Flights to Safety, Volatility Risk, and Monetary Policy

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Abstract

I propose a novel explanation for the flight to safety in the cross-section of assets, based on volatility risk. I argue that investors seek the safety of Treasuries because they correlate positively with volatility surprises. Conversely, they flee risky assets such as stocks, because they correlate negatively. This dynamic results in a negative stock-bond return correlation. The significant role of volatility is further evidenced through a structural VAR model that interlinks volatility, the real economy, and monetary policy. Consequently, volatility can serve as a valuable toll in guiding monetary policy during turbulent times, and should be considered a leading economic indicator.

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1 Introduction

In times of market stress, investors often engage in a "flight to safety," moving capital from riskier assets to safer investments. This leads to an increased demand for government-backed securities, which are relatively safe due to their minimal default risk, and a reduced demand for securities issued by private agents. For example, the 2007-2008 financial market turmoil spurred investors to flee stocks and seek the safety of the U.S. Treasuries to mitigate exposure to stock market risk. As a result, one of the worst periods for stocks coincided with one of the best periods for Treasuries, which got reflected in a negative stock-bond return correlation, a metric that is usually positive as illustrated by Panel A of Figure 1 (also, see, e.g., Baele, Bekaert, and Inghelbrecht, 2010; and Campbell, Sunderam, and Viceira 2017).

The flight to safety thus underscores the interconnectedness between stocks and Treasuries during times of market stress, when there is a surge in stock market volatility (see Panel B of Figure 1). It is thus natural to investigate whether stock market dynamics, such as volatility risk, can explain the flight to safety. From here forth, I will refer to realized stock market volatility simply as "volatility".

I make the following contributions to the literature. First, I present a novel explanation for the flight to safety in the cross-section of assets, rooted in volatility risk. Specifically, I show that investors seek the safety of Treasuries, because they correlate positively with volatility surprises. Conversely, they flee risky assets such as stocks, because they correlate negatively. This dynamic results in the negative stock-bond return correlation typically observed during flights to safety. Furthermore, I connect the volatility risk premium that I find in the Treasury market to the inverted yield curve pattern usually observed at the onset of recessions.

Second, I identify the underlying economic mechanism that drives the impact of volatility on the cross-section of stock and Treasury bond returns. Specifically, I show that volatility has predictive power for both economic activity and monetary policy uncertainty (MPU), two key channels that influence equity returns and the yield curve. Informed by these findings, I then test the interaction between volatility, economic growth, and monetary policy using a structural vector autoregressive (SVAR) model that interlinks them with stock and Treasury bond returns. The results highlight the central role of volatility in driving the flight-to-safety phenomenon. Therefore, volatility can be a valuable tool for central bankers in times of market stress and should be regarded as a leading economic indicator.

Identifying the drivers of the flight to safety is a timely topic, as economists and policymakers alike increasingly recognize the importance of understanding this phenomenon.[1] Accordingly,

[1] See, e.g., the statements of the former Vice Chair Richard H. Clarida at the High-Level Conference on Global Risk, Uncertainty, and Volatility: https://www.federalreserve.gov/newsevents/speech/clarida20191112a.htm

the literature has examined this phenomenon, starting with Vayanos (2004), who proposed that managers become more risk averse during periods of high volatility, when the risk of withdrawals is elevated. Additionally, Caballero and Krishnamurthy (2008) argue that Knightian uncertainty is a key ingredient in the flight-to-quality episodes, as it leads agents to favor safe assets over risky financial claims. This shift results in a change in the stock-Treasury bond return correlation, which is generally positive, but becomes negative during recessions and financial crises, a phenomenon referred to as decoupling.

Baele, Bekaert, and Inghelbrecht (2010) attribute fluctuations in the stock-Treasury bond return correlation to flights to quality (or safety), rather than changing macroeconomic fundamentals. Similarly, Gulko (2002) finds that decoupling is associated with steep stock market declines. Connolly, Stivers, and Sun (2005), as well as Bansal, Connolly, and Stivers (2010) document that periods of low stock-bond return correlation are associated with higher volatility and higher bond returns. Baele, Bekaert, Inghelbrecht, and Wei (2020) empirically describe the flight to safety as episodes involving large positive bond market returns, large negative stock market returns, negative high-frequency correlations between bond and stock returns, and elevated market stress, as reflected by increased equity market volatility.

In contrast to prior studies, my research examines whether volatility risk can explain the flight to safety. I focus on establishing a link between volatility risk and stock and Treasury bond returns, followed by an exploration of the economic mechanisms underlying this relationship.

Because financial markets are subject to common macroeconomic shocks, stocks and bonds should be priced using a common stochastic discount factor. Consistent with this hypothesis, I show that (unexpected) volatility enters the joint pricing kernel by capturing macroeconomic shocks that affect asset prices in a non-linear way.[2]

Using both conditional and unconditional asset pricing models and monthly returns on 36 portfolios (25 size- and value-sorted equity portfolios, and 11 maturity-sorted Treasury bond portfolios), I document a significant price of volatility risk ranging from -116bp to -41basis points per month over the period from January 1952 to December 2020. Notably, I find a positive volatility risk premium in equity returns and a negative volatility risk premium in Treasury bond returns. This pattern helps explain the shift in the stock-bond return correlation from positive to negative during times of market stress, when volatility rises, consistent with the flight to safety.

To understand the negative price of volatility risk, it suffices to look at turbulent times, when market returns are often highly negative while volatility rises in response to a series of volatility surprises. Assets that covary positively with (unexpected) volatility are desirable because they

[2]Existing studies have looked at the pricing of shocks to long-term expected volatility (see, e.g., Bansal, Kiku, Shaliastovich, and Yaron, 2014; Campbell, Giglio, Polk, and Turley, 2018; and Campbell, Giglio, and Polk, 2024, among others).

enhance investors' ability to hedge against a deterioration in the investment opportunity set, and investors are willing to pay a premium for them. Furthermore, the contribution of volatility risk to asset risk premia provides insights into how market participants react during times of market stress, when aggregate risk aversion rises. Investors flee stocks, perceived as being riskier, and seek the safety of Treasury bonds, which provide downside protection. The economic explanation is that stocks and bonds have different risk-return profiles, making them natural hedges for each other during times of heightened volatility.

By uncovering a stock-bond relationship driven by shared exposure to volatility risk, I provide empirical support for a unified pricing model for these asset classes. I also show that asset pricing models tested in the joint markets exhibit strong explanatory power, with risk premia estimates that are both economically meaningful (closely matching realized analogs) and statistically significant. This provides further support for the existence of a common stochastic discount factor. For instance, a parsimonious pricing kernel that includes only the (excess) market return and (unexpected) volatility explains up to 83% (82%) of the joint cross-sectional variation in returns in an unconditional (conditional) asset pricing model.

An in-depth analysis of the stock market reveals that most stocks experience a drop in returns during times of heightened volatility, with small-cap stocks being most affected, while large-cap stocks remain relatively immune to volatility shocks. The greater ability of the latter group to weather volatility surprises, often associated with financial crises, partially explains their lower expected returns. Across the book-to-market quintiles, the volatility risk premium for small stocks ranges from 3.00% to 4.44% per annum.

The Treasury market analysis reveals that bonds pay off during times of heightened volatility, which helps explain why their expected returns are lower than those of stocks. Furthermore, volatility loadings increase monotonically with maturity: a long-term bond (e.g., 61-120 months to maturity) has a 1.56% lower volatility risk premium per annum compared to a short-term bond (e.g., 1-6 months to maturity), because it offers more insurance against volatility shocks. These results are consistent with the findings of Baker and Wurgler (2012), who show that government bonds have the strongest correlation with stocks of large, mature firms. Furthermore, the volatility risk premium found in Treasury bond returns aligns with the inverted yield curve pattern typically seen at the onset of recessions.

Since the flight to safety occurs during periods of market stress, one might argue that financial variables like the *VIX* (often called the "Fear Index") or *SKEW* (a measure of tail risk) could explain this phenomenon.[3] To address this concern, I investigate the relationship between these

[3]VIX has been shown to price the cross-section of stock returns (see, e.g., Ang, Hodrick, Xing, and Zhang, 2006). In addition, there is a large literature on disaster risk that points to tail risk having a crucial impact on asset returns (see, e.g., Rietz, 1988; Barro, 2006; Gabaix, 2012; Wachter, 2013; Kelly and Jiang, 2014). Also, Harvey and Siddique

indices and the flight to safety. My results show that, among these alternatives, only volatility risk provides a meaningful explanation for the phenomenon. Additionally, the findings are robust to the inclusion of classical risk factors in the asset pricing models and the methodology used to capture unexpected volatility.

Another important observation is that both stock prices and Treasury yields are highly responsive to monetary policy (see, e.g., Campbell, Evans, Fisher, and Justiniano, 2012; Hanson and Stein, 2015; Nakamura and Steinsson, 2018; Swanson, 2018; Cieslak, Morse, and Vissing-Jorgensen, 2019, Cieslak and Schrimpf, 2019; Jarocinski and Karadi, 2019). Monetary policy itself has become more responsive to inflation and real activity, particularly after the 1980s (see, e.g., Clarida, Gali and Gertler, 2000, Cogley and Sargent, 2005; Primiceri, 2005; Boivin, 2006; Kim and Nelson, 2006; Bianchi, Lettau and Ludvigson, 2021). Additionally, Campbell, Pflueger, and Viceira (2020) explain the change in the sign of the stock-bond return correlation in the early 2000s by showing that bond returns are affected by inflation, while stock returns are affected by output, and the correlation between inflation and the output gap switched from negative to positive in 2001. In light of these developments, I investigate the role of volatility in the flight to safety, while also considering its relationship with macroeconomic dynamics and monetary policy channels.

