2	0.225	0.401	0.810	0.181
Firm controls	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Time-Sector FE	yes	yes	yes	yes

Columns (1a) and (1b) are the results from estimating $s_{it} = \alpha_i + \alpha_{jt} + \beta l_{it-1}\epsilon_t^m + \delta l_{it-1} + \Gamma' Z_{it-1} + e_{it}$, where s_{it} is firm-level daily stock return, α_i is a firm fixed-effect, α_{jt} is a sector j by FOMC day fixed-effect, l_{it-1} is four-quarter moving average leverage normalized to have mean 0 and variance 1, ϵ_t^m is the monetary policy shock and Z_{it-1} is a vector of firm-level controls. Column (2) is the result from estimating $ivol_{i,t-1} = \alpha_i + \alpha_{jt} + \delta l_{i,t} + \beta l_{i,t-1} D_t^{post} + \Gamma Z_{i,t-1} + e_{i,t}$. Column (3) is the result from estimating $\Delta ln(y_{it}) = \alpha_i + \alpha_{jt} + \sum_{n\in N} \beta_{1n} l_{i,t-n-1}\epsilon_{t-n}^m + \beta_{2n} l_{i,t-n-1}\epsilon_{t-n}^m D_{t-n}^{post} + \Gamma' Z_{i,t-1} + e_{it}$, where y_{it} is the value of firm i's capital stock in quarter t. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in S&P 500 on date of FOMC announcement. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D17: Robustness of baseline results to full CRSP/Compustat sample: No firm entry/exit

	(1a)	(1b)	(2)
	Firm Share Price		Investment
	Pre-Crisis	Post-Crisis	Pre & Post
Leverage (Debt-to-Capital)	-0.004	0.046	-1.06***
	(0.038)	(0.054)	(0.258)
MP shock x Leverage	-2.336**	1.905**	-1.66
	(1.071)	(0.825)	(1.034)
D_t^{post} x Leverage			-0.25
			(0.390)
D_t^{post} x MP shock x Leverage			3.23*
			(1.747)
Observations	75,545	38,324	78,665
R^2	0.081	0.232	0.087
Firm controls	yes	yes	yes
Firm FE	yes	yes	yes
Time FE	yes	yes	yes

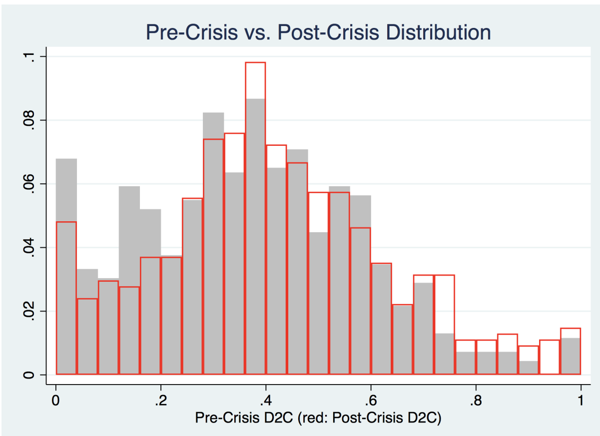
Columns (1a) and (1b) are the results from estimating $s_{it} = \alpha_i + \alpha_t + \beta l_{it-1}\epsilon_t^m + \delta l_{it-1} + \Gamma' Z_{it-1} + e_{it}$, where s_{it} is firm-level daily stock return, α_i is a firm fixed-effect, α_t is an FOMC day fixed-effect, l_{it-1} is four-quarter moving average leverage normalized to have mean 0 and variance 1, ϵ_t^m is the monetary policy shock and Z_{it-1} is a vector of firm-level controls. Column (2) is the result from estimating
$\Delta ln(y_{it}) = \alpha_i + \alpha_j t + \sum_{n \in N} \beta_{1n} l_{i,t-n-1}\epsilon_{t-n}^m + \beta_{2n} l_{i,t-n-1}\epsilon_{t-n}^m D_{t-n}^{post} + \Gamma' Z_{i,t-1} + e_{it}$, where y_{it} is the value of firm i's capital stock in quarter t. The monetary policy shock is normalized to have a unit effect on the 2 year yield and a positive value represents an expansionary shock. Pre-crisis is Jul-1991 to Jun-2008 (153 obs.) and post-crisis is Aug-2009 to Dec-2017 (68 obs.). Sample is non-financial firms in the CRSP/Compustat sample for the entire sample period. Two-way clustered standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

APPENDIX E

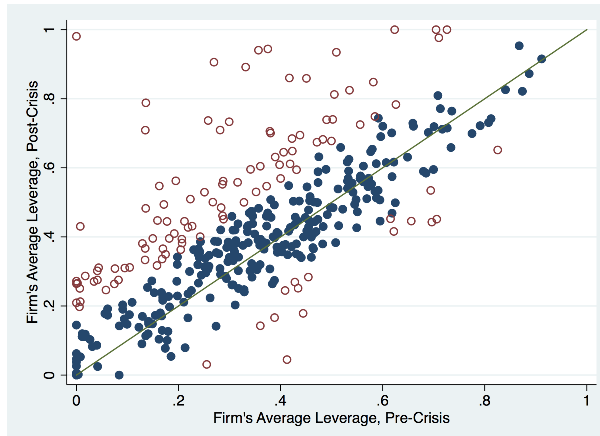
FIGURES FOR CHAPTER 2

Figure E1: Firm Leverage Plots

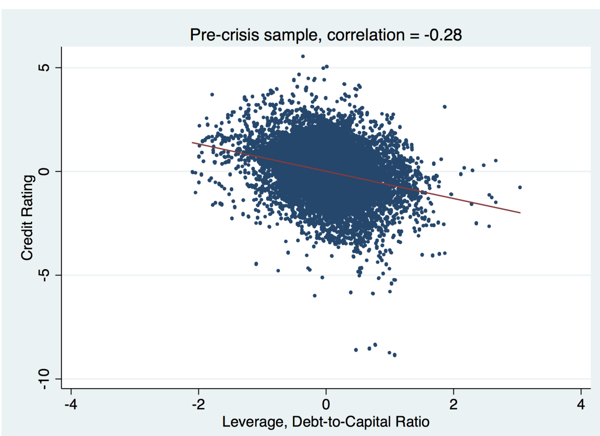
(a) Distribution of Firm Leverage



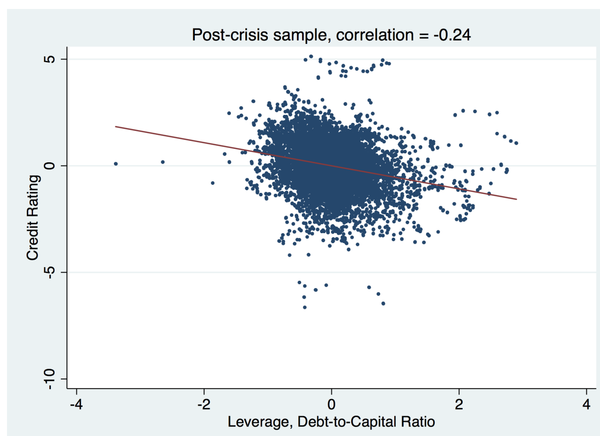
(b) Firm Leverage: Post vs. Pre



(c) Conditional Correlation of Credit Rating and Leverage: Pre-Crisis

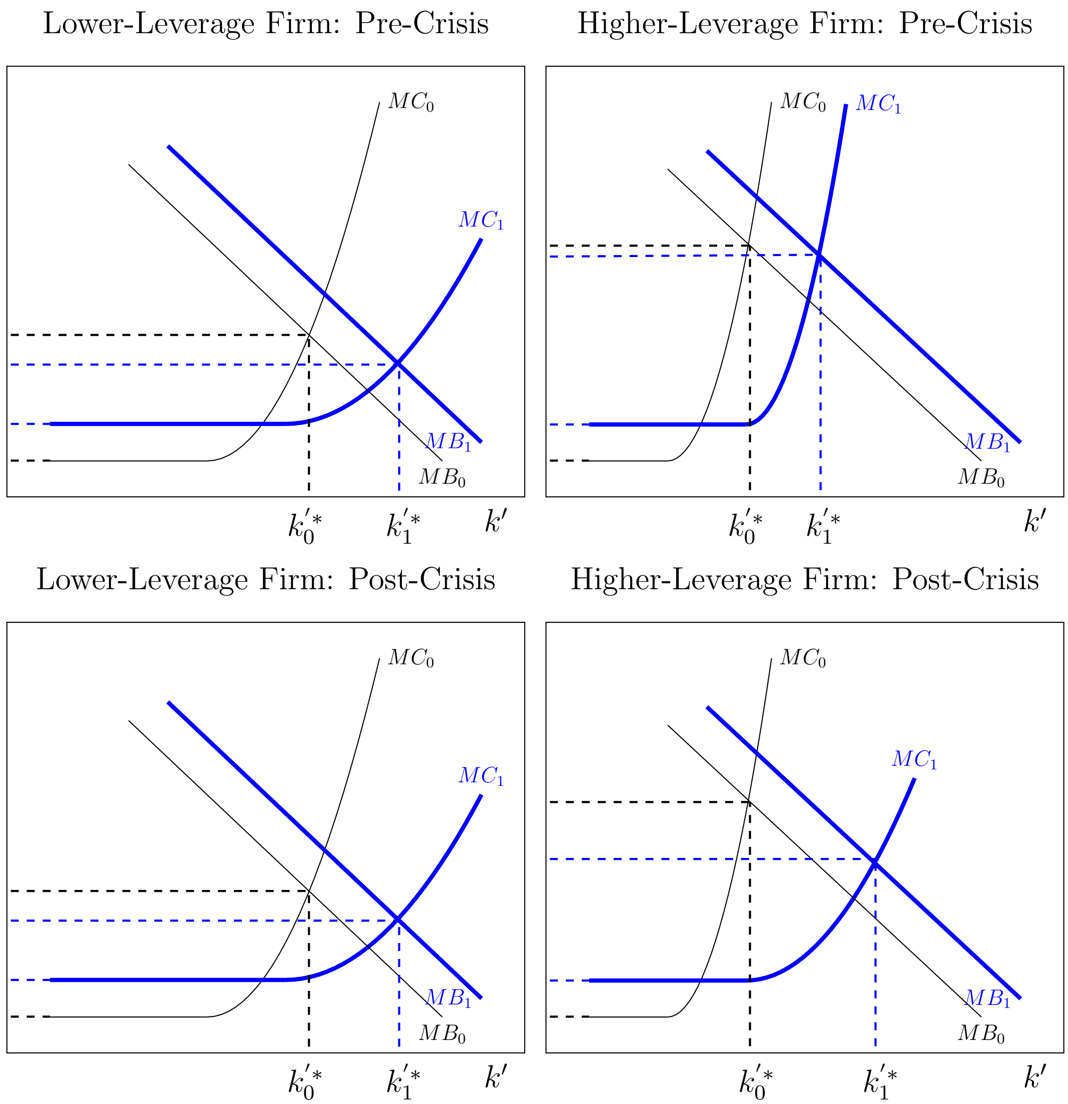


(d) Conditional Correlation of Credit Rating and Leverage: Post-Crisis



Panel (a) plots the histogram of the quarterly firm leverage (measured as debt-to-capital), averaged across the pre-crisis (grey, shaded) and post-crisis (red, transparent) samples. Panel (b) plots the scatter plot of quarterly firm leverage (measured as debt-to-capital) averaged across the post-crisis versus the average in the pre-crisis sample. Firms further than one standard deviation from the 45-degree line are shown in red. Panels (c) and (d) plot the residuals from regressing firm's S&P long-term credit rating on our set of control variables against the residuals from regressing firm's 4-qtr rolling leverage on a set of control variables.

Figure E2: Effects of an expansionary monetary policy shock



APPENDIX F

SUPPLEMENTAL INFO FOR CHAPTER 3

F.0.1 Interpretation of monetary policy uncertainty

In this section we discuss the interpretation of the monetary policy uncertainty from the perspective of a simple policy rule. Consider a general monetary policy rule of the ofrm

$$i_t = g\left(\Omega_t\right) + \varepsilon_t \tag{F.1}$$

where i_t is the short-term nominal interest rate, $g\left(.\right)$ is a linear function that depends on the central bank's information set (Ω_t) and ε_t is the monetary policy shock. In this framework uncertainty about the interest rates comes from i)variance of ε_t and ii)any uncertainty about reaction function $g\left(\Omega_t\right)$. Specifically the h period ahead variance of the interest rate can be written as

$$Var_t[i_{t+h}] = Var_t[g\left(\Omega_{t+h}\right)] + Var_t[\varepsilon_{t+h}] + \text{covariance terms} \tag{F.2}$$

What would cause changes in $Var_t[\varepsilon_{t+h}]$? As discussed in the survey on monetary policy shocks (Christiano et al. (1999)), there are various interpretations of what constitutes the shock ε itself. For example, the shock can arise due to changing political pressure on the Fed, changing composition of the voting members of the FOMC, technical factors like measurement error in the preliminary data available to the FOMC when it makes its decision or even strategic aspects as FOMC wanting to avoid disappointing market expectations. Any change in the expected importance of these factors would lead to a change in $Var_t[\varepsilon_{t+h}]$.

What could cause changes in $Var_t[g\left(\Omega_{t+h}\right)]$? Any uncertainty about future changes to the reaction function will drive this. For example, consider a simple version of the Taylor rule $g\left(\Omega_{t+h}\right) = r^* + \pi^* + \alpha y_t + \beta \pi_t$. Uncertainty about the parameters (α, β), inflation target (π^*) or equilibrium real interest rate (r^*) will drive $Var_t[g\left(\Omega_{t+h}\right)]$. [1]

[1]Note that short-rate uncertainty is also driven by uncertainty about economic fundamentals in addition to the two sources of monetary policy uncertainty discussed above. In other words, in the above example $Var_t[\pi_{t+h}]$ and

Thus changes in monetary policy uncertainty around FOMC announcements can be interpreted as changes in uncertainty about the monetary reaction function or changes in the variance of the shock to the policy rule.

