# Risk and Risk-Free Rates*

Mete Kilic  Zhao Zhang  Aleksandr Zotov

May 27, 2024

**Abstract**

Risk-free interest rates and the VIX index comove negatively on average, as predicted by precautionary savings. But this comovement turns positive on FOMC days. This pattern is consistently observed across a diverse array of risk-free interest rates, including nominal, real, swap, short-term, and long-term rates. Our high-frequency analysis reveals that the positive impact of monetary policy shocks on financial market risk drives this result. We provide an explanation for these findings in a model where levered investors akin to financial intermediaries hold and price a risky asset, such as equity. Upon an unexpected positive monetary policy shock, equilibrium interest rates and levered investors' borrowing costs increase persistently. This raises investors' leverage and the volatility of stochastic discount factor, leading to lower risk appetite and amplified financial market risks.

*Keywords: risk, interest rates, monetary policy, leverage, risk appetite, intermediaries*

*We are grateful to Viral Acharya, Ben Charoenwong, Xiang Fang, Jan Harren, Tarek Hassan, David Hirshleifer, Chris Jones, Jun E. Li, Wenhao Li, Yang Liu, Thomas Maurer, Lukas Schmid, Jincheng Tong, Selale Tuzel, Zhengyang Xu, and seminar participants at the University of Hong Kong, Hong Kong University of Science and Technology, National University of Singapore, University of Manchester, and Lancaster University for helpful comments. Kilic (mkilic@marshall.usc.edu) and Zotov (aleksandr.zotov@marshall.usc.edu) are at the Marshall School of Business, University of Southern California. Zhang (zzhang7@imf.org) is at the International Monetary Fund.

# 1 Introduction

What is the relation between equilibrium interest rates and financial market risk? On the one hand, standard asset pricing models predict a negative relation induced by precautionary savings during times of heightened risk in the economy. On the other hand, recent literature emphasizes the potential transmission of monetary policy to risk perceptions and sentiment in financial markets beyond cost-of-capital and credit channels (Bauer, Bernanke, and Milstein (2023), Kashyap and Stein (2023)). Hence, monetary policy may induce a positive relation between interest rates and financial market risk to the extent that tighter monetary policy increases interest rates and risk simultaneously.

In this paper, we show that the comovement between interest rates and financial market risk measured by the VIX index is negative on average, but positive on Federal Open Market Committee (FOMC) announcement days. This pattern is common to a wide spectrum of risk-free interest rates in the U.S. across maturities, inflation exposure, and markets (i.e., swaps vs. bonds). Using intraday data, we show that the positive comovement between interest rates and risk on FOMC announcement days is entirely driven by the tight window around the announcement.

We argue that the impact of monetary policy on risk is inherently related to cost of financing and leverage effects. In particular, we propose a model where a representative investor such as a financial intermediary uses short-term debt to finance risky asset holdings such as the aggregate stock market portfolio. Positive monetary policy shocks raise the real equilibrium interest rate and the investor's leverage persistently. Such a shock makes the investor's marginal utility conditionally more volatile and raises the conditional return volatility of the risky asset, elevating the VIX index. We illustrate this mechanism in the model and show that its quantitative predictions are consistent with the data. In particular, interest rates and VIX comove negatively on non-FOMC days due to precautionary savings but the comovement turns positive on FOMC days as a result of the causal effect of monetary shocks on financial market risk.

We start by showing that daily changes in U.S. government bond yields have a significantly negative relation with daily changes in the VIX index during the period from January 1995 to September 2022. However, the relation is significantly different on non-FOMC and FOMC days, and turns positive on FOMC days. We show that these patterns hold for both real and nominal Treasury bonds as well as overnight indexed swap (OIS) rates, suggesting that they are not driven by the impact of monetary policy on convenience yields or inflation expectations. Furthermore, we find similar effects for both short term and long term bonds (from 3 months to 10 years) consistent with the impact of monetary policy on long-term interest rates (Cochrane and Piazzesi (2002), Gürkaynak, Sack, and Swanson (2005), Hanson and Stein (2015)).

Our next step in the empirical analysis is the high frequency identification of the comovement between interest rates and VIX on FOMC days using intraday data on the VIX index, VIX futures, and monetary policy shocks from Nakamura and Steinsson (2018). We show that the positive relation between daily changes in interest rates and the VIX on FOMC days is entirely captured by their comovement in the 30-minute period around (from 10 minutes before to 20 minutes after) the announcement. This result is driven by FOMC announcements where interest rates and the stock market move in opposite directions, which is the sample with arguably weaker Fed information effects (Cieslak and Schrimpf (2019), Jarociński and Karadi (2020)). The positive comovement between interest rates and VIX on FOMC days is not purely driven by the risk premium component of VIX because we find that monetary policy shocks have predictive power for the future realized stock market volatility.

We then present a stylized model to shed light on the mechanisms behind the relation between interest rates and financial market risks. We assume that a representative investor holds a risky asset that delivers dividends as in a Lucas tree economy. However, the model deviates from traditional representative agent endowment economies in two dimensions. First, we assume that the representative investor finances the risky asset holding partially with risk-free short-term debt. As a result, the net endowment of the investor is given by dividends net of interest payments in the spirit of intermediary asset pricing models (He and Krishnamurthy (2013)). The second feature is that we embed monetary policy shocks modeled as transitory shocks to the cost of leverage similar to Coimbra and Rey (2023). Monetary policy shocks in our model occur at a deterministic frequency and are designed to capture the unexpected component of scheduled FOMC announcements reflected in interest rates.

In the model, there is a feedback loop between the investor's endowment growth and the equilibrium interest rate. When the interest rate is higher, the investor's expected endowment growth is lower because the risky asset's expected dividend growth is constant but future interest payments are elevated. The strength of this relation increases in leverage. At the same time, the interest rate is increasing in the investor's expected endowment growth due to the standard intertemporal smoothing channel. The slope of this relation is the inverse of the elasticity of intertemporal substitution (EIS) as in standard models. The equilibrium response of the investor's expected endowment growth and the interest rate to shocks is determined such that both of these conditions are satisfied at all times. In particular, a positive monetary policy shock exogenously increases expected endowment growth because it increases the one-period interest payment to the monetary authority that has a mean-zero balance sheet. This channel leads to lower current net endowment and increases the equilibrium interest rate persistently which amplifies the impact of a one-time monetary policy shock on the interest rate and leverage.

The conditional volatility of the stochastic discount factor (SDF) is increasing in the interest rate because of the impact of leverage. If interest rates are higher, the representative investor spends a larger fraction of the dividend from the risky asset on interest payments. Consequently, the growth of residual cash flows, that constitute the investor's endowment, becomes more volatile. As a result, a positive monetary policy shock raises SDF volatility even if the volatility of the risky asset's dividend growth is unchanged. We interpret this result as the causal effect of monetary policy shocks on risk appetite in financial markets. When marginal investors finance their asset holdings using leverage, an exogenous rise in the interest rate raises the effective quantity of risk and acts as if investors became more risk averse. This mechanism is consistent with Bauer, Bernanke, and Milstein (2023) who discuss the role of shifts in risk appetite in the transmission of monetary policy to financial markets. Our model suggests that shifts in risk appetite are an inherent feature of monetary policy transmission through levered investors' cost of financing. Importantly, tightening monetary policy lowers the risk appetite of investors even if there is no increase in the fundamental risk of cash flows from asset holdings. This effect is driven by the change in investors' exposure to cash flow risks rather than a shift in the structural risk aversion parameter.

We evaluate the quantitative implications of the model in a calibration that targets the average real interest rate, VIX dynamics, the average leverage of financial intermediaries, and the response of bond yields to monetary policy shocks. After calibrating the model, we investigate its implications for the relation between interest rates, VIX, and monetary policy shocks. The model delivers realistic magnitudes for the comovement of interest rates and VIX on both non-FOMC and FOMC days. In particular, the negative relation on non-FOMC days is driven by the precautionary savings effect resulting from the exogenous variation in the volatility of the risky asset's dividend growth. However, on FOMC days, monetary policy shocks are positively associated with the daily change in VIX due to the increase in conditional SDF volatility. Moreover, the VIX declines on FOMC days on average due to the drop in the uncertainty associated with the monetary policy shock. The impact of monetary policy is strong enough to explain the significant difference in the comovement between the interest rates and VIX on non-FOMC and FOMC days.

Our paper is related to the literature studying the impact of monetary policy on asset prices. Bernanke and Kuttner (2005) argue that the negative reaction of the stock market to interest rate hikes are largely driven by a spike in risk premiums. This finding motivates a recent strand of literature studying the link between monetary policy and risk premiums. For instance, Drechsler, Savov, and Schnabl (2018) argue that higher rates increase the opportunity cost of liquidity buffers for banks which decreases the demand for risky assets and increases risk premiums. In recent work, Pflueger and Rinaldi (2022) propose a model where monetary policy shocks increase risk aversion in an extended version of the habit model by Campbell and Cochrane (1999) augmented with New Keynesian features. Our model puts forward an alternative mechanism whereby leverage plays the key role in driving the positive effect of monetary policy shocks on conditional SDF volatility.

Alternatively, Kekre and Lenel (2022) develop a model where tightening monetary shocks redistribute wealth to agents with lower propensity to take risk. In contrast, our model uses leverage as the main mechanism to explain the interplay between interest rates and risk on non-FOMC and FOMC days. Monetary shocks in our model are one-time subsidies to levered risk-averse investors but they change the exposure of investors to fundamental shocks rather than redistribute wealth.

Empirically, Bauer, Bernanke, and Milstein (2023) document a positive relation between monetary policy shocks and willingness to take risks. Our findings on the interest rate-risk relation is robust to using their risk appetite index. They also point out the potential role of leverage in the transmission of monetary policy to risk which we systematically analyze in our model. Our findings are broadly consistent with the empirical literature that has studied the relation between interest rates, monetary policy, and risk (Vähämaa and Äijö (2011), Bekaert, Hoerova, and Duca (2013), Hartzmark (2016)). In particular, Dell'Ariccia, Laeven, and Suarez (2017) present direct evidence on the risk-taking channel of monetary policy for the U.S. banking system.

Our model is is developed in the spirit of asset pricing models that emphasize the role of investors' leverage such as financial intermediaries (e.g., Adrian and Shin (2010), Brunnermeier and Sannikov (2014), Santos and Veronesi (2022)). In particular, He and Krishnamurthy (2013) model constrained financial intermediaries that use leverage and determine equilibrium asset prices. The distance to the constraint in their model explains the behavior of asset prices in crisis times. While we do not model leverage constraints, the representative levered investor in our model can be interpreted as a financial intermediary who clears the risky asset market. The crucial feature for our empirical findings is leverage itself which facilitates the transmission of monetary policy shocks to conditional risks in asset returns. Furthermore, we document a positive response of intermediaries' interest expense to monetary shocks using data on primary dealers and broker-dealers motivated by the literature studying the empirical relevance of intermediary leverage for asset prices (Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017)).

Our paper is organized as follows. In Section 2, we introduce our empirical evidence on the comovement between interest rates and risk with a particular emphasis on the high frequency evidence on FOMC days. Section 3 presents our model, explicitly illustrating our channel using tractable analytical approximations and using the calibrated model to show the quantitative implications. Section 4 concludes.

# 2 Empirical evidence

This section introduces the empirical evidence that provides the basis for our subsequent model and quantitative evaluation. We start by documenting the relation between government bond yields and the VIX index on non-FOMC and FOMC days. We then use intraday data to identify a direct link between the surprise component of monetary policy announcements and VIX, and provide evidence that this link explains the differences in the relation between yields and VIX on non-FOMC and FOMC days.

## 2.1 Data

For our analysis, we use data on interest rates, monetary policy shocks, and the VIX index and futures. The baseline sample spans the period from January 1995 to September 2022 given the availability of monetary policy shocks from Nakamura and Steinsson (2018) in this period. The starting date of the sample is later for some our analyses based on data availability. We provide a detailed description of data sources in Appendix A and summary statistics in Appendix Table A.1.

## 2.2 Risk-free interest rates and the VIX

We start our analysis by examining the relation between daily changes in government bond yields and in VIX, with a particular focus on comparing this relation between non-FOMC and FOMC days. To do so, we introduce a variable $\Delta$Yield which is defined as the first principal component (PC) of daily changes in government bond yields with maturities of 3, 6, and 12 months.[1] We normalize $\Delta$Yield such that it has the same volatility as daily changes in the 12-month yield.

[1]We use yields up to 12 months to compute $\Delta$Yield to be consistent with the computation of monetary policy shocks in the literature, e.g., Nakamura and Steinsson (2018) and Bauer and Swanson (2023).

**Table 1**
Bond yields and VIX

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| FOMC | -1.317*** | | -1.527*** | -1.226*** |
| | (0.300) | | (0.308) | (0.311) |
| ΔVIX | | -0.373*** | -0.381*** | -0.403*** |
| | | (0.060) | (0.060) | (0.062) |
| FOMC × ΔVIX | | | | 0.590*** |
| | | | | (0.175) |
| Observations | 6930 | 6930 | 6930 | 6930 |
| Adjusted $R^2$ | 0.003 | 0.025 | 0.029 | 0.031 |

*Notes.* This table reports results from regressing the first principal component of daily changes in the 3-month, 6-month, and 12-month U.S. government bond yields on an FOMC day dummy, the daily change in the VIX index, and their interaction term. The sample period is from January 1995 to September 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Column 1 of Table 1 shows that yields have declined on FOMC days more than non-FOMC days in our sample period. This result is consistent with Hillenbrand (2023) who documents that most of the secular decline in interest rates over the last decades is attributable to yield changes in a window around FOMC announcements. Column 2 of Table 1 further shows that changes in VIX (ΔVIX) and ΔYield are negatively correlated. A 1 standard deviation (SD) increase in ΔVIX is associated with a 0.16 SD decline in ΔYield. This effect is consistent with the precautionary savings effect. In other words, economic shocks that cause an increase in conditional risk also cause an increase in the desire to save in risk-free assets lowering their yields. This effect is robust to controlling for the average difference in ΔYield between non-FOMC and FOMC days (Column 3 of Table 1).

However, the relation between ΔYield and ΔVIX is significantly different on FOMC compared to non-FOMC days. On FOMC days, the coefficient of ΔYield on ΔVIX is significantly higher relative to non-FOMC days, and the ΔYield-ΔVIX comovement is slightly positive (Column 4 of Table 1). Panel A of Figure 1 illustrates this finding graphically where the robust negative relation between ΔYield and ΔVIX on regular days becomes a weakly positive relation on FOMC days.

The results in Table 1 are robust to using individual bond yields and are not driven by inflation expectations. In particular, Appendix Table A.2 shows that same results hold using individual bond yields up to 10-year maturity. For all yields, the relation between ΔYield and ΔVIX is significantly negative on non-FOMC days. The interaction between the FOMC dummy and ΔVIX is significantly positive, and its magnitude is slightly larger than the negative coefficient on ΔVIX. Furthermore, Appendix Table A.3 shows that our findings in Table 1 remain unchanged using TIPS yields instead of nominal Treasury yields suggesting that expected inflation dynamics on FOMC days do not explain the results. Finally, we replace ΔVIX by the risk index developed by Bauer, Bernanke, and Milstein (2023) which is designed to measure daily changes in risk appetite. Appendix Table A.4 shows that risk appetite, which can be interpreted as an inverse risk premium, is positively correlated with yields on non-FOMC days and there is a significant negative interaction with the FOMC dummy consistent with the results obtained using ΔVIX in Table 1.

The difference in the ΔYield-ΔVIX relation between FOMC and non-FOMC days may seem puzzling at first, especially if one interprets this finding based on the precautionary savings mechanism, which predicts that a positive shock to risk in the economy should lead to lower rates. We instead argue that the difference is rooted in the causal effect of monetary policy shocks on risk for levered investors. In particular, our model in Section 3 shows that unexpected changes in interest rates due to monetary policy shocks impact conditional risk exposure for levered investors. Hence, the comovement between ΔYield and ΔVIX on non-FOMC days can be driven by shocks to economic risks and the accompanying precautionary savings effect. In contrast, FOMC days are characterized by direct shocks to risk-free interest rates which affect levered investors' exposure to shocks and, as a result, the VIX index.