Using the growth in (log) industrial production (*dlindpr*) and the Chicago Fed National Activity Index (*CFNAI*) for robustness, I show that volatility predicts economic activity over the period from January 1962 to December 2020 (and March 1967 to December 2020 for CFNAI). Specifically, an increase in volatility predicts a significant negative growth in industrial production for up to 8 months ahead, with a stronger effect in the near term.

I also find that volatility has predictive power for monetary policy uncertainty (*MPU*) over the period from January 1985 to December 2020. Using the *MPU* index developed by Baker, Bloom, and Davis (2016), which is based on a balanced panel of 10 major national and regional US newspapers, I show that an increase in volatility forecasts a significant increase in *MPU* for up to ten months into the future, with stronger effects in the near term.

Furthermore, I find that volatility impacts the monetary policy stance between January 1962 and December 2020. To assess this, I follow Bernanke and Blinder (1992), using the effective Federal Funds Rate (*FFR*) as a proxy for the monetary policy stance from January 1962 to December 1989. Given the inclusion of the zero lower bound (ZLB) period in my sample, I append the shadow interest rate from Wu and Xia (2016) for the period January 1990 to December 2020, obtaining a variable called shadow *FFR* (SFFR). My analysis shows that an increase in volatility leads to a decrease in *SFFR*, suggesting a more accommodative monetary policy. The fact that yields generally respond quickly to changes in monetary policy, which are often preceded by volatility,

(2000) document the effect of higher moments in the cross-section of stock returns.

helps explain why volatility has a significant impact on the Treasury market.

These findings underscore volatility as a precursor to both economic activity and monetary policy. Building on this, I employ a structural VAR (SVAR) model to explore how volatility shocks propagate through the economy and influence both stock and bond returns. I start with a simplified version of the model in Christiano, Eichenbaum, and Evans (2005) that includes a proxy for economic conditions (*dlnindpr*), a measure of inflation (the Consumer Price Index for all urban consumers, *CPI*), and a (stationary) proxy for the monetary policy stance, the change in the *SFFR* (*dSFFR*).

I then enhance this framework by appending volatility, the return on the market portfolio (*Mktret*), which replaces the real profits variable in Christiano, Eichenbaum, and Evans (2005), and the 10-year Treasury bond return (*Bondret*). Acknowledging that expectations of future inflation play a critical role in shaping actual inflation, I include expected inflation (EInfl) in an alternative SVAR model for robustness.

For further robustness, I divide the analysis into three subperiods: January 1962 to July 1979 (the "Pre-Volcker Period"), August 1979 to September 1997 (the "Volcker & 1^{st} Part of Greenspan Period"), and October 1997 to December 2020 (the "2^{nd} Part of Greenspan, Bernanke, Yellen, and Powell Period"). Additionally, I use the monetary policy spread (*MPS*)—the difference between the real interest rate and the natural interest rate—proposed by Bianchi, Lettau, and Ludvigson (2022) as another robustness check.

The results reveal that volatility shocks have a significant impact on both asset classes: they positively affect *Mktret* and negative impact *Bondret*, which is consistent with the flight-to-safety phenomenon. In contrast, shocks to *dlindpr* and *CPI* significantly decrease *Bondret*, but have no effect on *Mktret*. Shocks to *dSFFR* have a significant and negative effect on both *Bondret* and *Mktret*. These findings further validate the robustness of the results from the main tests. Volatility is an important source of risk for both stocks and Treasuries, effectively explaining the flight-to-safety observed in the cross-section of their returns.

1.1 *Related Literature*

My work relates to three main strands of the literature. The first has explored the flight to safety, with some studies empirically characterizing this phenomenon (see, e.g., Baur and Lucey, 2009; Bekaert, Engstrom, and Xing, 2009; Adrian, Crump and Vogt, 2019; Baele, Bekaert, Inghelbrecht, and Wei, 2020). Other contributions have focused on understanding the drivers of the time-varying correlation between stock and bond returns (see, e.g., Baele, Bekaert, and Inghelbrecht, 2010; David and Veronesi, 2013; Campbell, Sunderam, and Viceira, 2017; Song, 2017; Campbell, Pflueger, and Viceira, 2020; Li, Zha, Zhang, and Zhou, 2021). I extend this literature by offering a novel explanation for the flight to safety in the cross-section of stock and Treasury bond returns

based on a stock market variable: volatility risk.

The second strand has worked toward developing a unified asset pricing model for stocks and bonds, with notable contributions from Ferson and Harvey (1991), Baker and Wurgler (2012), Bekaert, Engstrom, and Xing (2009), Lettau and Wachter (2011), Campbell, Sunderam, and Viceira (2017), Koijen, Lustig, and Van Nieuwerburgh (2017), Cieslak and Pang (2021), and Chen, Roussanov, Wang, and Zou (2023). My work is distinct from this literature, as I focus on the role of volatility risk in the relationship between stocks and bonds.

The third strand of the literature has examined the link between monetary policy and financial markets, focusing on how markets react to central bank communications (see, e.g., Bernanke and Kuttner, 2005; Campbell, Evans, Fisher, and Justiniano, 2012; Hanson and Stein, 2015; Nakamura and Steinsson, 2018; Swanson, 2018; Cieslak and Schrimpf, 2019; Jarocinski and Karadi, 2019; Cieslack and Vissing-Jorgensen, 2021; Bauer, Bernanke, and Milstein, 2023; Bianchi, Ludvigson, and Ma, 2023) and the impact of monetary policy on asset valuations (see, e.g., Bianchi, Lettau and Ludvigson, 2022). I contribute to this area by documenting that volatility predicts *MPU* and directly affects monetary policy. My results suggest that volatility should be an important consideration for central bankers, particularly during periods of market stress.

The remainder of the paper is structured as follows. Section 2 details the data sources. Section 3 documents the role of volatility in the flight to safety. Section 4 examines the connection between volatility, real activity and monetary policy. Section 5 presents a structural VAR model that interlinks all these variables with stock and Treasury bond returns. Section 6 performs robustness checks. Section 7 concludes. The Appendix presents technical details on the *GJR Asymmetric Volatility Model* of Glosten, Jagannathan, and Runkle (1993) and on the *Griddy-Gibbs Sampler* of Geman and Geman (1984) and Gelfand and Smith (1990). It also presents the complete set of structural impulse response functions corresponding to the SVAR models used in the main analysis.

2 Data Sources

Data for this study come from multiple sources. From the CRSP database, I extract a range of data spanning from January 1952 to December 2020. The daily value-weighted market returns are used to calculate monthly volatility. Additionally, I use daily stock-level return and trading volume to construct the Amihud (2002) illiquidity factor, *Amih*. The yields on the thirty-year and the one-year government bonds are used to build the term spread, $TERM$, which is the difference between the two yields. The level of S&P500 and its dividend series are used to build the dividend yield on the S&P500 value-weighted portfolio, DY, which is the sum of dividends over the last 12 months, divided by the level of the index. Furthermore, I gather the monthly value-weighted returns for 11 Fama maturity-sorted Treasury portfolios, sorted by maturity into groups such as

1-6 months, ..., 55-60 months, and 61-120 months.[4]

From the Federal Reserve Bank Reports in WRDS, I acquire the yields on long-term corporate Baa and Aaa bonds. The difference between these two yields is used to compute the default spread (DEF).

From Kenneth French's website at Dartmouth, I obtain monthly value-weighted returns for 25 size-and value-sorted equity portfolios, and data on the Fama-French (1993, 1996) size (SMB) and value (HML) factors, and the Jegadeesh and Titman (1993) momentum factor (MOM).

From the Chicago Board Option Exchange (CBOE), I collect daily data on the VIX and SKEW indices covering January 1990 to December 2020.[5] For my monthly analysis, I use the final daily value of each month.

From the Chicago Fed, I download monthly values for the Chicago Fed National Activity Index ($CFNAI$) for the period from January 1985 to December 2020. $CFNAI$ has been designed to gauge overall economic activity and related inflationary pressure.[6]

From the Federal Reserve Bank of St. Louis, I download monthly values for the 6-month Treasury yield, the 10-year Treasury yield, the effective Federal Funds Rate (FFR), and the Consumer Price Index (CPI), for the period from January 1982 to December 2020.

From the Federal Reserve Bank of Cleveland, I download monthly data on the real interest rate, and on the Haubrich, Pennachi, and Ritchken (2012) short-term inflation expectation ($EInfl$) series for the period from January 1982 to December 2020.

From the Federal Reserve Bank of New York, I download monthly data on the natural rate of interest for the period from January 1962 to December 2020, which is used to build the monetary policy spread (MPS).

From the data directory of the Baker, Bloom, and Davis (2016) paper, I download monthly values for the MPU index for the period from January 1985 to December 2020.

3 Volatility Risk and Flights to Safety

Flights to safety typically occur during times of market stress and are characterized by a shift in the stock-Treasury bond return correlation from positive to negative. Generally, this correlation is expected to be positive, as both stocks and bonds are long-duration assets (see, e.g., Baele et

[4] Only non-callable, non-flower notes and bonds are included in these portfolios. Treasury portfolio returns are computed as equal-weighted averages of the unadjusted holding period returns of individual bonds.