F.0.2 Construction of monetary policy uncertainty measure (*mpu*)

Our measure is based on the approach of Bauer et al. (2019) which uses options on Eurodollar futures and does not require distributional assumptions. Let $F_{t,T}$ be the time-t value of a Eurodollar futures contract expiring at T with value at expiration is $F_{T,T} = 100 - L_T$, where L_T is LIBOR in percent. For option contracts, denote the payoff $max(F_{T,T} - K, 0)$ for call options and $max(K - F_{T,T}, 0)$ for put options, where K is the strike price. For a given trading date t and an expiration date T we use the prices of call options, $c_{t,T}(K)$, and put options, $p_{t,T}(K)$ to calculate the market-based conditional variance of future LIBOR, $Var_t(L_T)$. Starting from the relationship $Var_t(L_T) = Var_t(F_{T,T}) = E_t F^2_{T,T} - (E_t F_{T,T})^2 = E_t F^2_{T,T} - F^2_{t,T}$, we can show that[2]

$$\begin{aligned} Var_t(L_T) &= \frac{2}{P_{t,T}} \int_0^\infty c_{t,T}(K)dK - F^2_{t,T} \\ &= \frac{2}{P_{t,T}} \left(\int_0^{F_{t,T}} p_{t,T}(K) + \int_{F_{t,T}}^\infty c_{t,T}(K)dK \right) \\ &= 2 \int_0^\infty \left[\frac{c_{t,T}(K)}{P_{t,T}} - \max(0, F_{t,T} - K) \right] dK \end{aligned}$$

We then approximate this integral with out-of-the money option prices. While Eurodollar contracts have a fixed maturity, we interpolate contracts to get a fixed-horizon measure. Our baseline measure *mpu* is the two-day change around FOMC announcements in $\sqrt{Var_t(L_{t+h})}$ with h equal to 12 months.

$Var_t[y_{t+h}]$ will also affect $Var_t[i_{t+h}]$. Fortunately, a decomposition of high-frequency uncertainty changes coming from macro variables and that coming from monetary policy (shock and reaction function) is not necessary for the purpose of our paper. Our solution to identifying changes to monetary policy uncertainty is to follow a large event-study literature and squarely focus on the changes in asset prices and our uncertainty measure over short time windows containing FOMC announcements. Over these short time windows, asset prices are driven by the news in these announcements. Since these changes in uncertainty are due to monetary policy announcements, we speak of monetary policy uncertainty.

[2]For details on the derivation see Bauer et al. (2019).

APPENDIX G

TABLES FOR CHAPTER 3

Table G1: Summary Statistics

	Mean	Median	Std Dev	Min	Max	Observations
Panel (a): US monetary policy shocks						
mps	0.00	0.08	0.91	-4.37	3.08	204
mpu	-0.49	-0.39	1.00	-4.96	2.07	204
Panel (b): International asset prices						
2 year yield						
Advanced	-0.01	-0.01	0.09	-1.28	2.04	4,154
Emerging	-0.01	0.00	0.16	-3.14	1.04	1,270
10 year yield						
Advanced	-0.01	-0.01	0.08	-0.98	0.41	4,154
Emerging	-0.02	-0.01	0.18	-2.19	0.81	1,270
Stock return						
Advanced	0.19	0.20	1.98	-12.21	13.86	5,129
Emerging	0.29	0.17	2.40	-18.41	18.41	3,102
Exchange rate						
Advanced	0.03	0.01	0.93	-10.05	7.10	5,709
Emerging	0.02	0.00	1.20	-13.74	30.76	3,130

Panel (a) shows summary statistics for the monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock measures calculated in a two day window around FOMC announcements. Panel (b) shows summary statistics for changes in 2 and 10 year government bond yields, stock returns, and exchange rate returns (foreign currency relative to US dollar) for the countries in our sample. All changes and returns are calculated in a two day window around FOMC announcements. We have government yield data for 22 advanced countries and 8 emerging countries. For exchange rates and stock prices we have data for 28 advanced countries and 16 emerging countries, see Table G13 for details.

Table G2: Response of US asset prices to monetary shocks

	Jan-1995 to Jun-2019					
	2 year yield		10 year yield		S&P 500	
mps	0.882***	0.876***	0.548***	0.382***	-0.179*	-0.137
	[0.097]	[0.104]	[0.106]	[0.095]	[0.093]	[0.096]
mpu		0.013		0.365***		-0.091
		[0.069]		[0.081]		[0.078]
Constant	-0.112***	-0.106*	-0.087	0.093	0.161**	0.116
	[0.042]	[0.056]	[0.061]	[0.070]	[0.069]	[0.085]
Observations	204	204	204	204	204	204
R-squared	0.646	0.646	0.249	0.359	0.027	0.033

	Jan-1995 to Nov-2007					
	2 year yield		10 year yield		S&P 500	
mps	0.911***	0.874***	0.573***	0.450***	-0.181	-0.216
	[0.087]	[0.102]	[0.119]	[0.125]	[0.139]	[0.141]
mpu		0.096		0.322***		0.091
		[0.072]		[0.113]		[0.099]
Constant	-0.059	-0.012	-0.056	0.100	0.314***	0.358***
	[0.051]	[0.063]	[0.082]	[0.100]	[0.095]	[0.112]
Observations	108	108	108	108	108	108
R-squared	0.724	0.732	0.286	0.377	0.029	0.036

	Dec-2007 to Jun-2019					
	2 year yield		10 year yield		S&P 500	
mps	0.840***	0.875***	0.547***	0.331**	-0.212*	-0.070
	[0.165]	[0.170]	[0.194]	[0.158]	[0.123]	[0.123]
mpu		-0.065		0.395***		-0.259**
		[0.110]		[0.116]		[0.110]
Constant	-0.203***	-0.236***	-0.115	0.085	0.018	-0.113
	[0.069]	[0.090]	[0.090]	[0.100]	[0.101]	[0.116]
Observations	96	96	96	96	96	96
R-squared	0.552	0.555	0.234	0.353	0.035	0.087

The table shows the response of 2 and 10 year Treasury bond yields and the S&P 500 to a monetary policy surprise and monetary policy uncertainty shock. All variables have been normalized to have unit standard deviation. The full sample consists of 204 FOMC announcements from January 1995 to June 2019, the pre-crisis sample consists of 108 FOMC announcements from January 1995 to November 2007, and the post-crisis sample consists of 96 FOMC announcements from December 2007 to June 2019. All changes are calculated in a two day window around FOMC announcements. Heteroskedasticity-robust standard errors are reported in parentheses.

Table G3: Response of international bond yields to monetary shocks

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.410***	0.360***	0.345***	0.221***
	[0.065]	[0.061]	[0.080]	[0.069]
mpu		0.107**		0.264***
		[0.048]		[0.059]
Constant	-0.103***	-0.051	-0.115**	0.014
	[0.036]	[0.042]	[0.048]	[0.054]
Observations	4,154	4,154	4,154	4,154
R-squared	0.137	0.146	0.097	0.154

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.238***	0.159***	0.214**	0.129*
	[0.050]	[0.043]	[0.070]	[0.056]
mpu		0.158***		0.171***
		[0.038]		[0.045]
Constant	-0.077**	-0.000	-0.108***	-0.025
	[0.031]	[0.033]	[0.028]	[0.030]
Observations	1,270	1,270	1,270	1,270
R-squared	0.044	0.065	0.036	0.060

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G4: Response of international bond yields to monetary and macro data news shocks

	Advanced countries		Emerging Countries	
	2 year yield	10 year yield	2 year yield	10 year yield
mps	0.382***	0.239***	0.163***	0.127**
	[0.066]	[0.074]	[0.045]	[0.053]
mpu	0.111**	0.283***	0.174***	0.179***
	[0.051]	[0.065]	[0.048]	[0.049]
Observations	4,154	4,154	1,270	1,270
R-squared	0.145	0.155	0.069	0.055
Unemployment	-0.004	0.017	-0.010	-0.007
	[0.019]	[0.017]	[0.010]	[0.012]
Observations	5,562	5,562	1,681	1,681
R-squared	0.000	0.001	0.000	0.000
GDP	0.023	0.010	0.018	-0.003
	[0.017]	[0.017]	[0.017]	[0.014]
Observations	1,900	1,900	573	573
R-squared	0.008	0.002	0.004	0.000
Retail Sales	0.099***	0.064***	0.019	0.005
	[0.029]	[0.020]	[0.013]	[0.015]
Observations	5,583	5,583	1,685	1,685
R-squared	0.045	0.019	0.001	0.000
CPI	0.037*	0.007	0.009	0.012
	[0.019]	[0.021]	[0.013]	[0.016]
Observations	5,583	5,583	1,685	1,685
R-squared	0.007	0.000	0.000	0.001
PPI	0.016	0.017	0.007	-0.004
	[0.017]	[0.020]	[0.013]	[0.020]
Observations	5,495	5,495	1,654	1,654
R-squared	0.001	0.001	0.000	0.000

The table shows the response of 2 and 10 year government bond yields in advanced and emerging countries to a monetary policy surprise (*mps*), monetary policy uncertainty (*mpu*) and news shocks. All variables have been normalized to have unit standard deviation. For the employment report, we use non-farm payrolls, for CPI and PPI we use headline inflation, retail sales are the total sales including automobiles, GDP is the advance GDP release. The sample runs from January 1995 to June 2019. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G5: Response of expected component and term premium component of international bond yields to monetary shocks

Panel (a)	Advanced countries				Emerging countries			
	2y ec	10y ec	2y tp	10y tp	2y ec	10y ec	2y tp	10y tp
mpu	-0.012	-0.004	0.129**	0.241***	0.094*	0.128***	0.070	0.056
	[0.049]	[0.052]	[0.048]	[0.060]	[0.044]	[0.034]	[0.039]	[0.040]

Panel (b)	Advanced countries				Emerging countries			
	2y ec	10y ec	2y tp	10y tp	2y ec	10y ec	2y tp	10y tp
mpu	0.041	0.040	0.037	0.067	0.109*	0.124***	0.044	0.036
	[0.045]	[0.053]	[0.035]	[0.053]	[0.047]	[0.030]	[0.035]	[0.046]
US 10y tp	-0.122**	-0.100*	0.210***	0.402***	-0.034	0.008	0.058*	0.043
	[0.048]	[0.051]	[0.044]	[0.046]	[0.031]	[0.029]	[0.029]	[0.041]

Panel (a) shows the response of the expected component (ec) and term premium (tp) of 2 and 10 year government bond yields to a monetary policy uncertainty (*mpu*) shock. The monetary policy surprise (*mps*) and a constant are included in the regressions, the coefficients are left out for space considerations. Yields are decomposed into the expected component and term premium using the methodology of Joslin et al. (2011). All variables have been normalized to have unit standard deviation. Panel (b) adds the US 10 year yield term premium to the specification. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G6: Response of exchange rates to monetary shocks

	Advanced		Emerging	
	(1)	(2)	(1)	(2)
mps	0.240***	0.281***	0.130***	0.085*
	[0.064]	[0.067]	[0.044]	[0.041]
mpu		-0.091		0.098**
		[0.062]		[0.044]
Constant	0.034	-0.011	0.008	0.056
	[0.049]	[0.058]	[0.035]	[0.034]
Observations	5,709	5,709	3,130	3,130
R-squared	0.048	0.054	0.014	0.022

The table shows the response of international exchange rate returns to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. The sample consists of 204 FOMC announcements from January 1995 to June 2019. Exchange rate returns have been normalized to have unit standard deviation. Exchange rates are in units of foreign currency per US dollar such that an increase represents a depreciation of the foreign currency relative to the dollar. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G7: Response of term premium component of international bond yields to monetary shocks (bond substitutability interaction)

	10 year term premium		
	All Countries	Advanced	Emerging
mpu	-0.33***	-0.16***	-0.12
	(0.080)	(0.044)	(0.302)
mpu x bond sub.	0.72***	0.53***	0.29
	(0.148)	(0.077)	(0.526)
Observations	5,410	4,140	1,270
R-squared	0.045	0.062	0.008

The table shows the response of 10 year government bond yield term premia to a monetary policy uncertainty (*mpu*) shock and the interaction with a measure of bond substitutability with the United States. The monetary policy surprise (*mps*), its interaction with bond substitutability and a constant are included in the regressions, the coefficients are left out for space considerations. The term premium is calculated using the methodology of Joslin et al. (2011). Bond substitutability is calculated as the correlation between the 10 year term premium for country i and the United States using all non-FOMC days for the entire sample period of January 1995 to June 2019. Bond substitutability is standardized to the interval 0 to 1, representing a range in the correlation between -1 and 1. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All term premium changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G8: Response of US holdings of foreign bonds to monetary shocks

	Advanced	Emerging
mps	-0.034*	0.082
	[0.019]	[0.104]
mpu	-0.017	-0.225**
	[0.033]	[0.066]
idiff	-0.003	-0.023
	[0.014]	[0.016]
mps x idiff	0.000	0.014
	[0.010]	[0.016]
mpu x idiff	0.004	-0.023***
	[0.008]	[0.005]
Constant	0.129***	-0.033
	[0.024]	[0.091]
Observations	3,528	929
R-squared	0.052	0.061

The table shows the response of changes in US holdings of foreign bonds to a monetary policy surprise (*mps*), monetary policy uncertainty (*mpu*) shock, and their interaction with the interest rate differential between the 3 month rate in foreign countries relative to the US (idiff). US holdings of foreign bonds are from the monthly TIC data. Country fixed effects and year dummies are included in the specification. The sample runs from January 1995 to December 2018 for a total of 187 FOMC meetings, which excludes the financial crisis period from December 2007 to June 2009. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G9: Understanding the cross-country heterogeneity of asset price responses: Emerging countries

	2 year yield	10 year yield
mpu	0.155***	0.168***
	[0.030]	[0.045]
FinDepth**mpu*	0.010	0.022
	[0.040]	[0.056]
KAopen**mpu*	0.120**	0.088**
	[0.039]	[0.033]
FXRegime**mpu*	0.077	0.221
	[0.128]	[0.159]
IRDiff3mChg**mpu*	-0.037	-0.026
	[0.039]	[0.031]
TradeOpen**mpu*	-0.059	-0.085*
	[0.034]	[0.040]
Observations	1,056	1,056
R-squared	0.0784	0.0739