Next, we ask whether the evidence in Table 1 is driven by changes in the risk-free rate embedded in bond yields or other features of Treasury securities (e.g., a convenience yield as in Krishnamurthy and Vissing-Jorgensen (2012)). We use the overnight indexed swap (OIS) rates as an alternative risk-free rate proxy because OIS rates are argued to have identical payoffs as Treasury bonds but do not feature the associated balance sheet costs and convenience yields (He, Nagel, and Song (2022), Du, Hébert, and Li (2023), Doshi, Kim, and Seo (2023)). We repeat the analysis in Table 1 using changes in the overnight indexed swap (OIS) rates ΔOIS and report results in Table 2. Table 2 shows that the conclusions drawn from the comovement between ΔYield and ΔVIX remain unchanged when we replace ΔYield with ΔOIS.[2]

**Table 2**
Overnight indexed swap rates and VIX

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| FOMC | -0.618* | | -0.713** | -0.475 |
| | (0.327) | | (0.331) | (0.311) |
| ΔVIX | | -0.174*** | -0.177*** | -0.196*** |
| | | (0.067) | (0.067) | (0.069) |
| FOMC × ΔVIX | | | | 0.479** |
| | | | | (0.233) |
| Observations | 5681 | 5681 | 5681 | 5681 |
| Adjusted $R^2$ | 0.001 | 0.007 | 0.007 | 0.009 |

*Notes.* This table reports results from regressing the first principal component of daily changes in the 3-month, 6-month, and 12-month OIS rates on an FOMC day dummy, the daily change in the VIX index, and their interaction term. The sample period is from January 2000 to September 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

[2]Panel B of Figure 1 illustrates the relation between ΔOIS and ΔVIX on FOMC and non-FOMC days. Appendix Table A.5 shows that the results in Table 2 also hold using individual OIS rates up to 10-year maturity rather than the first PC of yields up to 1 year.

In sum, changes in risk-free rates and risk measured using VIX are unconditionally negatively correlated but the correlation has a large and significantly positive component on FOMC days. This result is driven by the common risk-free rate component across nominal government bond yields, real yields, and OIS rates. Next, we use intraday data on FOMC days to identify the impact of monetary shocks on risk in tighter time windows.

## 2.3 VIX dynamics around monetary policy shocks

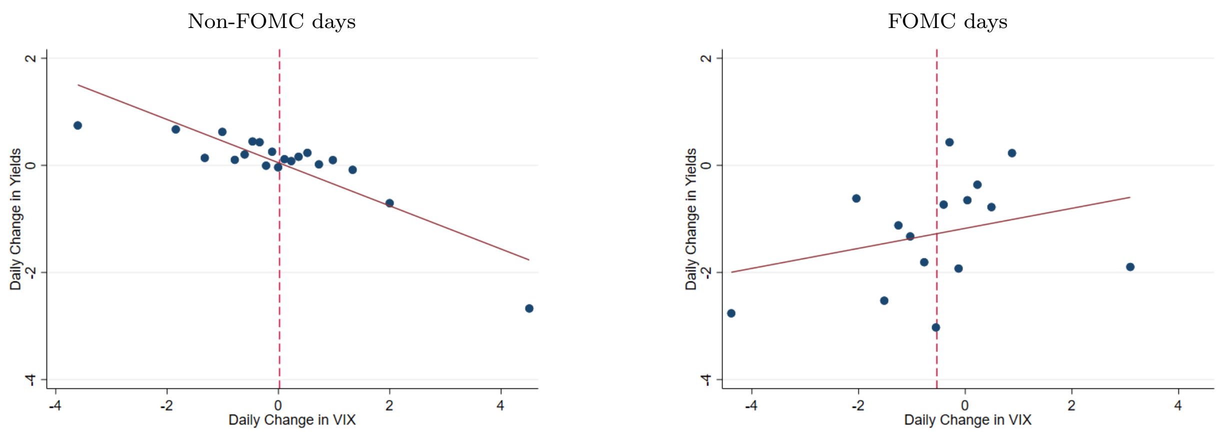
A common approach to measure unexpected monetary policy shocks is to use high frequency changes in yields around FOMC announcements (Gürkaynak, Sack, and Swanson (2007b), Nakamura and Steinsson (2018), Bauer and Swanson (2023)). The underlying assumption is that interest rate movements within a 30-minute window (from 10 minutes before to 20 minutes after the announcement) around scheduled Fed announcements are causally driven by the unexpected component of monetary policy news. In this section, we examine whether monetary policy shocks measured as the 30-minute change in interest rates following Nakamura and Steinsson (2018) (hereafter, NS shocks) explain the positive relation between $\Delta$Yield and $\Delta$VIX on FOMC days relative to non-FOMC days.[3]

We obtain intraday data on the VIX index and investigate the relation between NS shocks and intraday changes in VIX. Panel A of Table 3 first shows results from regressing the daily $\Delta$VIX on NS shocks (Column "Daily"). We find that VIX drops on average by -0.537 on announcement days and it is significantly positively correlated with the NS shock. That is, if interest rates rise in the 30-minute window around the FOMC announcement, VIX will drop less than usual or even increase. Next, we find that the relation between $\Delta$VIX and the NS shock is indeed driven by their comovement in the 30-minute FOMC window. While VIX

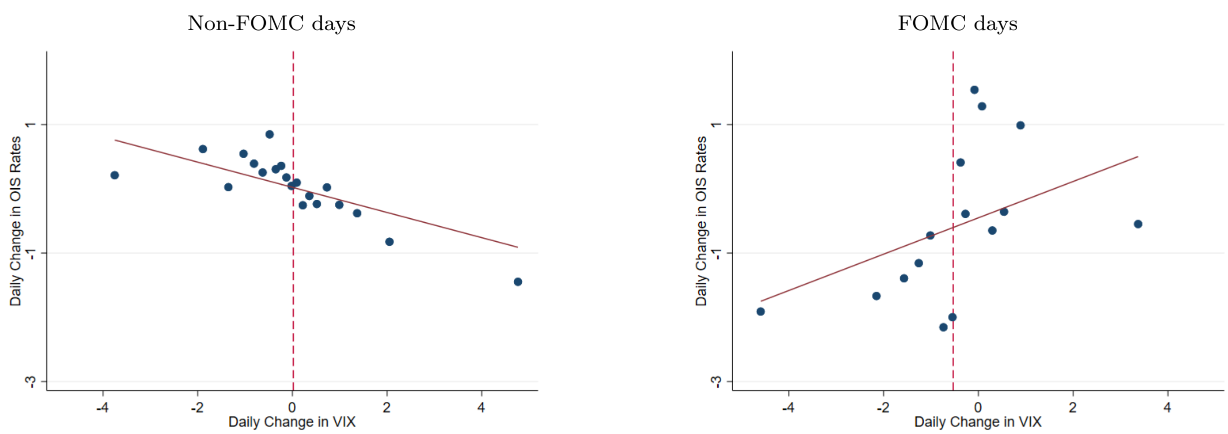
[3] Nakamura and Steinsson (2018) construct the shocks as the first principal component of 30-minute changes in five futures quotes: federal funds rate futures maturing immediately after the FOMC meeting, the same futures maturing after the next meeting, and Eurodollar futures on 3-month interest rate expiring in 2, 3 and 4 quarters after the FOMC meeting.

**Figure 1.** Daily changes in VIX and risk-free rates

Panel A: Yields




Panel B: OIS rates




*Notes.* This figure plots binscatters of daily changes in interest rates (U.S. government bond yields in Panel A, OIS rates in Panel B) against daily changes in the VIX index on non-FOMC and FOMC days. The red solid line is the fitted linear line. The vertical red dashed line is at the sample average of the daily change in VIX in each sample. The sample period is from January 1995 to September 2022 for U.S. government bond yields and from January 2000 to September 2022 for OIS rates.

drops from last day's close to the 30-minute FOMC announcement period on average as well, its movement in this period is not correlated with the NS shock (Column "Pre-FOMC"). Indeed, all of the comovement between the NS shock and the daily ΔVIX can be attributed to the 30-minute FOMC window (Column "FOMC"). The NS shock does not have significant impact on the post-FOMC VIX change on the FOMC days either (Column "post-FOMC").

**Table 3**
Intraday VIX dynamics and monetary policy shocks

| | Daily | Pre-FOMC | FOMC | Post-FOMC |
|---|---|---|---|---|
| Panel A: Intraday VIX index: 1/1995 - 9/2022 | | | | |
| Constant | -0.537*** | -0.239*** | -0.157*** | -0.141* |
| | (0.126) | (0.071) | (0.038) | (0.083) |
| NS | 0.309** | 0.032 | 0.183*** | 0.094 |
| | (0.140) | (0.060) | (0.048) | (0.084) |
| Observations | 219 | 219 | 219 | 219 |
| Adjusted $R^2$ | 0.022 | -0.004 | 0.092 | 0.001 |
| Panel B: Intraday VIX futures: 5/2004 - 9/2022 | | | | |
| Constant | -0.316*** | -0.236*** | -0.098*** | 0.018 |
| | (0.105) | (0.058) | (0.025) | (0.065) |
| NS | 0.172 | -0.020 | 0.161*** | 0.031 |
| | (0.153) | (0.076) | (0.035) | (0.083) |
| Observations | 147 | 147 | 147 | 147 |
| Adjusted $R^2$ | 0.006 | -0.006 | 0.164 | -0.006 |
| Panel C: Intraday VIX index: 5/2004 - 9/2022 | | | | |
| Constant | -0.546*** | -0.259*** | -0.207*** | -0.080 |
| | (0.180) | (0.095) | (0.051) | (0.114) |
| NS | 0.496* | 0.043 | 0.288*** | 0.165 |
| | (0.254) | (0.107) | (0.075) | (0.153) |
| Observations | 147 | 147 | 147 | 147 |
| Adjusted $R^2$ | 0.029 | -0.006 | 0.133 | 0.003 |

*Notes.* This table reports results from regressing changes in the VIX index on NS shocks on FOMC days. The dependent variable is the daily change in VIX in the column "Daily", the change from the previous day's close to 10 minutes prior to the FOMC announcement in the column "Pre-FOMC", the change from 10 minutes before to 20 minutes after the FOMC announcement in the column "FOMC", and the change from 20 minutes after the FOMC announcement to market close in the column "Post-FOMC". Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The results in Panel A of Table 3 suggest that VIX dynamics on FOMC days are dominated by the impact of monetary policy shocks. Therefore, we argue that the shocks driving the comovement between ΔVIX and ΔYield are different on non-FOMC days and FOMC days. For instance, on FOMC days, monetary shocks raising interest rates exogenously also increase conditional risk in financial markets. However, interest rates change endogenously on non-FOMC days based on prevailing economic conditions. If the economy and markets become riskier for reasons other than monetary policy, equilibrium interest rates decline due to a flight to safety by investors. Our model in Section 3 builds on this intuition.

The evidence in Panel A of Table 3 also suggests that the measured NS shock plausibly captures the unexpected component of monetary policy news. While VIX starts to decline already in the pre-FOMC period, the pre-FOMC movements are unrelated to the upcoming monetary shock realization. That is, monetary policy uncertainty may start being resolved prior to the announcement explaining the VIX decline in the pre-FOMC period. However, the NS shock captures the remaining unexpected component.

We repeat the exercise in Panel A of Table 3 with intraday VIX futures prices (Panel B) which are based on actual prices from a liquid market rather than the synthetic VIX index.[4] The VIX futures sample period is shorter but the results convey the same message: there is a strong positive relation between ΔVIX and NS shocks in the 30-minute FOMC announcement window suggesting that interest rate shocks dominate VIX movements on FOMC days.[5] Panel C shows that the evidence holds with the high-frequency VIX index in the VIX futures sample as well.[6]

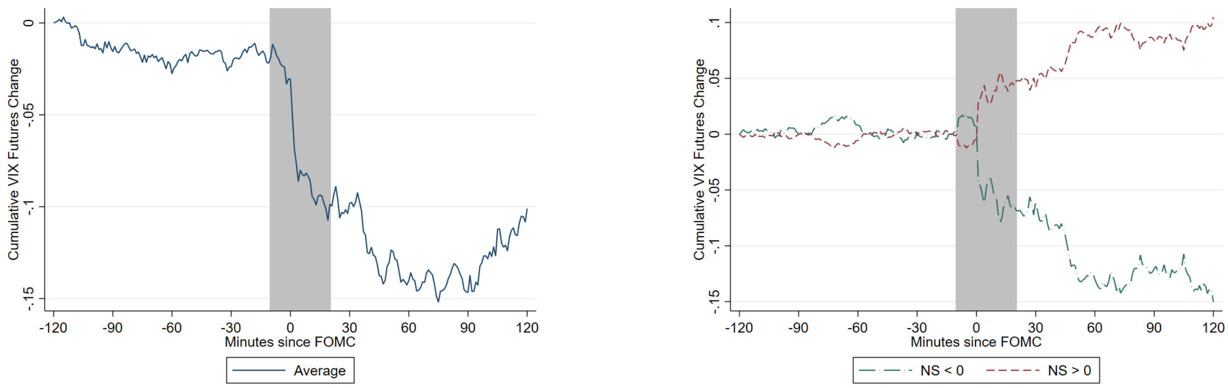
We further illustrate the average high frequency VIX futures dynamics around the FOMC

[4]We use VIX futures that are the closest to maturity on the FOMC day conditional on having at least three days to maturity. VIX futures prices typically move less than the index itself because they capture expected rather than realized VIX.

[5]See Appendix Figure A.1 for a binscatter of VIX changes and NS shocks.

[6]Appendix Tables A.6 and A.7 show that the evidence in Tables 1 and 3 are robust to excluding NBER recession periods from the sample.

**Figure 2.** Intraday VIX futures dynamics and monetary policy shocks




*Notes.* The left panel of the figure plots the average cumulative VIX futures price changes from 120 minutes before to 120 minutes after the FOMC announcement. The right panel plots the average cumulative VIX futures price changes for the subsample of positive and negative NS shocks, relative to the unconditional average in the left panel. The gray region is the 30-minute window around the FOMC announcement. The sample period is from May 2004 to September 2022.

announcement window in the left panel of Figure 2. VIX futures decline significantly in the 30-minute FOMC announcement window consistent with the evidence in Table 3. Moreover, the right panel of Figure 2 shows that positive NS shocks are associated with an increase in VIX futures prices during the announcement window relative to the average decline in the left panel, while negative NS shocks lead to a further decline in VIX illustrating the evidence in Panel B of Table 3. The divergence of average VIX conditional on the sign of NS shocks is primarily driven by the variation within the announcement window, while the post-announcement period is characterized by further divergence.[7]

[7] Appendix Figure A.2 shows that the similarity of VIX dynamics before announcements and the divergence of average VIX based on the sign of NS shocks in a longer window from 24 hours before to 48 hours after the announcement.

## 2.4 VIX on FOMC days and monetary policy transmission

The impact of monetary policy shocks on asset prices depends on the transmission mechanism: through the interest rate channel as in New Keynesian models or through the Fed information effect. Our evidence so far suggests that positive interest rate shocks on FOMC days increase risk in the stock market. Our model in Section 3 interprets this finding from the perspective of levered investors whose cost of capital increases due to positive interest rate shocks. Alternatively, asset price reactions to monetary policy shocks may reflect information effects where the Fed reveals the state of the economy to the public at announcements (Nakamura and Steinsson (2018), Cieslak and Schrimpf (2019), Jarociński and Karadi (2020)) or the public learns about the Fed's policy function at announcements (Bauer and Swanson (2023)). For instance, a positive interest rate shock may reveal positive news indicating that expected economic growth is higher than the public's perception prior to the Fed announcement. Jarociński and Karadi (2020) argue that a surprise policy tightening raises interest rates and reduces stock prices because of heightened cost of capital. In contrast, the information effect would predict that a positive interest rate shock raises growth expectations, and hence stock prices. As a result, the relation between ΔVIX and NS shocks may differ based on whether an FOMC announcement primarily induces the cost of capital or the information effect.