[5] VIX measures market's expectation of 30-day S&P500 volatility implicit in the prices of near-term S&P options. $SKEW$ measures the perceived tail risk in the S&P500 based on the implied volatility of out-of-the-money options.

[6] $CFNAI$ is methodologically similar to the index of economic activity developed by Stock and Watson (1999), and it is the first principal component of 85 existing monthly indicators of national economic activity, drawn from four broad categories of data that measure some facet of the overall macroeconomic activity: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories.

al., 2010). Consistent with this observation, the unconditional correlation between the monthly stock market return and the 10-year Treasury bond return is positive, averaging 10% over the period from January 1952 to December 2020. However, as shown in Panel A of Figure 1, the conditional correlation fluctuates over time. While it remains positive for much of the period, it turns negative during recessions and financial crises. This countercyclical pattern in the stock-bond return correlation is a stylized fact that has been previously documented in the literature (see, e.g., Bansal, Connolly, and Stivers (2010); Connolly, Stivers, and Sun (2005); Baele, Bekaert, and Inghelbrecht (2010); Campbell, Sunderam, and Viceira (2017); and Campbell, Pflueger, and Viceira (2020), among others).

Volatility itself also follows a strong countercyclical pattern, typically peaking just before or during recessions and falling sharply late in recessions or early in recovery periods, as illustrated in Panel B of Figure 1. The literature has documented utility gains from volatility timing (see, e.g., Moreira and Muir (2017, 2019)).

Based on these observations, I hypothesize that stock market dynamics such as volatility risk can explain the flight to safety. To test this hypothesis, I need to establish a link between volatility risk and the returns on stocks and Treasury bonds. As noted by Campbell (1993, 1996), investors are concerned with unexpected volatility, as they seek to hedge against changes in their forecasts of future volatilities. Therefore, I start by estimating unexpected volatility (UV_t). To this end, I follow Engle (1982) and use the residual from an AR(1) model applied to the volatility series ($Volat_t$):

$$Volat_t = \mu_V + \phi_1^V Volat_{t-1} + UV_t. \tag{1}$$

UV_t represents the difference between time t volatility and its conditional expectation, where $Volat_t$ is a monthly model-free measure of volatility built using daily market returns (see, e.g., Andersen et al., 2003):

$$Volat_t = \sqrt{\sum_{j=1}^{N_t} R_{j,t}^2}. \tag{2}$$

Above, N_t represents the number of trading days in a specific month t.

Figure 1 Panel B plots the monthly realized volatility series, $Volat_t$. As expected from a recession and financial crisis proxy, $Volat$ increases during times of economic stress, such as the recessions of July 1953 - May 1954, August 1957 - April 1958, December 1969 - November 1970, November 1973 - March 1975, January 1980 - July 1980, July 1981 - November 1982, July 1990 - March 1991, March 2001 - November 2001, December 2007 - June 2009, the Cuban missile crisis of October 1962, the Credit crunch of August 1966, the stock market crash of October 1987, the Asian crisis of July 1997, the Russian debt default and the LTCM crisis of 1998, the burst of the hi-tech bubble in 2000, the accounting scandals (Enron, WorldCom) and the Gulf War of 2002, the

European sovereign-debt crisis of 2010-2012, the U.S. debt downgrade of 2011, the Brexit and the US-China trade war that started in 2018, and the COVID-19 pandemic of 2020.

3.1 *Results Using an Unconditional Asset Pricing Model*

To assess the link between volatility and stock and Treasury bond returns, I use the following return generating process:

$$R^e_{i,t} = \alpha_i + \beta^m_i R^e_{m,t} + \beta^{UV}_i UV_t + \epsilon_{i,t}, \qquad i = 1, 2, ..., 36. \tag{3}$$

Above, $R^e_i = (R^e_{b,1}, ..., R^e_{b,11}, R^e_{s,1}, ..., R^e_{s,25})'$ is a vector of excess returns on the 11 Treasury bond portfolios and the 25 equity portfolios, and R^e_m is the excess market return.

Panel A of Table 1 reports the monthly average excess returns (i.e., in excess of the one-month T-bill rate) for the Treasury portfolios. There is a monotonic pattern here, with average bond excess returns increasing with maturity from 3 bp to 16 bp per month, all statistically significant. This is consistent with the liquidity preference hypothesis, which states that long-term bonds should be more sensitive to interest rate risk.

Panel B of the same table reports the monthly average excess returns for the equity portfolios. Consistent with existing literature (see, e.g., Fama and French (1993, 2008), among others), stocks sorted based on size and book-to-market display a sizeable dispersion in returns in both dimension, with the exception being the small-growth portfolio.

Next, I proceed to estimate the risk factors' loadings on each portfolio according to equation (3). Table 2 reports the results. Because both stocks and bonds are long duration assets with a mostly positive return correlation, it is not surprising to see positive time-invariable market beta estimates for Treasuries. The increasingly monotonic pattern in market betas recorded in the bond space aligns with the findings in Fama and French (1993). Short maturity bonds have a beta close to zero (as expected, since short-term Treasuries are considered riskless assets), while long maturity bonds have a significant market beta of 0.05 (at the 1% level). For stocks, market betas are all significantly positive, as expected.

However, the novel result in this table concerns the opposite signs of volatility loadings recorded for the two asset classes. For Treasuries, these loadings are all positive and statistically significant (at 1% level). They also display a strictly monotonic pattern, increasing from 0.01 for short maturity bonds to 0.17 for long maturity ones. Meanwhile, volatility loadings are mostly negative for stocks. They exhibit a strictly monotonic pattern in the size dimension: small-cap portfolios have significantly negative volatility exposures, whereas large-cap portfolios are not affected by volatility surprises or even pay off, holding the market return constant, which aligns with the findings in Coval and Shumway (2001). For instance, for the growth quintile, volatility loadings increase in the size dimension from -0.32 to 0.14 (and significant), while for the value quintile, they

increase from -0.46 (and significant) to -0.10 (insignificant), respectively. In the value dimension, value portfolios tend to have more negative volatility risk exposure than growth portfolios. This result aligns with the findings in Campbell, Giglio, and Polk (2024), who document a negative loading of volatility on the *HML* factor.

The positive volatility loadings on bonds, together with the countercyclical pattern in volatility, indicate that Treasuries act as safer investments during times of market stress, by paying off when aggregate risk aversion rises. Meanwhile, the (mostly) negative loadings on stocks reveal that stocks and bonds have different risk-return profiles, making them natural hedges for each other. This result explains the shift in demand from stocks to Treasuries during times of market stress, when there is a surge in volatility, and is consistent with flights to safety. Note that, because both stocks and Treasury bonds have positive exposure to market risk, this factor cannot explain the flight to safety. Only volatility can do this.

As we have seen so far, stocks and bonds are interconnected via their joint exposure to volatility risk. However, if volatility proxies for some common underlying source of macroeconomic risk, then it should be priced across the two asset classes.[7] To this end, I rely on an asset pricing model that employs a linear pricing kernel m:

$$m_t = 1 + b_i' f_t, \quad E(m_t R_{i,t}^e) = 0, \qquad i = 1, 2, ..., 36, \tag{4}$$

Above, b_i represent factor loadings, while f_t is a vector of pricing factors.

This linear factor representation of the stochastic discount factor is equivalent to an expected-return beta model. In this model, the equilibrium expected excess returns are linear combinations of the betas of the asset returns with the risk factors (see, e.g., Cochrane, 2001):

$$E(R_i^e) = \lambda_i^{'} \widehat{\boldsymbol{\beta}_i}. \tag{5}$$

In equation (5), β_i is a vector of exposures to the risk factors included in the vector f, while λ_i is a vector that contains the corresponding prices of risk.

I start with a two-factor asset pricing model, containing R_m^e and UV. The equilibrium expected excess returns are thus expressed as a linear combination of the two betas:

$$E(R_i^e) = \lambda_0 + \lambda_m \widehat{\boldsymbol{\beta}_i^m} + \lambda_{UV} \widehat{\boldsymbol{\beta}_i^{UV}}. \tag{6}$$

The regressors in equation (6) are the slope coefficients in the return generating process (3), while λ_0 represents the pricing error.

[7] If the test assets have a factor structure (as is the case with the equity portfolios), and if the variables tested have some correlation with these factors, then one obtains a good model fit (see, e.g, Lewellen, Nagel, and Shanken, 2010). Testing the asset pricing model outside the stock market addresses this issue.

The pricing kernel and the expected-return beta model give us a testable implication for the asset pricing models: if a factor is priced, its cross-sectional price of risk should be nonzero. To test this hypothesis, I estimate the prices of risk (the lambdas) using the second-pass regression outlined in the asset pricing model (6) and the Fama-MacBeth (1973) methodology. Specifically, for each month t, I perform a cross-sectional regression and then analyze the distribution of the lambda estimates. To compare my results with the existing asset pricing literature, I assume time invariant betas for now. While conducting this exercise, I also address the Harvey, Liu, and Zhu (2016) critique by reporting the *multiplicity-adjusted p-values* for the parameter estimates, using the Benjamini and Hochberg (1995) approach.