The table shows the response of 2 and 10 year government bond yields to a monetary policy uncertainty (*mpu*) shock and the interactions with measures for financial depth (FinDepth), capital account openness (KAopen), exchange rate regime (FXRegime), the change in the 3 month interest rate differential with the US on an FOMC day (IRiff3mChg), and trade openness (TradeOpen). The monetary policy surprise (*mps*), its interactions with the country measures and a constant are included in the regressions, the coefficients are left out for space considerations. These observables are orthogonalized recursively as in Iacoviello & Navarro (2019). See Section 3.4.4 for details on the specification and variable creation. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G10: Response of international equity indices to monetary shocks

	Advanced countries					
	Full sample		Pre-crisis		Post-crisis	
mps	-0.081	-0.042	-0.031	-0.047	-0.157*	-0.052
	[0.064]	[0.068]	[0.085]	[0.093]	[0.085]	[0.078]
mpu		-0.084		0.044		-0.191**
		[0.062]		[0.078]		[0.085]
Constant	0.098*	0.057	0.217***	0.237***	-0.010	-0.106
	[0.048]	[0.059]	[0.067]	[0.076]	[0.066]	[0.076]
Observations	5,129	5,129	2,441	2,441	2,688	2,688
R-squared	0.005	0.011	0.001	0.002	0.019	0.047

	Emerging countries					
	Full sample		Pre-crisis		Post-crisis	
mps	-0.175***	-0.125**	-0.125**	-0.123**	-0.270**	-0.144*
	[0.056]	[0.048]	[0.056]	[0.053]	[0.098]	[0.071]
mpu		-0.110*		-0.005		-0.228**
		[0.061]		[0.061]		[0.101]
Constant	0.128***	0.074	0.208***	0.206***	0.043	-0.071
	[0.041]	[0.048]	[0.050]	[0.060]	[0.062]	[0.065]
Observations	3,102	3,102	1,592	1,592	1,510	1,510
R-squared	0.025	0.034	0.013	0.013	0.055	0.094

The table shows the response of returns on international equity indices to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. The full sample consists of 204 FOMC announcements from January 1995 to June 2019, the pre-crisis sample has 108 announcements from January 1995 to November 2007 and the post-crisis sample has 96 announcements from December 2007 to June 2019. Equity returns have been normalized to have unit standard deviation. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G11: Response of international bond yields accounting for zero lower bound

	Advanced countries		Emerging countries	
	2 Year Yield	10 Year Yield	2 Year Yield	10 Year Yield
mps	0.386***	0.224***	0.156**	0.110*
	[0.064]	[0.072]	[0.047]	[0.056]
mpu	0.065	0.226***	0.165**	0.113***
	[0.067]	[0.079]	[0.062]	[0.032]
*mps**ZLB	-0.431***	-0.076	0.031	0.187
	[0.134]	[0.232]	[0.100]	[0.172]
*mpu**ZLB	0.252**	0.113	-0.022	0.051
	[0.100]	[0.151]	[0.098]	[0.110]
ZLB	-0.006	-0.061	0.073	0.113
	[0.085]	[0.133]	[0.077]	[0.090]
Constant	-0.033	0.031	-0.027	-0.083***
	[0.053]	[0.058]	[0.037]	[0.021]
Observations	4,154	4,154	1,270	1,270
R-squared	0.158	0.159	0.066	0.067

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. The zero lower bound (ZLB) dummy takes on a value of one from December 2008 to December 2015. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G12: Response of forecast dispersion to monetary shocks

Panel (a)	SPF forecast	
	GDP	GDP Deflator
mps	0.32	0.37
	[0.49]	[0.23]
mpu	0.52	0.75**
	[0.84]	[0.30]
Constant	0.07	0.02
	[0.04]	[0.02]
Observations	97	97
R-squared	0.023	0.113

Panel (b)	SEP forecast	
	PCE inflation	Unemployment
mps	0.01	-0.02
	[0.09]	[0.07]
mpu	0.12**	0.09*
	[0.05]	[0.05]
Constant	0.04	0.01
	[0.05]	[0.04]
Observations	39	39
R-squared	0.119	0.097

The table shows the results of regressing the changes in the cross-sectional dispersion of SPF forecasts (GDP and GDP deflator) and SEP forecasts (PCE inflation and unemployment rate) on the monetary policy shock measures. The SPF regression (Panel (a)) is at a quarterly frequency with the monetary policy shock series summed for a given quarter. The SEP regression (Panel (b)) is at the FOMC meeting frequency. Heteroskedasticity-robust standard errors are reported in parentheses.

Table G13: Data coverage for sample countries

	Emerging Economy?	Exchange Rate	Equity Index	Yields
Argentina	Y	X	X	
Australia		X	X	2/1/1995
Austria		X	2/3/1999	5/19/1998
Belgium		X	X	5/19/1998
Canada		X	X	2/1/1995
Chile	Y	X	X	
China	Y	8/23/2010	8/23/2010	9/12/2003
Czech Republic		X	2/1/1995	7/1/1998
Denmark		X	X	2/1/1995
Estonia		X	6/26/2002	
Finland		X	2/1/1995	7/1/1998
France		X	2/3/1999	5/19/1998
Germany		X	2/3/1999	X
Hong Kong		X	X	7/1/1998
Hungary	Y	X	2/1/1995	7/1/1998
Iceland		X	5/9/2007	
India	Y	X	X	11/17/1998
Indonesia	Y	X	X	3/18/2003
Ireland		X	X	5/19/1998
Israel		X	X	
Italy		X	2/4/1998	2/4/1998
Japan		X	X	X
Korea, Republic of		X	X	
Malaysia	Y	X	X	10/5/1999
Mauritius	Y	X	X	
Netherlands		X	2/3/1999	5/19/1998
New Zealand		X	1/3/2001	2/1/1995
Norway		X	1/31/1996	8/18/1998
Pakistan	Y	X	X	
Peru	Y	X	X	
Philippines	Y	X	X	
Poland	Y	X	X	7/1/1998
Portugal		X	2/3/1999	5/19/1998
Russian Federation	Y	X	9/30/1997	1/31/2007
Singapore		X	10/5/1999	7/1/1998
Slovakia		X	2/3/1999	
Slovenia		5/20/1997	6/26/2002	
South Africa	Y	X	7/6/1995	2/1/1995
Spain		X	2/3/1999	5/19/1998
Sweden		X	1/31/1996	2/1/1995
Switzerland		X	X	2/1/1995
Thailand	Y	X	8/22/1995	
Turkey	Y	X	X	
United Kingdom		X	X	2/1/1995
United States			X	2/1/1995

This table displays the availability for each country's data series. The full sample period covers all FOMC announcements between January 1995 and June 2019, excluding the announcements on Sep. 17, 2001, Oct. 8, 2008, May 22, 2013 and May 2, 2018. Cells with an X indicate a start date of Jan. 1, 1995, cells with a date indicate the first date with available data, and blank cells indicate the data series was not available.

Table G14: Response of international bond yields to monetary shocks with QE dummy

	Advanced countries		Emerging countries	
	2 Year Yield	10 Year Yield	2 Year Yield	10 Year Yield
mps	0.365***	0.205***	0.140**	0.098
	[0.063]	[0.070]	[0.044]	[0.055]
mpu	0.091*	0.233***	0.117***	0.099**
	[0.053]	[0.061]	[0.033]	[0.029]
*mps**QE	-0.439	0.203	0.150	0.235
	[0.310]	[0.500]	[0.151]	[0.206]
*mpu**QE	0.292	0.063	0.153	0.305*
	[0.222]	[0.422]	[0.177]	[0.159]
QE	0.016	0.054	0.268	0.557***
	[0.202]	[0.421]	[0.180]	[0.155]
Constant	-0.048	0.007	-0.025	-0.075**
	[0.041]	[0.048]	[0.028]	[0.022]
Observations	4,154	4,154	1,270	1,270
R-squared	0.150	0.160	0.075	0.096

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*), monetary policy uncertainty (*mpu*) shock, and interactions with a quantitative easing dummy. The QE dummy is 1 for the dates listed in Fawley et al. (2013) and 0 otherwise. All variables have been normalized to have unit standard deviation. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G15: Response of international bond yields to monetary shocks (Pre-crisis sample)

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.502***	0.452***	0.373***	0.289***
	[0.074]	[0.073]	[0.099]	[0.094]
mpu		0.131**		0.220**
		[0.062]		[0.086]
Constant	-0.026	0.036	-0.009	0.094
	[0.055]	[0.060]	[0.070]	[0.074]
Observations	2,042	2,042	2,042	2,042
R-squared	0.216	0.231	0.119	0.160

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.181**	0.160**	0.118	0.113
	[0.067]	[0.065]	[0.082]	[0.090]
mpu		0.053		0.014
		[0.063]		[0.047]
Constant	-0.062	-0.038	-0.095***	-0.089**
	[0.045]	[0.054]	[0.021]	[0.026]
Observations	502	502	502	502
R-squared	0.027	0.029	0.011	0.012

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 108 FOMC announcements from January 1995 to November 2007. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G16: Response of international asset prices to monetary shocks (Post-crisis sample)

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.340***	0.275***	0.313**	0.128
	[0.090]	[0.089]	[0.127]	[0.079]
mpu		0.117		0.337***
		[0.080]		[0.088]
Constant	-0.191***	-0.132**	-0.222***	-0.051
	[0.051]	[0.059]	[0.071]	[0.081]
Observations	2,112	2,112	2,112	2,112
R-squared	0.089	0.100	0.076	0.162

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.325***	0.178***	0.327***	0.171**
	[0.081]	[0.041]	[0.092]	[0.055]
mpu		0.268***		0.284***
		[0.059]		[0.072]
Constant	-0.103*	0.032	-0.123**	0.021
	[0.046]	[0.047]	[0.049]	[0.056]
Observations	768	768	768	768
R-squared	0.082	0.137	0.083	0.145

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 96 FOMC announcements from December 2007 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension

Table G17: Response of US bond term premia to monetary policy shocks

	JSZ		ACM		KW	
	2 year	10 year	2 year	10 year	2 year	10 year
mps	0.225	-0.124	0.119	-0.009	0.571***	0.310***
	[0.125]	[0.099]	[0.094]	[0.080]	[0.122]	[0.088]
mpu	0.256*	0.393***	0.373***	0.458***	0.246***	0.395***
	[0.139]	[0.113]	[0.085]	[0.079]	[0.097]	[0.088]
Constant	0.323***	0.344***	0.110	0.140**	0.155***	0.164***
	[0.099]	[0.091]	[0.073]	[0.070]	[0.076]	[0.075]
Observations	204	204	204	204	204	204
R-squared	0.151	0.130	0.185	0.207	0.437	0.329

The table shows the response of the expected component (ec) and term premium (tp) of 2 and 10 year government bond yields to a monetary policy uncertainty (*mpu*) shock. Yields are decomposed into the expected component and term premium using the methodology of Joslin et al. (2011) (JSW), Adrian et al. (2013) (ACM) and Kim & Wright (2005) (KW). All variables have been normalized to have unit standard deviation. Panel (b) adds the US 10 year yield term premium to the specification. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Heteroskedasticity-robust standard errors are reported in parentheses.

Table G18: Understanding the cross-country heterogeneity of asset price responses: Advanced countries

	2 year yield	10 year yield
mpu	0.111***	0.251***
	[0.035]	[0.053]
IRDiff3mChg**mpu*	-0.075***	-0.026
	[0.020]	[0.027]
FinDepth**mpu*	-0.039	0.007
	[0.042]	[0.048]
FXRegime**mpu*	0.039	0.001
	[0.036]	[0.052]
TradeOpen**mpu*	-0.012	0.018
	[0.022]	[0.024]
Observations	3,391	3,391
R-squared	0.170	0.179

The table shows the response of 2 and 10 year government bond yields to a monetary policy uncertainty (*mpu*) shock and the interactions with measures for financial depth (FinDepth), capital account openness (KAopen), exchange rate regime (FXRegime), the change in the 3 month interest rate differential with the US on an FOMC day (IRiff3mChg), and trade openness (TradeOpen). These observables are orthogonalized recursively as in Iacoviello & Navarro (2019). See Section 3.4.4 for details on the specification and variable creation. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G19: Understanding the cross-country heterogeneity of asset price responses: Emerging countries with dollar debt exposure

	2 year yield	10 year yield
mpu	0.124***	0.134**
	[0.030]	[0.043]
TradeOpen**mpu*	0.007	-0.013
	[0.041]	[0.033]
KAopen**mpu*	0.193***	0.146*
	[0.047]	[0.069]
FXRegime**mpu*	-0.068	0.134
	[0.138]	[0.168]
DollarDebt**mpu*	0.094	0.154*
	[0.079]	[0.064]
IRDiff3mChg**mpu*	-0.046	-0.034
	[0.039]	[0.029]
Observations	808	808
R-squared	0.0660	0.0559

The table shows the response of 2 and 10 year government bond yields to a monetary policy uncertainty (*mpu*) shock and the interactions with measures for trade openness (TradeOpen), capital account openness (KAopen), exchange rate regime (FXRegime), dollar debt exposure (DollarDebt), and the change in the 3 month interest rate differential with the US on an FOMC day (IRiff3mChg). These observables are orthogonalized recursively as in Iacoviello & Navarro (2019). See Section 3.4.4 for details on the specification and variable creation. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G20: Response of international bond yields to monetary shocks (1-day window)

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.340***	0.263***	0.266**	0.164*
	[0.075]	[0.070]	[0.096]	[0.084]
mpu		0.192***		0.257***
		[0.055]		[0.049]
Constant	-0.086**	0.045	-0.084*	0.092
	[0.038]	[0.046]	[0.048]	[0.059]
Observations	4,154	4,154	4,154	4,154
R-squared	0.101	0.132	0.062	0.117

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.196***	0.131***	0.139*	0.092
	[0.046]	[0.036]	[0.066]	[0.059]
mpu		0.161**		0.117*
		[0.063]		[0.053]
Constant	-0.086**	0.021	-0.075*	0.003
	[0.036]	[0.043]	[0.033]	[0.038]
Observations	1,270	1,270	1,270	1,270
R-squared	0.034	0.055	0.017	0.028

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a one day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G21: Response of international bond yields to monetary shocks, controlling for LIBOR-OIS spread

