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Financial intermediary leverage and monetary policy transmission ☆

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ABSTRACT

Monetary policy is more effective when financial intermediaries have a higher equity share in their total assets. When the leverage ratio is one standard deviation below average, the marginal effect of a monetary policy shock on realized S&P 500 returns is 89% larger in an event window study. In a VAR exercise, the impulse responses of real variables to a given monetary policy shock also have larger magnitudes when financial intermediaries have a lower leverage. The financial intermediary leverage is counter-cyclical, explaining why monetary policy is less effective during recessions as found in the literature.

1. Introduction

Recent developments in the financial economic literature suggest that the effects of output and financial shocks on macroeconomic variables largely depend on financial intermediary wealth. Less is known whether monetary policy transmission also depends on financial intermediary wealth. To the extent that the financial intermediaries are the ones who directly interact with the Fed in the implementations of monetary policy, this paper contributes to the empirical literature by studying whether fluctuations in financial intermediary wealth are associated with nonlinearities in monetary policy transmission. Using a simple, flexible regression framework, I show that U.S. monetary policy is more effective when financial intermediaries are well-capitalized.

I identify the financial intermediaries as the primary dealers. For monetary policy transmission, the primary dealers are interesting in two aspects. Firstly, they are essential players in the financial markets. The primary dealers consist of a group of large and sophisticated financial institutions, including Goldman Sachs, J.P. Morgan, Deutsche Bank, and others. Over the period 1960–2012, primary dealers accounted for 96% of total assets of the broker–dealer's sector and 60% of total assets of all banks in the U.S. He et al. (2017) (HKM) show that the primary dealers are marginal investors in many asset markets, including the equity, government bond, corporate bond, derivatives, commodities, and foreign exchange markets. Secondly, they are the trading counterparties of the Federal Reserve Bank of New York in the implementations of monetary policy, so the monetary policy operations directly affect their portfolios. For example, an open market purchase increases reserve and decreases Treasury securities in the primary dealer portfolios. Subsequently, they should change the mix of other securities to reoptimize their portfolios. Such activities have significant impacts on asset prices due to the pivotal roles of the primary dealers. Asset prices determine wealth and funding costs for firms and households, so the responses of real activities should also depend on the primary dealer portfolio decisions.

Following He et al. (2017), I use the equity-to-asset ratio (capital ratio), which is the inverse of the leverage ratio, to measure the financial conditions of the primary dealers. A high capital ratio indicates good financial health. This paper uses the capital ratio

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as the conditioning variable to investigate the nonlinear effects of a surprise in the short-term interest rate on asset prices and real activities in the aggregate data. I conduct two exercises. First, I study the instantaneous effects of monetary policy shocks on stock prices. I regress the changes in stock prices on monetary policy shocks and an interaction between the capital ratio and the monetary policy shocks. The monetary policy shocks are identified as changes in the Fed Funds futures rate in short event windows bracketing FOMC press releases. This exercise expands the literature on event window studies of monetary policy transmission by considering state-dependent effects. A higher primary dealer capital ratio amplifies the instantaneous responses of stock prices to unanticipated changes in the short-term interest rate. When the capital ratio is one standard deviation above the mean level, the magnitude of the marginal effect of the monetary policy shock increases by 89%. Interestingly, it seems that most of the changes in stock prices are due to expansionary (i.e., negative) monetary policy surprises.

Second, I estimate a vector autoregression (VAR) model consisting of the capital ratio, nominal interest rate, and measures of real activities. The structural interest rate shocks are identified through high frequency instrumental variables. I interact the capital ratio with the interest rate to investigate whether a high capital ratio amplifies the impulse responses to a monetary policy shock. The interacted VAR offers a tractable framework for studying whether the effects of an exogenous shock depend on the level of the state variable. Crucially, the capital ratio and interest rate are both endogenous in the VAR. Generalized impulse response functions (GIRFs) are computed to reflect that monetary policy transmission depends on the initial level and endogenous responses of the primary dealer capital ratio throughout the paths of the responses. The responses of macroeconomic variables to an interest rate shock are stronger when the primary capital ratio on impact is high. Since the capital ratio in the sample is strongly procyclical, the nonlinear effects of monetary policy in this paper are consistent with the finding of Tenreyro and Thwaites (2016) that U.S. monetary policy is more powerful in business cycle expansions than in recessions.

Bank lending is an essential function of financial intermediaries in the transmission of monetary policy. For nonlinear effects of monetary policy, Kashyap and Stein (2000) and Kishan and Opiela (2000) find that bank loans respond more strongly to monetary policy shocks for banks with weaker balance sheets. However, they do not focus on nonlinear aggregate effects of the monetary policy shock on real activities. This paper differs from the literature in three aspects.

First, Kashyap and Stein (2000) and Kishan and Opiela (2000) study the bank lending channel by using loan growth as the dependent variable, while this paper uses asset prices and real activities as the dependent variable. Interacting the growth rate of total U.S. commercial bank loans with the interest rate, this paper finds little evidence that a high loan growth amplifies the effects of monetary policy shocks. On the other hand, asset prices seem to be more important for the nonlinear responses of aggregate real variables to monetary policy shocks. In the event-study exercise, the stock prices respond more strongly to monetary policy shocks when the primary dealer capital ratio is high. The VAR exercise also confirms the asset pricing channel. Corporate financing costs are more sensitive to monetary policy shocks in the high capital ratio state, so real activities also respond more strongly.

Second, the definition of financial intermediaries in this paper is different from the literature. Many authors find that the financial intermediary capital ratio is countercyclical, but the primary dealer capital ratio in this paper is procyclical. The discrepancy is mainly due to the compositional differences. The primary dealer capital ratio is computed at the holding company level, while the literature typically focuses on a subsidiary or standalone institution. For example, Adrian and Shin (2014) focus on broker–dealers; Kashyap and Stein (2000) and Kishan and Opiela (2000) focus on commercial banks. If the commercial banking subsidiary suffers a large loss, it will be reflected as commercial banking financial distress. However, if other businesses, such as the broker–dealer subsidiary, are thriving, internal capital flows may mitigate the losses in the commercial banking subsidiary. On the other hand, if other subsidiaries suffer significant losses, it will reduce risk-bearing capacity in the commercial banking subsidiary even though the distress is not reflected on the commercial bank's balance sheet. If internal capital flows are important sources of funds for subsidiaries, the holding company balance sheet may be a superior measure of financial intermediary risk-bearing capacity. Indeed, He et al. (2017) show that the holding company capital ratio has superior explanatory power for cross-sectional asset returns than the subsidiary capital ratio. This paper shows that the holding company capital ratio also has substantial impacts on monetary policy transmission.

Third, the primary dealer capital ratio is measured by the market value, which is more consistent with intermediary asset pricing models (e.g., He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Gertler and Karadi (2011)). The nonlinear effects of monetary policy shocks are much more pronounced when the capital ratio is measured by the market value. In a robustness exercise, where the market capital ratio is replaced with the book capital ratio, the differences in the impulse responses between the high and low capital ratio states become less significant though the relative magnitudes do not switch order.

The rest of the paper is organized as follows. Section 2 reviews related literature; Section 3 describes the data; Section 4 studies how contemporaneous effects of a surprise in the short-term interest rate on stock prices depend on the primary dealer capital ratio; Section 5 studies the dynamic interactions of the capital ratio, monetary policy, and real variables in a VAR framework; Section 6 concludes.

2. Literature review

This paper is part of the literature on nonlinear monetary policy transmission. Tenreyro and Thwaites (2016) and Mumtaz and Surico (2015) employ different methods to show that U.S. monetary policy is more effective in expansions. Cloyne et al. (2020) and Auclert (2019) attribute the asymmetry to household's portfolio compositions and credit constraints. Eickmeier et al. (2016), Aastveit et al. (2013), Pellegrino (2021) and Caggiano et al. (2017) explain the asymmetry with counter-cyclical uncertainty. In particular, Eickmeier et al. (2016) show empirically and theoretically that the state-dependent effects of uncertainty shocks operate through intermediary leverage. Relative to these papers, this paper uses the capital ratio instead of the uncertainty index

Table 1
Summary statistics of the primary dealer capital ratio and macroeconomic variables.

	Mean	s.d.	Min	Max	
Capital ratio	6.22	2.36	2.6	13.15	
Correlations with macroeconomic variables					
	GDP deflator	GDP	Investment	Consumption	S&P Composite P/D ratio
FD	−0.43	0.19	0.14	0.30	0.19
Filtered	−0.22	0.45	0.36	0.52	0.62

Note. The table shows summary statistics of the capital ratio (top panel) and its contemporaneous correlations with the macroeconomic variables (bottom panel). The capital ratio is measured in percentage points. GDP deflator, real GDP, real investment, real consumption are all measured in logarithms. The first row of the correlation panel shows correlations between the capital ratio and the first differences of the macroeconomic variables; the second row shows correlations between the capital ratio and the cyclical components of the macroeconomic variables obtained from the Hamilton filter (Hamilton, 2017).

as the state variable and emphasizes the asset pricing channel. Since uncertainty is one of the many factors that affect the primary dealer capital ratio, this paper can be viewed as a generalization of Eickmeier et al. (2016).

The choice of the primary dealer capital ratio as the state variable is motivated by the intermediary asset pricing literature, which argues that the financial intermediary balance sheet is crucial for determining asset prices and real activities. Stronger financial intermediary balance sheets improves credit creation, as emphasized by Gertler and Karadi (2011), Brunnermeier and Sannikov (2014), Brunnermeier and Sannikov (2016), He and Krishnamurthy (2019), Gertler et al. (2020). Using linear VAR models, Bruno and Shin (2015) and Istiak and Serletis (2017) show that intermediary leverage adjustment also amplifies the effects of monetary policy shocks. An important feature of financial frictions is that the effects of exogenous shocks depend on the financial intermediary capital ratio. Dou et al. (2020) provide a review of incorporating nonlinear dynamics in monetary policy studies. Empirically, Kashyap and Stein (2000) and Kishan and Opiela (2000) provide cross-sectional evidence that the responses of bank lending to monetary policy shocks depend on bank balance sheets.

The financial intermediaries are also crucial for determining asset prices. He and Krishnamurthy (2012), He and Krishnamurthy (2013), Drechsler et al. (2018) show that the asset returns are nonlinear functions of the net wealth of the financial intermediaries. Importantly, the financial intermediaries are the marginal investors in the asset markets in these papers. The time series of the primary dealer capital ratio is constructed by He et al. (2017). They use the variable to show that the primary dealers are pivotal in many asset markets. Shocks to the primary dealer capital ratio possess strong explanatory power of cross-sectional asset returns. Haddad and Muir (2021) show that financial intermediary wealth also predicts aggregate time series of asset prices, especially the heavily intermediated ones. Therefore, they argue that financial intermediary wealth does not simply reflect or correlate with other frictionless asset pricing factors, such as household risk appetite.

The interacted VAR employed in this paper is based on Kilian and Vigfusson (2011) and Koop et al. (1996). The interacted VAR has been employed in the study of energy prices on macroeconomic variables (Kilian and Vigfusson (2011)) and the interaction between uncertainty and interest rate (Aastveit et al., 2013; Caggiano et al., 2017, and Pellegrino, 2021) to generate state-dependent impulse responses. This paper is one of the first to adopt the interacted VAR to study how the monetary policy transmission depends on the financial intermediary capital ratio.

3. Data

The macroeconomic variables are obtained from the FRED database of the Federal Reserve Bank of St. Louis. Inflation is the first difference of the logarithm of the GDP deflator series (GDPDEF), GDP is the real GDP series (GDPC1), real investment is the real gross private domestic investment series (GPDIC1), consumption is the real personal consumption expenditures series (PCECC96), and the nominal interest rate is the 1-year Treasury yield. GDP, investment, and consumption are transformed to natural logs, and the inflation and interest rate are annualized percentage points.

Data for computing the capital ratio are described in He et al. (2017).[1] The capital ratio is computed as the sum of market equity values of the primary dealer holding companies divided by the sum of market equity values and book debt:

$$\mathrm{CAP}_t = \frac{\sum_i \text{Market equity}_{i,t}}{\sum_i \left(\text{Market equity}_{i,t} + \text{Book debt}_{i,t}\right)}$$

where CAP_t is the capital ratio at quarter t and i is a primary dealer.

Fig. 1 plots the time series of the capital ratio along with the U.S. recession dates. The recession dates are obtained from NBER's website. In all recessions, the capital ratio dropped. In four out of the five recessions, the capital ratio dropped to the minimum; and in all expansions since 1990, the capital ratio reached a local maximum. Table 1 shows the correlations between the capital ratio and the contemporaneous macroeconomic variables over 1970: Q1–2017: Q2. The capital ratio is positively correlated with components of GDP and the price-to-dividend ratio of the S&P Composite Index.

[1] Data are available at http://apps.olin.wustl.edu/faculty/manela/data.html.

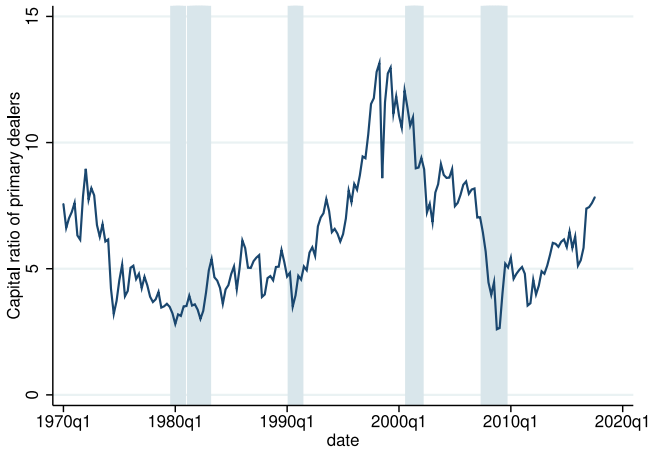

Fig. 1. Time series of the primary dealer capital ratio. The capital ratio is defined as the total market value of equity divided by the sum of the total market value of equity and book debt of the primary dealers. Shaded areas are recessions dates (peaks to troughs) according to NBER's Business Cycle Dating Committee.