Table 3 reports the results. The first two rows document the findings for the Capital Asset Pricing Model (CAPM), while the next two rows report the prices of risk and the associated *p-values* for the two-factor model from equation (6). I highlight three novel findings here. First, results support volatility's role as a priced risk factor across the two financial markets. Controlling for market risk, volatility has a significant risk premium of -81 bp per month (*adjusted p-value* = 0.0012). Second, according to the theory, for the risk factors to form a basis for the space of returns, their risk prices need to be close in value to their means (see, e.g., Cochrane, 2001).[8] It is reassuring to see that this theoretical result holds here: the estimated market risk premium in the CAPM model equals 59 bp per month (*adjusted p-value* = 0.0004), which is close to its realized analog of 63 bp per month, as reported in Panel A of Table 4. Third, the two asset pricing models explain a sizable amount of the cross-sectional variation in the asset returns: CAPM has an R^2_{adj} of 76%, and by adding the volatility factor, the R^2_{adj} increases to 83%.

The first finding above suggests that, although there is, on average, a significant trade-off between market risk and return over the period January 1952 to December 2020 across the two markets, volatility also plays an important and apparently systematic role, with a noticeable cross-markets influence and a significantly negative price of risk. Because investors are not fully insured against systematic volatility risk, the premium they pay for assets that covary positively with volatility reflects their attempt to reduce this risk exposure. This result is consistent with Merton's (1973) intertemporal asset-pricing model (ICAPM), with volatility being a hedging factor that captures unanticipated changes in the opportunity set.

The other two findings may be due to the fact that the stock market does not represent all the assets that should be priced by asset pricing models. Adding Treasuries to the test assets leads to a better performance of these models, while also translating into an estimated market risk premium that makes economic sense.

Next, I estimate the volatility premia (i.e., the product between λ_{UV} and $\boldsymbol{\beta}_i^{UV}$) for the two asset

[8] This result refers only to traded factors.

classes. Table 5 documents three additional novel findings. First, there is a negative volatility risk premium in the yield curve, that ranges from -12bp (=12*(-0.01)) to -168bp (=12*(-0.14)) per annum (see Panel A). Second, long term Treasury bonds have a 1.56% (=12*(-0.14+0.01)) lower premium per annum because they provide insurance against volatility shocks (compared to short term bonds). Third, the volatility risk premium is mostly positive in the equity space. Moreover, Panel B shows that large-cap stocks have between 3.00% (=12*(0.02-0.27)) and 4.44% (= 12*(-0.11-0.26)) lower premium per annum when compared to small-cap stocks (across the value quintiles), while growth stocks have between 1.32% (=12*(0.26-0.37)) and 2.76% (= 12*(0.15-0.38)) lower premium per annum when compared to value stocks (across the size quintiles). The latter finding indicates that the small-firm and the value premia are explained, to some extent, by assets' exposure to volatility risk.

Having documented the presence of a volatility risk premium in the yield curve, I now turn my attention to the economics behind this finding. The term premium is the compensation demanded by investors for holding longer term bonds instead of a revolving sequence of investments into short term bonds. The strictly increasing pattern in volatility loadings across maturity-sorted Treasury portfolios reported in Table 2 suggests that long maturity bonds serve as better hedges against volatility risk due to their higher comovement with this risk factor (relative to short maturity bonds). This result implies that long maturity bonds should be in relatively higher demand, leading investors to require lower returns for holding them.

Why, then, do we then observe higher rates of return on long-maturity bonds in Table 1 compared to short-maturity bonds?

To answer this question, let us remember that the market beta estimates from Table 2 show that long term bonds comove to a higher extent with the market portfolio, which makes them relatively riskier when compared to short term bonds. Additionally, long term bonds are exposed to interest rate risk. These results imply that they should have higher expected returns, which is what the unconditional bond returns reported in Table 1 indicate. In other words, Table 1 points to the usually upward sloping shape of the yield curve.

That being said, there is another factor at play here: the significant exposure of bond returns to volatility risk. The increasing pattern in bond volatility betas documented in Table 2, together with the negative volatility price of risk, translate into a decreasing pattern in the corresponding volatility risk premia, according to Table 5. This result pertains to periods of high volatility and suggests a downward sloping yield curve during such times. Because volatility peaks just before or during recessions (and falls sharply late in recessions or early in recovery periods), it makes sense to see an "inverted" yield curve at the onset of recessions. This is another novel finding, which aligns with Harvey (1989), who argues that the price of long term bonds must rise and the price of short term bonds must fall before an economic downturn, for the markets to clear.

Meanwhile, the stock market results indicate that investors demand large-cap and growth stocks during turbulent times because small-cap and value stocks expose them to larger volatility risk. According to rational asset pricing, this hedging demand drives up the price for the former group of stocks, which in turn leads to lower expected returns, partially explaining the pattern in returns documented in Table 1.

Finally, the cross-markets results indicate that bonds earn lower returns compared to stocks since they represent good hedges against downside risk. The economic intuition is that investors' increased risk aversion during times of market stress pushes up the risk premia for risky assets and drives down the premia for safe assets. Investors are willing to pay a premium for holding safe assets (Treasury bonds), which correlate positively with volatility, and they require a premium for holding risky assets (most stocks), which correlate in a negative fashion. This result explains the negative sign of the stock-bond return correlation recorded during episodes of flights to safety.

3.1.1 *Controlling for Other Risk Factors*

In this subsection, I ensure that the cross-markets volatility pricing effect is robust with respect to the inclusion of classical risk factor in the model. Therefore, I assume the existence of S state variables, X_s, that affect stock returns:

$$E(R_i^e) = \lambda_0 + \sum_{s=1}^{S} \lambda_s \widehat{\boldsymbol{\beta}_i^s}. \tag{7}$$

Again, the regressors are the slope coefficients in the corresponding return generating process:

$$R_{i,t}^e = \alpha_i + \sum_{s=1}^{S} \beta_i^s X_{s,t} + \epsilon_{i,t}, \qquad i = 1, 2, ..., 36. \tag{8}$$

The additional risk factors are: the Fama and French (1993, 1996) size and value factors, SMB and HML, the Jegadeesh and Titman (1993) momentum factor, MOM, and the Amihud (2002) illiquidity factor, $Amih$.

Panel A of Table 4 documents the realized average returns for the traded risk factors, while Panel B reports the cross-correlation matrix for all the asset pricing factors. There is a significant correlation of -40% between UV and the market return, which was expected because rises in volatility tend to correspond to downturns in the market. There is also a significant correlation of -27% between UV and SMB, which aligns with the results reported in the previous section, where returns of small stocks are more (negatively) affected by volatility risk. Additionally, there is a significant correlation of 47% between volatility and aggregate illiquidity, which aligns with the observation that times of heightened volatility tend to coincide with times of low aggregate liquidity. Finally, there is a significant correlation of 28% between UV and ΔVIX, which was

expected because both factors proxy for bad time risk.

Rows 5 - 14 of Table 3 report the estimates for the prices of risk (i.e., the lambdas) for the model displayed in equation (8). The estimated market price of risk is still significant and close to its realized analog, while volatility risk is robustly priced across the different model specifications. Volatility has a significant price of risk of -0.83 bp per month (*adjusted p-value = 0.0073*) in the presence of the *SMB* and *HML* factors, and a price of risk of -115 bp per month (*adjusted p-value* = 0.0003) when *MOM* is also included in the model.

Finally, I add *Amih* to the asset pricing model in light of the literature that documents that stock market liquidity prices the cross-section of Treasury bond returns (see, e.g., Li et al., 2009). I find that volatility continues to price the cross-section of asset returns in the joint space, with a price of risk of -113 bp per month (*adjusted p-value* = 0.0009). Meanwhile, *SMB* has an insignificant price of risk, while *HML*, *MOM*, and *Amih* have significant prices of risk. Furthermore, the estimated prices of risk for the traded factors are close to the realized analogs, the exception being the *MOM* factor, a result probably due to the factors not being completely orthogonal to each other.

Finally, I use the R^2_{adj} statistic from the cross-sectional regressions to compare the relative performance of the different asset pricing models (see, e.g., Jagannathan and Wang, 1996). I find an improvement in the model fit when volatility is also included. For example, when CAPM is augmented with volatility, R^2_{adj} goes up from 76% to 83%. Similar results occur for the the Fama-French (1993) and the Carhart (1997) models.

3.2 *Results Using a Conditional Asset Pricing Model*

Given the dynamic nature of the stock-bond correlation, it is natural to extend the analysis by using a conditional framework. To this end, I use a stochastic discount factor m_{t+1} with time variable coefficients:

$$m_{t+1} = 1 + b'_{i,t}(\Omega_t) f_{t+1}, \quad E_t[m_{t+1} R^e_{i,t+1} | \Omega_t] = 0, \qquad i = 1, 2, ..., 36, \tag{9}$$

where E_t denotes the expectation operator based on information available at date *t*.

I estimate the conditional loadings at time *t+1* by conditioning on the set of information available at time *t,* Ω_t. I follow the literature and assume that the information set is spanned by three macro variables that can affect the two aspects of the stochastic investment opportunity set: the yield curve and the conditional distribution of asset returns. Therefore, I include the aggregate dividend yield (DY), the term spread ($TERM$), and the default spread (DEF) in the information set.[9] The vector of predetermined instruments is thus $Z_t = (DY, TERM, DEF)_t$.

[9] See, e.g., Ferson and Schadt (1996), or Petkova and Zhang (2005).