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.382***	0.301***	0.341***	0.162*
	[0.079]	[0.077]	[0.115]	[0.086]
mpu		0.139**		0.305***
		[0.056]		[0.072]
LIBOR-OIS Spread	-0.002	0.002	-0.014	-0.005
	[0.021]	[0.017]	[0.010]	[0.008]
Constant	-0.099**	-0.032	-0.123**	0.023
	[0.043]	[0.047]	[0.058]	[0.064]
Observations	3,212	3,212	3,212	3,212
R-squared	0.115	0.132	0.099	0.173

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.230***	0.137**	0.195**	0.104
	[0.054]	[0.042]	[0.062]	[0.057]
mpu		0.164***		0.159**
		[0.041]		[0.046]
LIBOR-OIS Spread	-0.006	-0.001	-0.038***	-0.033***
	[0.006]	[0.004]	[0.006]	[0.007]
Constant	-0.071*	0.008	-0.096**	-0.019
	[0.031]	[0.035]	[0.030]	[0.037]
Observations	1,103	1,103	1,103	1,103
R-squared	0.051	0.076	0.089	0.114

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock while controlling for the LIBOR-OIS spread. The sample consists of 146 FOMC announcements from December 2001 (when LIBOR-OIS data becomes available) to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G22: Response of international bond yields to monetary shocks, 2 year yield as *mps*

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps (2yr)	0.389***	0.345***	0.399***	0.313***
	[0.051]	[0.051]	[0.053]	[0.050]
mpu		0.125**		0.240***
		[0.051]		[0.053]
Constant	-0.065*	-0.008	-0.076	0.034
	[0.036]	[0.038]	[0.045]	[0.048]
Observations	4,154	4,154	4,154	4,154
R-squared	0.146	0.160	0.154	0.204

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps (2yr)	0.170**	0.101*	0.156**	0.084*
	[0.054]	[0.051]	[0.052]	[0.043]
mpu		0.188***		0.194***
		[0.040]		[0.051]
Constant	-0.061*	0.024	-0.092**	-0.005
	[0.031]	[0.030]	[0.029]	[0.030]
Observations	1,270	1,270	1,270	1,270
R-squared	0.025	0.056	0.021	0.055

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) (measured as the change in the 2 year Treasury yield) and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G23: Response of international bond yields to monetary shocks, 10 year yield as *mps*

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps (10 yr)	0.293***	0.230***	0.527***	0.479***
	[0.063]	[0.067]	[0.056]	[0.062]
mpu		0.121*		0.093*
		[0.059]		[0.050]
Constant	-0.080*	-0.026	-0.072*	-0.030
	[0.040]	[0.044]	[0.038]	[0.042]
Observations	4,154	4,154	4,154	4,154
R-squared	0.088	0.099	0.287	0.293

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps (10 yr)	0.174***	0.087*	0.215***	0.142***
	[0.044]	[0.045]	[0.039]	[0.036]
mpu		0.173***		0.145**
		[0.044]		[0.056]
Constant	-0.064*	0.013	-0.092***	-0.027
	[0.031]	[0.033]	[0.026]	[0.031]
Observations	1,270	1,270	1,270	1,270
R-squared	0.032	0.054	0.050	0.065

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) (measured as the change in the 10 year Treasury yield) and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G24: Response of expected component and term premium component of international bond yields to monetary policy uncertainty (pre- and post-crisis samples)

	Jan-1995 to Nov-2007							
Panel (a)	Advanced countries				Emerging countries			
	2y ec	10y ec	2y tp	10y tp	2y ec	10y ec	2y tp	10y tp
mpu	-0.013	-0.011	0.147**	0.206**	0.020	0.017	0.049	0.007
	[0.060]	[0.057]	[0.067]	[0.084]	[0.065]	[0.038]	[0.046]	[0.030]

Panel (b)	Advanced countries				Emerging countries			
	2y ec	10y ec	2y tp	10y tp	2y ec	10y ec	2y tp	10y tp
mpu	0.026	0.024	0.051	0.052	0.025	0.019	0.048	0.006
	[0.050]	[0.055]	[0.046]	[0.061]	[0.071]	[0.042]	[0.052]	[0.032]
US 10y tp	-0.111**	-0.101*	0.276***	0.439***	-0.017	-0.004	0.005	0.001
	[0.046]	[0.052]	[0.053]	[0.063]	[0.032]	[0.024]	[0.042]	[0.042]

	Dec-2007 to Jun-2019							
Panel (c)	Advanced countries				Emerging countries			
	2y ec	10y ec	2y tp	10y tp	2y ec	10y ec	2y tp	10y tp
mpu	-0.012	0.010	0.141*	0.297***	0.192***	0.246***	0.084	0.094
	[0.077]	[0.090]	[0.080]	[0.099]	[0.028]	[0.056]	[0.051]	[0.060]

Panel (d)	Advanced countries				Emerging countries			
	2y ec	10y ec	2y tp	10y tp	2y ec	10y ec	2y tp	10y tp
mpu	0.052	0.051	0.047	0.103	0.214***	0.244***	0.034	0.055
	[0.079]	[0.098]	[0.060]	[0.085]	[0.032]	[0.053]	[0.041]	[0.076]
US 10y tp	-0.139*	-0.089	0.205***	0.422***	-0.049	0.003	0.109**	0.084
	[0.069]	[0.077]	[0.064]	[0.055]	[0.066]	[0.049]	[0.037]	[0.070]

The table shows the response of the expected component (ec) and term premium (tp) of 2 and 10 year government bond yields to a monetary policy uncertainty (*mpu*) shock. Yields are decomposed into the expected component and term premium using the methodology of Joslin et al. (2011). All variables have been normalized to have unit standard deviation. Panels (a) and (b) show results for the pre-crisis sample, consisting of 108 FOMC announcements from January 1995 to November 2007. Panels (c) and (d) show results for the post-crisis sample, consisting of 96 FOMC announcements from December 2007 to June 2019. Panels (a) and (c) report the effects of *mpu* only. Panels (b) and (d) add the US 10 year yield term premium to the specification. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G25: Response of term premium component of international bond yields to mpu shocks (bond substitutability interaction)

	10 year term premium		
	All Countries	Advanced	Emerging
mpu	-0.16**	-0.08	-0.10
	(0.069)	(0.114)	(0.102)
mpu x bond sub.	0.50***	0.42**	0.26
	(0.120)	(0.156)	(0.197)
Observations	5,410	4,140	1,270
R-squared	0.044	0.062	0.008

The table shows the response of 10 year government bond yield term premia to a monetary policy uncertainty (*mpu*) shock and the interaction with a measure of bond substitutability with the United States. The term premium is calculated using the methodology of Joslin et al. (2011). Bond substitutability is calculated as the correlation between the 10 year term premium for country i and the United States using all non-FOMC days between January 1995 and the FOMC day on day t . Bond substitutability is standardized to the interval 0 to 1, representing a range in the correlation between -1 and 1. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All term premium changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G26: Response of US holdings of foreign bonds to monetary shocks (robustness)

	Advanced	Emerging
mps	-	-
mpu	-	-
idiff	-0.018	-0.027
	[0.015]	[0.019]
mps x idiff	-0.001	0.013
	[0.009]	[0.017]
mpu x idiff	0.005	-0.028**
	[0.006]	[0.011]
Constant	0.135***	0.054
	[0.002]	[0.069]
Observations	3,528	903
R-squared	0.149	0.290

The table shows the response of changes in US holdings of foreign bonds to the interaction between a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock with the interest rate differential between the 3 month rate in foreign countries relative to the US (idiff). US holdings of foreign bonds are from the monthly TIC data. Country and time fixed effects are included in the specification. The sample runs from January 1995 to December 2018 for a total of 187 FOMC meetings, which excludes the financial crisis period from December 2007 to June 2009. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G27: Response of international bond yields to monetary shocks, controlling for target and path factor

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
Target	0.429***	0.386***	0.369***	0.260***
	[0.058]	[0.058]	[0.066]	[0.057]
Path	0.254**	0.212	0.543***	0.435***
	[0.119]	[0.138]	[0.171]	[0.145]
mpu		0.086		0.221***
		[0.052]		[0.061]
Constant	-0.103***	-0.061	-0.114**	-0.006
	[0.035]	[0.041]	[0.046]	[0.051]
Observations	4,154	4,154	4,154	4,154
R-squared	0.147	0.153	0.146	0.184

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
Target	0.247***	0.159**	0.224**	0.129*
	[0.054]	[0.048]	[0.071]	[0.058]
Path	0.031	-0.045	0.048	-0.034
	[0.097]	[0.086]	[0.091]	[0.074]
mpu		0.163***		0.175***
		[0.034]		[0.043]
Constant	-0.077**	0.001	-0.107***	-0.023
	[0.030]	[0.034]	[0.028]	[0.030]
Observations	1,270	1,270	1,270	1,270
R-squared	0.044	0.065	0.036	0.060

The table shows the response of 2 and 10 year government bond yields to a target factor shock, path factor shock, and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. Column (1) includes the target and path factors as regressors, while column 2 adds *mpu* to the specification. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G28: Response of international bond yields to monetary shocks (only scheduled FOMC meetings)

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.435***	0.362***	0.440***	0.305***
	[0.075]	[0.078]	[0.068]	[0.070]
mpu		0.115**		0.213***
		[0.051]		[0.063]
Constant	-0.109***	-0.049	-0.133**	-0.021
	[0.036]	[0.043]	[0.048]	[0.055]
Observations	3,956	3,956	3,956	3,956
R-squared	0.128	0.138	0.128	0.161

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.220***	0.120*	0.216**	0.112
	[0.049]	[0.052]	[0.080]	[0.072]
mpu		0.145***		0.152**
		[0.038]		[0.051]
Constant	-0.055	0.020	-0.097**	-0.019
	[0.031]	[0.039]	[0.030]	[0.036]
Observations	1,209	1,209	1,209	1,209
R-squared	0.033	0.049	0.032	0.050

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. All variables have been normalized to have unit standard deviation. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 195 scheduled FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G29: Response of international bond yields to monetary shocks controlling for information effect

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.398***	0.367***	0.290***	0.221***
	[0.070]	[0.065]	[0.080]	[0.071]
mpu		0.079		0.175***
		[0.054]		[0.058]
Constant	-0.113**	-0.098*	-0.084	-0.050
	[0.051]	[0.052]	[0.061]	[0.059]
Observations	2,680	2,680	2,680	2,680
R-squared	0.135	0.141	0.085	0.119

	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.151***	0.116**	0.147*	0.103
	[0.037]	[0.036]	[0.073]	[0.062]
mpu		0.085**		0.104**
		[0.035]		[0.043]
Constant	-0.078*	-0.062	-0.086*	-0.067*
	[0.040]	[0.041]	[0.037]	[0.034]
Observations	739	739	739	739
R-squared	0.020	0.027	0.020	0.031

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock. *mps* and *mpu* have been purged of information effects in this specification. Each monetary shock is regressed on the difference between Federal Reserve Greenbook forecasts and private sector Blue Chip forecasts of CPI, GDP, and the unemployment rate. The residual from these regressions is taken as an information-robust measure of *mps* and *mpu*. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 204 FOMC announcements from January 1995 to December 2011. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

Table G30: Response of international bond yields to monetary shocks with country fixed-effects

	Advanced countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.410***	0.360***	0.345***	0.221***
	[0.065]	[0.062]	[0.080]	[0.069]
mpu		0.107**		0.264***
		[0.048]		[0.060]
Constant	-0.103***	-0.051	-0.115**	0.014
	[0.033]	[0.040]	[0.047]	[0.053]
Observations	4,154	4,154	4,154	4,154
R-squared	0.140	0.150	0.100	0.157

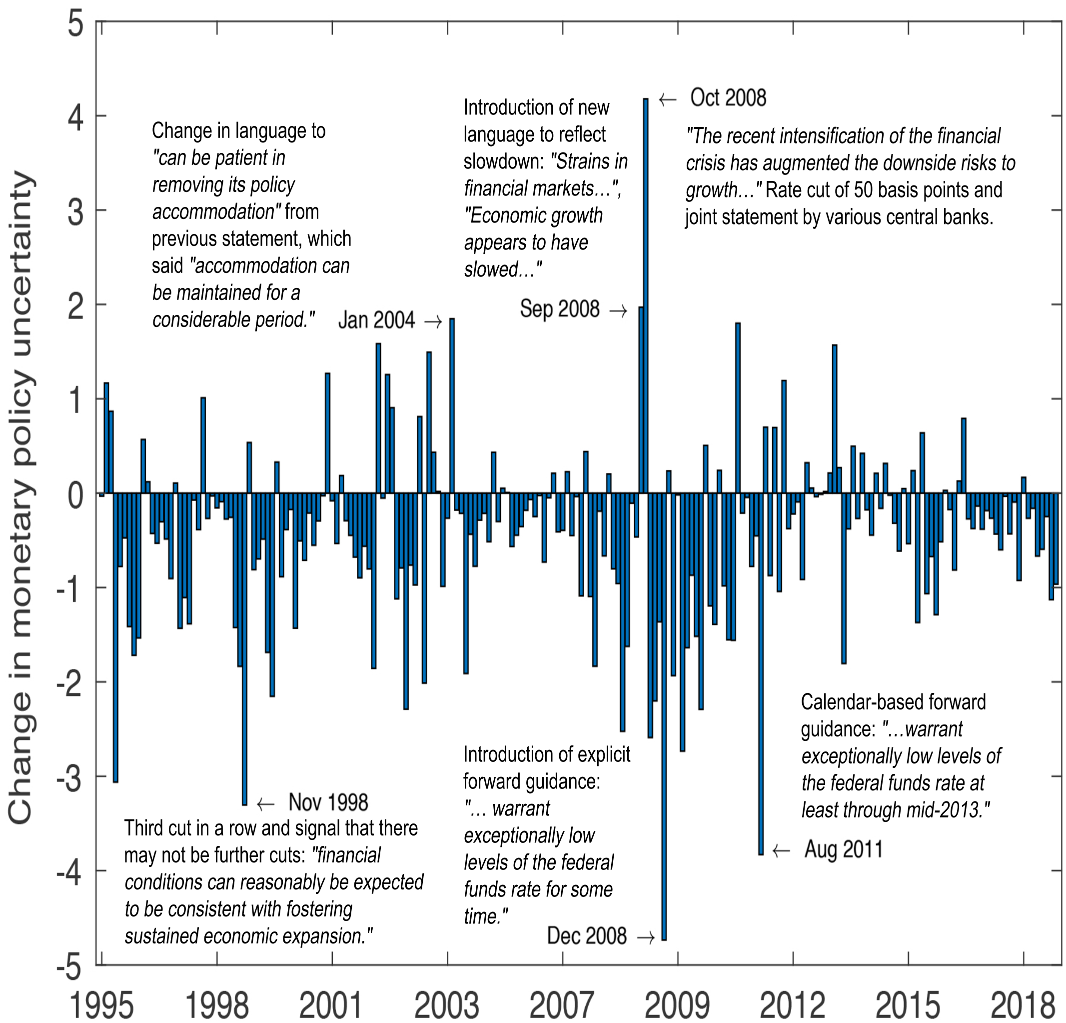
	Emerging countries			
	2 year yield		10 year yield	
	(1)	(2)	(1)	(2)
mps	0.239***	0.159***	0.215**	0.129*
	[0.051]	[0.043]	[0.070]	[0.057]
mpu		0.160***		0.172***
		[0.039]		[0.046]
Constant	-0.077***	0.000	-0.108***	-0.024
	[0.020]	[0.029]	[0.024]	[0.033]
Observations	1,270	1,270	1,270	1,270
R-squared	0.048	0.069	0.038	0.062

The table shows the response of 2 and 10 year government bond yields to a monetary policy surprise (*mps*) and monetary policy uncertainty (*mpu*) shock, with country fixed effects included in the specification. All variables have been normalized to have unit standard deviation. Column (1) has only *mps* as a regressor, while column 2 adds *mpu* to this specification. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Standard errors reported in parentheses are calculated with two-way clustering (along the country and time dimension).