4. Instantaneous effects on stock prices

The stock market responds to news instantaneously. When the short-term interest rate changes, investors change their portfolios to exploit the arbitrage opportunities. The extent to which investors change their portfolios depends on their wealth. An unexpected change in the short-term interest rate is a shock to the discount rate. When the level of wealth is higher, the present value of wealth changes more in response to a given unit of discount rate shock. So the investor should trade more, and thus asset prices change more. This section confirms the conjecture that a given unit change in the short-term interest rate leads to larger changes in stock prices when the primary dealer capital ratio is higher.

The short-term interest rate endogenously responds to changes in economic conditions. Hence, the identification hinges on exogenous changes in the short-term interest rate that are not anticipated by the market. The identification strategy exploits the changes in stock prices over short time intervals bracketing FOMC press releases. The underlying assumption is that the event window is so short that the only source of change in the short-term interest rate is the Fed's decision. Following Gorodnichenko and Weber (2016), the monetary policy surprise (MPS) is computed as

$$\mathrm{MPS}_t = \frac{D}{D-t}\left(ff_{t+\Delta t^+} - ff_{t-\Delta t^-}\right)$$

where t is the time when the FOMC issues an announcement, $ff_{t+\Delta t^+}$ is the Fed Funds futures rate shortly after the press release, $ff_{t-\Delta^-}$ is the Fed Funds futures rate shortly before the press release, and D is the number of days in that month. The term $D/(D-t)$ adjusts for the fact that the Fed Funds futures settle on the average effective overnight Fed Funds rate. I exploit the 30-min (tight) and 60-min (wide) event windows. The tight (wide) window starts 10 (15) min before the press releases are issued.

There are concerns that the monetary policy shocks in the event study approach may contain biased information. In the Appendix, I estimate the effects of monetary policy through heteroskedasticity identification à la Rigobon and Sack (2004). The results are consistent with the findings using the event study approach.

Baseline model

I estimate the static regression

$$\Delta\mathrm{SP}_t = \text{constant} + \alpha\mathrm{MPS}_t + \beta\left(\mathrm{CAP}_{t-1} \times \mathrm{MPS}_t\right) + \varepsilon_t, \tag{1}$$

where t denotes the month of the FOMC press release, $\Delta\mathrm{SP}_t$ is the realized percentage return on the S&P 500 index over the event window, MPS_t is the monetary policy surprise, and CAP_{t-1} is the primary dealer capital ratio of the previous month, normalized to zero mean. I use the lagged capital ratio to rule out contemporaneous responses of the capital ratio to the monetary policy shock, but the results are robust to using the contemporaneous capital ratio. All variables are measured in percentage points. The full sample ranges from February 1994 to December 2009, excluding the release of September 17, 2001, with 137 observations.

As a benchmark, I first estimate the model without the interaction term. Table 2 reports the estimates of α based on different samples. The first two columns use the pre-2008 subsample, and the last two columns use the full sample. It appears that monetary policy shocks have stronger effects on stock prices in the pre-crisis sample. The estimates are consistent with the results established in the literature: on average, a 25 basis point unanticipated cut in the interest rate leads to an increase in the S&P 500 realized return by more than one percentage point.

Table 3 presents the estimates of α and β in Eq. (1). Columns (1) and (3) are based on tight event windows. Columns (2) and (4) are based on wide event windows. The coefficient β on the interaction term is the focus of this exercise. If it has the same sign

Table 2
Response of the S&P 500 returns to monetary policy shocks.

	(1) tight, pre-2008	(2) wide, pre-2008	(3) tight, full sample	(4) wide, full sample
Tight surprise	−5.14***		−1.67	
	(1.36)		(2.93)	
Wide surprise		−4.91***		−1.34
		(1.22)		(2.66)
N	117	117	137	137
adj. R^2	0.332	0.274	0.020	0.009

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note. This table reports the estimation results for α in the equation $\Delta \mathrm{SP}_t = \text{constant} + \alpha \mathrm{MPS}_t + \varepsilon_t$. $\Delta \mathrm{SP}_t$ denotes the realized percentage returns of the S&P 500 in an event window bracketing the FOMC press releases, MPS_t denotes monetary policy shocks identified by the changes in the federal funds futures rate in that event window. The wide (tight) window is 60 (30) min and starts 15 (10) min before the press releases are issued. The full sample ranges from February 1994 to December 2009, excluding the release of September 17, 2001, with a total of 137 observations.

Table 3
Response of the S&P 500 returns to monetary policy shocks with interactions.

	(1) tight, pre-2008	(2) wide, pre-2008	(3) tight, full sample	(4) wide, full sample
Surprise	−3.93***	−4.05**	−2.23	−2.23
	(0.95)	(1.22)	(1.52)	(1.59)
Surprise * capital ratio	−1.49**	−1.20*	−2.12**	−1.87*
	(0.47)	(0.53)	(0.76)	(0.78)
N	117	117	137	137
adj. R^2	0.440	0.334	0.294	0.217

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note. This table reports the estimation results for α and β in the equation $\Delta \mathrm{SP}_t = \text{constant} + \alpha \mathrm{MPS}_t + \beta \left(\mathrm{CAP}_{t-1} \times \mathrm{MPS}_t\right) + \varepsilon_t$. $\Delta \mathrm{SP}_t$ denotes the realized percentage returns of the S&P 500 in an event window bracketing the FOMC press releases, MPS_t denotes monetary policy shocks identified by the changes in the federal funds futures rate in that event window, CAP_{t-1} denotes the capital ratio of the previous month. The wide (tight) window is 60 (30) min and starts 15 (10) min before the press releases are issued. The full sample ranges from February 1994 to December 2009, excluding the release of September 17, 2001, with a total of 137 observations.

with α (negative), then a higher capital ratio amplifies the effects of the monetary policy surprise on stock prices. The estimation results suggest that a higher capital ratio amplifies the effects of a monetary policy shock. The estimated state-dependent effect $\hat{\beta}$ is roughly one-third of the linear effect $\hat{\alpha}$ in the pre-2008 sample and almost as large as the linear effect in the full sample. Prior to 2008, within the tight event window, the marginal effect of the monetary policy shock on S&P 500 returns is 1.49 percentage points larger when the capital ratio is one percentage point above average. This implies that if the capital ratio increases by one standard deviation (2.36 percent) relative to the mean, the marginal effect increases by 89% ($1.49 * 2.36/3.93$). The effect is also statistically significant at the 1% significance level. Within the wide event window, a one basis point surprise in the short-term interest rate has 1.20 percentage points additional impacts on realized stock returns when the capital ratio is one percentage point above average.

Sign dependence

Are the results mainly driven by expansionary (negative) shocks, contractionary (positive) shocks, or both? Cieslak (2018) documents that investors make large and persistent errors in short-term interest rate expectations. The largest errors arise in economic downturns and when the Fed lowers the interest rate. Interestingly, the investors tend to overestimate future short rates in those cases, so the monetary policy surprises are negative. Fig. 2 shows that the largest surprises are indeed negative and are in recessions. However, large negative shocks also exist in non-recession periods, while positive shocks exist in recession periods. In this subsection, I investigate whether the effects of the monetary policy surprises on stock returns depend on the signs of the surprises.

Table 4 reports estimates of Eq. (1) without the interaction term on the pre-crisis sample. Furthermore, I split the sample into two subsets: (1) positive monetary policy surprises and (2) negative monetary policy surprises. Observations with zero monetary policy surprises are dropped. Over the 1994–2007 period, the numbers of positive and negative surprises are comparable, with a ratio of 4:5. Since the numbers of zero surprises are different across event windows, the total numbers of wide window surprises and tight window surprises are not equal. I run the regression on the two samples separately. Columns (1) and (2) report the marginal response of the S&P 500 returns to the monetary policy shocks (α in Eq. (1) without the interaction term) on the negative surprise sample. The magnitude of the slope coefficient is larger than that estimated on the full sample. Within the tight event window, a 25 bps unanticipated reduction in the Fed Funds rate increases the S&P 500 return by 1.7 percent. Within the wide event window, a 25 bps unanticipated reduction in the Fed Funds rate increases the S&P 500 return by 1.6 percent. Columns (3) and (4) report the estimates of α on the positive surprise sample. The response of the S&P 500 return to a positive monetary policy surprise is not significantly different from zero. Within the tight event window, an unanticipated 25 bps increase in the Fed Funds rate decreases

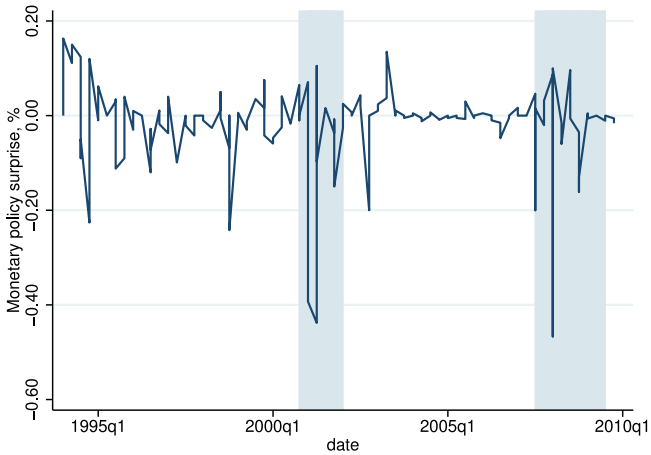

Fig. 2. Monetary policy surprises identified in the tight event window. NBER recession dates are shaded.

Table 4
Response of the S&P 500 returns to monetary policy shocks conditional on signs.

	(1) tight−	(2) wide−	(3) tight+	(4) wide+
Tight surprise	−6.77***		−1.12	
	(1.73)		(1.64)	
Wide surprise		−6.42***		0.81
		(1.39)		(3.93)
N	52	51	42	39
adj. R^2	0.501	0.444	−0.019	−0.024

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note. This table reports the estimation results for α in the equation $\Delta\text{SP}_t = \text{constant} + \alpha\text{MPS}_t + \varepsilon_t$. The equation is estimated separately on the negative and positive shock samples. ΔSP_t denotes the realized percentage returns of the S&P 500 in an event window bracketing the FOMC press releases, MPS_t denotes monetary policy shocks identified by the changes in the federal funds futures rate in that event window. The wide (tight) window is 60 (30) min and starts 15 (10) min before the press releases are issued. The first two columns show the effects of negative monetary policy shocks, while the last two columns show the effects of positive monetary policy shocks. The sample ranges from February 1994 to December 2007, excluding the release of September 17, 2001. The total observations for wide and tight event windows are not equal because zero shocks are excluded.

the S&P 500 return by 0.28 percent. Within the wide event window, an unanticipated 25 bps increase in the Fed Funds rate seems to increase the S&P 500 return by 0.2 percent, but the estimate is very noisy.

Table 5 presents the results of the model with the interaction. Like in the full sample, a high capital ratio amplifies the effects of monetary policy surprises, but the effects are primarily due to negative shocks. When the primary dealer capital ratio is at the mean level, a 25 bps unanticipated reduction in the Fed Funds rate increases the S&P 500 return by more than 1 percent. Additionally, a 1 percent increase in the capital ratio further amplifies the S&P 500 return response by 0.26 (0.35) percent within the wide (tight) event window. Positive monetary policy surprises have limited effects on the S&P 500 returns. Intuitively, when the short-term interest rate turns out to be lower than expected, investors increase their demand for stocks. A higher portfolio weight on stocks exposes the investor's wealth to larger risk. When the capital ratio is low, the investors are more concerned about the downside risk, so they demand fewer stocks than the states when the capital ratio is high. Therefore, the response of realized stock returns to an expansionary monetary policy surprise is smaller when the capital ratio is low.

Financial frictions v.s. expectations

Since the primary dealer capital ratio is closely related to asset prices which are forward-looking, it may simply reflect the market's belief about future economic outcomes. In that case, financial frictions play little role and the response of stock returns to monetary policy surprises simply depend on the market's expectation of future dividend flows. I study the expectation channel by estimating the following regression:

$$\Delta\text{SP}_t = \alpha\text{MPS}_t + \beta_1\left(\text{CAP}_{t-1} \times \text{MPS}_t\right) + \sum_{s=0}^{4} \beta_{2,s}\left(\text{Exp}_{t-1,s} \times \text{MPS}_t\right) + \varepsilon_t, \tag{2}$$

Table 5
Response of the S&P 500 returns to monetary policy shocks conditional on signs and capital ratio.

	(1) tight−	(2) wide−	(3) tight+	(4) wide+
Surprise	−4.09*	−4.42**	−1.92	−0.99
	(1.62)	(1.40)	(1.75)	(3.20)
Surprise * capital ratio	−1.39*	−1.04*	−0.84	−1.52
	(0.52)	(0.47)	(0.79)	(1.22)
N	52	51	42	39
adj. R^2	0.624	0.507	−0.026	0.016

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note. This table reports the estimation results for α and β in the equation ΔSP_t = constant + $\alpha MPS_t + \beta\left(CAP_{t-1} \times MPS_t\right) + \varepsilon_t$. The equation is estimated separately on the negative and positive shock samples. ΔSP_t denotes the realized percentage returns of the S&P 500 in an event window bracketing the FOMC press releases, MPS_t denotes monetary policy shocks identified by the changes in the federal funds futures rate in that event window, CAP_{t-1} denotes the capital ratio of the previous month. The wide (tight) window is 60 (30) min and starts 15 (10) min before the press releases are issued. The first two columns show the effects of negative monetary policy shocks, while the last two columns show the effects of positive monetary policy shocks. The sample ranges from February 1994 to December 2007, excluding the release of September 17, 2001. The total observations for wide and tight event windows are not equal because zero shocks are excluded.

where $Exp_{t-1,s}$ denotes the market's time-$t-1$ expectation of a future macroeconomic outcome in period t+s. I focus on expected GDP growth and corporate profit growth that are taken from the Survey of Professional Forecasters published by the Federal Reserve Bank of Philadelphia.