Similarly to the previous subsection, I assume a return generating process of the form:

$$R^e_{i,t+1} = \alpha_i + \beta^m_i(Z_t)R^e_{m,t+1} + \beta^{UV}_i(Z_t)UV_{t+1} + \epsilon_{i,t+1}, \qquad i = 1, 2, ..., 36, \tag{10}$$

where $\beta^m_i(Z_t)$ and $\beta^{UV}_i(Z_t)$ are asset i's time t conditional market beta and conditional volatility beta,respectively. The factor $R^e_{i,t+1}$ denotes the time *t+1* excess return on asset i, while $R^e_{m,t+1}$ is the time *t+1* excess return on the market portfolio.

The two conditional betas have the linear functional forms:

$$\beta^m_i(Z_t) = b^m_{0i} + B^{m'}_i Z_t, \tag{11}$$

$$\beta^{UV}_i(Z_t) = b^{UV}_{0i} + B^{UV'}_i Z_t, \tag{12}$$

where $B^{m'}_i$ and $B^{UV'}_i$ are vectors of coefficients corresponding to the set of instruments.

Substituting equations (11) and (12) into equation (10), leads to:

$$R^e_{i,t+1} = \alpha_i + (b^m_{0i} + B^{m'}_i Z_t)R^e_{m,t+1} + (b^{UV}_{0i} + B^{UV'}_i Z_t)UV_{t+1} + \epsilon_{i,t+1}, \qquad i = 1, 2, ..., 36. \tag{13}$$

After estimating the parameters in equation (13), I construct the fitted betas $\widehat{\beta^m_i(Z_t)}$ and $\widehat{\beta^{UV}_i(Z_t)}$, according to equations (11) and (12). The fitted betas then enter as regressors in the conditional asset pricing model that gives us the equilibrium expected excess returns:

$$E_t[R^e_{i,t+1}|Z_t] = \lambda_0(Z_t) + \lambda_m(Z_t)\widehat{\beta^m_i(Z_t)} + \lambda_{UV}(Z_t)\widehat{\beta^{UV}_i(Z_t)}, \qquad i = 1, 2, ..., 36. \tag{14}$$

In equation (14), $\lambda_m(Z_t)$ and $\lambda_{UV}(Z_t)$ represent the conditional prices of risk for the market return and volatility, respectively, while $\lambda_0(Z_t)$ represents the model pricing error.

For robustness checks, I generalize the return generating process to the case with S risk factors:

$$R^e_{i,t+1} = \alpha_i + \sum_{s=1}^{S} \beta^s_i(Z_t)X_{s,t+1} + \epsilon_{i,t+1}, \qquad i = 1, 2, ..., 36. \tag{15}$$

As in equations (11) and (12), the conditional beta for any generic factor s from equation (15) depends in a linear fashion on the vector Z_t:

$$\beta^s_i(Z_t) = b^s_{0i} + B^{s'}_i Z_t. \tag{16}$$

Equilibrium expected excess returns then follow:

$$E_t[R^e_{i,t+1}|Z_t] = \lambda'_i(Z_t)\widehat{\boldsymbol{\beta}_i(Z_t)} = \lambda_0(Z_t) + \sum_{s=1}^{S} \lambda_s(Z_t)\widehat{\beta^s_i(Z_t)}, \qquad i = 1, 2, ..., 36. \tag{17}$$

For each month, I compute the cross-sectional average conditional volatility beta for stocks and

bonds, and I display these time series in Panel A of Figure 2. The novel result is that the average conditional volatility beta has, outside the hyperinflationary period of the 1970s, opposite signs in the two financial markets: it is mostly positive for Treasuries and negative for stocks. This finding indicates again that bonds are safer investments because they provide a hedge against volatility risk, which is consistent with the flight to safety.

Next, I assess the pricing ability of volatility in a conditional asset pricing framework, as specified by equations (14) and (17). Table 6 presents the conditional prices of risk. The top rows document the results for the conditional CAPM. I find that the market return carries a significant price of risk of 60 bp per month (*adjusted p-value* = 0.0003), which closely aligns with its realized analog. The conditional CAPM has substantial explanatory power for the cross-section of stock and Treasury bond returns, reflected in an R^2_{adj} of 76%. Additionally, volatility is robustly priced across the two asset classes. When controlling for market risk, volatility has a conditional price of risk of -41 bp per month (*adjusted p-value* = 0.0347). Including the *SMB* and *HML* factors in the model, volatility maintains a significant price of risk of -0.49 bp per month (*adjusted p-value0 = 0.0171*). Furthermore, volatility's pricing ability persists when *MOM* and *Amih* are added to the model, with prices of risk of -55 bp per month (*adjusted p-value* = 0.0095) and -49 bp per month (*adjusted p-value* = 0.0205), respectively.

Figure 2 Panel B plots the time series of the conditional market and volatility prices of risk, derived from regressing each factor's price of risk on the conditioning variables. A visual inspection reveals a procyclical pattern in the volatility price of risk, with low (i.e., more negative) values during economic downturns and higher (i.e., less negative) values during periods of economic expansion.

During downturns, income and employment decline, and stock prices tend to fall as companies, especially smaller ones, struggle to sustain profitability. In contrast, during periods of economic growth, a healthy and growing economy leads stock prices to often reach all-time highs. Assets that covary positively with (unexpected) volatility are desirable because they enhance investors' ability to hedge against a deterioration in the investment opportunity set, which explains the observed pattern in the volatility price of risk. Meanwhile, as expected, there is a countercyclical variation in the market price of risk.

Having established the role of volatility during flights to safety, the next step is to investigate the underlying economic mechanism driving these observations.

4 Volatility, Real Economic Activity, and Monetary Policy

Both equity returns and the yield curve respond strongly to economic shocks and monetary policy (see, e.g., Campbell, Evans, Fisher, and Justiniano, 2012; Hanson and Stein, 2015; Nakamura and Steinsson, 2018; Swanson, 2018; Cieslak, Morse, and Vissing-Jorgensen, 2019, Cieslak and

Schrimpf, 2019; Jarocinski and Karadi, 2019). It is thus natural to explore the connection between volatility, real economic activity, and monetary policy. By examining this relationship, we can better understand why volatility affects the cross-section of stock and Treasury bond returns.

4.1 *Volatility and Monetary Policy Uncertainty*

Building on existing literature that highlights the role of uncertainty about monetary policy (or the inflation target) as a key driver of term premium size and bond volatility (see, e.g., Jorda and Salyer, 2003; Cogley, 2005; Arnold and Vrugt, 2010; Wright, 2011; Ulrich, 2013; Leippold and Matthys, 2015; Sinha, 2016; Tillmann, 2019), I investigate the link between volatility and Monetary Policy Uncertainty (*MPU*). Specifically, I assess the forecasting power of volatility for *MPU* over the period January 1985 to December 2020 using a linear regression model.

To conduct this analysis, I need an instrument for *MPU*. Historically, shocks to the second moment of the monetary policy instrument, the *FFR*, have been used to proxy for *MPU* (see, e.g., Stulz, 1986). However, the Federal Reserve target rate reached the Zero Lower Bound (ZLB) after the Great Recession began in December 2008 and remained there until November 2015. The binding ZLB on short-term interest rates presents a significant challenge when using the variability in the target *FFR* to proxy for *MPU*. To circumvent this problem, I leverage recent work that utilizes natural language processing to develop *MPU* proxies. Specifically, I use the *MPU* index developed by Baker, Bloom, and Davis (2016), which is based on a balanced panel of 10 major national and regional US newspapers.[10] Table 7 reveals that an increase in volatility precedes a significant rise in the *MPU* index for up to ten months into the future, with results being more pronounced in the near term.

4.2 *Volatility and Real Economic Activity*

While previous literature has connected volatility to indicators of economic fundamentals (see, e.g., Schwert, 1989; Hamilton and Lin, 1996; Chen, 2003; Vayanos, 2004; Engle, Ghysels, and Sohn, 2006), in this subsection, I examine its predictive power for economic activity.

Classical literature uses the output gap (i.e., the percentage deviation of real GDP from potential GDP) to proxy for economic activity. However, the output gap is available at a quarterly frequency, while the variables used in this study are available on a monthly basis. Therefore, I follow Bekaert, Hoerova, and Lo Duca (2013) and use the monthly change in the log industrial production (*dlindpr)* as a benchmark indicator for the output gap, because the two variables cap-

[10] Baker, Bloom, and Davis (2016) use the following major newspapers to constrcut their *MPU* Index: USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the Wall Street Journal.

ture similar sources of variation in the economy.[11] Table 8 Panel A indicates that an increase in volatility predicts significantly negative growth in industrial production over the period from January 1962 to December 2020. Although the effect of volatility diminishes over time (with the R^2_{adj} dropping substantially in the second month), it persists for up to eight months into the future. This finding is consistent with Berger, Dew-Becker, and Giglio (2020), who report that innovations in realized stock market volatility are robustly followed by economic contractions.

For robustness checks, I use the Chicago Fed National Activity Index (*CFNAI*), a monthly index designed to gauge overall economic activity and related inflationary pressure.[12] Figure 1 in the Appendix plots *CFNAI* alongside the volatility series. The two series tend to exhibit opposite dynamics during times of market stress, which is expected as the economy typically experiences below trend growth when volatility rises. Furthermore, Panel B of Table 8 shows that an increase in volatility predicts a significantly negative *CFNAI* for up to ten months into the future, indicating below trend economic growth from March 1967 to December 2020. Once again, the result is stronger in the near term.

To better capture the dynamics between volatility and economic activity, I need to estimate impulse response functions (IRFs), which are obtained using a vector autoregressive (VAR) system specification, detailed below.