Following Jarociński and Karadi (2020), we split the sample of FOMC announcements into those with opposite and same signs for the high frequency response of interest rates (NS shock) and the stock market (S&P 500 futures prices). Out of 221 scheduled FOMC announcements in our sample, NS shocks and the change in S&P500 futures have different signs for 138 meetings and the same sign for 83 meetings during the FOMC announcement window. We then regress daily ΔVIX as well as the 30-minute ΔVIX from futures on the NS shock in both samples, and report results in Table 4. The results show that NS shocks have

**Table 4**
The role of the Fed information effect

| | Daily VIX index | | | High freq. VIX futures | | |
|---|---|---|---|---|---|---|
| | All | Diff. sign | Same sign | All | Diff. sign | Same sign |
| NS | 0.316** | 0.406*** | -0.230 | 0.161*** | 0.229*** | -0.450*** |
| | (0.137) | (0.150) | (0.280) | (0.035) | (0.027) | (0.159) |
| Constant | -0.532*** | -0.425*** | -0.763*** | -0.098*** | -0.077*** | -0.070* |
| | (0.125) | (0.155) | (0.199) | (0.025) | (0.026) | (0.036) |
| Observations | 221 | 138 | 83 | 147 | 91 | 56 |
| Adjusted $R^2$ | 0.024 | 0.057 | -0.006 | 0.164 | 0.468 | 0.358 |

*Notes.* This table reports results from regressing changes in the VIX index on NS shocks on FOMC days. In the "Daily VIX index" columns, the dependent variable is the daily change in VIX and the sample period is from January 1995 to September 2022. In the "High freq. VIX futures" columns, the dependent variable is change in VIX futures during the 30-minute FOMC announcement window and the sample period is from May 2004 to September 2022. "Diff sign." ("Same sign") is the sample of FOMC announcements where the NS shock and the change S&P 500 futures during the FOMC window have different (the same) signs. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

a positive impact on ΔVIX only in the sample with a different sign which is consistent with the cost of capital channel. In the sample with the same sign, NS shocks have essentially no impact on daily ΔVIX and a negative impact on ΔVIX in the FOMC announcement window. This result is consistent with the information effect: when an unexpected rise in interest rates signals higher expected growth, stock market valuations rise which can lower the risk exposure of levered investors and the VIX index as a result. Hence, our results are entirely driven by FOMC announcements where the Fed information effect is likely to be least prevalent as a monetary transmission mechanism.

## 2.5 VIX, yields, and monetary policy shocks

Finally, we ask whether the impact of monetary shocks on the VIX on FOMC days (Table 3) explains the difference in the daily ΔVIX-ΔYield comovement on non-FOMC and FOMC days (Table 1). For this analysis, we make ΔVIX the dependent variable and investigate its comovement with ΔYield and monetary policy shocks. Column 1 of Table 5 shows that the VIX change is lower on FOMC days compared to non-FOMC days consistent with the evidence on daily VIX changes in Table 3. We then add ΔYield and its interaction with the FOMC dummy, and reproduce the result from Table 1 that the loading of ΔVIX on ΔYield is negative on non-FOMC days but significantly larger and positive on FOMC days (Column 2 of Table 5).

**Table 5**

VIX, yields, and monetary policy shocks

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| FOMC | -0.552*** | -0.511*** | -0.552*** | -0.582*** |
| | (0.128) | (0.130) | (0.126) | (0.138) |
| NS | | | 0.316** | 0.377* |
| | | | (0.137) | (0.192) |
| ΔYield | | -0.072*** | | -0.072*** |
| | | (0.010) | | (0.010) |
| FOMC × ΔYield | | 0.106*** | | 0.050 |
| | | (0.033) | | (0.043) |
| Observations | 6930 | 6930 | 6930 | 6930 |
| Adjusted $R^2$ | 0.003 | 0.031 | 0.004 | 0.031 |

*Notes.* This table reports results from regressing the daily change in the VIX index on an FOMC day dummy, the NS shock (set to zero on non-FOMC days), the first principal component of daily changes in the 3-month, 6-month, and 12-month U.S. government bond yields, and its interaction with the FOMC dummy. The sample period is from January 1995 to September 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To understand the role of monetary policy shocks, we regress ΔVIX on NS shocks which are zero on non-FOMC days and represent the high frequency (30-minute) change in interest rates on FOMC days. Column 3 of Table 5 shows that ΔVIX is positively correlated with the NS shock, controlling for the unconditional negative effect of FOMC days on ΔVIX.[8] That

[8]Focusing on FOMC days, Bauer, Bernanke, and Milstein (2023) also find that a surprise tightening of monetary policy leads to a persistent increase in VIX.

is, while the VIX drops on announcement days on average consistent with the resolution of monetary policy uncertainty, unexpected shocks to interest rates have a positive effect on the VIX. Crucially, the NS shock weakens the positive association between ΔVIX and ΔYield on FOMC days (Column 4 of Table 5) which suggests that unexpected interest rate shocks on FOMC days have a positive impact on the VIX, breaking the negative relation between ΔVIX and ΔYield on non-FOMC days.[9]

**Table 6**

Future realized volatility and monetary policy shocks

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| NS | | 1.066** | | 1.740** |
| | | (0.485) | | (0.820) |
| ΔYield | | | 0.003 | -0.250 |
| | | | (0.101) | (0.184) |
| Lagged RV | 0.587*** | 0.611*** | 0.588*** | 0.592*** |
| | (0.102) | (0.106) | (0.107) | (0.102) |
| Observations | 221 | 221 | 221 | 221 |
| Adjusted $R^2$ | 0.428 | 0.440 | 0.425 | 0.446 |

*Notes.* This table reports results from regressing realized volatility (RV) between the current and next FOMC announcements on the NS shock, the first PC of 3-month, 6-month, and 12-month yield changes, and the lagged RV between the current and last FOMC announcements. Realized volatility is measured as the square root of the annualized sum of squared log stock market returns from one day after the current FOMC announcement to two days before the next FOMC announcement. The sample period is from January 1995 to September 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The VIX index captures the market's risk-neutral expectation of stock market volatility over the next month. Hence, the positive relation between NS shocks and VIX changes could be driven by the risk premium associated with volatility fluctuations, or they could also be related to physical expectations of future stock market volatility. We examine the relation

[9] Appendix Table A.8 shows that the impact of NS shocks on ΔVIX also explains the positive relation between ΔVIX and ΔOIS on FOMC days.

between NS shocks and realized stock market volatility between the current and the next FOMC day, and find that NS shocks are a significant predictor of future realized volatility (Table 6).[10] Strikingly, the daily change in yields on FOMC days does not predict volatility. This evidence suggests that the relation between monetary policy shocks and the VIX on FOMC days is not purely driven by variance premium fluctuations, and is related to changes in expected stock market return volatility.

In sum, VIX drops on FOMC days on average but the magnitude of this drop depends on the direction of monetary policy shocks. When interest rates unexpectedly rise on FOMC days, conditional stock market risk drops less than usual, while unexpected declines in the interest rate result in particularly large declines in risk. This pattern is dominantly driven by VIX movements in the 30-minute window around FOMC announcements, and explains differences in the comovement of interest rate and risk dynamics between non-FOMC and FOMC days. Rate changes are negatively correlated with risk changes on non-FOMC days consistent with precautionary savings, but the positive impact of monetary policy shocks on financial market risks results in a large positive component in the relation between rates and risk on FOMC days. These results are robust across alternative proxies for interest rates and risk, suggesting that they are not driven by factors such as inflation, balance sheet costs, or convenience yields. The impact of monetary policy shocks on VIX is even stronger in a sample of FOMC announcements where the Fed information effect is unlikely to be prominent. In light of this evidence, we next provide a model with a representative investor holding risky assets using leverage and investigate the causal link from monetary policy shocks to conditional risk dynamics.

[10]To isolate the effect on future volatility, we follow Cieslak and Vissing-Jorgensen (2021) and compute realized volatility from the first day after the FOMC day until two days before the next FOMC day.

# 3 Model

We present a model that sheds light on our empirical findings in Section 2. Our empirical evidence consists of asset price responses in the bond and options markets at the daily frequency and, on FOMC days, at higher frequencies. Therefore, our results are likely to be driven by sophisticated financial institutions that trade frequently and use leverage (Adrian, Etula, and Muir (2014)). Hence, we start by presenting model assumptions including the key assumption that the representative investor uses leverage to finance risky asset holdings. We then inspect the mechanism using approximate analytical solutions for the key variables in the model, in particular, the effect of monetary policy shocks on interest rates and conditional risk. We then calibrate the model using standard target moments and investigate its implications for the empirical evidence on the relation between interest rates and risk dynamics in financial markets.

## 3.1 Model setup

We assume that there is a representative investor that holds one unit of a risky asset, e.g. the aggregate stock market portfolio, which pays a dividend $D_t$ at time $t$. Dividend growth is given by

$$\frac{D_{t+1}}{D_t} = 1 + g + \epsilon_{t+1}, \tag{1}$$

where $g$ is the average growth rate, $\epsilon_{t+1} \sim N(0, \sigma_t)$ with $\epsilon_t$ being serially independent, and $\sigma_t$ follows a Markov process.

The representative investor in the risky asset market finances part of the risky asset holdings using risk-free short-term debt. In particular, we assume that the investor maintains a 1-period liability of $L_t = sD_t$ with $s > 0$. The investor's interest payment at $t+1$ depends on whether there is a scheduled monetary policy shock (FOMC days) or not (non-FOMC days) at $t+1$. If $t+1$ is a non-FOMC day, then the interest payment at $t+1$ is given by $r_t L_t$ where $r_t$ is the 1-period interest rate. We calibrate the model at the daily frequency later in Section 3.5. Hence, $r_t$ can be interpreted as the overnight interest rate that represents the cost of leverage for investors such as financial intermediaries.

We model monetary policy shocks $m_t$ as an exogenous change in the cost of leverage for period $t$. That is, a monetary policy shock $m_{t+1}$ changes the interest payment at $t+1$ from $r_t L_t$ to $(r_t + m_{t+1})L_t$. We assume that $m_{t+1}$ is drawn independently from the distribution $N(0, \sigma_m)$ once every $T_m$ periods (on FOMC days), and is zero on all other days (non-FOMC days):

$$m_{t+1} \begin{cases} \sim N(0, \sigma_m) & \text{if } \tau_t = 1 \\ = 0 \end{cases} \tag{2}$$

where $\tau_t \in \{1, ..., T_m\}$ denotes the time until the next monetary policy shock. In what follows, we write $m_{t+1} \sim N(0, \sigma_{mt})$ where $\sigma_{mt} = \sigma_m$ if $\tau_t = 1$, and $\sigma_{mt} = 0$ otherwise.

Monetary policy shocks $m_t$ capture interest rate surprises on scheduled FOMC days. Therefore, the shocks occur at a deterministic frequency, are not predictable, and are assumed to be *iid* over time for simplicity. For instance, a negative value for $m_t$ indicates that funding costs for investors' leverage are lower than expected on day $t$. This approach to modeling monetary policy shocks is similar to the borrowing subsidy experiments in He and Krishnamurthy (2013). Furthermore, Coimbra and Rey (2023) also model monetary policy shocks as exogenous changes in the cost of external funds. While these shocks are persistent in Coimbra and Rey (2023), we model them as one-time shocks which endogenously have a long-lasting impact on the equilibrium interest rate as we will discuss below in Section 3.4.[11]

[11] The monetary policy shock is akin to a (positive or negative) borrowing subsidy from a monetary authority. As in Coimbra and Rey (2023), we assume that the monetary authority is a deep-pocketed institution that can finance the subsidy to the representative levered investor $-m_t L_{t-1}$ at any point in time, while the average subsidy is zero, i.e. $\mathbb{E}[-m_t L_{t-1}] = 0$.

In the spirit of He and Krishnamurthy (2013), the levered investor plays the key role in determining asset prices in our model. Therefore, we assume a household sector that has a very simple structure. In particular, we assume that there is a measure $N$ of overlapping generation households each period that live for two periods and have log utility. Each household receives risky labor income $wD_t$, which is proportional to the risky asset's dividends, and decides how much to save by lending to the levered investor. Households take the interest rate $r_t$ as given and exclusively save through risk-free lending. Appendix B shows that the optimal consumption-savings decision of households implies that savings are equal to a constant fraction of their labor income. As a result, the liabilities of the representative investor are equal to household savings $L_t = sD_t$. While our assumptions on the household sector provide a way to think about the levered investor's balance sheet in equilibrium, households play no further role in equilibrium asset prices.

## 3.2 Cash flows and asset pricing

The representative investor receives dividends from the risky asset holdings every period and makes interest payments. We call the dividends from the risky asset minus the interest payments the "representative investor's endowment".[12] As a result, the endowment is given by:

$$E_t = D_t - s(r_{t-1} + m_t)D_{t-1}. \tag{3}$$

Hence, the crucial feature of our model compared to standard a Lucas tree economy is that the endowment of the representative investor is not exogenously given but depends on the endogenous interest rate and exogenous monetary policy shocks.

[12]The investor's endowment is equal to dividends from asset holdings minus interest expense similar to operating profits of a financial intermediary. We assume that the proceeds from the difference between old debt's repayment and new debt's issuance given by $L_t - L_{t-1}$ does not affect the investor's endowment. In the calibrated model, we find that the annualized value of this term is 1.14% of asset holdings. See Section 3.5.1 for details.

We assume that the representative investor consumes their endowment and has constant relative risk aversion (CRRA) preferences:

$$U_t = \mathbb{E}_t \left[ \sum_{\tau=0}^{\infty} \beta^{\tau} \frac{E_{t+\tau}^{1-\gamma}}{1-\gamma} \right], \tag{4}$$

where $\beta$ is the time discount factor and $\gamma$ is relative risk aversion.[13] As a result, the stochastic discount factor (SDF) is given by

$$\Pi_{t+1} = \beta \left( \frac{E_{t+1}}{E_t} \right)^{-\gamma}, \tag{5}$$

where $\mathbb{E}_t[\Pi_{t+1} \tilde{R}_{t+1}] = 1$ for any random return $\tilde{R}$. Furthermore, the 1-period risk-free interest rate is given by

$$r_t = \frac{1}{\mathbb{E}_t[\Pi_{t+1}]} - 1. \tag{6}$$

We can write the investor's endowment growth as

$$\frac{E_{t+1}}{E_t} = \frac{\frac{D_{t+1}}{D_t} - s(r_t + m_{t+1})}{\frac{E_t}{D_t}}, \tag{7}$$

which follows from equation (3). The expected endowment growth of the investor is decreasing in the current interest rate $r_t$ due to higher interest payments at $t+1$ which will make $E_{t+1}$ smaller relative to $D_{t+1}$. Furthermore, positive dividend growth shocks translate to positive endowment growth shocks for the investor. In contrast, positive monetary policy shocks $m_{t+1}$ raise the cost of debt and lower cash flows at $t+1$.

Importantly, the endogenous state variable in the economy is the ratio of investor endowment to dividends:

$$\frac{E_t}{D_t} = 1 - s(r_{t-1} + m_t) \frac{D_{t-1}}{D_t}, \tag{8}$$

[13] In the quantitative analysis, we ensure that $E_t$ remains positive in the entire state space so that the utility function is always well-defined.

which represents the investor's equity ratio in cash flow terms. That is, the investor's asset holdings deliver the cash flow $D_t$ and the investor receives $E_t$ after servicing outstanding debt.

Substituting (8) into (7), we observe that endowment growth depends on the risky asset's dividend growth as well as the growth of interest payments. Therefore, interest rate dynamics directly affect endowment growth dynamics and the stochastic discount factor. As such, investors' leverage introduces rich dynamics into the model even though the risky asset's dividend growth is serially uncorrelated and follows a simple stochastic process.

## 3.3 Model solution

We solve for the interest rate $r_t$ and the price-dividend ratio of the risky asset $\frac{P_t}{D_t}$ using the representative investor's Euler equations. Our model has three state variables: the volatility of dividend growth, $\sigma_t$, time to the next monetary shock, $\tau_t \in \{1, ..., T_m\}$, and the ratio of endowment to dividends, $\frac{E_t}{D_t}$. While the dynamics of $\sigma_t$ and $\tau_t$ are exogenous, the distribution of future $\frac{E_t}{D_t}$ is endogenous and depends on the current interest rate. The interest rate $r_t$ is given by a function $f$ of state variables:

$$r_t = f\left(\sigma_t, \tau_t, \frac{E_t}{D_t}\right) = \frac{1}{\mathbb{E}_t\left[\beta\left(\frac{1+g+\epsilon_{t+1}-s(r_t+m_{t+1})}{\frac{E_t}{D_t}}\right)^{-\gamma}\right]} - 1.$$

Conditional on the state variables, we can easily solve for the interest rate function $f\left(\sigma_t, \tau_t, \frac{E_t}{D_t}\right)$. To solve for the risky asset's $\frac{P_t}{D_t}$ as a function of state variables, we rearrange the Euler equation $\mathbb{E}_t[\Pi_{t+1}\tilde{R}_{t+1}] = 1$ with $\tilde{R}_{t+1} = \frac{P_{t+1}+D_{t+1}}{P_t}$ as:

$$\begin{aligned}
\frac{P_t}{D_t} &= h\left(\sigma_t, \tau_t, \frac{E_t}{D_t}\right) \\
&= \mathbb{E}_t\left[\Pi_{t+1}\left(1 + \frac{P_{t+1}}{D_{t+1}}\right)\frac{D_{t+1}}{D_t}\right] \\
&= \mathbb{E}_t\left[\beta\left(\frac{1+g+\epsilon_{t+1} - s(r_t + m_{t+1})}{\frac{E_t}{D_t}}\right)^{-\gamma}\left(1 + h\left(\sigma_{t+1}, \tau_{t+1}, \frac{E_{t+1}}{D_{t+1}}\right)\right)(1+g+\epsilon_{t+1})\right].
\end{aligned}$$

We numerically solve for $h\left(\sigma_t, \tau_t, \frac{E_t}{D_t}\right)$ recursively on grids for the state variables. Once we obtain $r_t$ and $\frac{P_t}{D_t}$ as a function of $\sigma_t, \tau_t$, and $\frac{E_t}{D_t}$, we can compute all conditional moments and simulate returns.