I take the mean forecasts for GDP growth and corporate profit growth as the measures for expectations. The survey is taken each quarter. In each survey conducted in quarter t, the forecasters are asked to forecast a set of macroeconomic variables for the next four quarters $t+1, \ldots, t+4$. Since the survey is conducted before the macroeconomic data for quarter t are available, the forecasters are also asked to nowcast the variables for quarter t. In the regression, I include the nowcast, the four forecasts, and the realized value of the variable in quarter t as measurements of the market's expectation.

Table 6 compares how the S&P 500 responses to monetary policy surprises depend on expected GDP growth and the capital ratio. In columns (1) and (3), I replace the interaction term in Eq. (1) with interactions between the monetary policy surprise and expected GDP growth. The purpose is to investigate whether the expectation measures lead to nonlinear monetary policy transmission in a way similar to the primary dealer capital ratio. Consistent with the benchmark linear model, the slope coefficient on the monetary policy surprise suggests that a 25 bps unanticipated reduction in the short-term interest rate raises the realized S&P 500 return by roughly 1 percent. Unlike the primary dealer capital ratio, expectations of GDP growth do not seem to amplify or dampen the responses of S&P 500 to monetary policy surprises. In columns (2) and (4), I estimate Eq. (2) to run a horse race between expected GDP growth and the capital ratio. Controlling for expected GDP growth, a one percentage point increase in the capital ratio increases the S&P 500 response to a monetary policy shock by 1.35 percent within the tight event window and 1.75 percent within the wide event window.

Table 7 compares how the S&P 500 responses to monetary policy surprises depend on expected corporate growth and the capital ratio. Similar to expected GDP growth, there is little evidence that expected corporate profit growth amplifies or dampens the responses of S&P 500 returns to monetary policy surprises. Controlling for expected corporate profit growth, a 1 percent increase in the capital ratio amplifies the response of S&P return to any given level of expansionary monetary policy shock by 1.10 percent within the tight event window and 1.09 percent in the wide event window.

It does not seem that expectations of future dividend flows have any significant impact on the responses of S&P 500 returns to monetary policy surprises. Instead, an increase in the capital ratio significantly amplifies the effects of the monetary policy shocks on stock returns. The horse race between the market expectations and the primary dealer capital ratio suggests that the capital ratio does not simply reflect the market expectation of future macroeconomic outcomes.

Household wealth v.s. intermediary wealth

In traditional business cycle models, the financial sector is only an accounting device, and its wealth has no direct impact on asset prices. Households are marginal in the asset markets, and their consumption-to-wealth ratio captures risk aversion in the market (Lettau and Ludvigson, 2001a), so it is crucial for determining asset prices. Suppose the primary dealer capital ratio only reflects risk aversion in the market. In that case, we should expect the household consumption-to-wealth ratio to affect the responses of stock returns to monetary policy surprises similar to the primary dealer capital ratio. I investigate whether the household consumption-to-wealth ratio significantly impacts the S&P 500 response to monetary policy surprises. Although household consumption-to-wealth is not observable, Lettau and Ludvigson (2001a) show that the deviation from the shared trend in consumption c, asset wealth a, and labor income y captures salient predictive power of the consumption-to-wealth ratio for stock returns.

Denoting the deviation from the trend as cay, Table 8 presents the impact of cay on the responses of S&P 500 returns to monetary policy surprises. Columns (1) and (3) show that the interaction between the surprise and cay is not statistically significant, and the

Table 6
Capital ratio and expected GDP growth serving as state variables.

	(1) tight, pre-2008	(2) tight, pre-2008	(3) wide, pre-2008	(4) wide, pre-2008
Surprise	−3.71***	−2.84**	−4.39***	−3.42**
	(0.98)	(0.97)	(1.16)	(1.19)
Surprise* E. GDP growth$_t$	−1.31	−0.72	−0.54	−0.20
	(1.77)	(1.53)	(2.37)	(2.13)
Surprise* E. GDP growth$_{t+1}$	7.95*	3.28	2.93	−2.86
	(3.54)	(2.93)	(3.39)	(3.57)
Surprise* E. GDP growth$_{t+2}$	−7.29	−4.29	−1.84	2.76
	(4.97)	(4.24)	(6.57)	(5.57)
Surprise* E. GDP growth$_{t+3}$	−1.73	−2.55	4.23	2.22
	(3.97)	(3.50)	(5.33)	(4.62)
Surprise * E. GDP growth$_{t+4}$	6.29	6.99	−2.71	−1.19
	(5.55)	(4.34)	(5.33)	(3.67)
Surprise * actual GDP growth	0.29	0.44	0.42	0.77
	(0.60)	(0.51)	(0.87)	(0.75)
Surprise * capital ratio		−1.35**		−1.75**
		(0.42)		(0.63)
N	117	117	117	117
adj. R^2	0.391	0.448	0.267	0.355

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note. This table reports the estimation results for α, β_1, and $\boldsymbol{\beta}_2$ in the equation $\Delta\mathrm{SP}_t = \mathrm{constant} + \alpha\mathrm{MPS}_t + \beta_1\left(\mathrm{CAP}_{t-1} \times \mathrm{MPS}_t\right) + \mathrm{MPS}_t \cdot \boldsymbol{E}'_{t-1}\boldsymbol{\beta}_2 + \epsilon_t$. $\Delta\mathrm{SP}_t$ denotes the realized percentage returns of the S&P 500 in an event window bracketing the FOMC press releases, MPS_t denotes monetary policy shocks identified by the changes in the federal funds futures rate in that event window, CAP_{t-1} denotes the capital ratio of the previous month, $\boldsymbol{E}_{t-1}$ is a vector of forecasts for GDP growth at different horizons. The wide (tight) window is 60 (30) min and starts 15 (10) min before the press releases are issued. The sample ranges from February 1994 to December 2007, excluding the release of September 17, 2001.

Table 7
Capital ratio and expected corporate profit growth serving as state variables.

	(1) tight, pre-2008	(2) tight, pre-2008	(3) wide, pre-2008	(4) wide, pre-2008
Surprise	−2.87*	−2.17*	−4.96***	−4.23**
	(1.15)	(1.08)	(1.27)	(1.27)
Surprise * E. corp. profit growth$_t$	0.45	0.45*	−0.13	−0.12
	(0.27)	(0.22)	(0.27)	(0.23)
Surprise * E. corp. profit growth$_{t+1}$	−0.04	−0.25	0.27	0.02
	(0.44)	(0.37)	(0.48)	(0.43)
Surprise * E. corp. profit growth$_{t+2}$	−0.12	−0.39	0.54	0.30
	(0.56)	(0.54)	(0.74)	(0.69)
Surprise * E. corp. profit growth$_{t+3}$	1.14*	0.97*	0.72	0.58
	(0.51)	(0.44)	(0.57)	(0.53)
Surprise * E. corp. profit growth$_{t+4}$	−1.04	−0.42	−1.53	−0.96
	(0.74)	(0.73)	(0.98)	(0.92)
Surprise * actual corp. profit growth	−0.02	−0.00	−0.02	0.01
	(0.04)	(0.03)	(0.05)	(0.05)
Surprise * capital ratio		−1.10***		−1.09**
		(0.27)		(0.41)
N	117	117	117	117
adj. R^2	0.441	0.476	0.330	0.361

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note. This table reports the estimation results for α, β_1, and $\boldsymbol{\beta}_2$ in the equation $\Delta\mathrm{SP}_t = \mathrm{constant} + \alpha\mathrm{MPS}_t + \beta_1\left(\mathrm{CAP}_{t-1} \cdot \mathrm{MPS}_t\right) + \mathrm{MPS}_t \cdot \boldsymbol{E}'_{t-1}\boldsymbol{\beta}_2 + \epsilon_t$. $\Delta\mathrm{SP}_t$ denotes the realized percentage returns of the S&P 500 in an event window bracketing the FOMC press releases, MPS_t denotes monetary policy shocks identified by the changes in the federal funds futures rate in that event window, CAP_{t-1} denotes the capital ratio of the previous month, $\boldsymbol{E}_{t-1}$ is a vector of forecasts for corporate profit growth at different horizons. The wide (tight) window is 60 (30) min and starts 15 (10) min before the press releases are issued. The sample ranges from February 1994 to December 2007, excluding the release of September 17, 2001.

magnitude of the coefficient is also small. Adding the interaction between the monetary policy surprise and the capital ratio, columns (2) and (4) show that a higher capital ratio significantly amplifies the stock return responses to monetary policy shocks, but cay still has no significant effects. The magnitudes of the coefficients on monetary policy surprise and its interaction with the capital ratio are consistent with the baseline results in Table 3. When the capital ratio is 1 percent above average, the response of S&P 500 return to a monetary policy surprise is 1.4 percentage points larger.

The literature finds that household consumption-to-wealth ratio seems to perform well in explaining cross-section and time series of stock returns (e.g., Lettau and Ludvigson (2001a), Lettau and Ludvigson (2001b)). Nevertheless, the results in Table 8 suggest that the cay does not seem to be associated with the nonlinear responses of the S&P 500 returns to monetary policy surprises. Therefore, the nonlinear responses of the S&P 500 are not simply related to the time-varying risk appetite of households. The primary dealer

Table 8
Capital ratio and household consumption-wealth ratio serving as state variables.

	(1) tight, pre-2008	(2) tight, pre-2008	(3) wide, pre-2008	(4) wide, pre-2008
Surprise	−6.95***	−3.48	−5.17*	−2.63
	(1.63)	(2.92)	(2.61)	(3.48)
Surprise * cay	1.28	0.06	0.20	−0.55
	(0.69)	(1.37)	(1.37)	(1.59)
Surprise * capital ratio		−1.43*		−1.40*
		(0.64)		(0.70)
N	117	117	117	117
adj. R^2	0.350	0.448	0.268	0.366

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note. This table compares the effects of household's consumption-to-wealth ratio and capital ratio of the primary dealers on the responses of S&P 500 to monetary policy surprises. The wide (tight) window is 60 (30) min and starts 15 (10) min before the press releases are issued. The sample ranges from February 1994 to December 2007, excluding the release of September 17, 2001, with a total of 117 observations. The variable cay denotes the household consumption-to-wealth ratio in Lettau and Ludvigson (2001a).

capital ratio reflects the financial intermediary sector's unique features that contribute to the nonlinear effects of monetary policy transmission.

5. Dynamic effects on real variables

The financial market and macroeconomic quantities are closely related. High asset prices prop up investment, which is emphasized in the financial accelerators à la Bernanke et al. (1999), Gertler and Kiyotaki (2010), Gertler and Karadi (2011) and Brunnermeier and Sannikov (2014). If a high capital ratio amplifies the effects of monetary policy surprises on stock prices, it should also amplify the effects on real variables. In this section, I use VAR models to study the dynamic effects of monetary policy shocks. I interact the primary dealer capital ratio with the policy interest rate to investigate whether the dynamic effects of the monetary policy shock depend on the level of the capital ratio.

Interacted VAR

The interacted VAR is a standard linear VAR augmented by $\text{CAP}_{t-l} \times \text{interest rate}_{t-l}$ in each equation:

$$\boldsymbol{Y}_t = \boldsymbol{A}_0 + \sum_{l=1}^{p} \boldsymbol{A}_l \boldsymbol{Y}_{t-l} + \sum_{l=1}^{p} B_{t-l}\text{CAP}_{t-l} \times \text{interest rate}_{t-l} + \boldsymbol{u}_t. \tag{3}$$

$\boldsymbol{Y}_t$ is a vector of macroeconomic and financial variables that includes the capital ratio and the interest rate. Other components of $\boldsymbol{Y}_t$ shall be evident from the impulse response figures. The linear terms and the interaction terms have the same number of lags. $\boldsymbol{u}_t$ is a vector of reduced-form shocks with an unknown variance-covariance matrix. The structural monetary policy shocks are identified using high frequency surprises around monetary policy announcements as external instruments in the spirit of Gertler and Karadi (2015). The proxy identification approach makes the VAR exercise results comparable with the event study results. Following the practice of Gertler and Karadi (2015), the interest rate is measured by the 1-year Treasury rate and the sample ranges from 1979: Q3 to 2012: Q2. The interaction terms allow the capital ratio to endogenously amplify or dampen the effects of a monetary policy shock.

Following Kilian and Vigfusson (2011), the generalize impulse response function (GIRF) of the interacted VAR is defined as

$$I_{\boldsymbol{Y}}\left(h, \varepsilon_t, \omega_{t-1}\right) = \mathbf{E}\left(\boldsymbol{Y}_{t+h} | \varepsilon_t = \delta, \omega_{t-1}\right) - \mathbf{E}\left(\boldsymbol{Y}_{t+h} | \varepsilon_t = 0, \omega_{t-1}\right), \tag{4}$$

where h is the number of periods after the shock, ε_t is the structural monetary policy shock, δ is the size of the shock. The initial state, $\omega_{t-1} = \left(\boldsymbol{Y}_{t-1}, \ldots, \boldsymbol{Y}_{t-p}\right)$, consist of the full set of lagged variables (not just the interacted variables) of the VAR. I refer to ω_{t-1} as the "initial condition", and $t-1$ as the "initial date" of the GIRF. In the estimation, this amounts to estimating a GIRF for each observation. GIRFs corresponding to each initial state are averaged into two subsets: the "low capital ratio" state and the "high capital ratio" state. The "low capital ratio" state is defined as the state in which the primary dealer capital ratio is below the 10th percentile of the capital ratio time series. The cutoff threshold is chosen such that the Great Recession period belongs to the low capital ratio state. This state also contains periods in some previous recessions, such as those in the early 1980s. The "high capital ratio" state includes the rest of the observations.[2] Formally, I estimate and plot the average GIRF for the high and low capital ratio states:

$$I_{\boldsymbol{Y}}\left(h, \varepsilon_t, \Omega\right) = \int_{\omega_{t-1} \in \Omega} I_{\boldsymbol{Y}}\left(h, \varepsilon_t, \omega_{t-1}\right) \mathrm{d}P\left(\omega_{t-1}\right).$$

[2] The definition of the high capital ratio state is intended to represent the non-crisis episodes. We can also define the high capital ratio state as, for example, the state in which the primary dealer capital ratio is above the 90th percentile. The differences in the impulse responses will be more stark under such definition. Appendix D provides an example of GIRFs conditioning on different levels of capital ratio.