APPENDIX H

FIGURES FOR CHAPTER 3

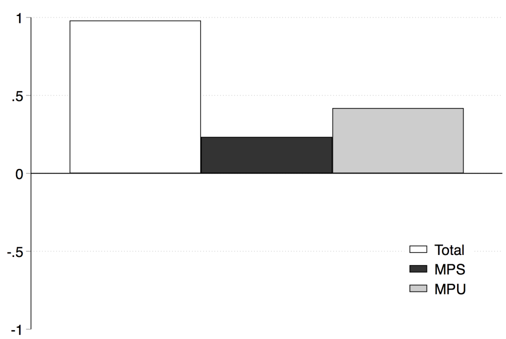
Figure H1: Monetary policy uncertainty changes (*mpu*) on FOMC meeting days



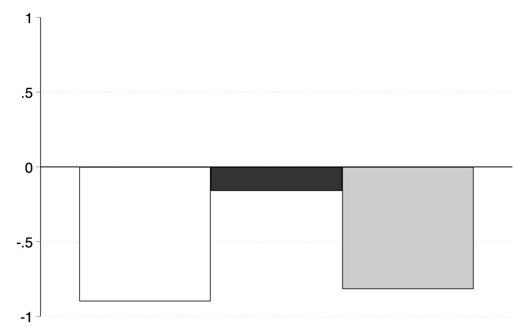
The figure shows the two-day change in the standard deviation of the 1 year ahead rate on FOMC meeting days (our baseline *mpu* measure). The measure has been normalized to have unit standard deviation. The labeled dates are the three largest declines and three largest increases in *mpu*.

Figure H2: 10 Year Yield Response on Prominent Monetary Policy Uncertainty Dates

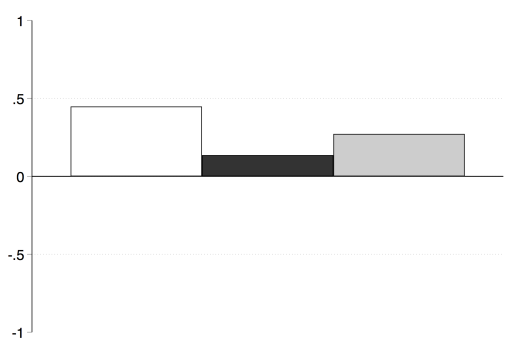
(a) Advanced: MPU Increase Dates



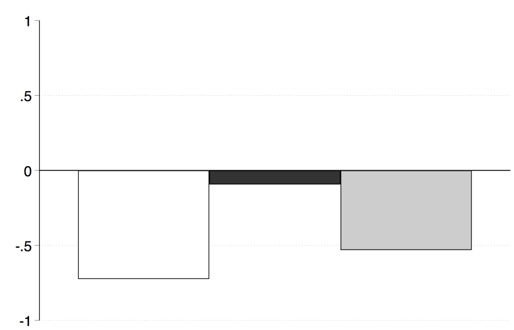
(b) Advanced: MPU Decrease Dates



(c) Emerging: MPU Increase Dates

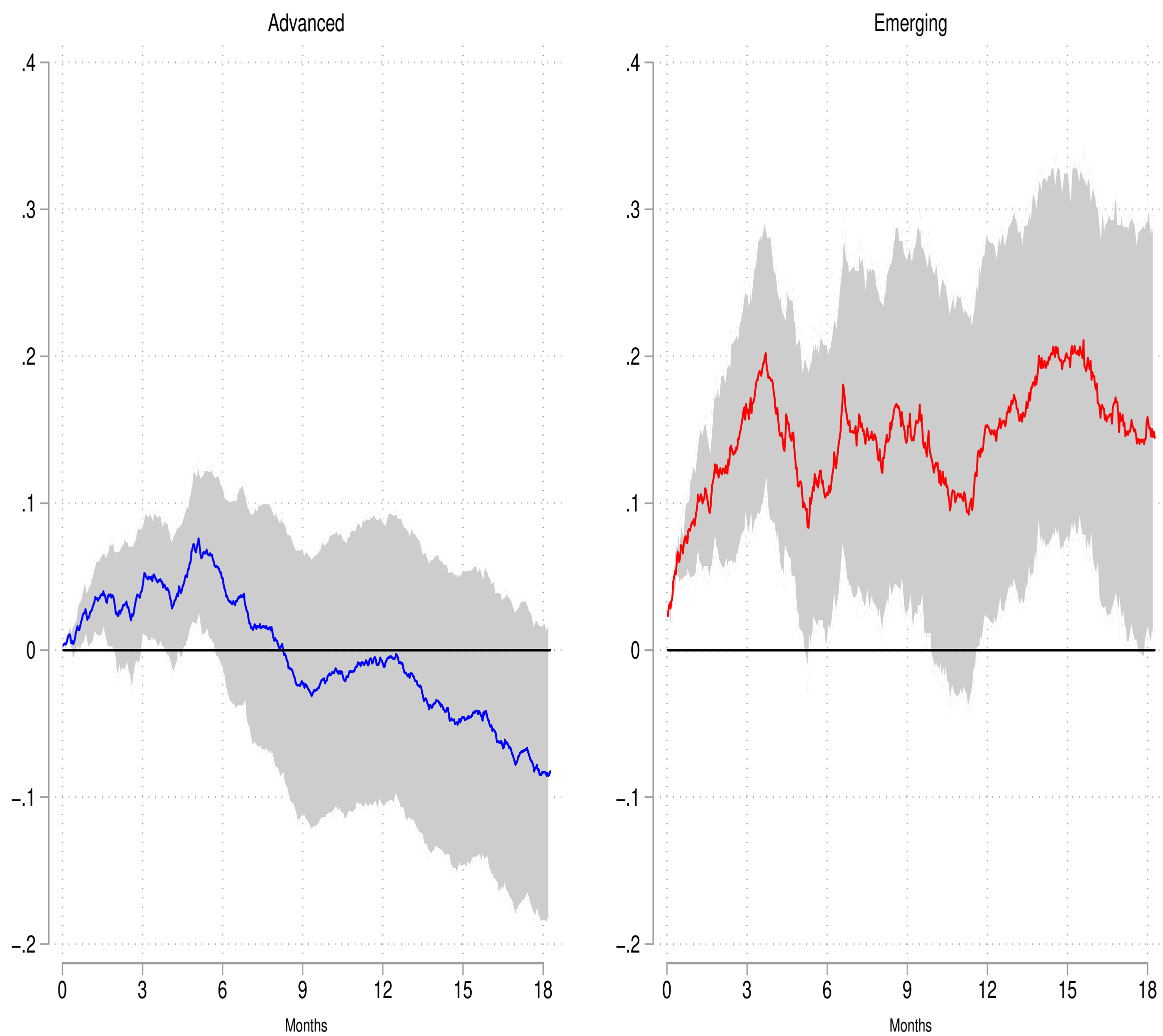


(d) Emerging: MPU Decrease Dates



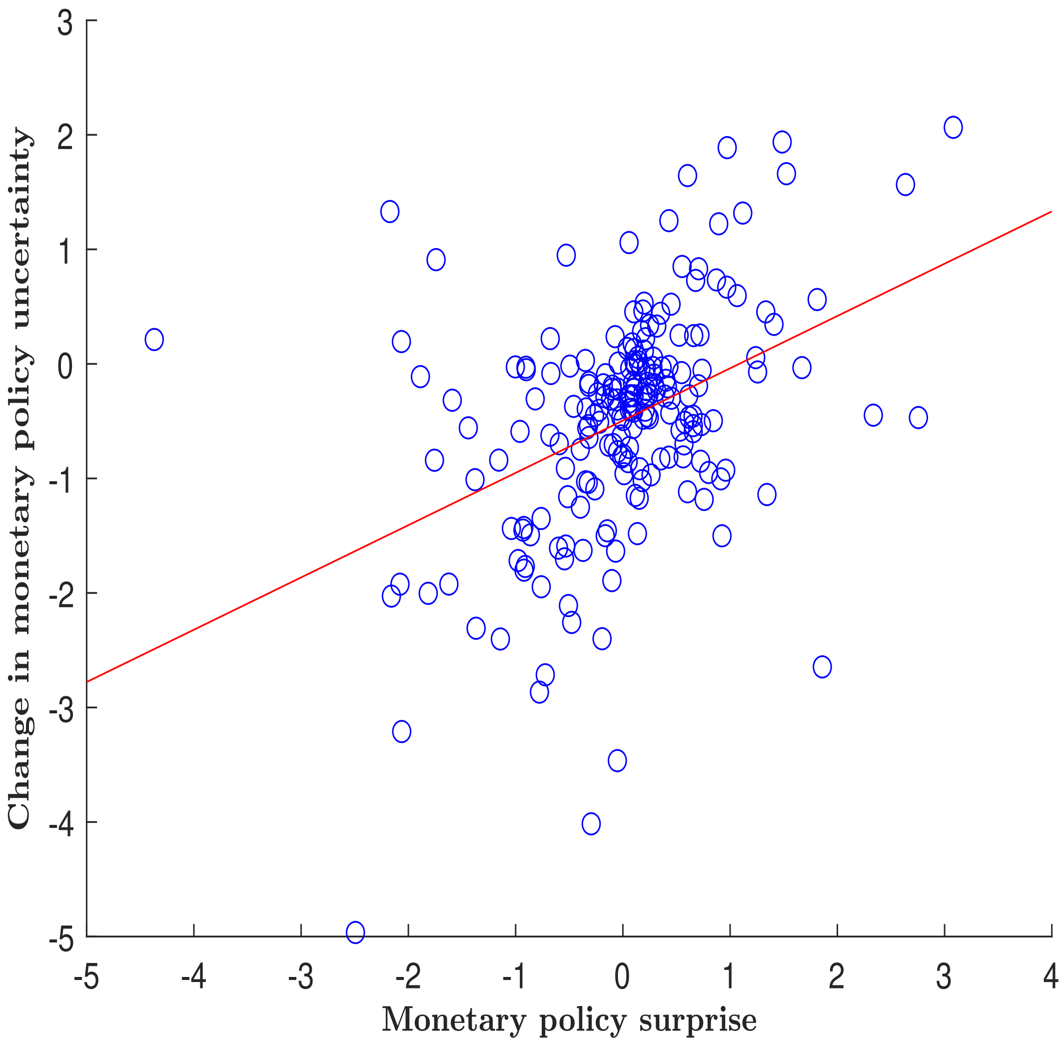
The figure shows the average total change in 10 year bond yields on ten FOMC dates with the largest increase or decrease in the monetary policy uncertainty (*mpu*) shock, along with the average predicted component due to *mpu* and the average predicted component due to the monetary policy surprise (*mps*). The average predicted components are based on the coefficients estimated in Equation 3.3.