## 3.4 Inspecting the mechanism

Before we explore the quantitative implications of our model, we illustrate the interest rate and conditional risk dynamics using Taylor approximations of the model solution. We first show the impact of monetary shocks on the equilibrium interest rate and the role of leverage. We then illustrate the role of monetary policy shocks for the dynamics of conditional SDF volatility. Appendix C includes the derivations for the results in this section.

### 3.4.1 Interest rate dynamics and monetary shocks

We start with a first order Taylor approximation of the numerator and the denominator of endowment growth in equation (7) which results in the following expression for $\Delta e_{t+1} = \log\left(\frac{E_{t+1}}{E_t}\right)$:

$$\Delta e_{t+1} \approx \underbrace{g + \epsilon_{t+1}}_{\text{dividend growth}} \underbrace{-s(r_t + m_{t+1}) + s(r_{t-1} + m_t)\frac{1}{1+g+\epsilon_t}}_{\text{interest payment growth}}. \tag{9}$$

Endowment growth in equation (9) has two components: the risky asset's dividend growth and the growth of interest payments. In particular, the last two terms in equation (9) show that if the interest rate is low at $t$ relative to $t-1$, interest payments decline from $t$ to $t+1$, which has a positive effect on $\mathbb{E}_t[\Delta e_{t+1}]$.

The facts that $\Delta e_{t+1}$ is conditionally normal under the approximation and the representative investor has CRRA utility imply

$$r_t \approx -\log\beta + \gamma\mathbb{E}_t[\Delta e_{t+1}] - \frac{1}{2}\gamma^2 Var_t(\Delta e_{t+1}). \tag{10}$$

Plugging the conditional expectation and variance of endowment growth from (9) into (10) and solving for $r_t$, we can write the law of motion for the interest rate as follows:

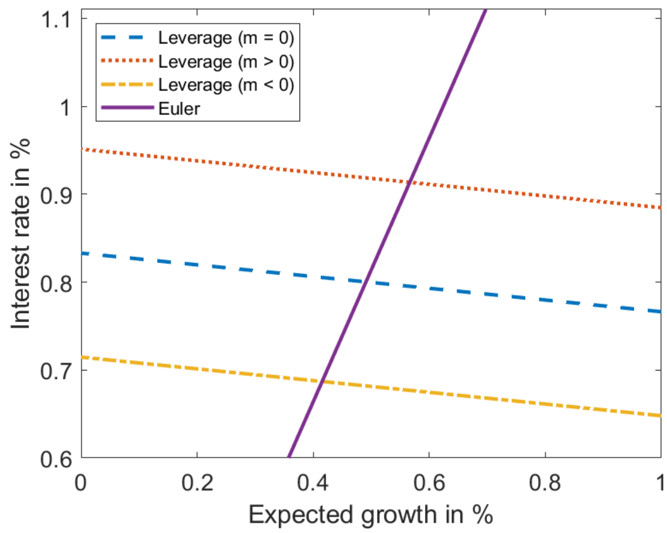
$$r_t \approx = \frac{-\log\beta + \gamma g}{1+\gamma s} \quad + \frac{\gamma}{1+\gamma s}\frac{s}{1+g+\epsilon_t}(r_{t-1}+m_t) - \frac{1}{2}\frac{\gamma^2}{1+\gamma s}(\sigma_t^2 + s^2\sigma_{mt}^2). \tag{11}$$

Equation (11) shows that changes in $r_t$ on non-FOMC days are driven by dividend shocks $\epsilon_t$ and shocks to volatility $\sigma_t$. A higher dividend growth shock lowers expected growth as can be seen in the last term of equation (9). Higher dividends at $t$ imply higher $E_t$ at $t$, but lower $E_{t+1}$ relative to $E_t$ due to higher interest payments at $t+1$. Lower expected growth then leads to a lower interest rate due to intertemporal smoothing effects represented by the second term in (10). Moreover, volatility $\sigma_t$ has a negative impact on the interest rate $r_t$ due to the precautionary savings effect. Therefore, exogenous time variation in $\sigma_t$ induces a negative relation between changes in interest rates and conditional risk.

To understand the implications of leverage for the interest rate dynamics in (11), it is helpful to compare it with the special case of no leverage ($s = 0$) where the interest rate takes the standard form $r_t = -\log\beta + \gamma g - \frac{1}{2}\gamma^2\sigma_t^2$. Leverage introduces the second term in (11) which is responsible for a serial dependence between $r_{t-1}$ and $r_t$, and the transmission of monetary shocks $m_t$ to the equilibrium interest rate $r_t$.

In the model, shocks jointly change the $\mathbb{E}_t[\Delta e_{t+1}]$ and $r_t$, and there are two relations

**Figure 3.** Monetary policy shocks and equilibrium interest rates




*Notes.* This figure plots the relation between the annual interest rate in the model and the expected endowment growth of the representative investor. We set $s = 15$, $\gamma = 1.5$, $\beta = 0.98$, $\sigma_t^2 = 0.0174$, , $\sigma_{mt}^2 = 0$, and $g = 0.02$. The blue dashed line plots the relation between $r_t$ and $\mathbb{E}_t[\Delta e_{t+1}]$ based on equation (9) with $m_t = 0$. The purple solid line plots the relation between $r_t$ and $\mathbb{E}_t[\Delta e_{t+1}]$ based on equation (10). The red dotted line (yellow dashed-fotted line) is equivalent to the blue dashed line except it assumes $m_t = 0.12\%$ ($m_t = -0.12\%$).

between $\mathbb{E}_t[\Delta e_{t+1}]$ and $r_t$ that both have to hold in equilibrium. First, leverage implies that $\mathbb{E}_t[\Delta e_{t+1}]$ is decreasing in $r_t$ (equation (9)) and the slope of this relation is $-s$. That is, if $r_t$ is higher holding other quantities constant, $\mathbb{E}_t[\Delta e_{t+1}]$ is lower due to higher interest payments at $t + 1$. Second, $r_t$ is increasing in $\mathbb{E}_t[\Delta e_{t+1}]$ based on investors' Euler equation and the slope of this equation is the inverse of EIS which is equal to risk aversion $\gamma$ under CRRA utility (equation (10)). That is, when expected growth is high, the investor's willingness to save is low due to the intertemporal smoothing effect pushing the interest rate up. The equilibrium interest rate is at the fixed point where both of these relations are satisfied. Figure 3 illustrates this intuition. The blue dashed line shows the leverage effect and the purple solid line shows the Euler equation effect. The interest rate and expected growth are jointly determined where these two lines cross.

The effect of a monetary shock on the equilibrium interest rate is also determined by the leverage and Euler equation effects. A positive monetary shock $m_t > 0$ in isolation raises $\mathbb{E}_t[\Delta e_{t+1}]$ by exogenously lowering endowment at $t$ and leaving endowment at $t+1$ unaffected keeping everything else constant (equation (9)). However, this in turn raises $r_t$ (equation (10)) which lowers $\mathbb{E}_t[\Delta e_{t+1}]$ (equation (9)). Hence, the response of the $r_t$ and $\mathbb{E}_t[\Delta e_{t+1}]$ to $m_t$ is determined jointly by the leverage effect in (9) and the Euler equation effect in (10). The red dotted line in Figure 3 illustrates how the leverage-induced relation between $r_t$ and $\mathbb{E}_t[\Delta e_{t+1}]$ changes when $m_t$ goes from zero to a positive value. While the slope of the line stays at $-1/s$, the intercept goes up by $\frac{1}{1+g+\epsilon_t} m_t$. As a result, the equilibrium interest rate goes up because the Euler equation relation is quite steep compared to the leverage-induced relation. When the equilibrium interest rate goes up due to a monetary shock, it stays high persistently due to the same channel resulting in the law of motion in (11).

Equation (11) shows that a monetary policy shock $m_t$ translates into a shock to the equilibrium interest rate by a factor of $\frac{\gamma s}{1+\gamma s} \frac{1}{1+g+\epsilon_t} > 0$ which is close to one for large values of $\gamma s$. And a unit change in $r_t$ translates into a change in $r_{t+1}$ by a factor of $\frac{\gamma s}{1+\gamma s} \frac{1}{1+g+\epsilon_t}$ as well. Therefore, even though $m_t$ is just a one-time shock to the interest rate, it has a persistent impact on interest payments endogenously. This channel has two important implications. First, monetary shocks affect long term yields as well due to a persistent change in short term rates. Second, even if the effective subsidy by the monetary authority is small, it has a much larger impact on the cumulative interest payments over time due to the persistent change in the equilibrium interest rate.

### 3.4.2 Leverage and risk

To illustrate the impact of interest rate dynamics on conditional risk, we use a second order approximation of the model. In this case, the conditional variance of the log SDF

$\pi_{t+1} = \log\beta - \gamma\Delta e_{t+1}$ is given by

$$Var_t(\pi_{t+1}) \approx \gamma^2 \left[1 - g + sr_t\right]^2 (\sigma_t^2 + s\sigma_{mt}^2) + \zeta(\sigma_t, \sigma_{mt}, s, \gamma), \tag{12}$$

where $\partial\zeta/\partial\sigma_t > 0$ and $\partial\zeta/\partial\sigma_{mt} > 0$.

Equation (12) shows that the volatility of the SDF depends on the interest rate $r_t$. In the calibrated model in Section 3.5, we have $1 - g + sr_t > 0$ in the simulated population which implies that $Var_t(\pi_{t+1})$ is increasing in $r_t$.[14] The positive relation between SDF volatility and the interest rate is the direct consequence of leverage: higher interest rates increase debt payments and lower the residual cash flows (i.e., endowment) for levered investors, making endowment growth more volatile. This effect vanishes if the investor is not levered, i.e. $s = 0$, and as a result, the SDF volatility is only driven by the exogenous volatility process $\sigma_t$.

The dependence of SDF volatility on the interest rate links monetary shocks to movements in risk which is the core message of our paper. Exogenous monetary shocks $m_t$ directly impact the equilibrium interest rate $r_t$ as illustrated in Section 3.4.1. Equation (12) implies that monetary shocks also change $Var_t(\pi_{t+1})$ due to their impact on the interest rate.[15] This relation can be interpreted as the causal effect of monetary policy shocks on risk appetite (Bauer, Bernanke, and Milstein (2023)). This channel operates through an increase in the risk exposure for levered investors, and its asset pricing implications are akin to an exogenous increase in risk aversion as in the habit model of Campbell and Cochrane (1999).

What do these insights imply for the comovement between interest rates and conditional risk? The answer lies in the nature of the shock driving their joint variation. Exogenous

[14] This condition will be violated if $r_t$ becomes highly negative. That is, $r_t < -\frac{1-g}{s}$. For instance, suppose that $g = 0.02$ in annualized terms. With a $P/D$ of 30 for the risky asset and targeting a leverage ratio $sD/P = 0.5$, we have $s = 15$. As a result, the condition is violated if $r_t < -0.065$. While our calibrated model in Section 3.5 is at the daily frequency, it is close to this example in annualized terms and unrealistically low interest rates do not occur within the simulated population.

[15] In particular, we consider $\frac{\partial Var_t(\pi_{t+1})}{\partial m_t} = \frac{\partial Var_t(\pi_{t+1})}{\partial r_t}\frac{\partial r_t}{\partial m_t}$ where $\frac{\partial Var_t(\pi_{t+1})}{\partial r_t} > 0$ under reasonable parameters as illustrated above and $\frac{\partial r_t}{\partial m_t} > 0$ as shown in equation (11).

positive shocks to volatility $\sigma_t$ lower the interest rate $r_t$ due to the precautionary savings effect. While an interest rate decline has a dampening effect on the SDF volatility, the increase in $\sigma_t$ dominates in the calibrated model in Section 3.5. In contrast, a direct increase in $r_t$ due to an exogenous monetary policy shock $m_t$ (that is uncorrelated with fundamental volatility $\sigma_t$) also increases SDF volatility (equation (12)). This gives rise to a positive comovement between conditional risk and interest rates. Hence, consistent with the empirical evidence in Section 2, the leverage channel induces a positive relation between changes in interest rates and conditional risk on FOMC days, which can undo the negative relation induced by the precautionary savings effect on all days.

Another implication of equation (12) is that conditional SDF volatility, on average, drops on FOMC days. On the day prior to an FOMC day, we have $\tau_t = 1$ and $\sigma_{mt} > 0$ while we have $\tau_t = T_m$ and $\sigma_{mt} = 0$ on the FOMC day. Hence, our model predicts that conditional volatility falls on FOMC days on average, and positive (negative) monetary policy shocks will lead to an increase (decrease) in risk relative to the average monetary policy uncertainty resolution effect.

## 3.5 Quantitative analysis

### 3.5.1 Calibration and target moments

We assume that the dividend growth variance $\sigma_t^2$ evolves according to the following process:

$$\sigma_t^2 = \exp(\nu_t) \text{ where } \nu_{t+1} = (1-\rho)\bar{\nu} + \rho\nu_t + \eta_{t+1}, \tag{13}$$

and $\eta_{t+1} \overset{\text{iid}}{\sim} N(0, \sigma_\nu)$.

We calibrate the model at a daily frequency consistent with the empirical evidence in Section 2. When calibrating moments related to the risky asset, we consider empirical

**Table 7**
Model parameters

| Parameter | Value |
|---|---|
| Relative risk aversion, $\gamma$ | 1.5 |
| Time discount factor, $\beta$ | 0.99984 |
| Mean dividend growth, $g$ | 7.8585e-05 |
| Average log variance, $\bar{\nu}$ | -9.5813 |
| Persistence of log variance, $\rho$ | 0.98 |
| Volatility of log variance, $\sigma_\nu$ | 1.0079 |
| Leverage parameter, $s$ | 3780 |
| Volatility of monetary shock, $\sigma_m$ | 2.3938e-06 |
| Days between monetary shocks, $T_m$ | 31 |

*Notes.* This table reports the parameter values from the baseline calibration. The model is calibrated at a daily frequency.

moments for aggregate equity. For instance, the VIX index corresponds to the expected volatility of S&P 500 index returns. Hence, we assume that the representative investor holds the stock market index itself or an asset portfolio that has similar dividend dynamics as aggregate equity, and finances these asset holdings partially with short-term risk-free debt.

The model has nine parameters and Table 7 reports the parameter values in our calibration. We set the average number of days between monetary shocks $T_m$ to 31 which is the average number of business days between scheduled FOMC announcements in the period from January 1995 to September 2022. We also fix average dividend growth $g$ to an annualized value of 2% and risk aversion to 1.5 which are both within the standard values used in the literature.

This procedure leaves us with six parameters which we use to target six empirical moments listed in Table 8. In what follows, we discuss the parameter values based on the target moments that they affect the most. In particular, we set the annualized value of $\beta$ to 0.96 targeting the average real 1-year interest rate of 0.40% which is the average rate published by Cleveland Fed based on the methodology in Haubrich, Pennacchi, and Ritchken (2012).

The volatility of the 1-year interest rate is 0.65% in the model which is lower than 1.78% in the data. Even though expected endowment growth is volatile due to variation in interest payments, the leverage effect (high rates lowering expected growth in equation (9)) stabilizes expected growth leading to low interest rate volatility. The interest rate dynamics in our model are therefore different from recursive utility models where expected growth is time-varying but EIS is assumed to be high to avoid high interest rate volatility (e.g., Bansal and Yaron (2004)).

For the leverage parameter $s$, we use the target debt-to-asset ratio of 0.55 from He and Krishnamurthy (2013) which is close to the average ratio for financial intermediaries in their empirical sample and the unconditional average debt-to-asset ratio in their model. Even though we do not model a leverage constraint, the representative investor in our model can represent the financial intermediation sector whose cash flow dynamics driven by their leverage, and whose preferences determine equilibrium asset prices. The amount of interest-bearing debt for the representative investor in our model is given by $sD_t$ and the asset value is equal to the value of the risky asset $P_t$, resulting in $sD_t/P_t$ for the debt-to-asset ratio. This results in an average annualized log price-dividend ratio of 3.26 for the risky asset in the model which is close to the historical average for the aggregate U.S. stock market.