The conditional expectations are estimated by Monte Carlo simulations, as described in Appendix B.

Notice that the coefficients of the interacted VAR are independent of the state and time and are estimated using the full sample. Therefore, the estimates of the coefficients are independent of the classification of the high and low capital ratio states. The GIRF given each initial condition ω_{t-1} is pinned down by the estimates of coefficients, so it is also independent of the classification of high versus low capital ratio states. The classification only affects the average GIRFs.

Why interacted var? The interacted VAR allows the GIRF to depend on the realizations of the endogenous variables along the entire path of the response. This feature is crucial for investigating how the endogenous interactions between the capital ratio and the short-term interest rate amplify the effects of monetary policy shocks. For example, suppose that the interest rate shock hits at time t. The real variables respond at $t+1$. The capital ratio, which is the result of the primary dealer portfolio choice decisions and asset price reactions, also endogenously responds to changes in the real variables at $t+1$, and thus the interaction between the capital ratio and the interest rate endogenously changes at $t+1$. This process continues throughout the impulse response function. Therefore, the endogenous changes in the capital ratio in response to changes in the real variables are essential for the nonlinear monetary transmission. In simpler setups such as putting a dummy variable for high/low capital ratio states in front of the slope coefficients or the exogenous interacted VAR model à la Aastveit et al. (2013), the endogenous responses of the state variable (capital ratio) after the shock are not explicitly incorporated in the computation of impulse response functions.

Baseline results

The left column of Fig. 3 plots the average generalized impulse response functions to a negative one standard deviation interest rate shock in the two states. In the Appendix, I also show the responses to a positive one standard deviation interest rate shock. The solid blue line is the point estimate of the average GIRF in the low capital ratio state, while the solid red line is the point estimate of the average GIRF in the high capital ratio state. The 95% and 90% bootstrap confidence intervals are illustrated with dashed and dotted lines correspondingly. The interest rate shocks in both states are of the same magnitude. On impact, the 1-year interest rate falls by 29 basis points regardless of the initial value of the capital ratio. The nominal price level has almost identical responses to the interest rate shock in both states. However, the real variables respond more strongly and persistently to the interest rate shock in the high capital ratio state than in the low capital ratio state. GDP increases by 0.30% in the low capital ratio state and 0.46% in the high capital ratio state. Investment increases by 1.55% in the low capital ratio state and 1.82% in the high capital ratio state. The difference in consumption responses is more pronounced. In the low capital ratio state, consumption increases by 0.15%, but in the high capital ratio state, it increases by 0.50%. The primary dealer capital ratio increases by 0.26 percentage points in response to the monetary policy shock, and there seems to be little difference in the responses across the two states. The right column of Fig. 3 shows the difference in the GIRFs ("low state" minus "high state"). The 95% and 90% confidence intervals for the difference are illustrated with dashed and dotted lines. For GDP, investment, and consumption, the differences are all statistically significant at the 5% significance level.

Interestingly, the nonlinearities in the impulse responses do not seem to be due to the differential responses of the capital ratio. The impulse responses of the capital ratio in the two states are very close to each other, despite a slightly stronger response in the high capital ratio state. In the interacted VAR, the interest rate shock is multiplied by the *level* of the state variable. Thus, both the initial level and the impulse response of the capital ratio could lead to nonlinear effects of the monetary policy shock. It appears that the initial level of the capital ratio is the key to the state-dependent patterns of the impulse responses.

Responses of financing costs

As Gilchrist and Zakrajšek (2012) show, the spread between corporate bond yields and the risk-free rate possesses considerable predictive power for business cycle fluctuations. A widening of the spread increases corporate borrowing costs and depresses real activities. On the other hand, He et al. (2017) show that the primary dealers are pivotal intermediaries in the corporate bond market. So the primary dealer capital ratio should affect the corporate bond credit spread responses to monetary policy shocks. Using the interacted VAR, I investigate whether the excess bond premium[3] in Gilchrist and Zakrajšek (2012) responds more strongly to a monetary policy shock when the primary dealer capital ratio is high. The exercise utilizes monthly data. Fig. 4 shows the generalized impulse responses to a negative one standard deviation interest rate shock along with the differences between the low and high capital ratio state responses. The high capital ratio state impulse responses of real activities are initially weaker than the low state impulse responses, but become stronger after 20 months. The time of reversal is consistent with the quarterly impulse responses (around 7 quarters after impact). However, the impulse response of the excess bond premium is always stronger when the capital ratio is initially high. The excess bond premium decreases by 6 basis points following the expansionary interest rate shock in the high capital ratio state. In the low capital ratio state, the excess bond premium only decreases by 3 basis points. The difference in the excess bond premium responses across the two states is significant at the 10% level. In the high capital ratio state, an expansionary monetary policy shock more effectively reduces corporate borrowing costs. Therefore, real activities expand more, as the responses of industrial production and consumption show.

[3] The excess bond premium is the credit spread on corporate bonds minus the default premium.

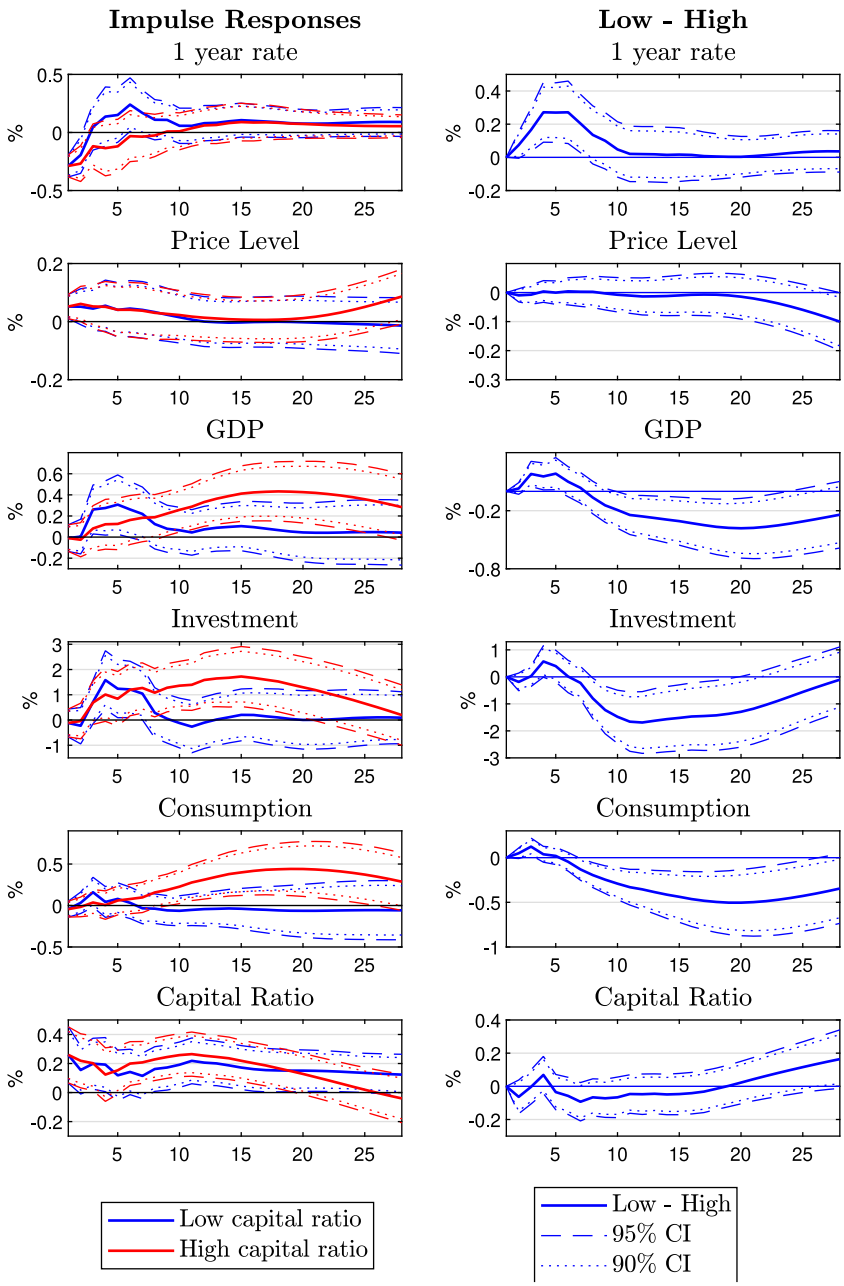

Fig. 3. GIRFs to a negative interest rate shock, high initial capital ratio v.s. low initial capital ratio. The left column shows GIRFs to a −1 standard deviation interest rate shock with 95% and 90% confidence intervals. The right column shows the difference between responses (low capital state minus high capital state). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Normalizing the path of interest rates

In the high capital ratio state, the interest rate path after the shock displays a stronger reaction. Could it be that the paths of the real variables display a stronger reaction simply because they endogenously respond to a different interest rate path? To rule this out, the entire interest rate path is normalized by feeding into the VAR in the low capital ratio state interest rate shocks such that the median path of the interest rate in the high capital ratio state is identical to the one in the low capital ratio state. The following algorithm is used to normalize the interest rate path:

1. Compute the unnormalized high capital ratio state and low capital ratio state impulse responses. Adjust the interest rate shocks along the impulse response path according to the following steps.

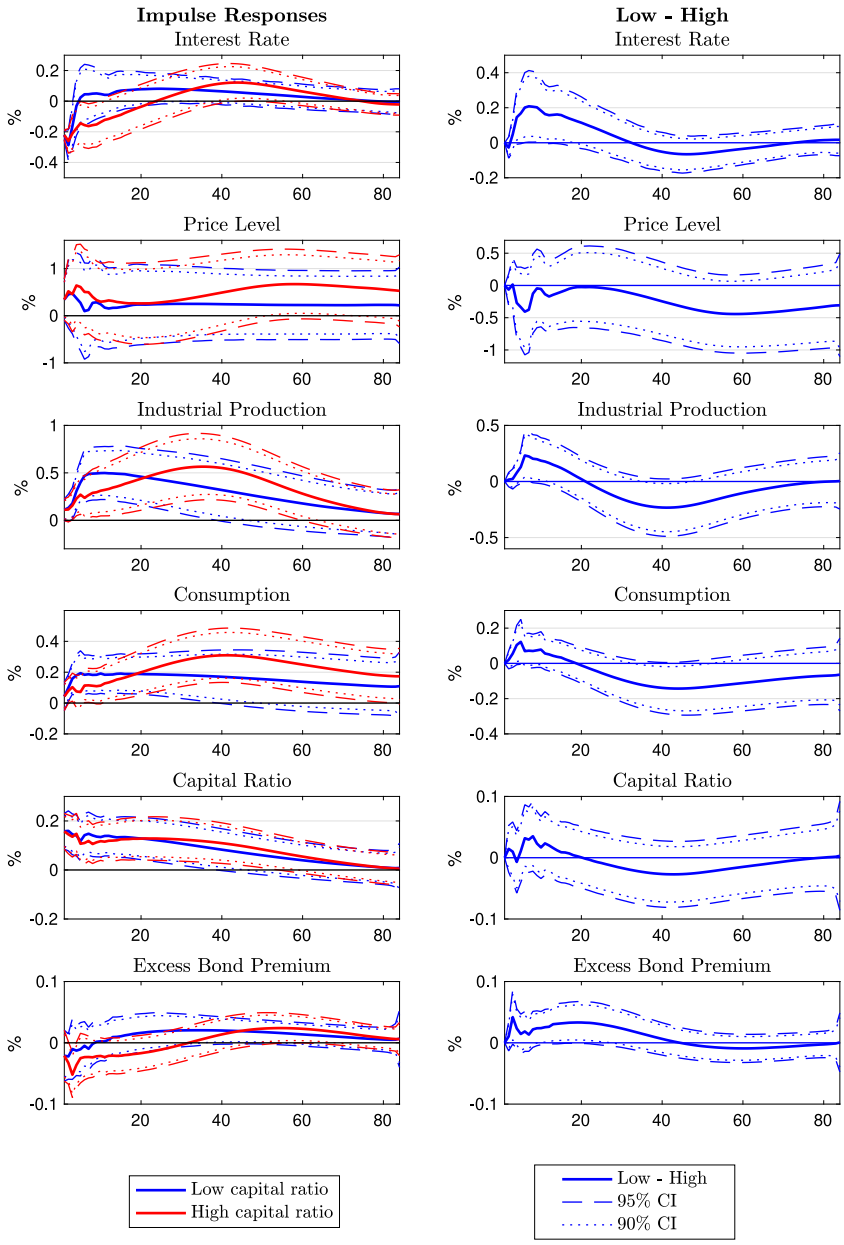

Fig. 4. GIRFs to a negative interest rate shock, where the excess bond premium is included. The left column shows GIRFs to a −1 standard deviation interest rate shock with 95% and 90% confidence intervals. The right column shows the difference between responses (low capital state minus high capital state). The sample frequency is monthly.

2. Pick the high capital ratio state impulse response as the benchmark. Feed in the initial shock to the low capital ratio state initial state.
3. For each $h \geq 2$, compute $Y_{t+h}^{imp} = Y_{t+h-1}^{imp}\boldsymbol{\beta} + e_{t+h}^{imp}$ and $Y_{t+h}^{noimp} = Y_{t+h-1}^{noimp}\boldsymbol{\beta} + e_{t+h}^{noimp}$. The superscripts *imp* and *noimp* denote the paths with and without the interest rate shocks, respectively. The impulse response at horizon h is obtained by $\tilde{I}(h) = Y_{t+h}^{imp} - Y_{t+h}^{noimp}$. To match the benchmark, set the value of e_{t+h}^{imp} such that $\tilde{I}_{\text{policy rate}}(h) = I_{\text{policy rate}}^{benchmark}(h)$.