Figure H3: Response of 3 month yield to monetary policy uncertainty



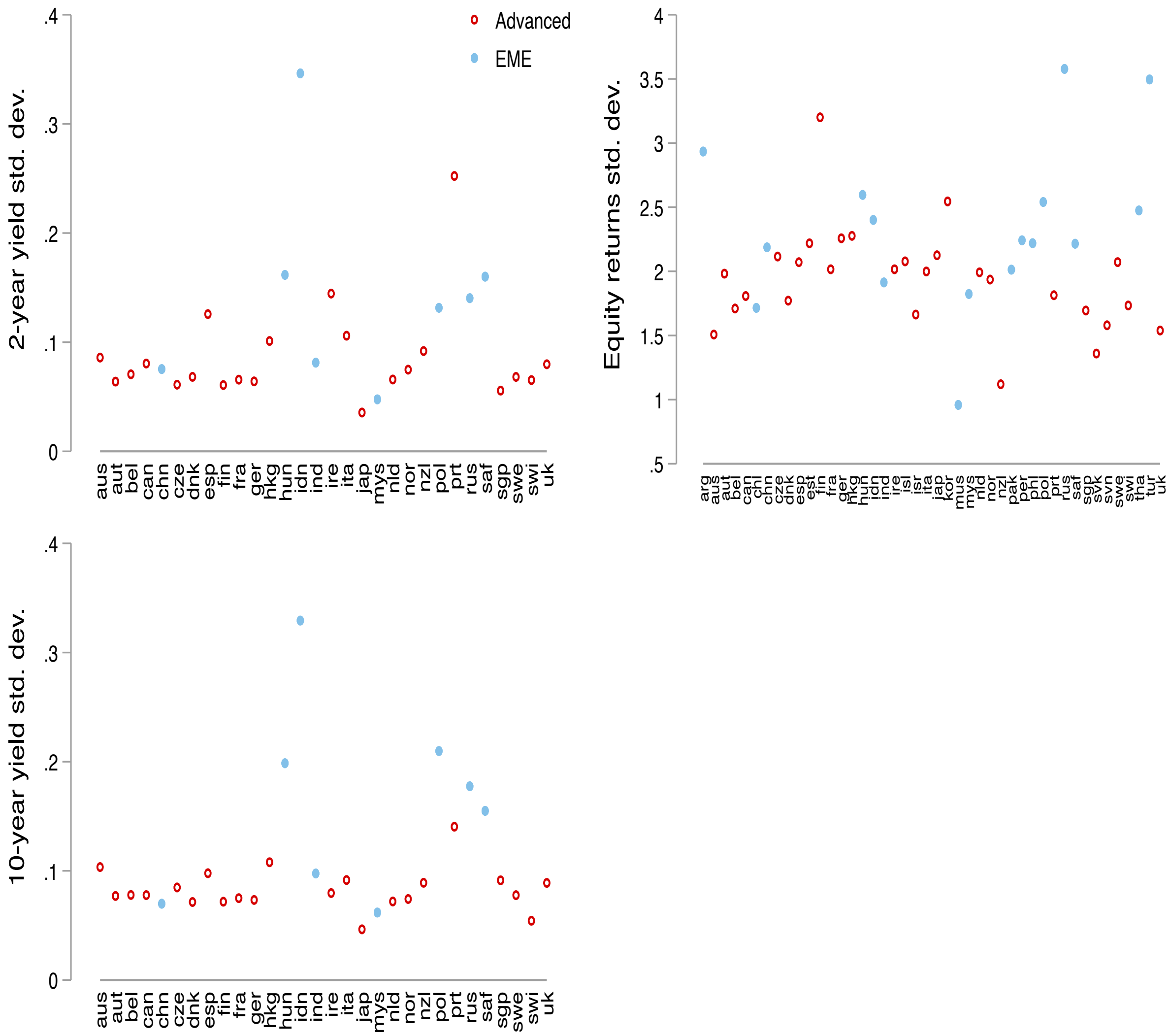
The figure shows the dynamic response of 3 month government bond yields to a monetary policy uncertainty (*mpu*) shock over an 18 month horizon. The change in 3 month yields has been normalized to have unit standard deviation. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. 68% confidence bands are constructed from Driscoll and Kraay standard errors.

Figure H4: Correlation between change in monetary policy uncertainty (*mpu*) and monetary policy surprise (*mps*)



The figure plots the monetary policy uncertainty (*mpu*) shock against the monetary policy surprise (*mps*). Both measures are calculated in a two day window around FOMC announcements. The sample consists of 204 FOMC announcements from January 1995 to June 2019. The diagonal line shows the fit from the regression of *mpu* on *mps*.

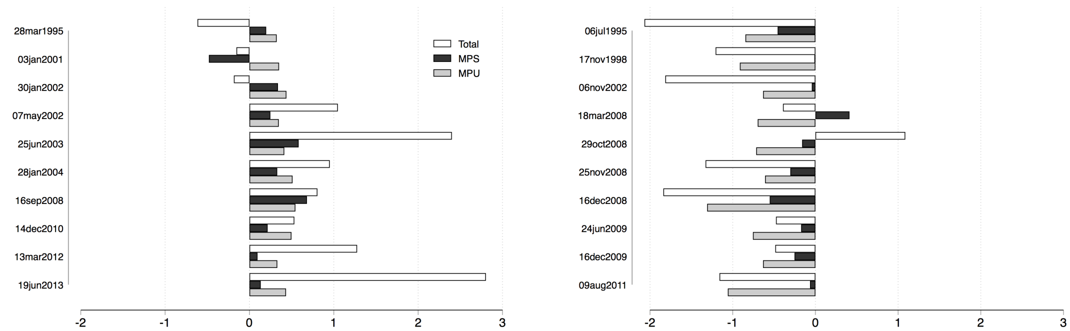
Figure H5: Standard deviation of international asset prices



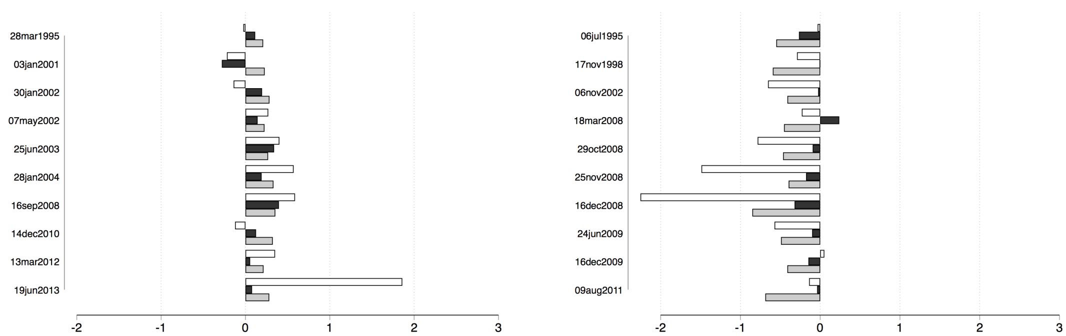
The figure plots the standard deviation of the 2-day change in the 2 and 10 year bond yields and stock market return by country.

Figure H6: 10 Year Yield Response on Prominent Monetary Policy Uncertainty Dates

(a) Advanced: MPU Increase Dates (b) Advanced: MPU Decrease Dates

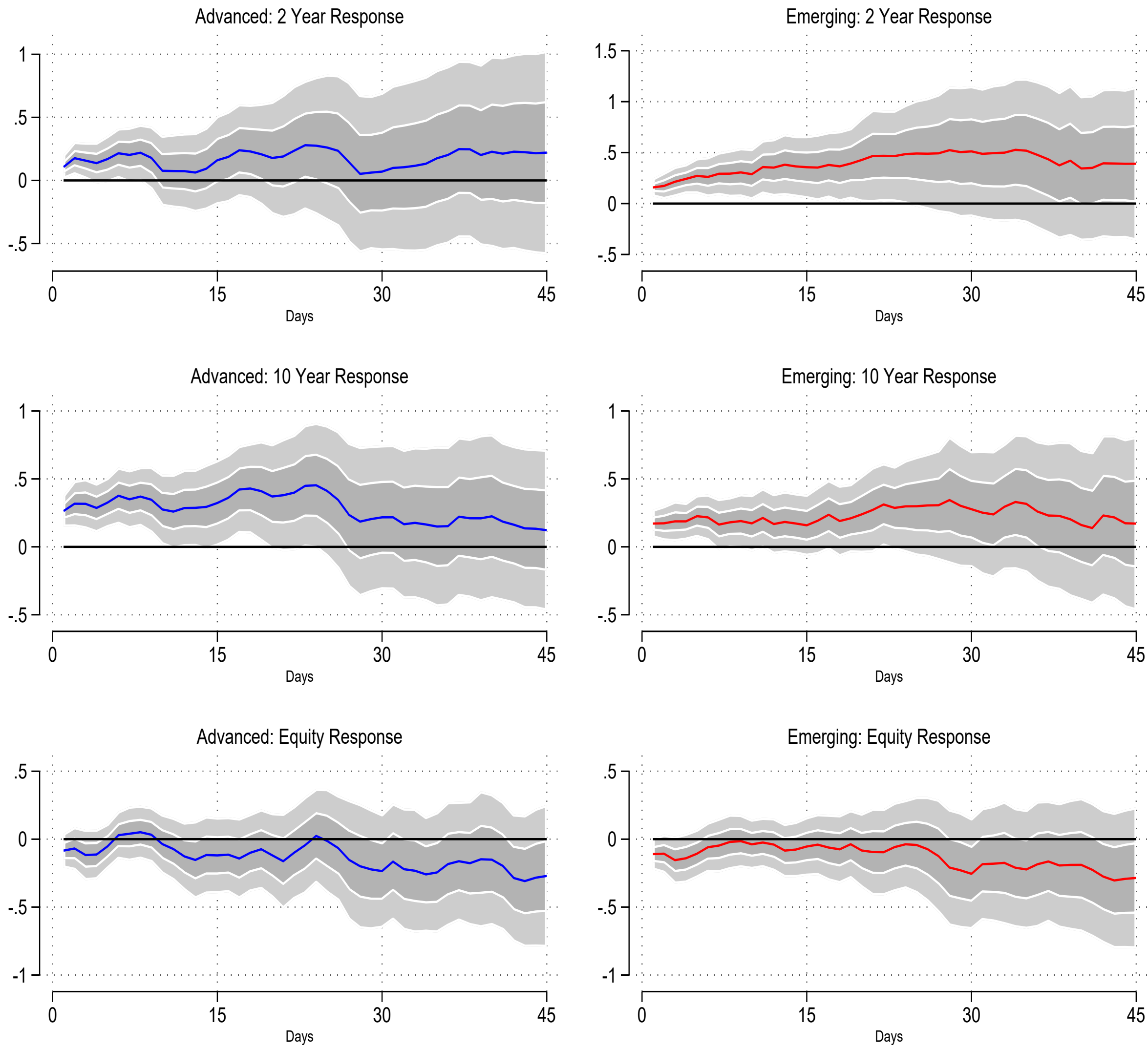


(c) Emerging: MPU Increase Dates (d) Emerging: MPU Decrease Dates



The figure shows the change in 10 year yields, the change attributable to the monetary policy surprise (*mps*) and the change attributable to the monetary policy uncertainty (*mpu*) shock on FOMC dates with prominent changes in *mpu*. Panel (a) displays the reaction of advanced yields for dates with large *mpu* increases, panel (b) displays the reaction of advanced yields for dates with large *mpu* decreases, panel (c) displays the reaction of emerging yields for dates with large *mpu* increases, and panel (d) displays the reaction of emerging yields for dates with large decreases in *mpu*.

Figure H7: Persistence of international asset price response to *mpu*

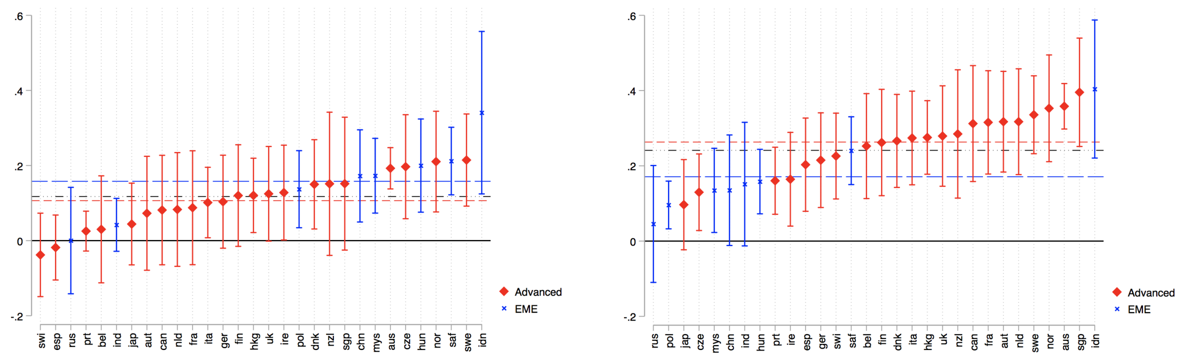


The figure shows the dynamic response of 2 year government bond yields, 10 year month government bond yields, and equity returns to a monetary policy uncertainty (*mpu*) shock over a 45 day horizon. The change in asset prices have been normalized to have unit standard deviation. The sample consists of 204 FOMC announcements from January 1995 to June 2019. *mpu* is calculated over a two day window around FOMC announcements. 95% and 68% confidence bands are constructed from Driscoll and Kraay standard errors.

Figure H8: Heterogeneity in response to *mpu* across countries

(a) 2 year yields

(b) 10 year yields

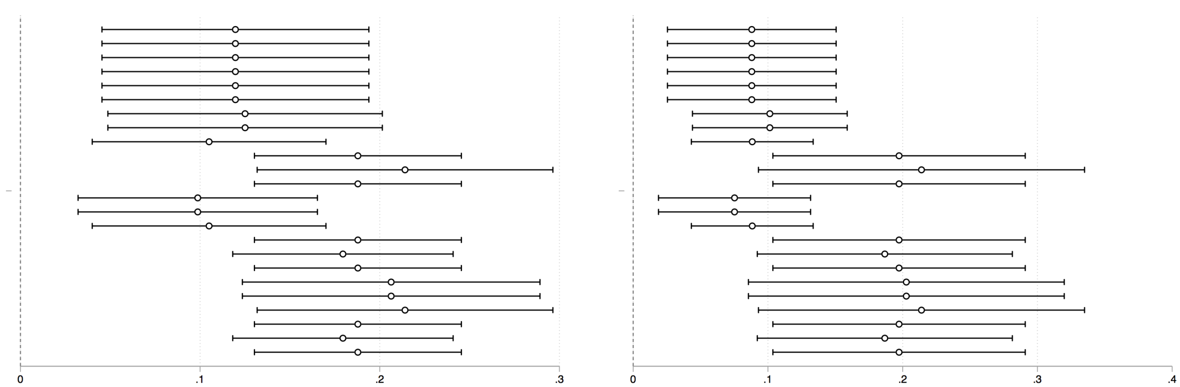


The figure shows country specific responses to a monetary policy uncertainty (*mpu*) shock. Panel (a) shows the response of 2 year yields and panel (b) shows the response of 10 year yields. Coefficients are estimated for the full sample period available for each country. 90% confidence intervals are reported. The dashed-with-3-dots line is the pooled OLS estimate. The long-dashed line is the emerging OLS estimate. The short-dashed line is the advanced OLS estimate.