We calibrate the parameters, $\bar{\nu}, \sigma_\nu$, and $\rho$, for the volatility process targeting the average, volatility, and daily persistence of the VIX index in our sample period.[16] Finally, we set the volatility of monetary policy $\sigma_m$ targeting the high frequency response of interest rates to a one standard deviation monetary shock. In particular, we find that the sensitivity of the four-quarter Eurodollar interest rate to a 1 standard deviation monetary shock in the 30-minute FOMC announcement window is 5.88bps in the data.

To compare the model and data quantitatively, we simulate the model at the daily fre-

[16] We compute VIX in the model as $\text{VIX}_t = 100\sqrt{12 \cdot \mathbb{E}_t^Q \sum_{\tau=1}^{21} Var_{t+\tau-1}^Q(\log(1 + r_{t+\tau}^d))}$ where $r_{t+1}^d = \frac{P_{t+1}+D_{t+1}}{P_t} - 1$ and $\mathbb{E}_t^Q[X_{t+1}] = \frac{\mathbb{E}_t[\Pi_{t+1}X_{t+1}]}{\mathbb{E}_t[\Pi_{t+1}]}$ for all random payoffs $X_{t+1}$.

**Table 8**
Target moments

| | | Data | Model | | | |
|---|---|---|---|---|---|---|
| | | | Median | 5% | 95% | Population |
| $\mathbb{E}[r_t]$ | Average interest rate | 0.40 | 0.66 | 0.07 | 1.46 | 0.71 |
| $\mathbb{E}[sD_t/P_t]$ | Average debt-to-asset ratio | 0.55 | 0.57 | 0.52 | 0.66 | 0.58 |
| $\mathbb{E}[VIX_t]$ | Average VIX | 20.12 | 18.08 | 16.52 | 20.76 | 18.32 |
| $\sigma(VIX_t)$ | Volatility of VIX | 8.24 | 7.11 | 6.22 | 8.63 | 7.51 |
| $AC(VIX_t)$ | Autocorrelation of VIX | 0.98 | 0.98 | 0.97 | 0.98 | 0.98 |
| $\beta_{r_t,m_t}$ | IR response to monetary shock | 5.88 | 5.93 | 5.51 | 6.38 | 5.96 |

*Notes.* This table reports the target moments in the data and in the model. Data values are for the period from January 1995 to September 2022. In the model, we simulate 10,000 samples at the daily frequency with the same length as the data period and report the $5^{th}$, $50^{th}$, and $95^{th}$ percentile values of the model statistics. The population statistics are obtained from a simulation path of 10,000 years.

quency and report results from a long simulation of 10,000 years (Population). We also simulate 10,000 samples from the model that are as long as our sample period from January 1995 to September 2022. We obtain the distribution of each moment from these simulations, and report the $50^{th}$, $5^{th}$, and $95^{th}$ percentiles.

Table 8 reports the empirical target moments and their counterparts from model simulations. Overall, the model provides a good fit to the empirical target moments and all target moments are within the 90% confidence band of their model-implied distributions. In addition, the model implies an annual risk premium of 5.74% for the risky asset which is close to the historical equity premium. The model delivers a high equity premium because endowment growth for the representative investor in the model is more volatile compared to the risky asset's dividends. This is in contrast with typical endowment economy models with low volatility for consumption growth mimicking dynamics at the aggregate level. In our model, we assume a leverage parameter that makes equity dividends more volatile. The investor uses leverage and their marginal utility depends on their endowment which is what remains from risky asset dividends after making interest payments.[17] This results in a volatile endowment growth and SDF implying a high risk premium.[18]

### 3.5.2 Asset prices in the model

Figure 4 presents model quantities as a function of the state variable $E_t/D_t$. Low values of $E_t/D_t$ corresponds to states where the representative investor spends a larger fraction of $D_t$ on interest payments that depend on $r_{t-1}$. When $r_{t-1}$ is high, $r_t$ is high as well due to the endogenous persistence of the interest rate discussed in Section 3.4.1. Panel A shows that low $E_t/D_t$ states indeed correspond to high $r_t$ states.

Consistent with our illustration in Section 3.4.2, the SDF is more volatile when interest rates are high (Panel B). Panel C confirms that the higher SDF volatility translates into a higher VIX level in low $E_t/D_t$ states. Hence, higher endowment growth volatility due to higher leverage makes equity returns conditionally more volatile even though dividend growth volatility is exogenous and does not depend on leverage.

The similar patterns of the interest rate and the SDF volatility may seem contradictory at first as higher SDF volatility should lower the interest rate due to the precautionary savings effect. However, Panel D shows that low $E_t/D_t$ imples high expected endowment growth for the representative investor dominating the precautionary savings effect and raising the interest rate. Panel E shows that the risk premium on the risky asset is high in low $E_t/D_t$ states consistent with a high VIX. Finally, the price-dividend ratio of the risky asset is increasing in $E_t/D_t$ due to the total discount rate effect. Recall that expected dividend

[17] We assume that the change in debt $L_t - L_{t-1}$, which is assumed not to have an impact on the investor's endowment, is spent on other expenses. For instance, the levered investor can be seen as a financial intermediary as discussed above. The average ratio of the debt issuance $L_t - L_{t-1}$ to $D_{t-1}$ in the model is 29%. This is similar to the ratio of SG&A expenses to revenue for Compustat broker-dealers (firms listed as primary dealers by He, Kelly, and Manela (2017)) given by 29%.

[18] The model implies a volatility of 20% for the annualized endowment growth. This is comparable to the dividend growth volatility for Compustat broker-dealers (firms listed as primary dealers by He, Kelly, and Manela (2017)) given by 21%.

growth is constant and equal to $g$, and therefore, does not lead to any variation in the price-dividend ratio. In low $E_t/D_t$ states, the price-dividend ratio is low because both the interest rate and the risk premium components of the discount rate are higher. This also implies that leverage in cash flow terms $(1 - E/D)$ and in asset value terms $(sD/P)$ behave similarly in the model.

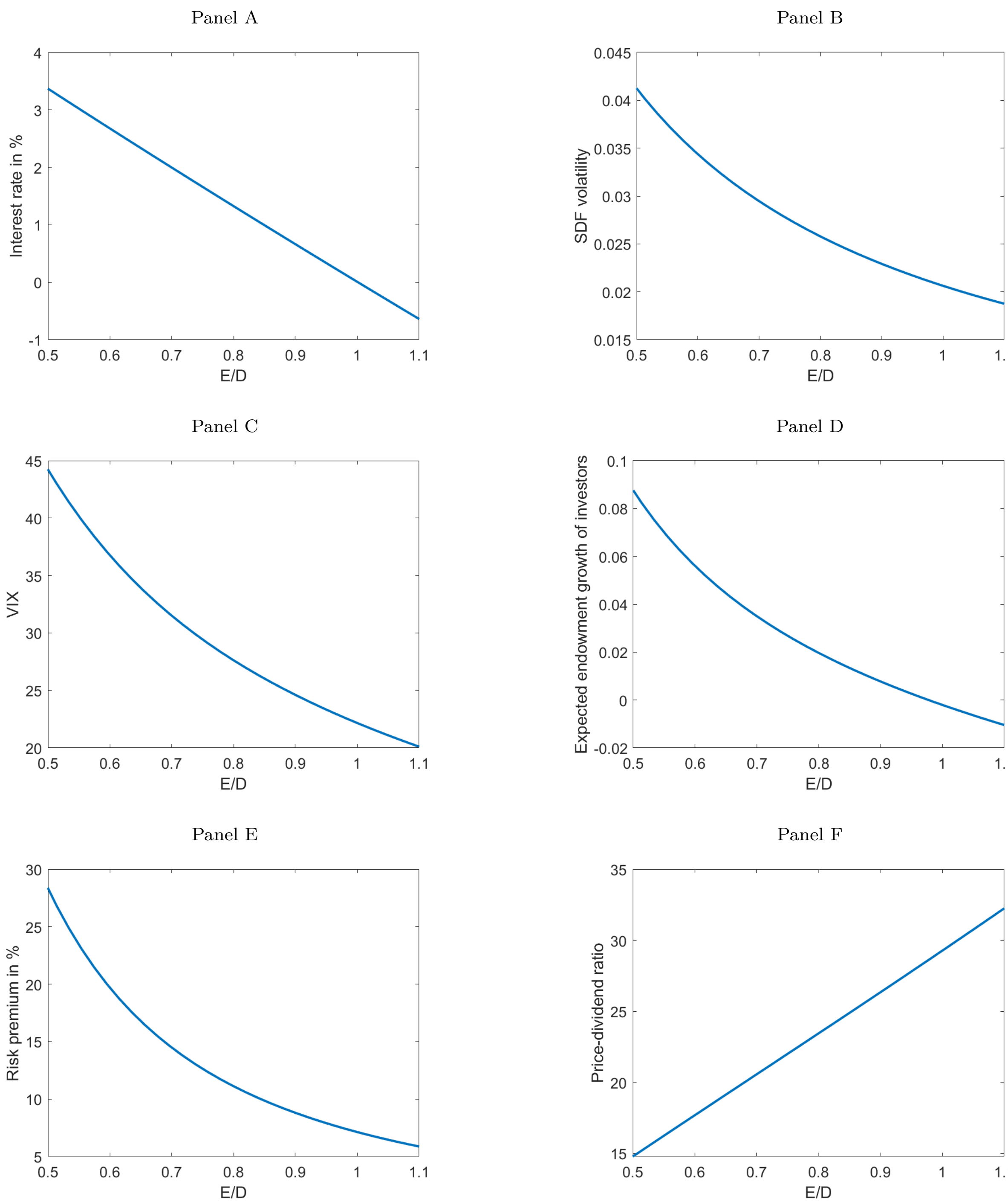
Figure 5 shows that the model generates a wide range of values for $E_t/D_t$. $E_t/D_t$ has a left-skewed distribution because lower $E_t/D_t$ implies a higher conditional volatility of $\Delta e_{t+1}$ due to higher $r_t$. $E_t/D_t$ goes above one only if the interest rate is negative which does not occur frequently in the model. We observe that $E_t/D_t$ is more persistent (0.9997 at the daily frequency) compared to $\sigma_t$ (0.9783 at the daily frequency) making monetary shocks more long-lived compared to volatility shocks.

Equation (8) implies that a monetary policy shock $m_t$ is a direct shock to $E_t/D_t$ in the model. Therefore, the effects of monetary shocks on model quantities can be interpreted using variations in $E_t/D_t$ in Figure 4. A negative monetary policy shock $m_t < 0$ is a subsidy to borrowers that increases $E_t/D_t$ and lowers the equilibrium interest rate. Long term interest rates reflect expectations of future short term rates and term premiums. In our model, the effect of monetary shocks on the short term interest rate is highly persistent. Therefore, long term rates are responsive to monetary shocks as well. Hence, our model provides a mechanism for the transmission of monetary policy shocks to long term interest rates documented, e.g., by Cochrane and Piazzesi (2002) and Hanson and Stein (2015), that is based on persistent changes in the equilibrium interest rate.[19]

Our model augments monetary policy shocks with an asset market where levered investors

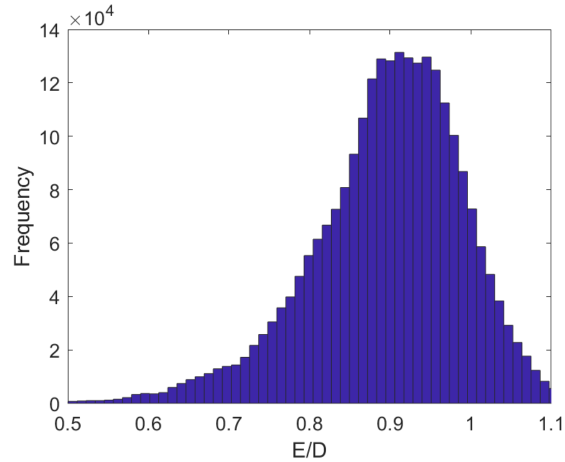
[19] Kekre, Lenel, and Mainardi (2022) study the effects of monetary policy on long term rates and the term premium in a model where monetary shocks generate a wealth effect for intermediaries similar to the impact on levered investors in our model. They also point out a U-shaped pattern in the response of yields to monetary shocks up to 20-year maturity. While our model implies monotonic impulse responses, we find that the term premium responds positively to monetary shocks in our model, i.e. forward rates at 10, 20, and 30-year maturities rise more than the expected 1-period interest rate at those horizons.

**Figure 4.** Asset prices as a function of the state variable $E_t/D_t$




*Notes.* This figure plots the equilibrium quantities in the model as a function of $E_t/D_t$. We set $\sigma_t$ to its median value and $\tau_t = 15$. Interest rate is the 12-month risk-free rate (Panel A). SDF volatility is the conditional volatility of the log stochastic discount factor and VIX is the VIX index (Panels B and C). Expected endowment growth of the representative investor is the expected value for $\Delta e_{t+1}$ over the next month (Panel D). Risk premium is the annualized expected excess return on the risky asset (Panel E). Price-dividend ratio is the risky asset's price divided by its daily dividend multiplied by 252 (Panel F).

**Figure 5.** Distribution of $E_t/D_t$




*Notes.* This figure plots the distribution of $E_t/D_t$ in a model simulation with length 10,000 years at the daily frequency.

such as intermediaries affect asset prices. For instance, He and Krishnamurthy (2013) model levered financial intermediaries as marginal investors in financial markets. In their model, intermediaries borrow at the risk-free interest rate similar to our model but they face a constraint which becomes binding during crises. The constraint introduces non-linearity and helps the model replicate asset price behavior during crisis times. Coimbra and Rey (2023) also model levered intermediaries with a value-at-risk constraint. Both papers consider the effects of monetary policy shocks on risk premiums in the economy as policy experiments. While intermediary constraints are certainly crucial in explaining crisis phenomena, we focus on the role of leverage itself in an attempt to shed light on the role of the feedback loop between interest rates, endowment dynamics for levered investors, and asset prices. We show that the existence of leverage in marginal investors' balance sheets is crucial to understand our empirical findings. Nevertheless, we interpret the relevance of a levered representative investor for asset prices in the same spirit as intermediary-based asset pricing models. In our model, a positive monetary policy shock $m_t > 0$ increases the leverage of the representative investor measured both as $E_t/D_t$ and $sD_t/P_t$. Consistent with this evidence, we find that a

1 standard deviation NS shock leads to a 4.3bps increase in financial intermediaries' market debt-to-asset ratio using the data from He, Kelly, and Manela (2017). In the data, this is driven by the price response of financial intermediaries' publicly traded equity. Similarly, the price-dividend ratio of the risky asset in the model responds negatively to monetary policy shocks, which directly affects the representative investor's equity value and leverage.