Note that this algorithm estimates

$$\tilde{I}_y\left(h, \varepsilon_t, \omega_{t-1}\right) = \mathbf{E}\left[y_{t+j}\middle|\omega_{t-1}, \varepsilon_t = 1, \varepsilon_{t+1} = \varepsilon^1, \varepsilon_{t+2} = \varepsilon^2, \ldots, \varepsilon_{t+h} = \varepsilon^h\right] - \mathbf{E}\left[y_{t+j}\middle|\omega_{t-1}, \varepsilon_t = 0\right],$$

where $\varepsilon^1, \varepsilon^2, \ldots, \varepsilon^h$ are such that $\tilde{I}_{\text{policy rate}}(h, 1, \text{low capital ratio}) = I_{\text{policy rate}}(h, 1, \text{high capital ratio})$. The definition of the generalized impulse response in Eq. (4) only specifies the shock at period t in the conditioning information, so $\tilde{I}$ may not equal to I.

Fig. 5 plots the normalized generalized impulse responses. Overall, the high-state impulse responses of the real variables have larger magnitudes than those in the low state, especially for investment and consumption. In the baseline model, the high state investment response is 1.69 percentage points higher than its low state response. The high state consumption response is 0.50 percentage points higher than the low state response. In the normalized interest rate model, the high state investment response is 0.97 percentage points higher than the low state response. The high state consumption response is 0.34 percentage points higher than the low state response. Both numbers are more than 50% of the their counterparts in the baseline model. Therefore, the differences in the initial capital ratio is more important than the differences in the interest rate paths for the nonlinear monetary policy transmission. However, the differences for the GDP and investment impulse responses are not significant at the 10% significance level, suggesting that some of the macro effects in the baseline are indeed attributable to the more persistent reaction of the interest rate to the shock when the capital ratio is initially high.

Low capital ratio vs. ZLB

A concern is that the "low capital ratio" state is intertwined with the "zero lower bound" (ZLB) period when the conventional monetary policy is relatively ineffective. Therefore, the fact that the monetary policy is less effective in the "low capital ratio" state might be mainly caused by the zero lower bound. To investigate whether the ZLB period is the primary cause of the difference in the monetary transmission, I redo the classification as "normal times" versus "low interest rate period". The latter are the periods in which the interest rate is within the lowest 10 percent of the sample, and the former consists of the remaining periods. The individual state GIRFs, are averaged according to the new classifications. Fig. 6 plots the average GIRFs in normal times and the low interest rate state. The point estimates of the real variable responses in the two states almost coincide with each other in the first 10 to 15 quarters after the shock. If anything, the real variables show stronger responses to the interest rate shock when the initial interest rate is low. However, the differences shown in the right column of Fig. 6 are not statistically significant. Such patterns are in sharp contrast to the fact that real variables show weaker responses to the interest rate shock when the initial capital ratio is low. Therefore, there is little evidence that the ZLB is the primary driving force of the weak effects of monetary policy in the low capital ratio state.

Book value of the capital ratio

Empirically, the capital ratio can be measured using market values or using book values. Whether the relevant empirical measure of the capital ratio is at the book or market values depends on the context and the question being addressed. Market values have to do with how much the bank is worth to its claim holders, and it matters for investment decisions, corporate takeovers, or the sale of new ownership stakes. The market capital ratio is also an essential determinant of asset returns in intermediary asset pricing models, such as Gertler and Kiyotaki (2010), Gertler and Karadi (2011), He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014). On the other hand, what matters for the bank lending decisions is book leverage. How does the book capital ratio affect the nonlinear monetary policy transmission?

To investigate the role of the book capital ratio in the nonlinear monetary policy transmission, I replace the HKM capital ratio with the book capital ratio in the interacted VAR, keeping other variables unchanged. The book capital ratio is the capital ratio of the holding companies in the Federal Reserve Board's Z.1 table. The choice is because the HKM capital ratio is computed at the holding company level. The correlation between the market and book capital ratio series is 0.57. Fig. 7 plots the generalized impulse responses to a −1 standard deviation monetary policy shock, where the policy rate interacts with the holding companies' book value capital ratio. The impulse responses of the real variables in the high capital ratio state have larger magnitudes than those in the low capital ratio state. However, the differences in the impulse responses are much smaller than those in the baseline model. For example, consumption increases by 0.46% in the high book capital ratio state and 0.25% in the low book capital ratio state. The high state response is 1.8 times as large as that in the low state. When the market capital ratio serves as the state variable, the high state consumption response is more than 3 times as large as the low state response. The right column of Fig. 7 shows the differences between the low state impulse responses and the high state impulse responses. The solid lines are point estimates; the dashed lines and dotted lines denote 95% and 90% confidence intervals. All the confidence intervals contain zero, indicating an insignificant difference in the impulse responses between the two states. Therefore, the primary dealer capital ratio measured by the market value has stronger impacts on monetary policy transmission than the book value.

The primary dealer capital ratio is procyclical, and the leverage is countercyclical. However, Adrian and Shin (2014) argue that the financial intermediary leverage is procyclical. The discrepancy is most likely due to compositional differences. Adrian and Shin (2014) focus on the broker–dealers in the Federal Reserve Flow of Funds data, which consists of standalone U.S. broker–dealers and broker–dealer subsidiaries of conglomerates. The primary dealer capital ratio in this paper is computed at the holding company level. If internal capital flow is essential for financial intermediary activities, the holding company capital ratio may be a better measure of financial soundness. He et al. (2017) show that the capital ratio at the holding company has superior asset pricing performance than the subsidiary capital ratio.

Next, I investigate two channels for the state-dependent monetary policy transmission. (1) A high capital ratio is related to low risk premia, which determine the household and corporate financing costs, and thus affect real activities. (2) The book capital

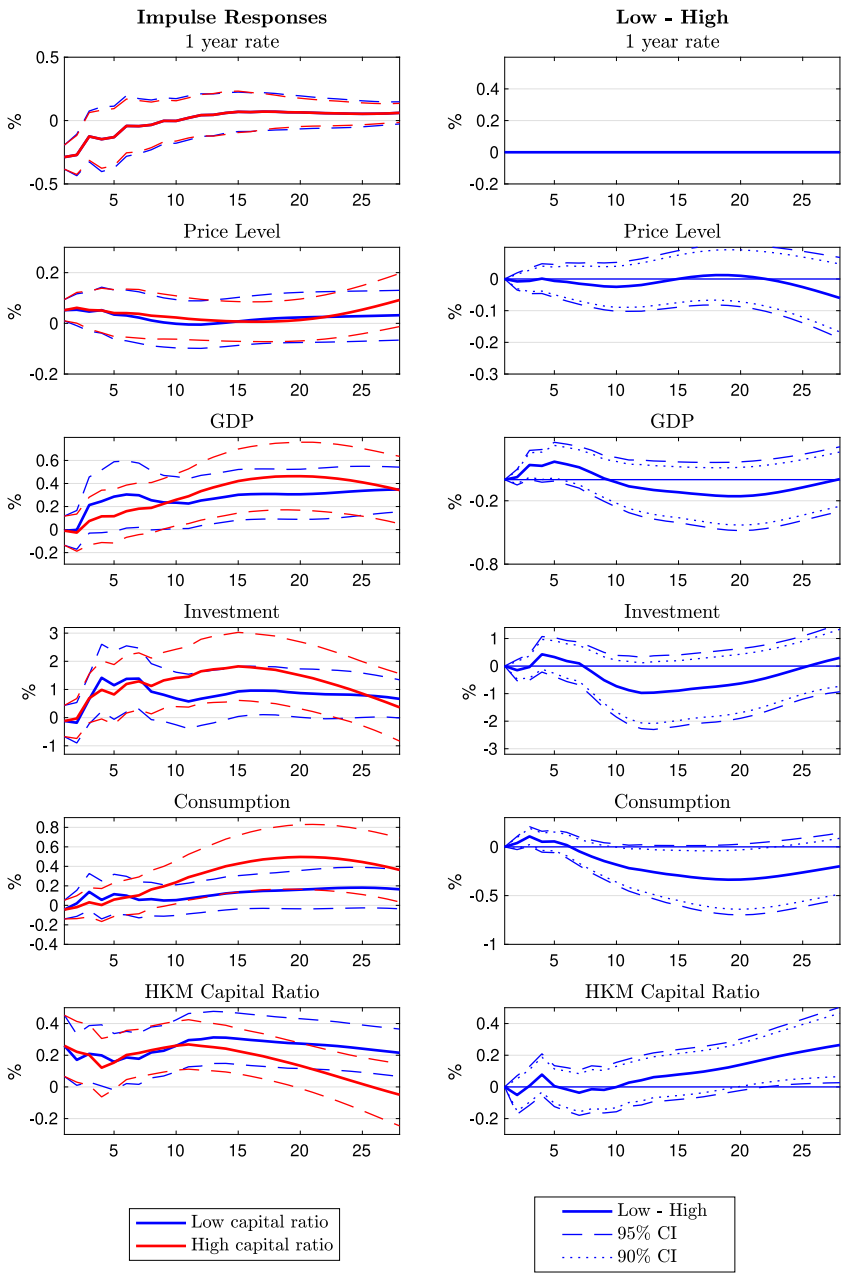

Fig. 5. Normalized general impulse responses to a negative interest rate shock. The entire interest rate path in the low capital ratio state is normalized by feeding into the VAR interest rate shocks such that the point estimate of the interest rate average impulse response in the high capital ratio state is identical to the one in the low capital ratio state. The left column shows GIRFs to a −1 standard deviation interest rate shock with 95% and 90% confidence intervals. The right column shows the difference between responses (low capital state minus high capital state).

ratio matters for bank lending, affecting real activities such as investment and consumption. To investigate the roles of these two channels in determining the nonlinearity of monetary policy transmission, I use asset returns and bank loans as the state variable in the interacted VAR and investigate the state-dependent impulse responses. Asset returns are measured by the price-to-dividend ratio (P/D ratio) of the S&P Composite Stock Price Index.[4] The P/D ratio is used as a measure of expected asset returns in the asset pricing literature, such as Muir (2017). The correlation between the HKM capital ratio and the S&P 500 P/D ratio is 0.81. Bank

[4] The data are obtained from Robert Shiller's website: http://www.econ.yale.edu/$\protect$\relax\svsim$$shiller/data.htm.

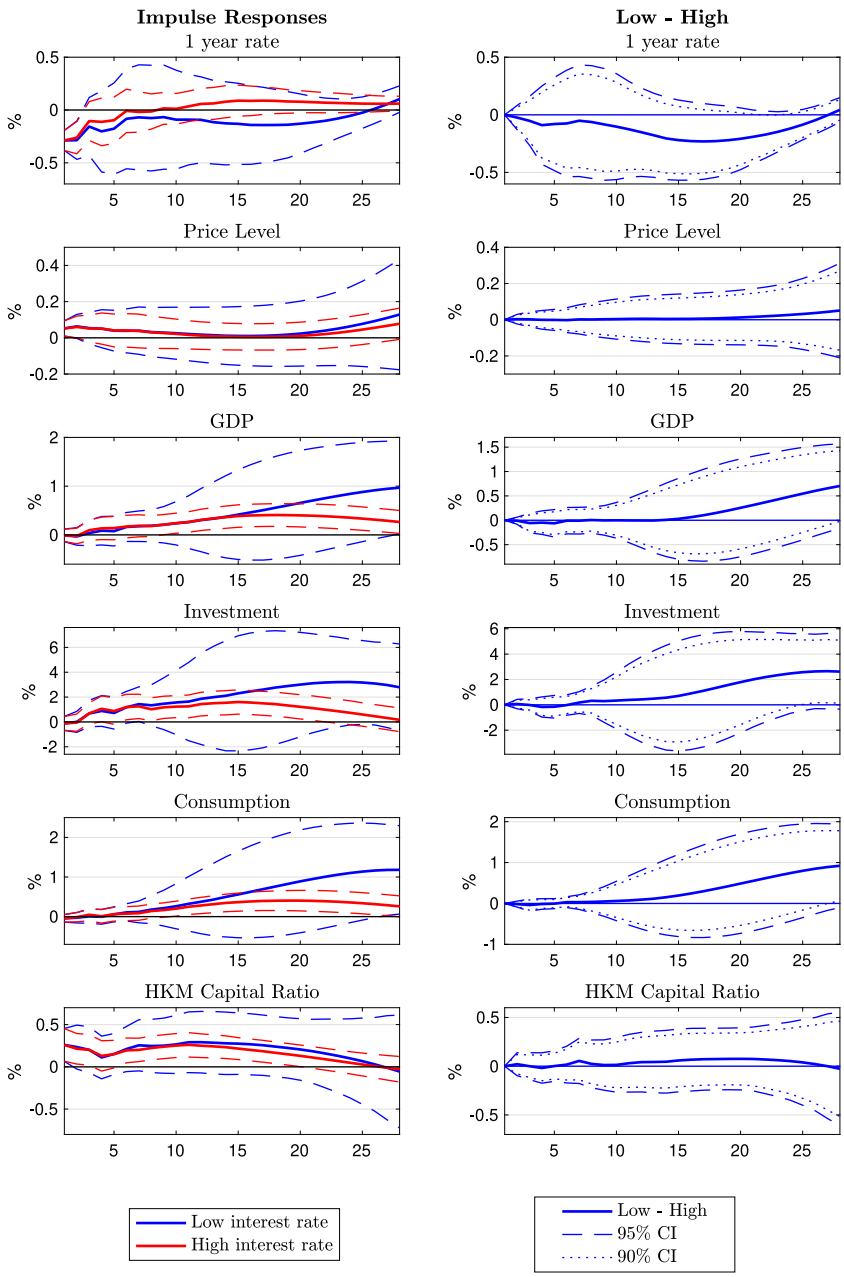

Fig. 6. GIRFs to a negative interest rate shock, non ZLB state v.s. ZLB state. The left column shows GIRFs to a −1 standard deviation interest rate shock with 95% and 90% confidence intervals. The "low interest rate" state represents the ZLB state, and the "high interest rate" state represents the non-ZLB state. The right column shows the difference between responses (ZLB state minus non-ZLB state).

loans are measured as commercial and industrial loans by all commercial banks in the U.S., taken from the H.8 table of the Board of Governors of the Federal Reserve System.

First, I interact the 1-year interest rate with the P/D ratio in model (3). Muir (2017) shows that a high P/D ratio indicates a low expected return and risk premium, suggesting a booming asset market. Since the HKM capital ratio is also strongly procyclical, a high P/D ratio is consistent with a high market value of the capital ratio. Fig. 8 shows the state-dependent impulse responses to a −1 standard deviation interest rate shock and the differences between the low and high P/D ratio state impulse responses. The impulse responses have similar shapes and magnitudes with those in the baseline model, suggesting that the amplification effects of the primary dealer capital ratio is likely to be associated with low levels of the risk premia on impact.