Figure H9: Robustness of capital account openness interaction with mpu

(a) 2 year yields

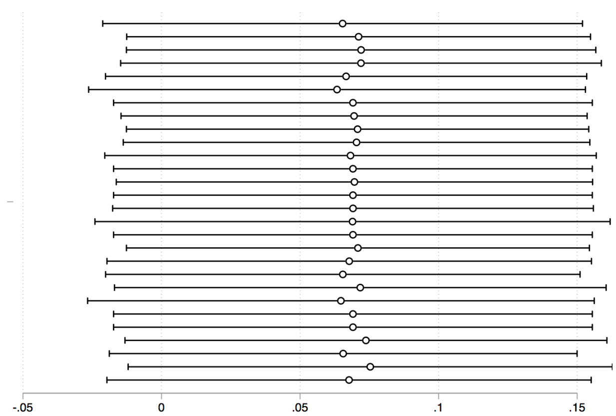
(b) 10 year yields



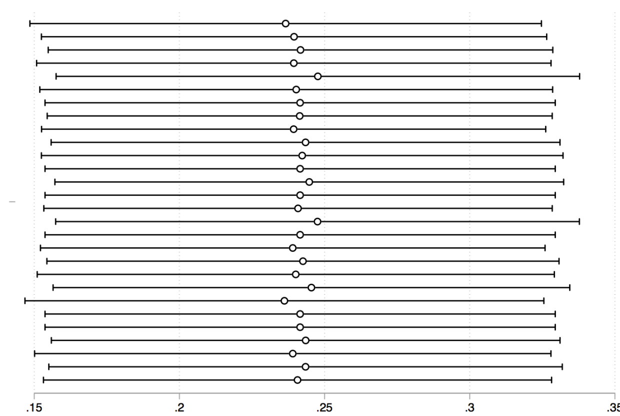
The figure shows the KAopen**mpu* coefficient from Table G9 for the 24 unique variable orderings with financial depth appearing first in the orthogonalization. The top estimate is the baseline specification. 90% confidence intervals are reported.

Figure H10: 2 and 10 Year Yield Response to Monetary Policy Uncertainty. Dropping One Country at a Time.

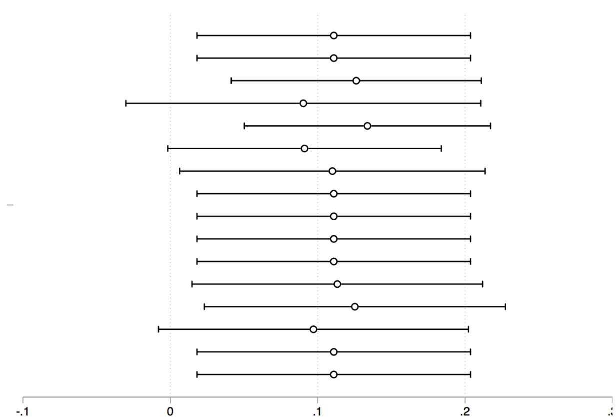
(a) Advanced: 2 Year Yield



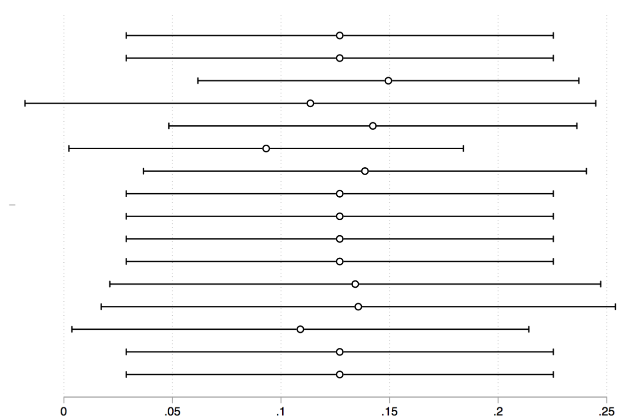
(b) Advanced: 10 Year Yield



(c) Emerging: 2 Year Yield



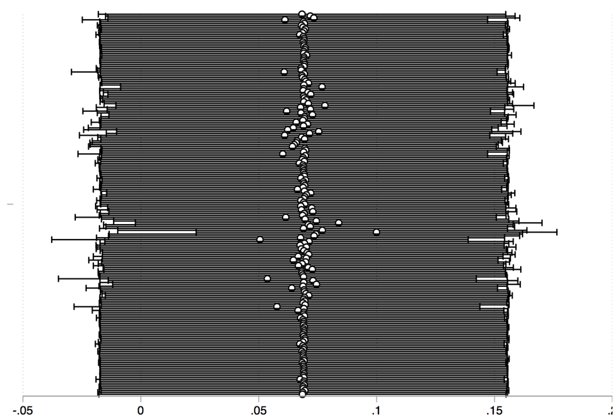
(d) Emerging: 10 Year Yield



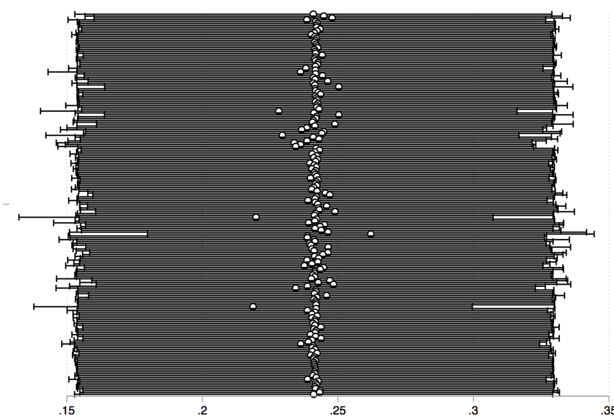
The figure shows the response of 2 and 10 year government bond yields to a monetary policy uncertainty (*mpu*) shock while dropping one country at a time from the advanced and emerging country samples, respectively. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Confidence intervals are constructed with two-way clustered standard errors (along the country and time dimension).

Figure H11: 2 and 10 Year Yield Response to Monetary Policy Uncertainty. Dropping One FOMC Date at a TIme.

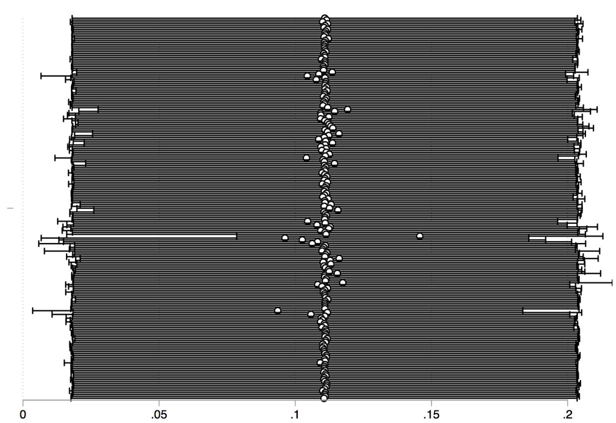
(a) Advanced: 2 Year Yield



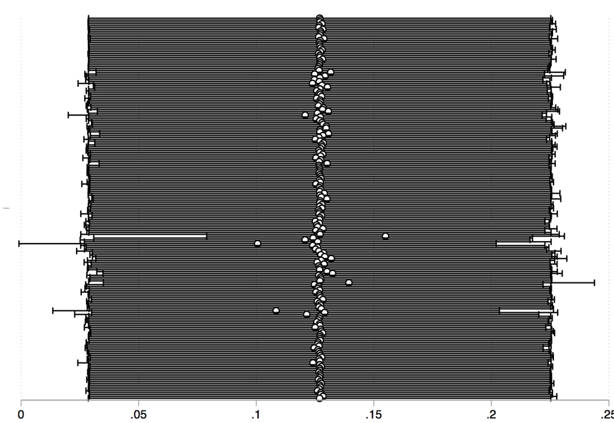
(b) Advanced: 10 Year Yield



(c) Emerging: 2 Year Yield



(d) Emerging: 10 Year Yield



The figure shows the response of 2 and 10 year government bond yields to a monetary policy uncertainty (*mpu*) shock while dropping one FOMC date at a time. The sample consists of 204 FOMC announcements from January 1995 to June 2019. All changes are calculated in a two day window around FOMC announcements. Confidence intervals are constructed with two-way clustered standard errors (along the country and time dimension).

BIBLIOGRAPHY

BIBLIOGRAPHY

Adrian, Tobias, Richard K Crump & Emanuel Moench. 2013. Pricing the term structure with linear regressions. *Journal of Financial Economics* 110(1). 110–138.

Ahmed, Shaghil & Andrei Zlate. 2014. Capital flows to emerging market economies: A brave new world? *Journal of International Money and Finance* 48. 221–248.

Albagli, Elias, Luis Ceballos, Sebastian Claro & Damian Romero. 2019. Channels of us monetary policy spillovers to international bond markets. *Journal of Financial Economics* .

Alpanda, Sami & Serdar Kabaca. 2019. International Spillovers of Large-Scale Asset Purchases. *Journal of the European Economic Association* Jvy053.

Anaya, Pablo, Michael Hachula & Christian J Offermanns. 2017. Spillovers of us unconventional monetary policy to emerging markets: The role of capital flows. *Journal of International Money and Finance* 73. 275–295.

Bacchetta, Philippe, Kenza Benhima & Céline Poilly. 2019. Corporate cash and employment. *American Economic Journal: Macroeconomics* 11(3). 30–66.

Bauer, Michael, Aeimit Lakdawala & Philippe Mueller. 2019. Market-based monetary policy uncertainty. *Federal Reserve Bank of San Francisco Working Paper* .

Bauer, Michael D & Christopher J Neely. 2014. International channels of the fed's unconventional monetary policy. *Journal of International Money and Finance* 44. 24–46.

Bauer, Michael D & Glenn D Rudebusch. 2014. The signaling channel for federal reserve bond purchases. *International Journal of Central Banking* .

Bauer, Michael D, Glenn D Rudebusch & Jing Cynthia Wu. 2012. Correcting estimation bias in dynamic term structure models. *Journal of Business & Economic Statistics* 30(3). 454–467.

Begenau, Juliane & Juliana Salomao. 2019. Firm financing over the business cycle. *The Review of Financial Studies* 32(4). 1235–1274.

Berger, Allen, Rebecca Demsetz & Philip Strahan. 1999. The consolidation of the financial services industry: Causes, consequences, and implications for the future. *Journal of Banking & Finance* 23(2-4). 135–194.

Berger, Allen, Nathan Miller, Mitchell Petersen, Raghuram Rajan & Jeremy Stein. 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics* 76(2). 237–269.

Bernanke, Ben. 2015. Why are interest rates so low, part 4: Term premiums. *https://www.brookings.edu/blog/ben-bernanke/2015/04/13/why-are-interest-rates-so-low-part-4-term-premiums/* .

Bernanke, Ben, Mark Gertler & Simon Gilchrist. 1999. The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics* 1. 1341–1393.

Bernanke, Ben S & Mark Gertler. 1995. Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic perspectives* 9(4). 27–48.

Bernanke, Ben S & Kenneth N Kuttner. 2005. What explains the stock market's reaction to federal reserve policy? *The Journal of finance* 60(3). 1221–1257.

Bertaut, Carol C & Ruth Judson. 2014. Estimating us cross-border securities positions: New data and new methods. *FRB International Finance Discussion Paper* (1113).

Bertaut, Carol C & Ralph W Tryon. 2007. Monthly estimates of us cross-border securities positions. *FRB International Finance Discussion Paper* (910).

Bhattarai, Saroj, Arpita Chatterjee & Woong Yong Park. 2015. Effects of us quantitative easing on emerging market economies .

Bhattarai, Saroj, Arpita Chatterjee & Woong Yong Park. 2019. Global spillover effects of us uncertainty. *Journal of Monetary Economics* .

Bhattarai, Saroj & Christopher Neely. 2016. *A survey of the empirical literature on us unconventional monetary policy*. Federal Reserve Bank of St. Louis, Research Division.

Boot, Arnoud. 2000. Relationship banking: What do we know? *Journal of Financial Intermediation* 9. 7–25.

Bowman, David, Juan M Londono & Horacio Sapriza. 2015. Us unconventional monetary policy and transmission to emerging market economies. *Journal of International Money and Finance* 55. 27–59.

Broner, Fernando, Tatiana Didier, Aitor Erce & Sergio L Schmukler. 2013. Gross capital flows: Dynamics and crises. *Journal of Monetary Economics* 60. 113–133.

Bundick, Brent, Trenton Herriford & A. Lee Smith. 2017a. Forward guidance, monetary policy uncertainty, and the term premium. Working Paper, Federal Reserve Bank of City.

Bundick, Brent, Trenton Herriford & Andrew Smith. 2017b. Forward guidance, monetary policy uncertainty, and the term premium. *Monetary Policy Uncertainty, and the Term Premium (July 2017)* .

Bustamante, Christian. 2018. Debt overhang, monetary policy, and economic recoveries after large recessions. *Working Paper* .

Campbell, Jeffrey R, Charles L Evans, Jonas DM Fisher, Alejandro Justiniano, Charles W Calomiris & Michael Woodford. 2012. Macroeconomic effects of federal reserve forward guidance [with comments and discussion]. *Brookings Papers on Economic Activity* 1–80.

Carow, Kenneth, Edward Kane & Rajesh Narayanan. 2003. How have borrowers fared in banking mega-mergers? *NBER Working Paper* (w10623).

Carrière-Swallow, Yan & Luis Felipe Céspedes. 2013. The impact of uncertainty shocks in emerging economies. *Journal of International Economics* 90(2). 316–325.

Chang, Xin, Sudipto Dasgupta, George Wong & Jiaquan Yao. 2014. Cash-flow sensitivities and the allocation of internal cash flow. *The Review of Financial Studies* 27(12). 3628–3657.

Chari, Anusha, Karlye Dilts Stedman & Christian Lundblad. 2020. Taper Tantrums: Quantitative Easing, Its Aftermath, and Emerging Market Capital Flows. *The Review of Financial Studies* .

Chinn, Menzie D & Hiro Ito. 2006. What matters for financial development? capital controls, institutions, and interactions. *Journal of development economics* 81(1). 163–192.

Christiano, Lawrence J, Martin Eichenbaum & Charles L Evans. 1999. Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics* 1. 65–148.

Cloyne, James, Clodomiro Ferreira, Maren Froemel & Paolo Surico. 2018. Investment, financial frictions and the dynamic effects of monetary policy. Tech. rep. Working paper.

Covas, Francisco & Wouter Den Haan. 2011. The cyclical behavior of debt and equity finance. *American Economic Review* 101(2). 877–99.