Let $F_t = (F_{1,t}, F_{2,t})'$ denote a *2*-dimensional time series vector, where the two variables that enter the system are monthly volatility V_t and the macroeconomic variable of interest. The p^{th}-order VAR process can be written as:

$$F_t = \delta + \Phi_1 F_{t-1} + ... + \Phi_p F_{t-p} + \varepsilon_t, \tag{18}$$

where $\epsilon_t = (\epsilon_{F_1}, \epsilon_{F_2})'_t$ is a white noise process with $E(\epsilon_t) = 0$, $E(\epsilon_t \epsilon'_{t-p}) = 0$ (i.e., there is no serial correlation in the individual error terms), and $Var(\epsilon_t) = \Sigma$ represents the positive-semidefinite contemporaneous covariance matrix of the error terms. Φ_i is a *2x2* matrix of parameters to be estimated for every $i = 1, ..., p$.

After ensuring the stationarity of the variables of interest and based on the information criteria, I select a VAR(2) model to capture the dynamics between monthly volatility ($F_{1,t}$) and the real activity proxy ($F_{2,t}$). After running the VAR, I visually examine the relationship between the two variables using IRFs.

Figure 3 plots the IRFs. They illustrate the impact over time of shocking one variable in vector F_t by one unit standard deviation on the other variable, with gray shaded areas indicating 95% confidence intervals from the VAR. Panel A shows that a positive shock to volatility results in

[11] I use the change in the log industrial production to ensure stationarity.

[12] The index has an average value of zero and a standard deviation of one, with a positive index reading corresponding to growth above trend, and a negative index reading corresponding to growth below trend.

significantly negative growth in industrial production over the subsequent seven months. Conversely, Panel B indicates that a shock to industrial production does not significantly affect future volatility, as the corresponding IRF remains close to zero across all horizons. Panels C and D confirm the robustness of these results, documenting a unidirectional effect from *Volat* shocks to *CFNAI* in the near future (i.e., over the next six months).

4.3 *Volatility and the Monetary Policy Stance*

To investigate the relationship between volatility and the monetary policy stance, I focus on the Federal Reserve's traditional policy instrument, the target Federal Funds Rate. The Federal Open Market Committee (FOMC) typically meets eight times per year to determine this rate, which further influences the effective Federal Funds Rate through open market operations. Consistent with existing research, I use the effective *FFR* as an indicator of the US monetary policy stance.

Because my sample includes the ZLB period, I start with the *FFR* from January 1962 to December 1989 and append the shadow interest rate from Wu and Xia (2016) for January 1990 to December 2020. I denote this combined series as *SFFR* (shadow *FFR*). While *SFFR* is not stationary, I use it for initial tests to align with the literature. Additionally, I apply the differencing operator to obtain a stationary series, labeled *dSSFR*, for further tests.

To capture the dynamics between volatility and monetary policy, I rely on a VAR(2) model. Figure 4 plots the corresponding IRFs. Panels A and B show that a volatility shock today leads to a drop in *SFFR* starting two months later, with the effect being long lasting. Meanwhile, a monetary policy shock does not have a significant effect on future volatility. Panels C and D show that a volatility shock today leads to a drop in *dSFFR* also starting two months later, with the effect lasting for eleven months. Meanwhile, *dSFFR* does not affect future volatility.

These results suggest that stock market leads monetary policy, with increases in volatility prompting a more accommodating monetary policy by the central banks in an attempt to stabilize the economy. This is consistent with Rigobon and Sack (2003), who document that stock market movements significantly impact the determination of monetary policy. My results also align with Cieslack and Vissing-Jorgensen (2021), who find that negative stock market returns, which coincide with high unexpected volatility as indicated by Panel B of Figure 1 and Table 4, precede monetary policy accommodation by the Federal Reserve.

Overall, this section shows that an increase in volatility is associated with a significant decline in future industrial production and a more accommodating future monetary policy. Additionally, volatility precedes monetary policy uncertainty. Informed by these findings, the next step is to estimate a structural vector autoregressive (SVAR) model that interlinks volatility, real activity, traditional monetary policy instruments, stock returns, and Treasury bond returns.

5 Structural VAR Model

The purpose of the SVAR model is to integrate the above findings into a macro-finance framework while assessing the robustness of volatility risk in explaining the flight to safety among potential macroeconomic drivers for this phenomenon. For this analysis, I collect all variables of interest into a vector Y_t assumed to follow a VAR specification:[13]

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + u_t. \tag{19}$$

Y_t includes K variables, each modeled as a function of p lags of the other variables included in Y_t, A_1, ..., A_p are KxK matrices of parameters, u_t is a $Kx1$ vector of serially uncorrelated innovations, $u_t \sim N(0, \Sigma)$ and $E(u_t u_s') = 0_k \; \forall \; t \neq s$.

The reduced-form VAR specification in equation (19) only captures the relations between the K variables in the Y_t vector through their lags. However, my aim is to assess which variables can explain the flight to safety. Therefore, I need to capture the contemporaneous relations between these variables. To this end, I multiply equation (19) by a KxK matrix A, resulting in:

$$AY_t = AA_1 Y_{t-1} + AA_2 Y_{t-2} + ... + AA_p Y_{t-p} + Au_t, \tag{20}$$

which is equivalent to

$$A(I_K - A_1 L - A_2 L^2 - ... - A_p L^p)Y = Au_t. \tag{21}$$

Next, to obtain a causal interpretation of the effects of the shocks in the individual variables on Y_t, I follow the literature and assume that the economy is driven by a set of serially uncorrelated primitive shocks, e_t (see, e.g., Ramey, 2006). I further assume that a primitive shock can affect only one variable at a time and use a recursive scheme for identification. The most commonly used identification method in macroeconomics imposes alternative sets of recursive zero restrictions on the contemporaneous coefficients. Following the literature, I assume that the structural shocks e_t follow $e_t = P^{-1} u_t$, with the Cholesky decomposition of the variance/covariance matrix of the reduced-form model being $\Sigma = PP'$, and P being a lower triangular matrix (see, e.g., Lutkepohl, 1993). This method, introduced by Sims (1980), is known as "triangularization".

By construction,

$$E(e_t e_t') \; = P^{-1} E(u_t u_t') P^{-1\prime} = P^{-1} \Sigma P^{-1\prime} = I_k. \tag{22}$$

Therefore, $e_t \sim N(0, I_k)$, where $E(e_t e_s') = 0_k \; \forall \; t \neq s$.

[13] For easier exposition, and without loss of generality, constants are ignored in these formulas.

One way to impose the Cholesky restrictions is to assume the following SVAR model:

$$\widetilde{A}(I_K - A(L))Y_t = \widetilde{B}e_t (= \widetilde{A}u_t), \tag{23}$$

where $P = \widetilde{A}^{-1}\widetilde{B}$ and *A(L)* denotes a matrix polynomial in the lag operator, $A(L) = \sum_{i=1}^{p} A_i L^i$. The dynamics of the economy are thus determined by the estimates of *A(L)*.

Choosing P as the Cholesky decomposition of Σ is equivalent to imposing a recursive structure for the corresponding dynamic structural equation model. Identification is achieved by imposing restrictions on the two matrices, $\widetilde{A}$ and $\widetilde{B}$, which are assumed to be nonsingular, based on the recursiveness assumption. Specifically, $\widetilde{A}$ is assumed to be a lower triangular matrix with ones on the diagonal, ensuring a just-identified model and, consequently, just-identified IRFs. $\widetilde{B}$ is assumed to be a diagonal matrix. The ordering of the recursive structure is the same as that imposed in the Cholesky decomposition.

The orthogonality assumption applies to the contemporaneous covariances between the elements of the e_t vector. As previously mentioned, the model allows shocks to one variable to affect the other variables via the *A(L)* operator. Additionally, shocks to one equation contemporaneously affect the variables below that equation, but only affect the variables above it with a lag.

The SVAR model considered here includes three sets of variables: business related, monetary policy related, and financial variables. To stay consistent with the literature, I begin with a macro SVAR specification that is a simplified version of Christiano, Eichenbaum, and Evans (2005). This specification includes a subset of variables whose dynamic relationships have been extensively studied in the macroeconomic literature: a proxy for economic activity, a measure of inflation (or expected inflation), and a proxy for the monetary policy stance.

To capture economic activity, I use changes in the log of industrial production (*dlindpr*), which serves as a proxy for the output gap in the Phillips curve. For inflation, I use the *CPI* rate. Following Bernanke and Blinder (1992), I use the effective Federal Funds Rate (*FFR*) to capture the monetary policy stance. To ensure all variables in the SVAR model are stationary, I employ the differenced shadow Federal Funds Rate (*dSFFR*).

My approach involves running SVARs on the data. As previously mentioned, I use a recursive scheme for identification on the SVARs to back out empirical impulse responses of stock return and bond returns to various shocks in the model. The identifying assumptions between the variables included in the vector Y_t follow the guidance provided by the existing literature, which is grounded in economic theory (see, e.g., Christiano, Eichenbaum, and Evans, 1999, 2005; Stock and Watson, 2001, among others): macroeconomic variables are slow moving and do not react to contemporaneous (i.e., within the month) monetary policy shocks, but monetary policy does respond to contemporaneous macroeconomic shocks.