Second, I interact the 1-year interest rate with the loan growth rate, which is measured by the first difference of the log level of bank loans. Fig. 9 shows the state-dependent impulse responses to a −1 standard deviation interest rate shock and the differences

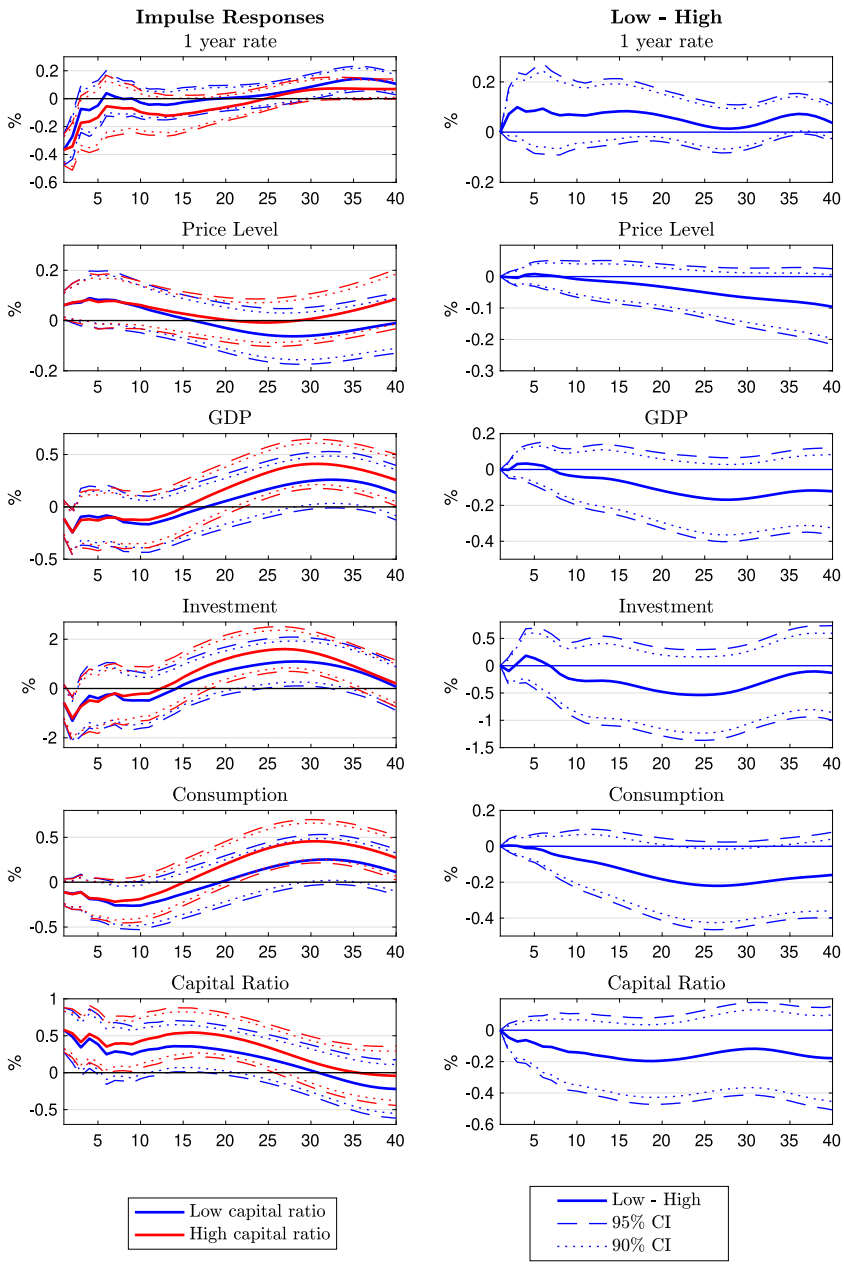

Fig. 7. GIRFs to a negative interest rate shock, with the book capital ratio as the state variable. The capital ratio is computed using data from FRB Z.1 table, following the method in Adrian et al. (2014). The left column shows GIRFs to a −1 standard deviation interest rate shock with 95% confidence intervals. The right column shows the difference between responses (low capital state minus high capital state).

between the low and high loan growth state impulse responses. Loan growth is positively correlated with the book capital ratio with a correlation coefficient of 0.26, corroborating that a high book capital ratio leads to more bank lending. The impulse responses in the high loan growth state are indistinguishable from those in the low loan growth state. The patterns of the impulse responses are also wildly different from those in the baseline model. Therefore, loan growth does not seem to be the main channel for the state-dependent monetary policy transmission in this paper.

In summary, the market value of capital ratio seems more important in determining the state-dependent effects of monetary policy transmission investigated in this paper, at least in aggregate time series. Monetary policy has stronger effects on real activities because the asset prices are higher and the risk premia are lower in the high capital ratio state, instead of the fact that banks lend more when they are well-capitalized.

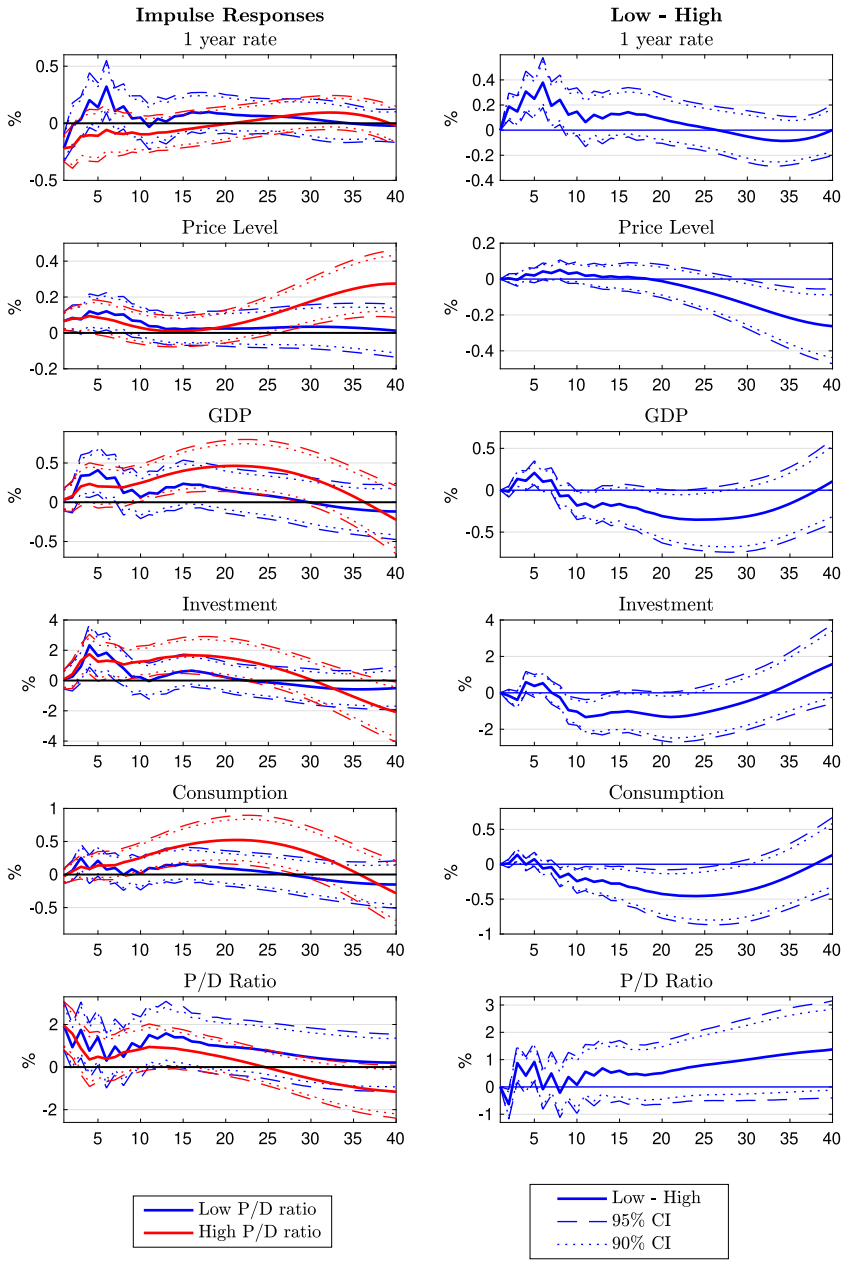

Fig. 8. GIRFs to a negative interest rate shock with the P/D ratio as the state variable. The interest rate interacts with the S&P Composite P/D ratio. The left column shows GIRFs to a −1 standard deviation interest rate shock. The right column shows the difference between responses (low P/D ratio state minus high P/D ratio state). The dashed and dotted lines denote the 95% and 90% confidence intervals.

6 Conclusion

The primary dealer capital ratio has strong influences on U.S. monetary policy transmission. Stock prices respond more strongly to a monetary policy surprise when the primary dealer capital ratio is high. Monetary policy also has stronger effects on real activities when the primary dealers are well-capitalized. It is unlikely that the primary dealer capital ratio simply approximates some frictionless asset pricing factors, such as the household consumption-to-wealth ratio or the market's expectation of future dividend flows. Rather, the findings in this paper suggest that frictions in the financial intermediary sector affects the strength of monetary policy transmission. The state dependent effects of monetary policy appears to be related to the fluctuations in asset values and borrowing costs, instead of the growth rate of bank loans.

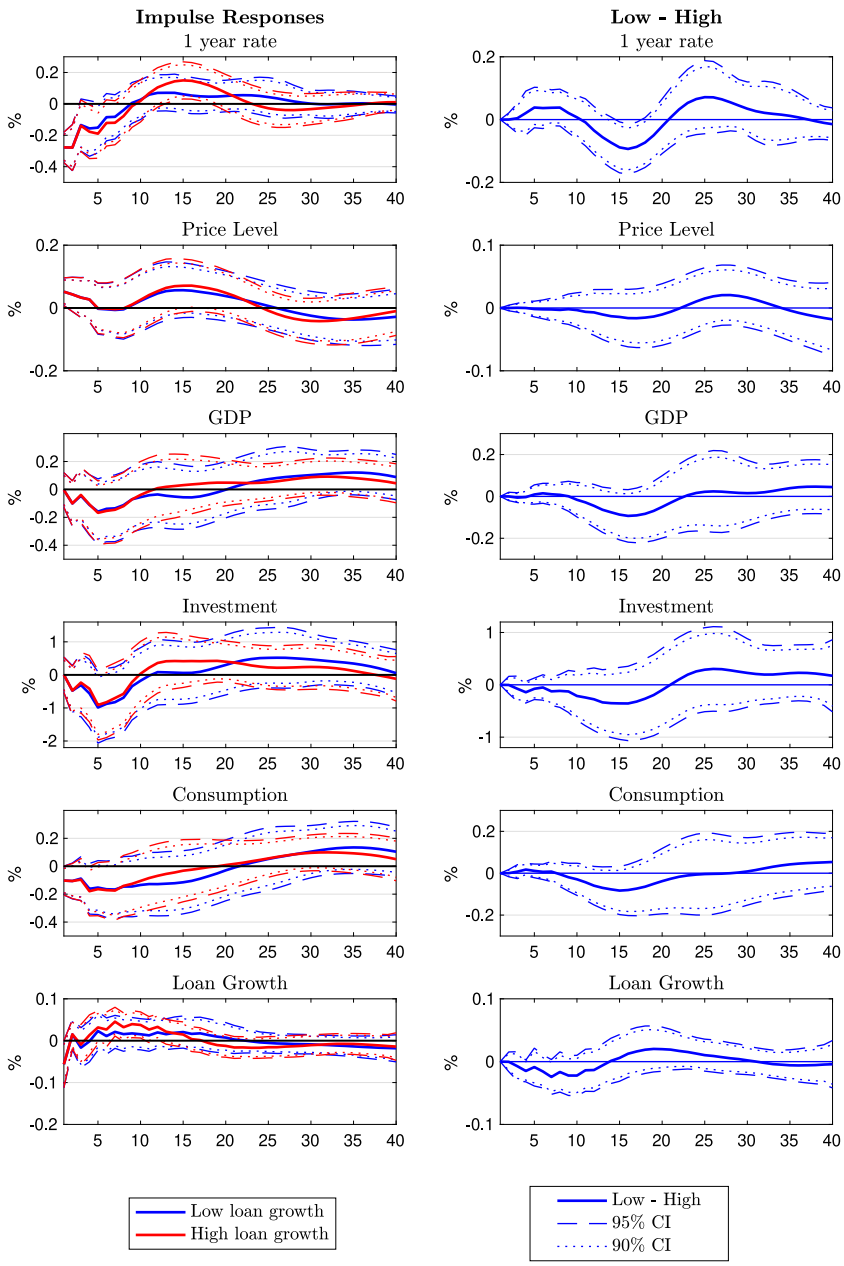

Fig. 9. GIRFs to a negative interest rate shock with loan growth rate as the state variable. The interest rate interacts with the growth rate of bank loans. The left column shows GIRFs to a −1 standard deviation interest rate shock. The right column shows the difference between responses (low bank loan growth state minus high bank loan growth state). The dashed and dotted lines denote the 95% and 90% confidence intervals.

Appendix A. Estimating the stock price responses through heteroskedasticity identification

I apply (Rigobon and Sack, 2004) estimator to estimate the effects of monetary policy shocks on S&P 500 returns. As in Rigobon and Sack (2004), the sample consists of daily changes in the eurodollar futures rates and daily changes in the log of S&P 500 on FOMC meeting days (F days) and the days before FOMC meeting days ($\sim F$ days). I extend the sample to run from February 3, 1994 to December 16, 2009, which is consistent with the event-study sample period in the first part. Following Rigobon and Sack (2004), I estimate the parameter α in equations

$$\Delta i_t = \beta \Delta s_t + \gamma z_t + \varepsilon_t,$$
$$\Delta s_t = \alpha \Delta i_t + z_t + \eta_t.$$

Table 9
Rigobon–Sack estimator for the response of S&P 500 to monetary policy.