Covas, Francisco & Wouter Den Haan. 2012. The role of debt and equity finance over the business cycle. *The Economic Journal* 122(565). 1262–1286.

Creal, Drew D & Jing Cynthia Wu. 2017. Monetary policy uncertainty and economic fluctuations. *International Economic Review* 58(4). 1317–1354.

Crouzet, Nicolas. 2020. Credit disintermediation and monetary policy Mimeo, Northwestern University.

Crouzet, Nicolas, Neil Mehrotra et al. 2017. Small and large firms over the business cycle. *Unpublished working paper* .

Curcuru, Stephanie E, Steven B Kamin, Canlin Li & Marius Rodriguez. 2018. International spillovers of monetary policy: Conventional policy vs. quantitative easing. *FRB International Finance Discussion Paper* (1234).

Daetz, Stine Louise, Marti G Subrahmanyam, Dragon Yongjun Tang & Sarah Qian Wang. 2018. Can central banks boost corporate investment: Evidence from the ecb liquidity injections. *Available at SSRN 2915800* .

Dahlhaus, Tatjana & Garima Vasishtha. 2014. The impact of us monetary policy normalization on capital flows to emerging-market economies. Tech. rep. Bank of Canada working paper.

Davis, Steven, John Haltiwanger, Ron Jarmin, Javier Miranda, Christopher Foote & Eva Nagypal. 2006. Volatility and dispersion in business growth rates: Publicly traded versus privately held firms. *NBER Macroeconomics Annual* 21. 107–179.

Dedola, Luca & Francesco Lippi. 2005. The monetary transmission mechanism: evidence from the industries of five oecd countries. *European Economic Review* 49(6). 1543–1569.

Delis, Manthos, Sotirios Kokas & Steven Ongena. 2017. Bank market power and firm performance. *Review of Finance* 21(1). 299–326.

Di Patti, Emilia Bonaccorsi & Giorgio Gobbi. 2007. Winners or losers? The effects of banking consolidation on corporate borrowers. *The Journal of Finance* 62(2). 669–695.

Diallo, Ibrahima. 2018. HAMILTONFILTER: Stata module to calculate the Hamilton filter for a single time series or for a panel dataset .

Diamond, Douglas & Raghuram Rajan. 2001. Liquidity risk, liquidity creation, and financial fragility: A theory of banking. *Journal of Political Economy* 109(2). 287–327.

Dick, Astrid A. 2006. Nationwide branching and its impact on market structure, quality, and bank performance. *The Journal of Business* 79(2). 567–592.

Ehrmann, Michael & Marcel Fratzscher. 2004. Taking stock: Monetary policy transmission to equity markets. *Journal of Money, Credit and Banking* 719–737.

Ehrmann, Michael, Marcel Fratzscher & Roberto Rigobon. 2011. Stocks, bonds, money markets and exchange rates: measuring international financial transmission. *Journal of Applied Econometrics* 26(6). 948–974.

Eisfeldt, Andrea & Tyler Muir. 2016. Aggregate external financing and savings waves. *Journal of Monetary Economics* 84. 116–133.

Fawley, Brett W, Christopher J Neely et al. 2013. Four stories of quantitative easing. *Federal Reserve Bank of St. Louis Review* 95(1). 51–88.

Ferguson, Roger. 2001. April 19th Remarks by Vice Chairman Roger W Ferguson before the National Economists Club and Society of Government Economists Https://www.federalreserve.gov/boarddocs/speeches/2001/20010419/default.htm.

Fernholz, Ricardo & Christoffer Koch. 2016. Why are big banks getting bigger? *Federal Reserve Bank of Dallas Working Paper* .

Foley-Fisher, Nathan, Rodney Ramcharan & Edison Yu. 2016. The impact of unconventional monetary policy on firm financing constraints: Evidence from the maturity extension program. *Journal of Financial Economics* 122(2). 409–429.

Frankel, Jeffrey A. 1982. A test of perfect substitutability in the foreign exchange market. *Southern Economic Journal* 406–416.

Fratzscher, Marcel, Marco Lo Duca & Roland Straub. 2018. On the international spillovers of us quantitative easing. *The Economic Journal* 128(608). 330–377.

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

Ghironi, Fabio & Galip Kemal Ozhan. 2019. Interest rate uncertainty as a policy tool .

Gilchrist, Simon, Vivian Yue & Egon Zakrajšek. 2019. Us monetary policy and international bond markets. Tech. rep. National Bureau of Economic Research.

Gilchrist, Simon & Egon Zakrajšek. 2013. The impact of the federal reserve's large-scale asset purchase programs on corporate credit risk. *Journal of Money, Credit and Banking* 45(s2). 29–57.

Greenwood, Robin, Samuel Hanson & Jeremy C Stein. 2010. A gap-filling theory of corporate debt maturity choice. *The Journal of Finance* 65(3). 993–1028.

Grosse-Rueschkamp, Benjamin, Sascha Steffen & Daniel Streitz. 2019. A capital structure channel of monetary policy. *Journal of Financial Economics* .

Guo, Xing. 2019. Financial shocks and investment fluctuation: Small firms vs. large firms. Mimeo, University of Michigan.

Gupta, Rangan, Chi Lau, Jacobus Nel, Xin Sheng et al. 2020. Monetary policy uncertainty spillovers in time-and frequency-domains. Tech. rep.

Gürkaynak, Refet, Brian Sack & Jonathan Wright. 2007. The U.S. Treasury yield curve: 1961 to the present. *Journal of Monetary Economics* 54. 2291–2304.

Gürkaynak, Refet, Brian Sack & Jonathan Wright. 2010. The TIPS yield curve and inflation compensation. *American Economic Journal: Macroeconomics* 2. 70–92.

Gürkaynak, RS, B Sack & ET Swanson. 2005. Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. *International Journal of Central Banking* 1(1). 55–93.

Gürkaynak, Refet S., Brian Sack & Eric Swanson. 2005. The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models. *American Economic Review* 95(1). 425–436. doi:10.1257/0002828053828446. `http://www.aeaweb.org/articles?id=10.1257/0002828053828446`.

Hamilton, James. 2018. Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics* 100(5). 831–843.

Hanson, Samuel G, David O Lucca & Jonathan H Wright. 2017. The excess sensitivity of long-term rates: A tale of two frequencies .

Hanson, Samuel G. & Jeremy C. Stein. 2015a. Monetary policy and long-term real rates. *Journal of Financial Economics* 115. 429–448.

Hanson, Samuel G & Jeremy C Stein. 2015b. Monetary policy and long-term real rates. *Journal of Financial Economics* 115(3). 429–448.

Hausman, Joshua & Jon Wongswan. 2011. Global asset prices and fomc announcements. *Journal of International Money and Finance* .

Heiney, Joseph. 2010. Consolidation and profitability in the US banking industry. *Journal of Business & Economics Research (JBER)* 8(1).

Hennessy, Christopher & Toni Whited. 2005. Debt dynamics. *The Journal of Finance* 60(3). 1129–1165.

Husted, Lucas, John H Rogers & Bo Sun. 2017. Monetary policy uncertainty. *FRB International Finance Discussion Paper* (1215).

Iacoviello, Matteo & Gaston Navarro. 2019. Foreign effects of higher us interest rates. *Journal of International Money and Finance* .

Ilzetzki, Ethan, Carmen M Reinhart & Kenneth S Rogoff. 2019. Exchange arrangements entering the twenty-first century: Which anchor will hold? *The Quarterly Journal of Economics* 134(2). 599–646.

Ippolito, Filippo, Ali K Ozdagli & Ander Perez-Orive. 2018. The transmission of monetary policy through bank lending: The floating rate channel. *Journal of Monetary Economics* 95. 49–71.

Istrefi, Klodiana & Sarah Mouabbi. 2018. Subjective interest rate uncertainty and the macroeconomy: A cross-country analysis. *Journal of International Money and Finance* 88. 296–313.

Jeenas, Priit. 2018. Monetary policy shocks, financial structure, and firm activity: A panel approach. *Working Paper* .

Jeenas, Priit. 2019. Firm balance sheet liquidity, monetary policy shocks, and investment dynamics. *Working Paper* .

Jermann, Urban & Vincenzo Quadrini. 2012. Macroeconomic effects of financial shocks. *American Economic Review* 102(1). 238–71.

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

Jordà, Òscar, Moritz Schularick, Alan M Taylor & Felix Ward. 2019. Global financial cycles and risk premiums. *IMF Economic Review* 67(1). 109–150.

Joslin, Scott, Kenneth J Singleton & Haoxiang Zhu. 2011. A new perspective on gaussian dynamic term structure models. *The Review of Financial Studies* 24(3). 926–970.

Kabaca, Serdar. 2016. Quantitative easing in a small open economy: An international portfolio balancing approach. Tech. rep. Bank of Canada Staff Working Paper.

Kalemli-Ozcan, Sebnem. 2019. Us monetary policy and international risk spillovers. *Proceedings—Economic Policy Symposium—Jackson Hole, Federal Reserve Bank of Kansas City* .

Kalemli-Ozcan, Sebnem, Luc Laeven & David Moreno. 2018. Debt overhang, rollover risk, and corporate investment: Evidence from the european crisis. Tech. rep. National Bureau of Economic Research.

Karabarbounis, Marios, Patrick Macnamara & Roisin McCord. 2014. A business cycle analysis of debt and equity financing. *Economic Quarterly* (1Q). 51–85.

Karceski, Jason, Steven Ongena & David Smith. 2005. The impact of bank consolidation on commercial borrower welfare. *The Journal of Finance* 60(4). 2043–2082.

Khan, Aubhik, Tatsuro Senga & Julia K Thomas. 2016. Default risk and aggregate fluctuations in an economy with production heterogeneity. *Unpublished Manuscript* .

Kim, Don H. & Jonathan H. Wright. 2005. An arbitrage-free three-factor term structure model and the recent behavior of long-term yields and distant-horizon forward rates. Finance and Economics Discussion Series 2005-33 Board of Governors of the Federal Reserve System.

Kolasa, Marcin & Grzegorz Wesołowski. 2020. International spillovers of quantitative easing. *Journal of International Economics* 103330.

Kroencke, Tim Alexander, Maik Schmeling & Andreas Schrimpf. 2018. The fomc risk shift. *Available at SSRN 3072912* .

Kudlyak, Marianna & Juan Sanchez. 2016. Revisiting gertler-gilchrist evidence on the behavior of small and large firms. *FRB St. Louis Working Paper* .

Kuttner, Kenneth N. 2001. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of monetary economics* 47(3). 523–544.

Lakdawala, Aeimit. 2018. The growing impact of us monetary policy on emerging financial markets: Evidence from india. *Available at SSRN 3274445* .

Lakdawala, Aeimit. forthcoming. Decomposing the effects of monetary policy using an external instruments svar. *Journal of Applied Econometrics* .

Lakdawala, Aeimit & Matthew Schaffer. 2019a. Federal reserve private information and the stock market. *Journal of Banking and Finance* 106. 34–49.

Lakdawala, Aeimit & Matthew Schaffer. 2019b. Federal reserve private information and the stock market. *Journal of Banking & Finance* 106. 34–49.

Lee, Jinsook. 2017. How do firms choose their debt types? Mimeo, Canisius College.

Li, Xinlei. 2017. *Relationship lending in syndicated loans: A participant's perspective*: Columbia University dissertation.

Lins, Karl, Henri Servaes & Peter Tufano. 2010. What drives corporate liquidity? An international survey of cash holdings and lines of credit. *Journal of Financial Economics* 98(1). 160–176.

Mehrotra, Aaron N, Richhild Moessner & Chang Shu. 2019. Interest rate spillovers from the united states: expectations, term premia and macro-financial vulnerabilities .

Milesi-Ferretti, Gian-Maria & Cédric Tille. 2011. The great retrenchment: international capital flows during the global financial crisis. *Economic policy* 26(66). 289–346.

Miranda-Agrippino, Silvia & Helene Rey. 2015. Us monetary policy and the global financial cycle. Tech. rep. National Bureau of Economic Research.

Mugasha, Agasha. 1998. *Law of multi-bank financing*. McGill-Queen's Press-MQUP.

Nakamura, Emi & Jón Steinsson. 2018. High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics* 133(3). 1283–1330.

Neely, Christopher J. 2015. Unconventional monetary policy had large international effects. *Journal of Banking & Finance* 52. 101–111.

Ongena, Steven & David Smith. 2001. The duration of bank relationships. *Journal of Financial Economics* 61(3). 449–475.

Ottonello, Pablo & Thomas Winberry. 2018. Financial heterogeneity and the investment channel of monetary policy. Tech. rep. National Bureau of Economic Research.

Ozdagli, Ali. 2018. Financial frictions and the stock price reaction to monetary policy. *The Review of Financial Studies* 31(10).

Petrosky-Nadeau, Nicolas & Etienne Wasmer. 2013. The cyclical volatility of labor markets under frictional financial markets. *American Economic Journal: Macroeconomics* 5(1). 193–221.

Rajan, Raghuram. 1992. Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of Finance* 47(4). 1367–1400.

Rey, Helene. 2013. Dilemma not trilemma: The global financial cycle and monetary policy independence. *Proceedings—Economic Policy Symposium—Jackson Hole, Federal Reserve Bank of Kansas City* .

de los Rios, Antonio Diez & Maral Shamloo. 2017. *Quantitative easing and long-term yields in small open economies*. International Monetary Fund.

Sharpe, Steven. 1990. Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance* 45(4). 1069–1087.

Swanson, Eric T. & John C. Williams. 2014. Measuring the effect of the zero lower bound on medium- and longer-term interest rates. *American Economic Review* 104(10). 3154–85. doi:10.1257/aer.104.10.3154. `http://www.aeaweb.org/articles.php?doi=10.1257/aer.104.10.3154`.

Whited, Toni M & Guojun Wu. 2006. Financial constraints risk. *The Review of Financial Studies* 19(2). 531–559.

Wu, Wenbin. 2018. The credit channel at the zero lower bound through the lens of equity prices. *Journal of Money, Credit and Banking* 50(2-3). 435–448.

Zetlin-Jones, Ariel & Ali Shourideh. 2017. External financing and the role of financial frictions over the business cycle: Measurement and theory. *Journal of Monetary Economics* 92. 1–15.