Therefore, I consider shocks to economic conditions to be purely exogenous and order them first. Furthermore, Taylor (1993) observed that inflation and the output gap tend to drive the short-term Federal Funds Rate set by the Fed.[14] While the Taylor rule represents one approach to targeting monetary policy used by central banks, the existing literature provides substantial evidence that the Fed's monetary policy has become more responsive to inflation and real activity, especially after the 1980s (see, e.g., Clarida, Gali and Gertler, 2000, Cogley and Sargent, 2005; Primiceri, 2005; Boivin, 2006; Kim and Nelson, 2006; Bianchi, Lettau and Ludvigson, 2021). This responsiveness could be motivated by the sluggish reactions of inflation and real activity to shocks in the policy variable, thereby justifying the ordering of real activity and inflation before the Federal Funds Rate in the SVAR model.[15]

Additionally, it has been shown that financial markets react swiftly to central bank communications and actions, with both Treasury yields and stock prices responding strongly to monetary policy (see details in the Introduction). Therefore, I include the return on the market portfolio (*Mktret*), which replaces the real profits variable in Christiano, Eichenbaum, and Evans (2005), and the 10-year Treasury bond return, (*Bondret*) below the macroeconomic variables in the SVAR model.

Given the significant contemporaneous effect of volatility on stock and Treasury bond returns, as well as its impact on future business activity and monetary policy, documented in the previous sections, I include volatility before *Mktret* and *Bondret* in the SVAR model, but after the macroeconomic and monetary policy variables.[16]

In sum, I collect in the vector $Y_t = (dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bond_t)'$ the variables of interest. Alternative SVARs are considered as part of an extensive series of robustness checks discussed in the next section.

The structural model specification considered here allows for the possible reactions in monetary policy and financial variables to business cycle fluctuations, with financial volatility serving as an endogenous propagation mechanism that has an immediate impact on the stock and Treasury market returns. The model reflects the fact that financial market variables respond more quickly to economic changes compared to monetary policy variables, due to decision lags on the part of policymakers or other adjustment costs. Its ordering also permits testing whether the flight to safety can be explained by the contemporaneous response of market and bond returns to alternative

[14] More precisely, the key ingredients in the Taylor rule are the gap between the rate of inflation and the Fed's desired rate of inflation, and the output gap (i.e., the gap between the gross domestic product gdp and a potential gdp value based on a long-term trend).

[15] Note that, in this setup, output is not allowed to respond to changes in the federal funds rate within the period, an assumption which is at odds with some later estimated New Keynesian DSGE models (see, e.g., Figure 6 in Smets and Wouters, 2007).

[16] Note that Bloom (2009), and Jurado, Ludvigson, and Ng (2015) have previously included log(S&P Index) and the VXO Index in their VAR specifications.

shocks, such as economic shocks, changes in inflation, or monetary policy surprises.

After collecting all the variables of interest in the vector Y_t, I check their stationarity. All variables are stationary at the 1% level. Additionally, I select the optimal lag for the SVAR model based on the Akaike Information Criteria, resulting in an SVAR(5) model for Y_t.

5.1 *Structural Impulse Response Functions*

After running the SVARs, I examine the structural impulse response functions (SIRFs), focusing on the responses of *Mktret* and *Bondret* to various shocks in the model. The SIRFs are displayed in Figure 5, with the gray shaded areas representing 95% confidence intervals from the SVAR. The left column shows the SIRFs for the responses of *Mktret* to structural shocks in the variables included in the vector Y_t, while the right column shows the SIRFs for the responses of *Bondret*.

Panels A and B show the response to a structural shock to volatility (*Volat)*. While the effect is short lived, the SIRFs indicate that a volatility shock leads to a fall in *Mktret* by around 1.8% on impact, and an increase in *Bondret* by around 0.18%. The opposite direction of the volatility shock effect is consistent with the flight to safety.

Panels C and D capture the response to a shock to industrial production (*dlindpr*). The SIRFs indicate that a shock to the real activity proxy leads to a contemporaneous drop in *Bondret* by about 0.2%, while it has an insignificant effect on *Mktret*.

Panels E and F show the response of *Mktret* and *Bondret* to a shock in inflation (*CPI*). I expect inflation to have an immediate effect on bond returns, as they have fixed nominal cash flows. Consistent with this hypothesis, the SIRFs show that a *CPI* shock has a significantly negative effect on *Bondret* of about 0.25% at impact. However, the *CPI* shock has no significant contemporaneous effect on market returns (or at any time horizon).

Panels G and H capture the response to a shock to the monetary policy instrument (*dSFFR*). Since monetary policy is an important determinant for the rate of inflation, and given that the *CPI* shock has a significantly negative contemporaneous effect only on bond returns, a similar result is expected for *dSFFR.* Consistent with this hypothesis, the SIRFs show that a *dSFFR* shock has a significantly negative effect on *Bondret* on impact of about 0.4%. *dSFFR* also has a contemporaneous effect on *Mktret*, with a *dSFFR* shock leading to a drop in *Mktret* of about 0.05%. Because the *dSFFR* shock affects the two returns in the same direction, it cannot explain flight to safety. The complete set of SIRFs are displayed in Figure 2 of the Appendix.[17]

[17] The SIRFs obtained by using *SFFR* in the vector *Y,* instead of *dSFFR,* lead to qualitatively similar results.

5.2 *Structural Forecast Error Variance Decomposition*

I next examine the variance decompositions for the structural forecast error. Figure 6 Panel A shows the percentage of variance of the j-step-ahead (with $j = 1, 2, ..., 12$ months) forecast error in the *Mktret* due to various shocks: *Mktret* itself (in blue), volatility shocks (in red), business cycle shocks (in gray), inflation shocks (in yellow), and monetary policy shocks (in purple). The results indicate that volatility shocks explain a significant and economically larger portion of the forecast error variance in stock returns compared to business cycle, inflation and monetary policy proxies, even though volatility is positioned below them in the SVAR model.

Panel B of the same figure displays the results for *Bondret*. The plot reveals that volatility shocks explain a significant and economically important amount of the forecast error variance in Treasury bond returns, surpassing the explanation provided by the business cycle proxy. The variation explained by volatility represents between 45% and 125% of the variation explained by *CPI* (depending on the j-step ahead), and between 16% and 56% of the variation explained by *dSFFR*. This results is noteworthy for a stock market variable.

Overall, the results in this section emphasize the economic mechanism driving the effect of volatility on the cross-section of stock and Treasury bond returns, underscoring the crucial role of volatility risk in explaining the flight to safety.

6 Robustness Checks

I now perform a series of robustness checks. While my results support the robust pricing effect of volatility risk in the presence of classical risk factors, I now ensure that the role of volatility in explaining the flight to safety holds when using an alternative methodology for capturing its shock. Additionally, I test whether alternative financial and macroeconomic variables can explain the flight to safety. Finally, I perform a sub-period analysis for the SVAR model.

6.1 *Using a Second Measure of Unexpected Volatility*

First, I ensure that my results are not a by-product of the method used to measure unexpected volatility. To this end, I construct a second unexpected volatility factor based on the difference between predicted and realized volatility. To predict volatility, I use a model that captures previously documented stylized facts. For instance, volatility increases after a drop in stock prices (see, e.g., Black, 1976; Nelson, 1990, 1991), it is persistent (see, e.g., Schwert, 1989; French, Schwert, and Stambaugh, 1987), there is usually leptokurtosis in returns and negative shocks to returns drive up volatility, called the leverage effect (see, e.g., Black, 1976), and there is usually a positive autocorrelation of order one in an index' return series (see, e.g., Campbell, Lo and MacKinley, 1997). Therefore, I follow Bauwens and Lubrano (1998) and use a *GJR Asymmetric Student-*

GARCH model with an AR(1) specification in the mean equation for the monthly market returns, a *Half-Cauchy* prior for the excess kurtosis parameter υ (υ represents the degrees of freedom of the *Student-t* distribution), and flat priors on finite intervals for all the other parameters:

$$R_{m,t} = \mu + \rho R_{m,t-1} + \eta_{t,} \tag{24}$$

$$\eta_t = \varepsilon_t \sqrt{h_t}, \tag{25}$$

$$h_t = \alpha + \phi h_{t-1} + \theta^{+}\eta_{t-1}^{2+} + \theta^{-}\eta_{t-1}^{2-}, \tag{26}$$

$$\eta_t^{2+} = \eta_t^2 1_{\{\eta_t > 0\}},\ \eta_t^{2-} = \eta_t^2 1_{\{\eta_t < 0\}} \tag{27}$$

$$\varepsilon_t / I_{t-1} \sim Student\ (\upsilon), t = 1, ..., T. \tag{28}$$

In the above model, h_t represents the conditional variance of market returns. The system of equations (24)-(28) accommodates the asymmetry in the news impact curve. The generalized autoregressive conditional heteroskedasticity (*GARCH*) model provides a flexible structure for modeling the volatility of financial time series (see. e.g., Bollerslev, 1986). I estimate equations (24)-(28) using the $Griddy - Gibbs\ sampler$, a very popular $Markov\ Chain\ Monte\ Carlo$ method. The estimates, along with details on the estimation process, are provided in Table 1 of the Appendix.[18]

After predicting volatility, I construct the second unexpected volatility factor (UV_2) as follows:

$$UV_{2,t} = Volat_t - \sqrt{h_t}. \tag{29}$$

Figure 1 Panel B displays the predicted volatility alongside the realized volatility, showing that the two series track each other closely. This result is expected since the GARCH predicting equation is a weighted average of past squared returns, with slowly declining weights. Table 9 presents the posterior estimates from the system of equations (24)-(28), where significant posterior estimates for θ^{-} and ϕ support the previously documented leverage and volatility clustering effects. Panel B of Table 4 reports the correlation of UV_2 with the other risk factors. Similar to the first volatility measure, UV_2 has a significantly negative correlation with *SMB* and significantly positive correlations with ΔVIX and *Amih*.