**Table 9**

Regression moments

| | | Model | | | |
|---|---|---|---|---|---|
| | Data | Median | 5% | 95% | Population |
| Panel A: $\Delta r_t^{1y}$ | | | | | |
| FOMC | -0.50 | -0.03 | -0.76 | 0.75 | -0.08 |
| $\Delta$VIX | -0.49 | -0.45 | -0.56 | -0.26 | -0.42 |
| FOMC $\times$ $\Delta$VIX | 0.57 | 0.53 | 0.02 | 1.45 | 0.49 |
| Panel B: $\Delta$VIX | | | | | |
| FOMC | -0.54 | -0.41 | -0.59 | -0.23 | -0.40 |
| $m$ | 0.31 | 0.18 | 0.02 | 0.37 | 0.19 |

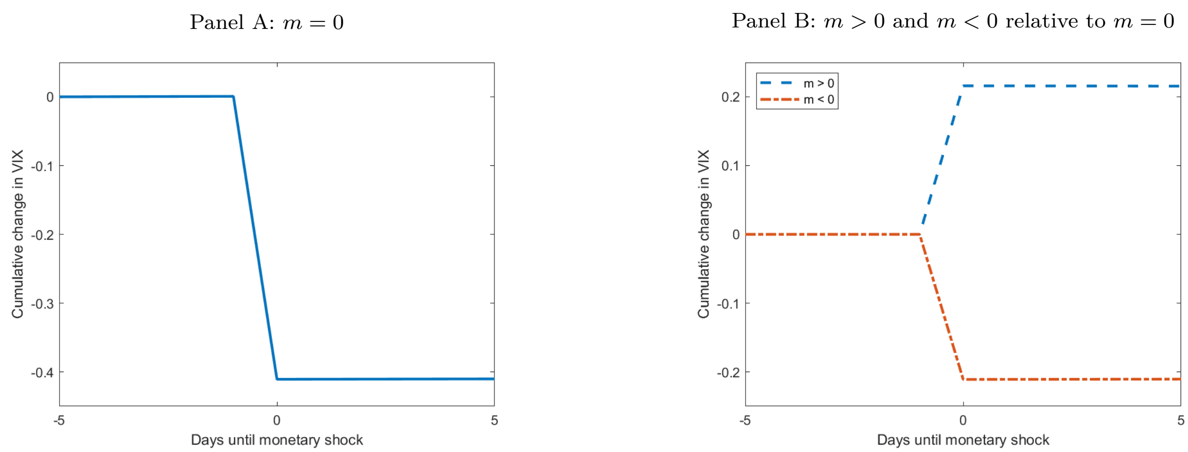
*Notes.* This table reports results from regressing daily changes in the 1-year interest rate on an FOMC dummy, the daily change in VIX, and their interaction term (Panel A) as well as regressing the daily change in VIX on an FOMC dummy and monetary policy shocks (Panel B) in the data and in the model. The monetary shock is $m$ in the model and the NS shock in the data. Data values in Panel A are for the period from January 1995 to September 2022. In the model, we simulate 10,000 samples at the daily frequency with the same length as the data period and report the $5^{th}$, $50^{th}$, and $95^{th}$ percentile values of the model statistics. The population statistics are obtained from a simulation path of 10,000 years.

## 3.6 The comovement between VIX and interest rates

In this section, we present the implications of our model for the empirical evidence in Section 2. Specifically, we assess the model's ability to explain the differential comovement between VIX and interest rates on non-FOMC and FOMC days as well as the impact of monetary shocks on VIX.

Panel A of Table 9 reports results from regressing changes in the 1-year interest rate at

**Figure 6.** VIX on FOMC days in the model




*Notes.* The left panel of the figure plots the cumulative VIX change from 5 days before to 5 days after an FOMC day (day 0) for $m = 0$ in the model. The right panel plots the cumulative VIX changes for a 1 standard deviation positive (blue dashed line) and negative (red dotted-dashed line) $m$, relative to the unconditional average in the left panel. For this figure, we simulate a long sample where all shocks are set to zero except $m$ for the right panel, and $\sigma_t$ is set to its median value.

the daily frequency on changes in VIX interacted with an FOMC day dummy. In the data, we document that the relation is significantly negative on non-FOMC days as can be seen from the coefficient on ΔVIX but there is a large and significantly positive loading on the interaction term FOMC × ΔVIX. The model matches both properties of the data quite well. Based on short samples from the model, the coefficient on ΔVIX is significantly negative and the coefficient on FOMC × ΔVIX is significantly positive. The negative relation on non-FOMC days is driven by the exogenous time variation in $\sigma_t$ and the resulting movements in the interest rate $r_t$ as a result of the precautionary savings effect. The positive relation between $\Delta r_t$ and ΔVIX on FOMC days can be well understood based on Panels A and C of Figure 4. Monetary shocks $m_t$ are direct shocks to $E_t/D_t$ which induce positive comovement between $r_t$ and VIX. That is, positive monetary shocks raise the equilibrium interest rate (Section 3.4.1) and the conditional endowment growth risk for the representative investor through the leverage channel (Section 3.4.2). This results in a stark difference in the comovement of $r_t$ and VIX on non-FOMC and FOMC days.[20]

We also assess the direct impact of monetary shocks on the VIX in the model comparing it to the high frequency evidence in Section 2.3. Panel B of Table 9 shows that VIX drops on FOMC days in the model by a comparable magnitude to the average drop in the data. In the model, this effect is driven by the resolution of monetary policy uncertainty on FOMC days. That is, $\sigma_{mt}$ drops to zero on FOMC days lowering the conditional volatility of stock returns over the next month.[21] Importantly, the magnitude of the monetary shock matters for the change in VIX. Relative to the average drop in VIX, the response of $\Delta$VIX is increasing in $m$ in the model consistent with the empirical evidence in Section 2.3. Figure 6 illustrates this effect showing the average VIX drop in case the monetary shock is zero (Panel A) and the deviations from the average effect in cases of 1 standard deviation positive and negative monetary shocks. The patterns are very similar to the empirical high frequency evidence using VIX futures data plotted in Figure 2. The impact of monetary shocks on asset return risk is driven by the impact of the instantaneous change in the cost of financing and leverage, changing the endowment growth volatility of the representative investor. In sum, the causal effect of monetary shocks induces a positive and the causal effect of volatility shocks induces a negative relation between $r_t$ and VIX.

[20]In the data, interest rates have been declining over our sample period. Consistent with Hillenbrand (2023), the decline mostly occurred on FOMC days resulting in the negative coefficient on the FOMC dummy (the data column in Panel A of Table 9). The interest rates in our model are stationary and do not have a trend. Therefore, the median coefficient in the model is close to zero but the estimate has a large confidence band due to strong effects of monetary shocks.

[21]Savor and Wilson (2013) document that the average realized stock market returns are significantly higher on macroeconomic announcement days. Consistent with their evidence, the average daily market return is 33.5bps on FOMC days and 3.1bps on non-FOMC days which implies an FOMC announcement premium of 32.4bps in the data. Our model features only a small announcement premium of 1.8bps due to the reduction of $\sigma_{mt}$ from $\sigma_m$ to zero on announcement days. Due to small number of FOMC days (i.e., 221) in each simulated sample, the premium has a large range of values across simulations from -15.8bps at the $5^{th}$ to 18.9bps at the $95^{th}$ percentile which is below the empirical value. We abstract from embedding mechanisms such as risk sensitive preferences and imperfect information (Ai and Bansal (2018)) to focus on the directional impact of monetary policy shocks on conditional risk in financial markets rather than the effect of uncertainty resolution about the future path of the economy.

## 3.7 Intermediaries' interest expense and monetary shocks

The mechanism in our model operates through the impact of monetary shocks on the borrowing cost for the levered investors. We consider financial intermediaries as the primary example for the levered investor in our model. Therefore, we next verify the response of intermediaries' interest expense to monetary policy shocks to validate the model mechanism.

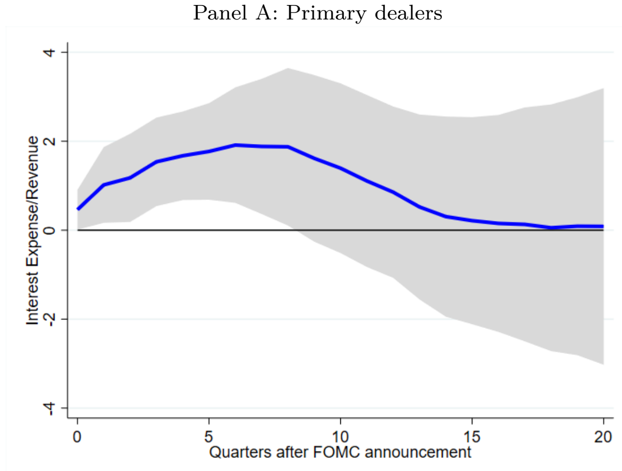
We consider two samples of firms in Compustat to compute the share of interest expense in revenues akin to $1 - E_t/D_t$ in the model. The first sample consists of primary dealers used in the construction of He, Kelly, and Manela (2017)'s intermediary asset pricing factor. We limit the sample to U.S. firms that are available in Compustat. The second sample represent broker-dealers in the spirit of Adrian, Etula, and Muir (2014). While they use the leverage ratio of these firms from flow of funds, we compute the interest expense for Compsustat firms with the SIC codes 6211 and 6221 ("Security Brokers, Dealers, and Flotation Companies" and "Commodity Contracts Brokers and Dealers") located in the U.S. Although only 13% of broker-dealers are also primary dealers based on our classification, primary dealers account for 75% for the total revenue of broker-dealers.[22] To obtain distinct variation, we exclude primary dealers from the set of broker-dealers in our main results.

For each quarter and subsample of firms, we compute the sum of interest expense (Compustat items *xintq* and *tieq*) and sales (Compustat item *salesq*). We then compute the first difference in the ratio of interest expense to sales from one quarter to the next for firms with available data in both quarters. And then, we compute the sum of changes in this ratio across horizons and regress it on the NS shocks. In other words, we run predictability regressions of the change in the interest expense share in sales using the NS shock for different horizons and report results in Figure 7. For both primary dealers (Panel A) and broker-dealers (Panel B), we verify that the ratio of interest expense to sales increases by

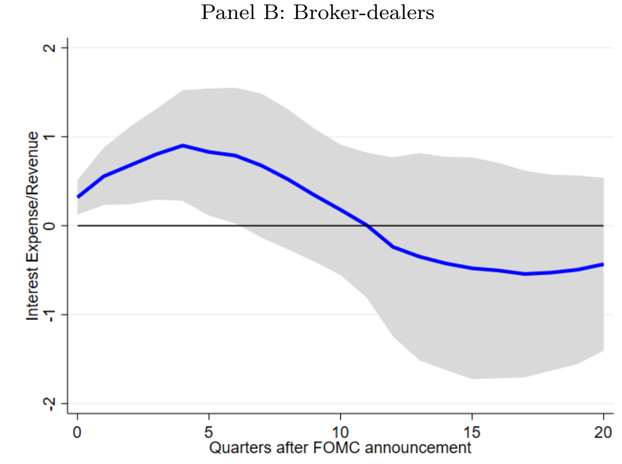
[22] Primary dealers are not a subset of broker-dealers and some of them are listed as depository banks, e.g. Bank of America and J.P. Morgan.

**Figure 7.** Response of intermediaries' interest expense to monetary shocks

Panel A: Primary dealers




Panel B: Broker-dealers




*Notes.* The figure plots the response of the interest expense-revenue ratio for primary dealers (Panel A) and broker-dealers excluding primary dealers (Panel B) to a 1 standard deviation NS shock. The sample period is from 1995Q1 to 2022Q2.

1 to 2 percentage points consistent with the model.[23] As a result, our model's mechanism that operates through leverage in cash flow terms holds in the data and serves as a valid assumption for why levered investors may face elevated levels of risk as a result of monetary policy shocks.[24]

### 3.8 Stock market response to monetary shocks

The stock market response to interest rate shocks on FOMC days can differentiate between monetary policy transmission mechanisms. In particular, higher rates may lower stock prices due to higher bond yields lowering the value of all long dated assets including equity, or they may raise the risk premium by increasing stock market risks or risk aversion. In a VAR framework, Bernanke and Kuttner (2005) argue that most of the stock market reaction to monetary shocks is driven by the expected excess return component and almost none by expected interest rates. Following this evidence, the literature has provided explanations for the transmission channels of monetary policy to risk premiums (e.g., Pflueger and Rinaldi (2022), Kekre and Lenel (2022)).

In recent work, Nagel and Xu (2024) challenge the conventional wisdom by showing that the stock market response to monetary shocks is primarily driven by yields. In particular, they decompose the stock market response to monetary shocks into components driven by yields and dividend futures prices. They then compute counterfactual announcement returns by setting movements in the dividend futures price on FOMC days to zero. With this approach, Nagel and Xu (2024) find that most of the announcement day return is attributable to bond yields and none to risk premiums.

We employ their Nagel and Xu (2024)'s methodology to compute the fraction of the

[23] A 1 standard deviation monetary shock increases $1 - E_t/D_t$ by 1pp in the model.

[24] Appendix Figure A.3 shows that we obtain comparable results in case of equaal-weighting the interst expense ratio across firms and for the sample of broker-dealers without excluding primary dealers.

stock market response to monetary shocks driven by yields in our model. We find that the counterfactual return's response to $m$ shocks accounts for 77.1% of the total equity price response.[25]

What drives this result in the model? A positive $m$ lowers the representative investor's endowment, and hence $E/D$, which increases both the interest rate and the equity premium as can be seen in Figure 4. The increase in the equity premium is due to higher leverage while the risk-free rate increases due to higher expected endowment growth for the investor. At the same time, we find that a positive $m$ shock raises the term premium because long-term bonds become riskier due to increased volatility in $E/D$. In sum, our model attributes a substantial fraction of equity return variation on FOMC days to yield variation consistent with recent findings in the literature.

## 3.9 Comparative statics

We next compare our baseline model with alternative specifications for leverage, volatility, and preferences. We conduct these exercises by changing one aspect of the model at a time and keeping all other parameters identical to those in Section 3.5.1.

We start by setting the leverage parameter to zero, i.e. $s = 0$. In this case, monetary policy shocks play no role in the model and the investor's endowment growth volatility is equal to the dividend growth volatility of the risky asset. Panel A of Appendix Table A.9 shows that the VIX and the interest rates do not respond to monetary policy shocks in this case. Importantly, changes in yields have a large negative loading on changes in VIX due to precautionary savings and time-varying volatility. But the model cannot explain any phenomena related to FOMC days by construction.

[25] In particular, we compute the counterfactual return ($\Delta p_B$) based on the Campbell-Shiller decomposition of price changes ($\Delta p$) into maturity-matched yield movements and dividend risk premiums. The loading of $\Delta p_B$ on $m$ is equal to 77.1% of $\Delta p$'s loading on $m$. See Appendix D for details.

Next, we drop the assumption of time-varying dividend growth volatility, and set $\nu_t = \log(\sigma_t)$ to a constant that is equal to its average value in our baseline calibration. This version of the model can still generate a high level of average VIX, but does not account for the high volatility of VIX (Panel B of Appendix Table A.9). That is, the variation in $E_t/D_t$ generates some volatility in VIX but it is far too small compared to the data. However, monetary policy shocks are still operational in the model. Therefore, the model still implies additional positive comovement between interest rates and VIX on FOMC days compared with non-FOMC days. But the model fails to account for the average negative comovement between interest rates and VIX because the precautionary savings term explains a negligible portion of the yield variation in the absence of time-varying volatility. Hence, time-varying volatility helps the model generate the negative comovement on non-FOMC days and make the orders of magnitude for regression coefficients and volatility of VIX consistent with the data.

In our model, the EIS is an important parameter for the transmission of monetary shocks to the interest rate as illustrated in Section 3.4.1. Therefore, we also investigate model implications assuming that the representative agent has recursive preferences (Epstein and Zin (1991)). Recursive preferences allow a separation of the elasticity of intertemporal substitution (EIS) $\psi$ and risk aversion $\gamma$ as opposed to CRRA utility where $\psi = 1/\gamma$ which is equal to $0.67 \approx 1/1.5$ in our baseline calibration. Specifically, the slope of the purple line in Figure 3 is equal to the inverse of EIS. Therefore, higher values for the EIS would imply a weaker transmission of monetary policy shocks to interest rates which means that a larger $m_t$ would be required to change the equilibrium interest rate by the same amount. Indeed, when we set $\psi = 1.2$, the sensitivity of the interest rate to monetary shocks goes down to 5.84 (from 5.93 in the original calibration) and it goes up to 5.97 in case we lower EIS to $\psi = 0.5$ (Panel A of Appendix Table A.10). The monetary transmission strength variation by EIS also translates into how much monetary policy shocks affect risk. In particular, a one standard deviation monetary policy shock moves VIX by 0.12 with $\psi = 1.2$ and by 0.22 with $\psi = 0.5$ compared to 0.18 in the baseline calibration. All in all, EIS has an impact on the transmission of monetary policy shocks to risk but the main mechanism of our model is qualitatively consistent with different EIS values.

# 4 Conclusion

This paper studies the interplay between interest rates, financial market risk, and monetary policy. We document that the comovement of interest rates and VIX is negative on non-FOMC and positive FOMC days. Using high frequency data, we verify that this difference is driven by monetary policy shocks. The empirical patterns are consistent across several types of interest rates, and are not driven by inflation expctations, the Fed information effect, or convenience yields.

We explain these findings in an endowment economy that features financial leverage and monetary policy shocks. The model highlights that monetary policy shocks have a persistent impact on equilibrium interest rates, due to investors' leverage, and change investors' exposure to aggregate shocks. We interpret investors' leverage in the tradition of the intermediary asset pricing literature, where monetary shocks directly impact the cost of financing risky asset holdings. Through this channel, monetary policy has an impact on risk appetite in financial markets, asset prices, and conditional risks.