	Point	Std dev
$\hat{\lambda}_{high}$	0.01	0.00
$\hat{\alpha}_{high}$	−6.10	2.19
$\hat{\lambda}_{low}$	0.02	0.01
$\hat{\alpha}_{low}$	−2.03	1.49
		p-value
$\mathrm{H}_0 : \lambda_{high} = \lambda_{low}, \alpha_{high} = \alpha_{low}$		0.04

Under the assumptions

$$\sigma_\varepsilon^F > \sigma_\varepsilon^{\sim F},$$
$$\sigma_\eta^F = \sigma_\eta^{\sim F},$$
$$\sigma_z^F = \sigma_z^{\sim F},$$

we can exploit the difference in the covariance matrices

$$\Omega_F = \mathbf{E}\left[\begin{pmatrix}\Delta i_t\\ \Delta s_t\end{pmatrix}(\Delta i_t, \Delta s_t)\middle| t \in F\right] \text{ and } \Omega_{\sim F} = \mathbf{E}\left[\begin{pmatrix}\Delta i_t\\ \Delta s_t\end{pmatrix}(\Delta i_t, \Delta s_t)\middle| t \in\sim F\right].$$

Rigobon and Sack (2004) show that

$$\Omega_F = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix}\sigma_\varepsilon^F + \beta^2\sigma_\eta^F + (\beta+\gamma)^2\sigma_z^F & \alpha\sigma_\varepsilon^F + \beta\sigma_\eta^F + (\beta+\gamma)(1+\alpha\gamma)\sigma_z^F\\ & \alpha^2\sigma_\varepsilon^F + \sigma_\eta^F + (1+\alpha\gamma)^2\sigma_z^F\end{bmatrix},$$
$$\Omega_{\sim F} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix}\sigma_\varepsilon^{\sim F} + \beta^2\sigma_\eta^{\sim F} + (\beta+\gamma)^2\sigma_z^F & \alpha\sigma_\varepsilon^{\sim F} + \beta\sigma_\eta^{\sim F} + (\beta+\gamma)(1+\alpha\gamma)\sigma_z^{\sim F}\\ & \alpha^2\sigma_\varepsilon^{\sim F} + \sigma_\eta^{\sim F} + (1+\alpha\gamma)^2\sigma_z^{\sim F}\end{bmatrix}.$$

Under the assumptions about z and the shocks, α is identified from the moment conditions

$$\Delta\Omega = \Omega_F - \Omega_{\sim F} = \lambda\begin{bmatrix}1 & \alpha\\ \alpha & \alpha^2\end{bmatrix}, \text{ where } \lambda \equiv \frac{\sigma_\varepsilon^F - \sigma_\varepsilon^{\sim F}}{(1-\alpha\beta)^2}.$$

To study the state-dependent effects of monetary policy, I estimate the Rigobon–Sack equation on a high capital ratio sample and a low capital ratio sample and test whether α and λ are significantly different on the two samples.

Formally, I split the sample into two parts: one with the capital ratio below its 50th percentile (low capital ratio sample), the other with the capital ratio above its 50th percentile. Assume that the assumptions on $\sigma_\varepsilon, \sigma_\eta, \sigma_z$ hold on each subsample, but they may not equal on both subsamples. I estimate λ and α on each subsample using efficient GMM, and test

$$\mathrm{H}_0 : \lambda_{low} = \lambda_{high}, \alpha_{low} = \alpha_{high}$$

against

$$\mathrm{H}_1 : \lambda_{low} \neq \lambda_{high} \text{ or } \alpha_{low} \neq \alpha_{high}$$

using the Wald test.[5] The results are shown in Table 9.

For comparison, I estimate the event-study model

$$\Delta s_t = \underset{(0.05)}{-0.11} - \underset{(1.32)}{1.13}\Delta i_t - \underset{(1.88)}{6.39}\Delta i_t \times 1_{high} + \varepsilon_t,$$

where 1_{high} is an indicator for the capital ratio being higher than its 50th percentile. White (1980) standard errors are presented in the parentheses.[6] The point estimate −1.13 on Δi_t corresponds to $\hat{\alpha}_{low}$(−2.03) and the sum −7.52 (−1.13 − 6.39) corresponds to $\hat{\alpha}_{high}$ (−6.10). The event-study approach yields a lower point estimate for the monetary policy effect in the low capital ratio state and a higher point estimate for the monetary policy effect in the high capital ratio state. However, the magnitudes of the coefficients are comparable using the event-study approach and the heteroskedasticity identification approach. Furthermore, the difference in the monetary policy effects in the high versus low capital ratio states is highly significant under both identification approaches.

Overall, the event-study approach yields similar results with the heteroskedasticity identification approach. The coefficients under the event-study approach are within 1 standard deviation from the corresponding coefficients under the heteroskedasticity approach. Using both methods, I find strong evidence for the fact that monetary policy has larger effects on stock prices when the primary dealer capital ratio is high.

[5] Refer to Andrews and Fair (1988) for details.

[6] White (1980) standard errors are generally used to allow for heteroskedasticity, but no allowance for serial correlation is required. See, e.g., Gürkaynak and Wright (2013).

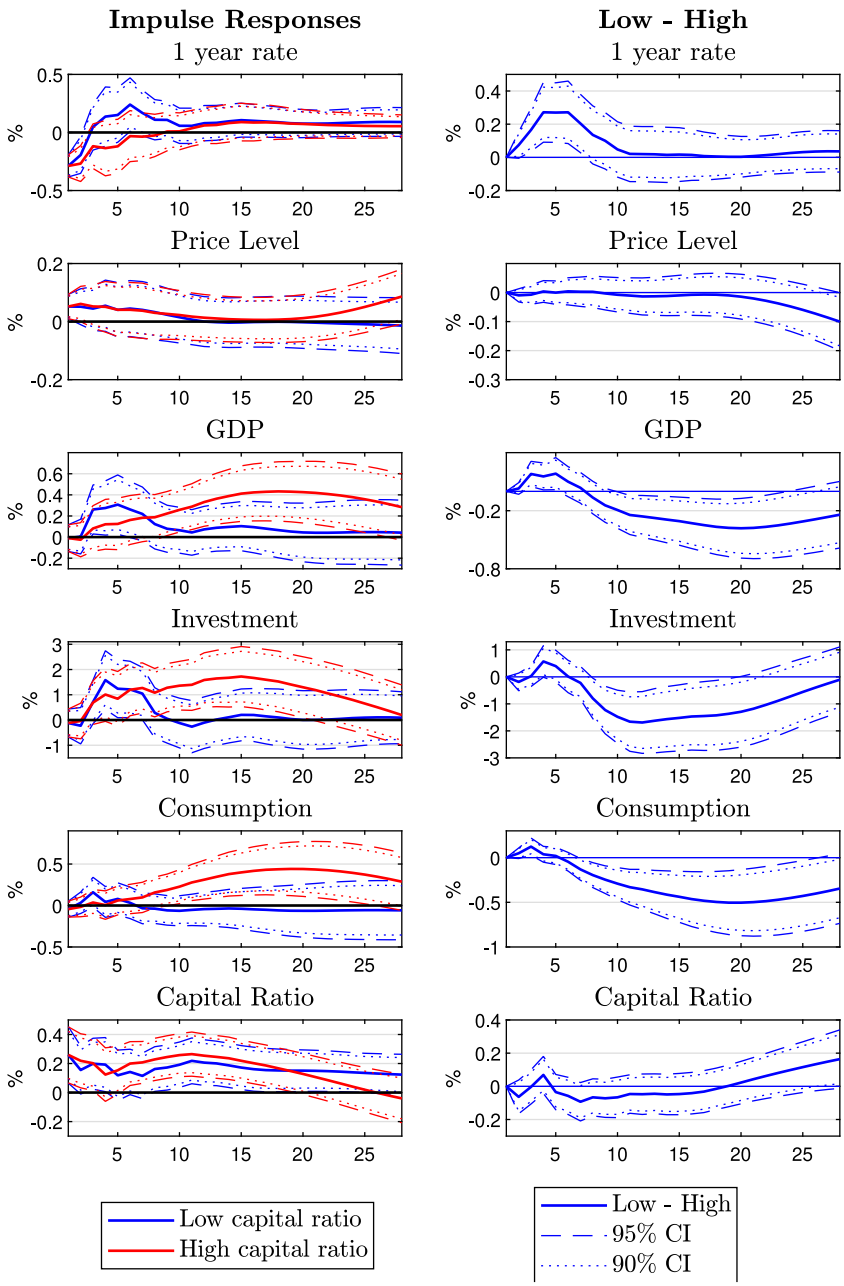

Fig. 10. GIRFs to a negative interest rate shock, high initial capital ratio v.s. low initial capital ratio. The left column shows GIRFs to a −1 standard deviation interest rate shock with 95% and 90% confidence intervals. The right column shows the difference between responses (low capital state minus high capital state).

Appendix B. Algorithms for estimating the GIRF and bootstrapping

1. Pick an initial state ω_{t-1} at a particular date $t \in \{p+1, \ldots, T\}$ from the sample.
2. Draw a sequence of residuals $\left\{\varepsilon^s_{t+h}\right\}_{h=0,1,2,\ldots,H}$ for the path of impulse response.
3. Conditional of ω_{t-1} and the estimated parameters of the model, use $\left\{\varepsilon^s_{t+h}\right\}_{h=0,1,2,\ldots,H}$ to simulate a path of the vector of endogenous variables $\left\{\boldsymbol{Y}^s_{t+h}\right\}_{h=0,1,2,\ldots,H}$.

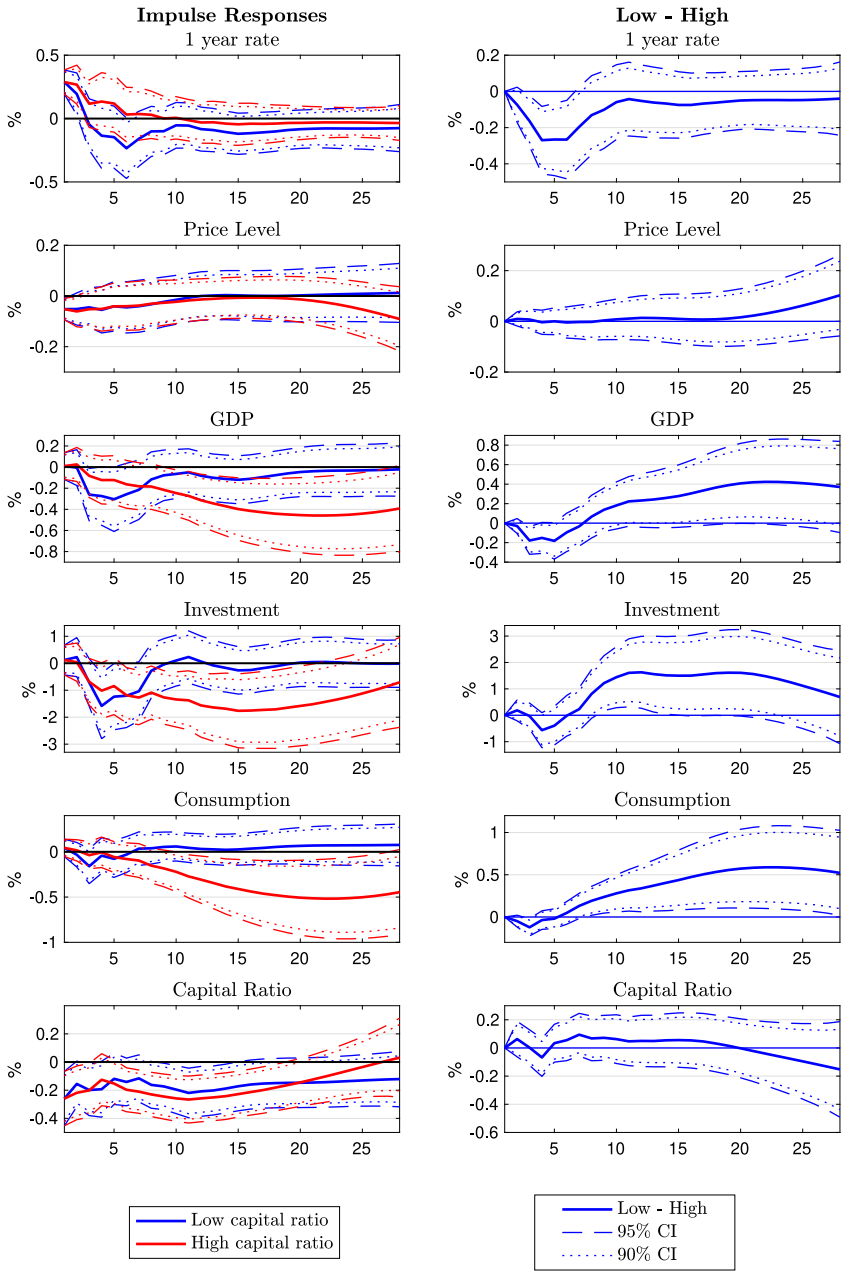

Fig. 11. GIRFs to a positive interest rate shock, high initial capital ratio v.s. low initial capital ratio. The left column shows GIRFs to a 1 standard deviation interest rate shock with 95% and 90% confidence intervals. The right column shows the difference between responses (low capital state minus high capital state).

4. Add δ to ε_t^s and keep the rest of the shock sequence unchanged. Call the new sequence $\left\{\varepsilon_{t+h}^{\delta,s}\right\}_{h=0,1,2,\ldots,H}$. Conditional of ω_{t-1} and the estimated parameters of the model, use $\left\{\varepsilon_{t+h}^{\delta,s}\right\}_{h=0,1,2,\ldots,H}$ to simulate a path of the vector of endogenous variables $\left\{\boldsymbol{Y}_{t+h}^{\delta,s}\right\}_{h=0,1,2,\ldots,H}$.
5. Compute the difference $\boldsymbol{Y}_{t+h}^{\delta,s} - \boldsymbol{Y}_{t+h}^{s}$ for each $h = 0, 1, 2, \ldots, H$.
6. Repeat steps 2–5 for a number of $S = 500$ independent sequences of shocks $\left\{\varepsilon_{t+h}^{s}\right\}_{h=0,1,2,\ldots,H}$. Take averages of $\boldsymbol{Y}_{t+h}^{\delta,s} - \boldsymbol{Y}_{t+h}^{s}$ over s for each $h = 0, 1, 2, \ldots, H$ to get $\hat{I}_{\boldsymbol{Y}}\left(h, \varepsilon_t, \omega_{t-1}\right)$. Note that the initial state ω_{t-1} is unchanged.