Our model can quantitatively account for the empirical patterns regarding the joint variation of interest rates, VIX, and monetary policy shocks. Hence, we show that the impact of monetary shocks on risk appetite in financial markets as formulated by Bauer, Bernanke, and Milstein (2023) can be explained through the conventional cost-of-capital channel. Interesting avenues for future work include the endogenous response of leverage to monetary policy shocks, how monetary policy shocks affect financial intermediaries' balance sheets, as well as the real effects of the causal impact of monetary policy shocks on asset market risks.

# Appendix

## A Data sources and summary statistics

In this section, we describe the data sources and the construction of variables used in the empirical analysis in Section 2. Table A.1 provides summary statistics for the variables.

**Interest rates.** We obtain Treasury yields from the constant maturity rates from FRED (for 3 and 6 months) and the zero-coupon fitted yields constructed by Gürkaynak, Sack, and Wright (2007a) (for 1, 2, 3, 5, 10 years). The overnight indexed swap-implied interest rates (OIS) are obtained from Bloomberg. The inflation-indexed TIPS yields for constant maturities (5 and 10 years) are also obtained from the FRED. We use all interest rates in annualized basis points throughout the paper.

**VIX index and futures.** We obtain the daily VIX index from Chicago Board Options Exchange (CBOE). Daily changes in VIX are computed as the difference between today's and yesterday's close. The high frequency VIX index data are also from CBOE and are available throughout our sample period except in the last three months of 2003. In the high frequency analysis on FOMC days, we also use high frequency VIX futures data from a private vendor starting from the introduction of VIX futures contracts in March 2004. When computing the intraday cumulative change in VIX futures, we use the change in the closest-to-maturity contract that still has at least three trading days to maturity.

**Monetary policy shocks.** We obtain monetary policy shocks from Acosta (2022) who extends the sample period in Nakamura and Steinsson (2018) until September 2022. There is a total of 221 scheduled FOMC meetings in our sample from January 1995 to September 2022. Following Nakamura and Steinsson (2018), we do not include unscheduled announcements as FOMC days because these are likely to be reactions to other concurrent economic shocks.

# B Household sector

Suppose that there is a measure $N$ of households. Every period, a new generation of households is born, and each generation lives for two periods. We assume that households have log utility and have a time discount factor of $\beta$. The generation born at $t$ receives labor income $wD_t$ at $t$ and can choose to consume a fraction $x$ of the labor income, and save the rest by holding short-term debt issued by the levered investor with risk-free interest rate $r_t$ which then finances household consumption at $t+1$. As a result, a household's problem is given by

$$\max_x \log(xwD_t) + \beta \log((1+r_t)(1-x)wD_t). \tag{A.1}$$

The optimality condition for (A.1) implies that households consume a constant fraction of their labor income given by $x = \frac{1}{1+\beta}$ and the saving rate is given by $1 - x = \frac{\beta}{1+\beta}$. The sum of savings from all households is then given by $N\frac{\beta}{1+\beta}wD_t$. Equating household savings to levered investors' liabilities is equivalent to setting $s = N\frac{\beta}{1+\beta}w$.

# C Model approximations

We first consider a first order approximation of $\log\left(\frac{E_{t+1}}{E_t}\right)$. Equations (7) and (8) imply

$$\Delta e_{t+1} = \log\left(\frac{E_{t+1}}{E_t}\right) = \log\left(1+g+\epsilon_{t+1} - s(r_t + m_{t+1})\right) - \log\left(1 - s(r_{t-1}+m_t)\frac{1}{1+g+\epsilon_t}\right), \tag{A.2}$$

which can be approximated as

$$\Delta e_{t+1} \approx g + \epsilon_{t+1} - s(r_t + m_{t+1}) + s(r_{t-1}+m_t)\frac{1}{1+g+\epsilon_t} \tag{A.3}$$

by applying $\log(1+x) \approx x$ to both terms in (A.2). Under this approximation, the conditional distribution of $\Delta e_{t+1}$ is normal. Therefore, it follows from (3.3) and the normality of $\Delta e_{t+1}$ that the log interest rate can be written as

$$\begin{aligned} r_t &= \log\left(\frac{1}{\mathbb{E}_t[\beta e^{-\gamma \Delta e_{t+1}}]}\right) \\ &\approx -\log\beta + \gamma \mathbb{E}_t[\Delta e_{t+1}] - \frac{1}{2}\gamma^2 Var_t(\Delta e_{t+1}). \end{aligned} \tag{A.4}$$

Plugging in $\mathbb{E}_t[\Delta e_{t+1}]$ and $Var_t(\Delta e_{t+1})$ implied by (A.3) and solving for $r_t$ results in the approximate interest rate dynamics in equation (11).

To obtain the conditional SDF volatility in equation (12), consider a second order Taylor approximation of the logarithmic function around zero: $\log(1+x) \approx x - \frac{1}{2}x^2$. Applying the approximation to logarithmic terms in (A.2), we obtain

$$\begin{aligned} \Delta e_{t+1} \approx\ & g - \frac{1}{2}g^2 - (1-g)sr_t - \frac{1}{2}s^2 r_t^2 - ed_t \\ & + (1-g+sr_t)\epsilon_{t+1} - \frac{1}{2}(\epsilon_{t+1})^2 - s(1-g+sr_t)m_{t+1} - \frac{1}{2}s^2(m_{t+1})^2 + s\epsilon_{t+1}m_{t+1}. \end{aligned} \tag{A.5}$$

For a standard normal variable $\tilde{\epsilon} \sim N(0,1)$, we have $cov(\tilde{\epsilon}, \tilde{\epsilon}^2) = 0$ and $\tilde{\epsilon}^2 \sim \chi_1^2$ with $Var(\tilde{\epsilon}^2) = 2$. Furthermore, we have $Var(\epsilon_{t+1}m_{t+1}) = \sigma_t^2\sigma_{mt}^2$ because the shocks are assumed to be independent. As a result, the variance of $\pi_{t+1} = \log\beta - \gamma\Delta e_{t+1}$ approximated as in (A.5) is given by (12) where

$$\zeta(\sigma_t, \sigma_{mt}, s, \gamma) = \gamma^2\left(\frac{1}{2}\sigma_t^2 + s^2\sigma_t^2\sigma_{mt}^2 + \frac{1}{2}s^4\sigma_{mt}^2\right). \tag{A.6}$$

# D Stock market response

Nagel and Xu (2024) show that the instantaneous response of log prices to a shock based on the Campbell-Shiller decompisition is given by

$$\Delta p_t = (\mathbb{E}_{t+} - \mathbb{E}_{t-}) \sum_{n=1}^{\infty} \rho^{n-1}[(1-\rho)d_{t+n} - x_{n,t+n}] + \sum_{n=1}^{\infty} \rho^{n-1}(f_{n,t-} - f_{n,t+}), \tag{A.7}$$

where $d$ is log dividend, $x$ is the excess return of the stock index relative to the forward rate, and $f_{n,t}$ is the $n$-period forward rate at $t$. The constant $\rho$ is given by $1/(1+\exp(\bar{dp}))$ where $dp$ is the log dividend yield.

The first term in equation (A.8) represents the change in the dividend risk premium relative to a maturity matched yield, and the second term represent the yield movements themselves. As a result, the counterfactual return driven by yield movements only is given by

$$\Delta p_{B,t} = \sum_{n=1}^{\infty} \rho^{n-1}(f_{n,t-} - f_{n,t+}). \tag{A.8}$$

**Table A.1**

Summary statistics

| Panel A: Full sample | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Daily Change | | | Level | | | | |
| | Mean | SD | Median | Mean | SD | Median | Observations | Sample period |
| VIX | 0.003 | 1.743 | -0.080 | 20.1 | 8.3 | 18.6 | 6930 | 01.1995–09.2022 |
| Yield (1st PC) | 0.000 | 4.135 | 0.055 | | | | 6930 | 01.1995–09.2022 |
| Yield (3 mo.) | -0.034 | 4.765 | 0.000 | 218.1 | 212.9 | 156.0 | 6930 | 01.1995–09.2022 |
| Yield (1 yr.) | -0.044 | 4.135 | 0.028 | 243.8 | 215.5 | 182.0 | 6930 | 01.1995–09.2022 |
| Yield (5 yr.) | -0.054 | 5.871 | -0.045 | 320.1 | 185.7 | 285.1 | 6930 | 01.1995–09.2022 |
| Yield (10 yr.) | -0.058 | 5.808 | -0.205 | 387.4 | 169.2 | 399.9 | 6930 | 01.1995–09.2022 |
| OIS (3 mo.) | -0.039 | 2.522 | 0.000 | 190.5 | 186.9 | 124.1 | 5681 | 01.2000–09.2022 |
| OIS (1 yr.) | -0.037 | 3.878 | 0.042 | 205.6 | 187.0 | 142.3 | 5681 | 01.2000–09.2022 |
| OIS (5 yr.) | -0.055 | 6.197 | -0.076 | 292.7 | 171.9 | 257.7 | 5681 | 01.2000–09.2022 |
| OIS (10 yr.) | -0.064 | 6.338 | -0.149 | 352.9 | 164.9 | 312.3 | 5681 | 01.2000–09.2022 |
| TIPS (5 yr.) | 0.003 | 6.567 | 0.000 | 36.0 | 111.6 | 30.0 | 4934 | 01.2003–09.2022 |
| TIPS (10 yr.) | -0.015 | 5.148 | 0.000 | 83.2 | 101.1 | 69.0 | 4934 | 01.2003–09.2022 |
| Panel B: FOMC days | | | | | | | | |
| | Daily Change | | | Level | | | | |
| | Mean | SD | Median | Mean | SD | Median | Observations | Sample Period |
| VIX | -0.532 | 1.881 | -0.430 | 19.9 | 7.9 | 18.2 | 221 | 01.1995–09.2022 |
| Yield (1st PC) | -1.275 | 4.404 | -0.259 | | | | 221 | 01.1995–09.2022 |
| Yield (3 mo.) | -1.489 | 4.314 | -1.000 | 218.7 | 214.4 | 156.0 | 221 | 01.1995–09.2022 |
| Yield (1 yr.) | -0.558 | 5.066 | -0.040 | 244.3 | 215.9 | 190.3 | 221 | 01.1995–09.2022 |
| Yield (5 yr.) | -0.614 | 7.293 | -0.110 | 320.1 | 184.9 | 285.3 | 221 | 01.1995–09.2022 |
| Yield (10 yr.) | -0.506 | 6.693 | 0.016 | 387.8 | 167.5 | 398.4 | 221 | 01.1995–09.2022 |
| OIS (3 mo.) | -0.094 | 1.492 | 0.000 | 190.6 | 187.5 | 125.0 | 181 | 01.2000–09.2022 |
| OIS (1 yr.) | -0.778 | 5.048 | -0.348 | 205.2 | 187.8 | 142.2 | 181 | 01.2000–09.2022 |
| OIS (5 yr.) | -0.982 | 8.272 | -0.650 | 292.7 | 171.2 | 260.4 | 181 | 01.2000–09.2022 |
| OIS (10 yr.) | -1.009 | 7.804 | -0.647 | 353.2 | 163.1 | 308.6 | 181 | 01.2000–09.2022 |
| TIPS (5 yr.) | -0.873 | 9.901 | -1.000 | 36.7 | 113.6 | 28.0 | 157 | 01.2003–09.2022 |
| TIPS (10 yr.) | -0.962 | 8.479 | 0.000 | 83.8 | 101.6 | 63.0 | 157 | 01.2003–09.2022 |
| NS | 0.000 | 1.000 | 0.079 | | | | 221 | 01.1995–09.2022 |
| VIX futures | -0.315 | 1.273 | -0.250 | | | | 147 | 05.2004–09.2022 |

*Notes.* This table reports summary statistics from daily data used in the paper. We report statistics for levels and changes. All interest rates are reported in basis points. Panel A reports statistics for all days, Panel B on scheduled FOMC announcement days.

# E Additional tables and figures

**Table A.2**
Individual yields and VIX

| | 3 mo. | 6 mo. | 1 yr. | 2 yr. | 3 yr. | 5 yr. | 10 yr. |
|---|---|---|---|---|---|---|---|
| FOMC | -1.369*** | -1.402*** | -0.497 | -0.360 | -0.358 | -0.447 | -0.414 |
| | (0.294) | (0.292) | (0.344) | (0.424) | (0.465) | (0.493) | (0.459) |
| $\Delta$VIX | -0.256*** | -0.335*** | -0.492*** | -0.670*** | -0.751*** | -0.804*** | -0.788*** |
| | (0.067) | (0.064) | (0.054) | (0.058) | (0.060) | (0.061) | (0.065) |
| FOMC $\times$ $\Delta$VIX | 0.517*** | 0.505*** | 0.573** | 0.886*** | 1.024*** | 1.084*** | 0.910** |
| | (0.198) | (0.182) | (0.238) | (0.289) | (0.322) | (0.361) | (0.366) |
| Observations | 6930 | 6930 | 6930 | 6930 | 6930 | 6930 | 6930 |
| Adjusted $R^2$ | 0.011 | 0.025 | 0.041 | 0.049 | 0.052 | 0.055 | 0.054 |

*Notes.* This table reports results from regressing daily changes in individual U.S. government bond yields on an FOMC day dummy, the daily change in the VIX index, and their interaction term. The sample period is from January 1995 to September 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Table A.3**
Real yields and VIX

| | 5 yr. | | 10 yr. | |
|---|---|---|---|---|
| | Nominal | Real | Nominal | Real |
| FOMC | -0.416 | -0.485 | -0.409 | -0.718 |
| | (0.645) | (0.756) | (0.594) | (0.664) |
| ΔVIX | -0.846*** | -0.391** | -0.862*** | -0.326*** |
| | (0.067) | (0.180) | (0.072) | (0.069) |
| FOMC × ΔVIX | 1.161*** | 1.196** | 0.968** | 0.828** |
| | (0.404) | (0.510) | (0.397) | (0.355) |
| Observations | 4934 | 4934 | 4934 | 4934 |
| Adjusted $R^2$ | 0.072 | 0.014 | 0.078 | 0.015 |

*Notes.* This table reports results from regressing daily changes in 5-year and 10-year nominal U.S. government bond yields and TIPS on an FOMC day dummy, the daily change in the VIX index, and their interaction term. The sample period is from January 2003 to September 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Table A.4**
Bond yields and risk index

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| FOMC | -1.188*** | | -1.545*** | -1.234*** |
| | (0.297) | | (0.305) | (0.309) |
| Risk index | | 1.191*** | 1.204*** | 1.231*** |
| | | (0.115) | (0.115) | (0.117) |
| FOMC × Risk index | | | | -1.115*** |
| | | | | (0.397) |
| Observations | 6844 | 6844 | 6844 | 6844 |
| Adjusted $R^2$ | 0.002 | 0.097 | 0.102 | 0.104 |

*Notes.* This table reports results from regressing the first principal component of daily changes in the 3-month, 6-month, and 12-month U.S. government bond yields on an FOMC day dummy, the daily change in the risk index by Bauer, Bernanke, and Milstein (2023), and their interaction term. The sample period is from January 1995 to May 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Table A.5**
Individual OIS rates and VIX

| | 3 mo. | 6 mo. | 1 yr. | 2 yr. | 3 yr. | 5 yr. | 10 yr. |
|---|---|---|---|---|---|---|---|
| FOMC | -0.068 | -0.342 | -0.590* | -0.768 | -0.733 | -0.811 | -0.992* |
| | (0.115) | (0.250) | (0.350) | (0.510) | (0.553) | (0.598) | (0.567) |
| Δ VIX | 0.018 | -0.121** | -0.326*** | -0.674*** | -0.820*** | -0.965*** | -1.040*** |
| | (0.060) | (0.050) | (0.056) | (0.062) | (0.062) | (0.065) | (0.070) |
| FOMC × Δ VIX | -0.039 | 0.375* | 0.677** | 1.042*** | 1.199*** | 1.281*** | 1.047*** |
| | (0.081) | (0.194) | (0.275) | (0.336) | (0.372) | (0.386) | (0.339) |
| Observations | 5681 | 5681 | 5681 | 5681 | 5681 | 5681 | 5681 |
| Adjusted $R^2$ | -0.000 | 0.007 | 0.024 | 0.056 | 0.068 | 0.078 | 0.086 |

*Notes.* This table reports results from regressing daily changes in individual OIS rates on an FOMC day dummy, the daily change in the VIX index, and their interaction term. The sample period is from January 2000 to September 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Table A.6**
Bond yields and VIX outside of NBER recessions

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| FOMC | -1.054*** | | -1.138*** | -0.871*** |
| | (0.286) | | (0.289) | (0.277) |
| ΔVIX | | -0.156*** | -0.164*** | -0.191*** |
| | | (0.040) | (0.040) | (0.041) |
| FOMC × ΔVIX | | | | 0.574*** |
| | | | | (0.178) |
| Observations | 6306 | 6306 | 6306 | 6306 |
| Adjusted $R^2$ | 0.003 | 0.005 | 0.008 | 0.011 |

*Notes.* This table reports results from regressing the first principal component of daily changes in the 3-month, 6-month, and 12-month U.S. government bond yields on an FOMC day dummy, the daily change in the VIX index, and their interaction term. The sample period is from January 1995 to September 2022 omitting NBER recession periods. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Table A.7**

Intraday VIX dynamics and monetary policy outside of NBER recessions

| | Daily | Pre-FOMC | FOMC | Post-FOMC |
|---|---|---|---|---|
| Panel A: Intraday VIX index: 1/1995 - 9/2022 | | | | |
| Constant | -0.518*** | -0.197*** | -0.195*** | -0.126 |
| | (0.131) | (0.073) | (0.039) | (0.088) |
| NS | 0.328** | 0.064 | 0.213*** | 0.050 |
| | (0.152) | (0.069) | (0.059) | (0.091) |
| Observations | 199 | 199 | 199 | 199 |
| Adjusted $R^2$ | 0.021 | -0.002 | 0.111 | -0.004 |
| Panel B: Intraday VIX futures: 5/2004 - 9/2022 | | | | |
| Constant | -0.268** | -0.171*** | -0.123*** | 0.026 |
| | (0.107) | (0.054) | (0.023) | (0.070) |
| NS | 0.210 | -0.016 | 0.191*** | 0.035 |
| | (0.189) | (0.097) | (0.035) | (0.111) |
| Observations | 133 | 133 | 133 | 133 |
| Adjusted $R^2$ | 0.007 | -0.007 | 0.200 | -0.007 |
| Panel C: Intraday VIX index: 5/2004 - 9/2022 | | | | |
| Constant | -0.498*** | -0.189* | -0.266*** | -0.043 |
| | (0.189) | (0.097) | (0.049) | (0.124) |
| NS | 0.550* | 0.081 | 0.378*** | 0.091 |
| | (0.311) | (0.136) | (0.076) | (0.192) |
| Observations | 133 | 133 | 133 | 133 |
| Adjusted $R^2$ | 0.026 | -0.005 | 0.192 | -0.005 |

*Notes.*This table reports results from regressing changes in the VIX index on NS shocks on FOMC days. The dependent variable is the daily change in VIX in the column "Daily", the change from the previous day's close to 10 minutes prior to the FOMC announcement in the column "Pre-FOMC", the change from 10 minutes before to 20 minutes after the FOMC announcement in the column "FOMC", and the change from 20 minutes after the FOMC announcement to market close in the column "Post-FOMC". Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample periods omit NBER recessions.

**Table A.8**

VIX, OIS rates, and monetary policy shocks

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| FOMC | -0.538*** | -0.502*** | -0.530*** | -0.536*** |
| | (0.152) | (0.150) | (0.150) | (0.150) |
| NS | | | 0.394** | 0.431* |
| | | | (0.167) | (0.232) |
| $\Delta$OIS | | -0.043*** | | -0.043*** |
| | | (0.015) | | (0.015) |
| FOMC $\times$ $\Delta$OIS | | 0.105** | | 0.033 |
| | | (0.045) | | (0.057) |
| Observations | 5681 | 5681 | 5681 | 5681 |
| Adjusted $R^2$ | 0.002 | 0.011 | 0.004 | 0.012 |

*Notes.* This table reports results from regressing the daily change in the VIX index on an FOMC day dummy, the NS shock (set to zero on non-FOMC days), the first principal component of daily changes in the 3-month, 6-month, and 12-month OIS rates, and its interaction with the FOMC dummy. The sample period is from January 2000 to September 2022. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Table A.9**

Models with no leverage or constant volatility

| | Data | Model | | | |
|---|---|---|---|---|---|
| | | Median | 5% | 95% | Population |
| Panel A: Model with no leverage ($s = 0$) | | | | | |
| Panel A.1: Target moments | | | | | |
| $\mathbb{E}[r_t]$ | 0.40 | 1.79 | 0.70 | 2.79 | 1.73 |
| $\mathbb{E}[sD_t/P_t]$ | 0.55 | 0.00 | 0.00 | 0.00 | 0.00 |
| $\mathbb{E}[VIX_t]$ | 20.12 | 15.97 | 14.73 | 17.27 | 15.93 |
| $\sigma(VIX_t)$ | 8.24 | 6.43 | 5.66 | 7.17 | 6.44 |
| $AC(VIX_t)$ | 0.98 | 0.98 | 0.97 | 0.98 | 0.98 |
| $\beta_{r_t,m_t}$ | 5.88 | 0.02 | -2.36 | 2.36 | -0.08 |
| Panel A.2: Regression moments for $\Delta r_t^{1y}$ | | | | | |
| FOMC | -0.50 | -0.00 | -0.13 | 0.13 | 0.00 |
| $\Delta$VIX | -0.49 | -16.13 | -16.33 | -15.90 | -16.12 |
| FOMC × $\Delta$VIX | 0.57 | 0.05 | -0.64 | 0.83 | -0.02 |
| Panel A.3: Regression moments for $\Delta$VIX | | | | | |
| FOMC | -0.54 | 0.00 | -0.15 | 0.15 | -0.00 |
| $m$ | 0.31 | -0.00 | -0.15 | 0.15 | 0.00 |
| Panel B: Model with constant volatility ($\nu_t = \bar{\nu}$) | | | | | |
| Panel B.1: Target moments | | | | | |
| $\mathbb{E}[r_t]$ | 0.40 | 0.63 | 0.17 | 1.28 | 0.69 |
| $\mathbb{E}[sD_t/P_t]$ | 0.55 | 0.57 | 0.53 | 0.65 | 0.58 |
| $\mathbb{E}[VIX_t]$ | 20.12 | 19.51 | 18.12 | 21.96 | 19.70 |
| $\sigma(VIX_t)$ | 8.24 | 0.99 | 0.56 | 2.27 | 1.88 |
| $AC(VIX_t)$ | 0.98 | 1.00 | 0.99 | 1.00 | 1.00 |
| $\beta_{r_t,m_t}$ | 5.88 | 5.94 | 5.51 | 6.37 | 5.96 |
| Panel B.2: Regression moments for $\Delta r_t^{1y}$ | | | | | |
| FOMC | -0.50 | 9.51 | 8.10 | 10.19 | 8.88 |
| $\Delta$VIX | -0.49 | 5.25 | 1.24 | 11.40 | 7.04 |
| FOMC × $\Delta$VIX | 0.57 | 25.20 | 11.43 | 33.53 | 21.10 |
| Panel B.3: Regression moments for $\Delta$VIX | | | | | |
| FOMC | -0.54 | -0.32 | -0.36 | -0.31 | -0.33 |
| $m$ | 0.31 | 0.19 | 0.16 | 0.25 | 0.20 |

*Notes.* This table demonstrates model simulation results for the case of no leverage $s = 0$ (Panel A) and constant volatility $\nu_t = \bar{\nu}$ (Panel B). All other model parameters are as reported in Table 7. Panels A.1 and B.1 report the same statistics as in Table 8. Panels A.2 and B.2 correspond to Panel A of Table 9 and Panels A.3 and B.3 correspond to Panel B of Table 9.

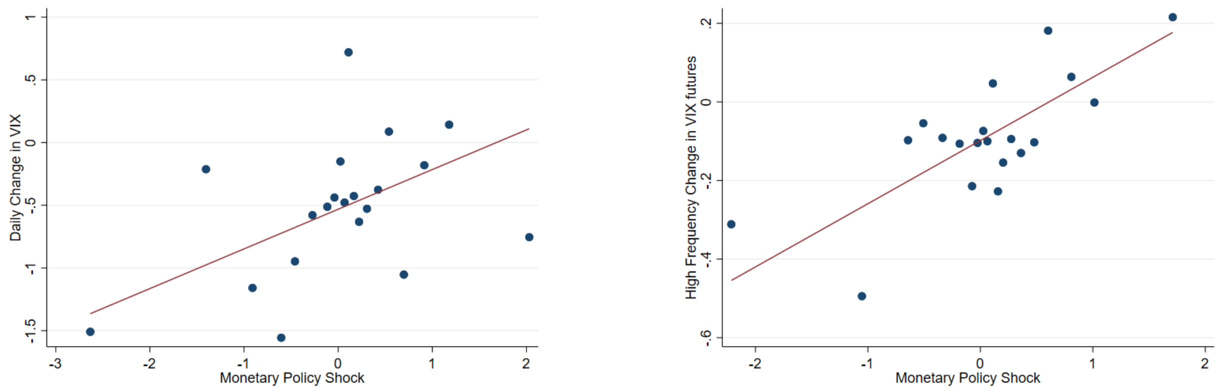
**Table A.10**

Models with recursive utility

| | Data | Model | | | |
|---|---|---|---|---|---|
| | | Median | 5% | 95% | Population |
| Panel A: Model with $\psi = 1.2$ | | | | | |
| Panel A.1: Target moments | | | | | |
| $\mathbb{E}[r_t]$ | 0.40 | 0.88 | 0.35 | 1.57 | 1.06 |
| $\mathbb{E}[sD_t/P_t]$ | 0.55 | 0.60 | 0.56 | 0.65 | 0.60 |
| $\mathbb{E}[VIX_t]$ | 20.12 | 17.70 | 16.55 | 19.23 | 17.74 |
| $\sigma(VIX_t)$ | 8.24 | 7.00 | 6.25 | 7.89 | 7.06 |
| $AC(VIX_t)$ | 0.98 | 0.98 | 0.97 | 0.98 | 0.98 |
| $\beta_{r_t,m_t}$ | 5.88 | 5.84 | 5.40 | 6.28 | 5.84 |
| Panel A.2: Regression moments for $\Delta r_t^{1y}$ | | | | | |
| FOMC | -0.50 | -0.09 | -0.77 | 0.61 | -0.09 |
| ΔVIX | -0.49 | -0.59 | -0.69 | -0.44 | -0.57 |
| FOMC × ΔVIX | 0.57 | 0.37 | -0.13 | 1.16 | 0.35 |
| Panel A.3: Regression moments for ΔVIX | | | | | |
| FOMC | -0.54 | -0.17 | -0.34 | 0.00 | -0.16 |
| $m$ | 0.31 | 0.12 | -0.04 | 0.29 | 0.13 |
| Panel B: Model with $\psi = 0.5$ | | | | | |
| Panel B.1: Target moments | | | | | |
| $\mathbb{E}[r_t]$ | 0.40 | 0.50 | -0.13 | 1.33 | 0.59 |
| $\mathbb{E}[sD_t/P_t]$ | 0.55 | 0.55 | 0.49 | 0.67 | 0.56 |
| $\mathbb{E}[VIX_t]$ | 20.12 | 18.10 | 16.20 | 21.36 | 18.37 |
| $\sigma(VIX_t)$ | 8.24 | 7.03 | 6.06 | 8.87 | 7.44 |
| $AC(VIX_t)$ | 0.98 | 0.98 | 0.97 | 0.98 | 0.98 |
| $\beta_{r_t,m_t}$ | 5.88 | 5.97 | 5.53 | 6.39 | 5.97 |
| Panel B.2: Regression moments for $\Delta r_t^{1y}$ | | | | | |
| FOMC | -0.50 | 0.04 | -0.73 | 0.96 | -0.02 |
| ΔVIX | -0.49 | -0.42 | -0.54 | -0.22 | -0.38 |
| FOMC × ΔVIX | 0.57 | 0.62 | 0.11 | 1.64 | 0.56 |
| Panel B.3: Regression moments for ΔVIX | | | | | |
| FOMC | -0.54 | -0.60 | -0.80 | -0.42 | -0.60 |
| $m$ | 0.31 | 0.22 | 0.05 | 0.41 | 0.22 |

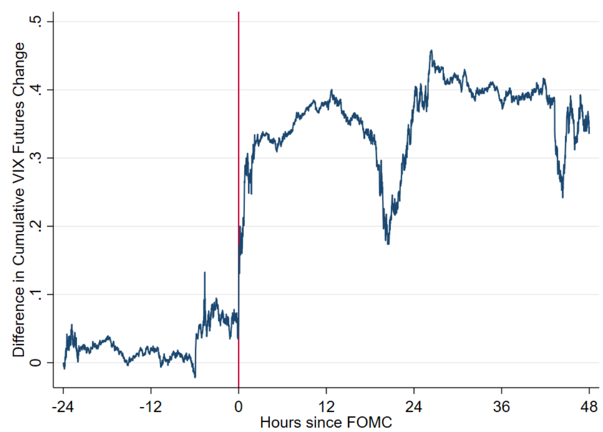
*Notes.* This table demonstrates model simulation results from models with recursive utility with EIS equal to 1.2 (Panel A) and EIS equal to 0.5 (Panel B). All other model parameters are as reported in Table 7. Panels A.1 and B.1 report the same statistics as in Table 8. Panels A.2 and B.2 correspond to Panel A of Table 9 and Panels A.3 and B.3 correspond to Panel B of Table 9.

**Figure A.1.** VIX and monetary policy shocks



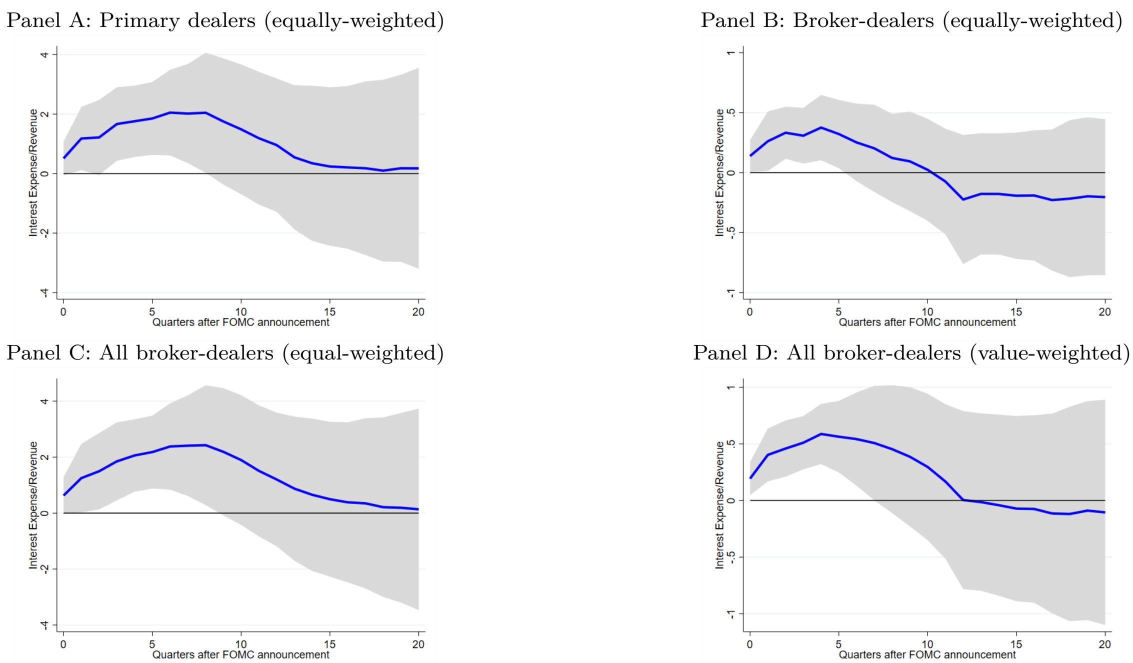

*Notes.* This figure plots a binscatter of daily changes in VIX against NS shocks on FOMC announcement days (left panel) and the 30-minute change in VIX futures against NS shocks (right panel).

**Figure A.2.** Difference in VIX dynamics by positive and negative monetary policy shocks




*Notes.* This figure plots the average cumulative VIX futures price changes from 24 hours before to 48 hours after the FOMC announcement. We first compute the average cumulative change for positive and negative NS shocks separately, and plot the difference between the two. The sample period is from May 2004 to September 2022.

**Figure A.3.** Alternative specifications for the response of intermediaries' interest expense to monetary shocks




*Notes.* The figure plots the response of the equally-weighted interest expense-revenue ratio for primary dealers (Panel A), broker-dealers excluding primary dealers (Panel B), all broker-dealers (Panel C) as well as the value-weighted response of all broker-dealers including those in the primary dealer sample (Panel D) to a 1 standard deviation NS shock. The sample period is from January 1995 to September 2022.

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