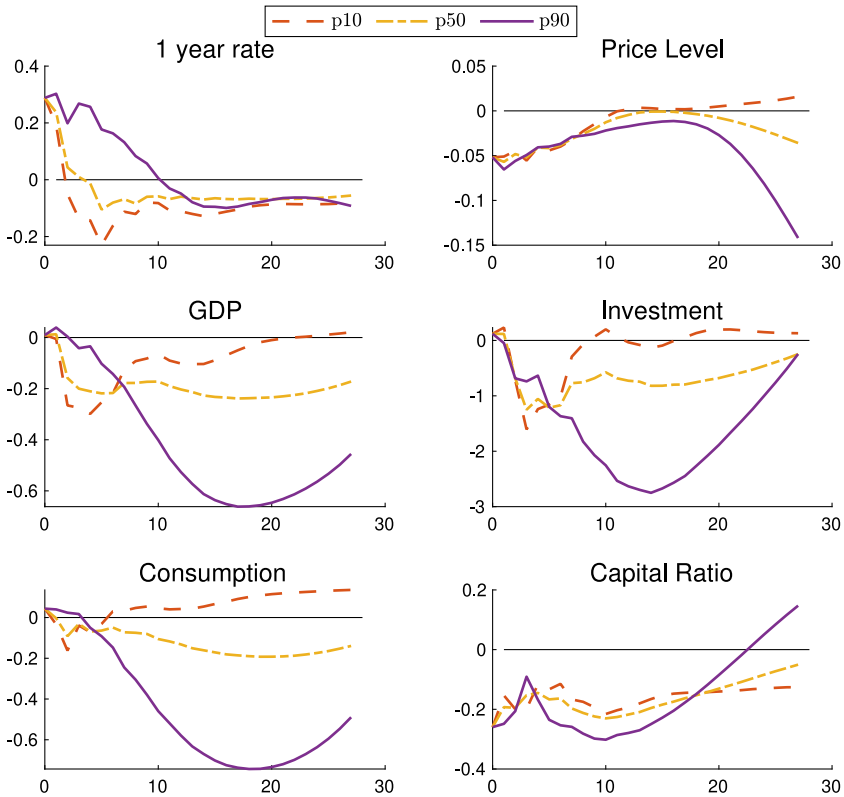

Fig. 12. Impulse responses to a positive 1 standard deviation monetary policy shock in the I-VAR. For each variable, the figure shows the impulse responses conditional on the 10th, 50th, and 90th percentiles of the capital ratio.

7. Classify individual initial states ω_{t-1} into sets of interest. Average $\hat{I}_{\boldsymbol{Y}}\left(h, \varepsilon_t, \omega_{t-1}\right)$ over all ω_{t-1} within the set to get the "high capital ratio state" and "low capital ratio state" generalized impulse responses.
8. The confidence intervals are computed using bootstrap. In each bootstrap draw, simulate a sample that has the same length as the actual sample. Then, estimate the interacted VAR on the simulated sample and implement steps 1–7 to compute the GIRF. The confidence intervals are computed as $\left[\hat{I}_y\left(h, \varepsilon_t\right) - z_{1-\frac{1-\alpha}{2}} s^{bootstrap}_{y,h,\varepsilon_t}, \hat{I}_y\left(h, \varepsilon_t\right) + z_{1-\frac{1-\alpha}{2}} s^{bootstrap}_{y,h,\varepsilon_t}\right]$, where α denotes the confidence level (90%,95%, ...), $z_{1-\frac{1-\alpha}{2}}$ denotes the $1-\frac{1-\alpha}{2}$ quantile of the $\mathcal{N}(0,1)$ distribution, and $s^{bootstrap}_{y,h,\varepsilon_t}$ denotes the sample standard deviation of the bootstrap generalized impulse responses of variable y at horizon h with initial monetary policy shock ε_t.

Appendix C. Expansionary and contractionary monetary policy shocks in the VAR

In the VAR framework, the coefficients are estimated using the entire sample. It is hard to estimate the parameters separately for positive or negative shocks as in the event study exercise. The impulse responses are strictly symmetric for positive and negative shocks in a linear VAR, but the nonlinear VAR allows for asymmetric generalized impulse response functions. Fig. 10 shows the GIRFs in response to a −1 standard deviation interest rate shock; Fig. 11 shows the GIRFs in response to a 1 standard deviation interest rate shock. In this exercise, the responses to positive and negative interest rate shocks are almost symmetric.

Appendix D. Conditioning on more initial capital ratio states

The Monte Carlo algorithm allows computation of the generalized impulse responses conditional on any level of initial capital ratio states. In this section, I show generalized impulse responses to a monetary policy shock conditional on the 10th, 50th, and 90th percentiles of the capital ratio. Fig. 12 shows responses to a positive 1 standard deviation interest rate shock, and Fig. 13 shows responses to a negative 1 standard deviation interest rate shock. Both figures suggest that the real variables respond much more strongly conditional on the 90th percentile of the capital ratio.

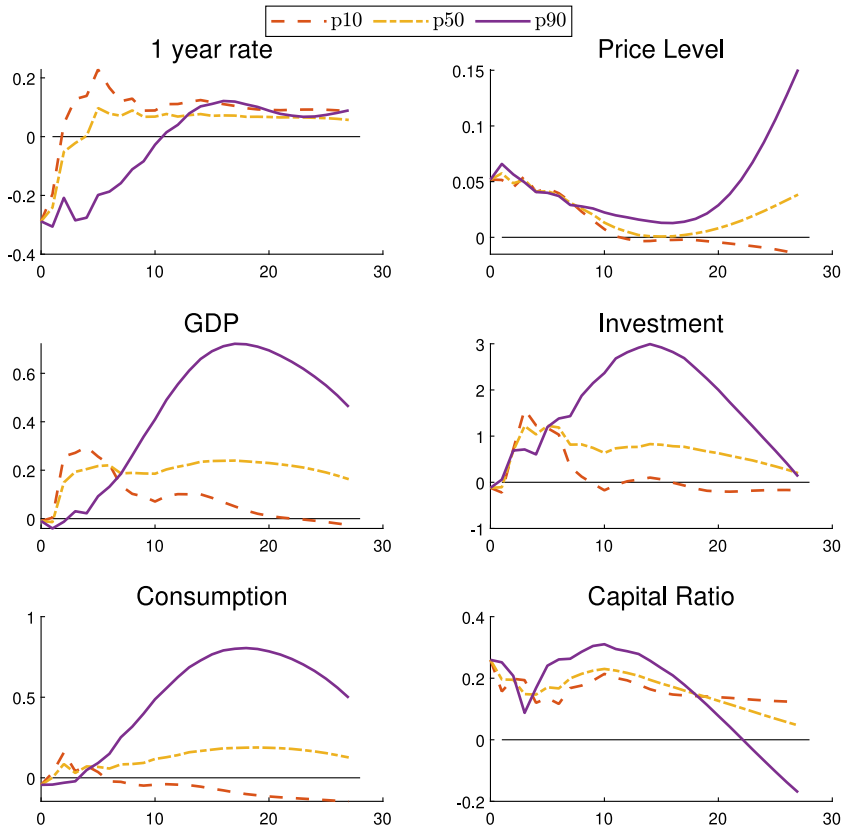

Fig. 13. Impulse responses to a negative 1 standard deviation monetary policy shock in the I-VAR. For each variable, the figure shows the impulse responses conditional on the 10th, 50th, and 90th percentiles of the capital ratio.

References

Aastveit, K., Natvik, G.J.J., Sola, S., 2013. Economic Uncertainty and the Effectiveness of Monetary Policy. SbrSRN Scholarly Paper ID 2353008, Social Science Research Network, Rochester, NY.

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. J. Finance 69 (6), 2557–2596.

Adrian, T., Shin, H.S., 2014. Procyclical leverage and value-at-risk. Rev. Financ. Stud. 27 (2), 373–403.

Andrews, D.W.K., Fair, R.C., 1988. Inference in nonlinear econometric models with structural change. Rev. Econom. Stud. 55 (4), 615–640.

Auclert, A., 2019. Monetary policy and the redistribution channel. Amer. Econ. Rev. 109 (6), 2333–2367.

Bernanke, B.S., Gertler, M., Gilchrist, S., 1999. Chapter 21 the financial accelerator in a quantitative business cycle framework. In: Handbook of Macroeconomics, Vol. 1. Elsevier, pp. 1341–1393.

Brunnermeier, M.K., Sannikov, Y., 2014. A macroeconomic model with a financial sector. Amer. Econ. Rev. 104 (2), 379–421.

Brunnermeier, M.K., Sannikov, Y., 2016. The I Theory of Money. Working Paper 22533, National Bureau of Economic Research.

Bruno, V., Shin, H.S., 2015. Capital flows and the risk-taking channel of monetary policy. J. Monetary Econ. 71, 119–132.

Caggiano, G., Castelnuovo, E., Pellegrino, G., 2017. Estimating the real effects of uncertainty shocks at the Zero Lower Bound. Eur. Econ. Rev. 100, 257–272.

Cieslak, A., 2018. Short-rate expectations and unexpected returns in treasury bonds. Rev. Financ. Stud. 31 (9), 3265–3306.

Cloyne, J., Ferreira, C., Surico, P., 2020. Monetary policy when households have debt: New evidence on the transmission mechanism. Rev. Econom. Stud. 87 (1), 102–129.

Dou, W.W., Lo, A.W., Muley, A., Uhlig, H., 2020. Macroeconomic models for monetary policy: A critical review from a finance perspective. Ann. Rev. Financial Econ. 12 (1), 95–140.

Drechsler, I., Savov, A., Schnabl, P., 2018. A model of monetary policy and risk premia. J. Finance 73 (1), 317–373.

Eickmeier, S., Metiu, N., Prieto, E., 2016. Time-Varying Volatility, Financial Intermediation and Monetary Policy. SSRN Scholarly Paper ID 2885074, Social Science Research Network, Rochester, NY.

Gertler, M., Karadi, P., 2011. A model of unconventional monetary policy. J. Monetary Econ. 58 (1), 17–34.

Gertler, M., Karadi, P., 2015. Monetary policy surprises, credit costs, and economic activity. Amer. Econ. J. Macroecon. 7 (1), 44–76.

Gertler, M., Kiyotaki, N., 2010. Chapter 11 - financial intermediation and credit policy in business cycle analysis. In: Friedman, B.M., Woodford, M. (Eds.), Handbook of Monetary Economics, Vol. 3. Elsevier, pp. 547–599.

Gertler, M., Kiyotaki, N., Prestipino, A., 2020. A macroeconomic model with financial panics. Rev. Econom. Stud. 87 (1), 240–288.

Gilchrist, S., Zakrajšek, E., 2012. Credit spreads and business cycle fluctuations. Amer. Econ. Rev. 102 (4), 1692–1720.

Gorodnichenko, Y., Weber, M., 2016. Are sticky prices costly? Evidence from the stock market. Amer. Econ. Rev. 106 (1), 165–199.

Gürkaynak, R.S., Wright, J.H., 2013. Identification and inference using event studies. The Manchester School 81, 48–65.

Haddad, V., Muir, T., 2021. Do intermediaries matter for aggregate asset prices? J. Finance 76 (6), 2719–2761.

Hamilton, J.D., 2017. Why you should never use the hodrick-prescott filter. Rev. Econ. Stat..

He, Z., Kelly, B., Manela, A., 2017. Intermediary asset pricing: New evidence from many asset classes. J. Financ. Econ. 126 (1), 1–35.
He, Z., Krishnamurthy, A., 2012. A model of capital and crises. Rev. Econom. Stud. 79 (2), 735–777.
He, Z., Krishnamurthy, A., 2013. Intermediary asset pricing. Amer. Econ. Rev. 103 (2), 732–770.
He, Z., Krishnamurthy, A., 2019. A macroeconomic framework for quantifying systemic risk. Amer. Econ. J. Macroecon. 11 (4), 1–37.
Istiak, K., Serletis, A., 2017. Monetary policy and leverage shocks. Int. J. Finance Econ. 22 (2), 115–128.
Kashyap, A.K., Stein, J.C., 2000. What do a million observations on banks say about the transmission of monetary policy? Amer. Econ. Rev. 90 (3), 407–428.
Kilian, L., Vigfusson, R.J., 2011. Are the responses of the U.S. economy asymmetric in energy price increases and decreases? Quant. Econ. 2 (3), 419–453.
Kishan, R.P., Opiela, T.P., 2000. Bank size, bank capital, and the bank lending channel. J. Money Credit Bank. 32 (1), 121–141.
Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econometrics 74 (1), 119–147.
Lettau, M., Ludvigson, S., 2001a. Consumption, aggregate wealth, and expected stock returns. J. Finance 56 (3), 815–849.
Lettau, M., Ludvigson, S., 2001b. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying. J. Polit. Econ. 109 (6), 1238–1287.
Muir, T., 2017. Financial crises and risk premia. Q. J. Econ. 132 (2), 765–809.
Mumtaz, H., Surico, P., 2015. The transmission mechanism in good and bad times. Internat. Econom. Rev. 56 (4), 1237–1260.
Pellegrino, G., 2021. Uncertainty and monetary policy in the US: A journey into nonlinear territory. Econ. Inq. 59 (3), 1106–1128.
Rigobon, R., Sack, B., 2004. The impact of monetary policy on asset prices. J. Monetary Econ. 51 (8), 1553–1575.
Tenreyro, S., Thwaites, G., 2016. Pushing on a string: US monetary policy is less powerful in recessions. Amer. Econ. J. Macroecon. 8 (4), 43–74.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica: journal of the Econometric Society 817–838.