Table 10 presents the factor loadings from equation (3) when using UV_2. Volatility loadings on Treasuries are all significantly positive and strictly increase with bond maturity: short maturity bonds have a volatility beta close to zero, while long maturity bonds have a volatility beta of 0.15 (see Panel A). For the stock market, most volatility betas are significantly negative and increase monotonically in both the size and value dimensions (see Panel B).

Table 11 reports the asset pricing results. UV_2 has a significant price of risk across the various

[18] I am grateful to the authors for making their code publicly available.

model specifications, ranging between -116 bp per month (*adjusted p-value* = 0.0008) and -65 bp per month (*adjusted p-value* = 0.0353). The volatility pricing effect in the joint markets remains robust when controlling for the *SMB*, *HML, MOM* and *Amih* factors. As before, augmenting the classical asset pricing models with volatility results in slightly higher explanatory power.

In summary, these results show that the flight to safety is robustly captured by volatility risk and is not merely due to the method used to measure volatility shocks. Next, I consider two potential alternatives for capturing the flight-to-safety episodes: the implied volatility index (VIX), which captures bad times risk, and the tail index ($SKEW$), which measures the perceived tail risk in the market portfolio.

6.2 *Using the Implied Volatility Index, VIX*

The literature has extensively used *VIX* as a proxy for turbulent times. For my exercise, I follow Ang et al. (2006) and construct the innovations in *VIX*, ΔVIX, using the month-to-month changes in implied volatility. To test whether *VIX* captures the flight to safety, I perform the time series regression from equation (3) while replacing UV with ΔVIX.

Panel A of Table 12 reports statistically significant and positive loadings for ΔVIX in the Treasury market. Short maturity bonds have a volatility beta close to zero, while long maturity bonds have a significant (at 1% level) volatility beta of 0.05. However, the spread between the loadings on the long term and the short term bonds is not as large as that documented for realized volatility. Panel B indicates that only a third of the ΔVIX beta estimates are significant in the stock market (with half significant at the 5% level and the other half at the 10% level).

6.3 *Using the Skewness Index, SKEW*

Another potential alternative for capturing the flight to safety is the *SKEW* index. Similar to the implied volatility index, I construct the month-to-month changes in the tail risk index, $\Delta SKEW$.

Table 13 presents the results when running the time series model in equation (3) by replacing UV with $\Delta SKEW$. Only half of the $\Delta SKEW$ betas are statistically significant (at the 10% level) in the Treasury market, with values ranging from 0 to 0.01. Meanwhile, most of the $\Delta SKEW$ betas are statistically insignificant in the stock market.

6.4 *Volatility Results for January 1990-December 2020*

To address a possible concern that the results for *VIX* and *SKEW* may be due to a lack of statistical power, given that these indices are available only over a shorter time period, I reassess the role of realized volatility over the most recent period, starting from January 1990.

Table 14 presents the results. I find that all Treasury bonds have significant (at the 1% level) volatility betas, which increase strictly monotonically from 0.01 to 0.12. Meanwhile, most volatility

betas are significant and negative for the stock portfolios. They are more negative for small firms in the size dimension and for value firms in the book-to-market dimension. These results are consistent with the findings documented in Table 2 and indicate that realized volatility continues to capture the flight to safety over the most recent period, January 1990 - December 2020.

6.5 *Using Expected Inflation in the SVAR Model*

Another robustness check consists of testing an alternative macroeconomic variable. Specifically,

Economists and policymakers often consider households' and firms' expectations of future inflation as key determinants of actual inflation. For instance, in his October 25, 2010 speech, former Fed chairman Ben Bernanke highlighted inflation expectations as a monetary policy objective.[19]

Because the financial market is an important channel for reflecting the expectations of economic agents, I assess the role of volatility in the flight to safety in the presence of inflation expectations. To this end, I use the short-run inflation expectation measure, *EInfl*, developed by Haubrich, Pennachi, and Ritchken (2012), which extracts expectations using a term structure model of interest rates.[20] I therefore consider an alternative SVAR model, where I replace CPI with *EInfl*, and I run SVARs on the data using the vector $Y_t = (dlindpr_t, EInfl_t, dSFFR_t, Volat_t, Mktret_t, Bond_t)'$. Since *EInfl* data is available starting from January 1982, I conduct this analysis for the period January 1982 - December 2020.

The SIRFs in Figure 7 indicate that a shock to *EInfl* does not significantly affect *Mktret* or *Bondret* on impact (see Panels E and F). However, it positively impacts *Bondret* one month later. Meanwhile, a volatility shock has significant and opposite effects on the two asset returns (see Panels A and B), consistent with the flight to safety. The complete set of SIRFs are displayed in Figure 3 of the Appendix.

6.6 *Subperiod Analysis for the SVAR Model*

Another robustness check involves estimating the SVAR model over three subperiods. The cutoff points are based on previous economic results and on examining the time series dynamics of the stock-bond return correlation series. The first period ends before Volcker's appointment as Fed chairman, as monetary and macroeconomic dynamics changed significantly after his appointment, with interest rate policy becoming much more sensitive to changes in expected inflation (see, e.g., Clarida, Gali, and Gertler, 1999). This subperiod is labeled as the "Pre-Volcker Period" in Figure 1 Panel A, and it covers January 1962 to July 1979. During this period, the stock-bond return correlation has an average value of 12%, with a 95% confidence interval of (8%, 16%).

[19] The transcript is available at the link https://www.federalreserve.gov/newsevents/speech/bernanke20101015a.htm

[20] Note that I multiply the inflation expectations series by 100 for better visualization of the results.

The second period is labeled "Volcker & 1^{st} Part of Greenspan Period". This period ends in September 1997, as the stock-bond return correlation drops significantly in the following month (by more than 3 standard deviations from the previous mean), and stays mostly in negative territory afterward, signaling a new regime. During this second period, the stock-bond return correlation has an average value of 39%, with a 95% confidence interval of (36%, 43%).

The third period is labeled "2^{nd} Part of Greenspan, Bernanke, Yellen, & Powell Period". It ends in December 2020. During this period, the stock-bond return correlation has an average value of -30%, with a 95% confidence interval of (-35%, -26%). Given the low correlation recorded during the first subperiod, I do not expect to find a significant volatility effect in that case. However, for completeness, I report the results for all three subperiods for the vector $Y_t = (dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bond_t)'$.

Figure 8 plots the SIRFs. According to Panels A and B, a volatility shock leads to a fall in *Mktret* by around 1.2% on impact, but has no significant effect on *Bondret* over the first subperiod. This result is in line with my expectation, as outlined above.

During the second subperiod, a volatility shock leads to a fall in *Mktret* by around 1.9% on impact, and an increase in *Bondret* by around 0.18% (see Panels C and D).

Finally, over the most recent subperiod, a volatility shock leads to a fall in *Mktret* by around 2.2% on impact, and an increase in *Bondret* by around 0.25% (see Panels E and F).

The opposite direction of the contemporaneous volatility effect on the two asset returns recorded over the two most recent periods explains the flight to safety, with the volatility effect becoming stronger over time. The complete set of SIRFs for is displayed in Figures 4-6 of the Appendix.

6.7 *Using Monetary Policy Spread in the Structural Model*

For another set of robustness checks, I use a different proxy for the monetary policy stance. Following Bianchi, Lettau, and Ludvigson (2022), I take the difference between the real interest rate ($RFRR$) and the natural rate of interest ($RSTAR$) from Laubach and Williams (2003), denoted as the monetary policy spread (MPS).

I then consider an alternative SVAR model, replacing $dSFFR$ with MPS, and I run SVARs on the data using the updated vector $Y_t = (dlindpr_t, CPI_t, MPS_t, Volat_t, Mktret_t, Bond_t)'$. Figure 7 of the Appendix plots $RFRR$ and $RSTAR$ in Panel A, and MPS in Panel B.

Figure 9 plots the SIRFs for an SVAR(5) model applied to the new vector Y. They confirm that my findings are robust: a structural volatility shock has significant and opposite effects on the two asset returns upon impact (see Panels A and B), consistent with the flight to safety. The complete set of SIRFs for this model specification is displayed in Figure 8 of the Appendix.

In summary, volatility can robustly explain the flight-to-safety phenomenon. The weaker results obtained when using VIX and $SKEW$ are not simply due to a lack of statistical power in the tests.

The *VIX* results may be due to this series being an expectation of future volatility. Additionally, the squared *VIX* includes both the equity variance premium and the conditional variance, which complicates things when trying to capture the flight to safety. Meanwhile, macroeconomic and the monetary policy variables cannot individually explain the negative correlation between stock and Treasury bond returns, which is characteristic of flights to safety. Only volatility risk has a significant and opposite effect on the two asset classes.

7 Conclusion

I contribute to the literature on the flight to safety by showing that volatility risk plays a central role in explaining this phenomenon. While historical events associated with financial crises attest to the interdependence between stocks and Treasuries, my research reveals that both asset classes are particularly sensitive to unexpected shifts in volatility. Crucially, I find that stocks tend to have a negative correlation with volatility surprises, while Treasuries show a positive correlation. This dichotomy leads investors to perceive stocks as risky investments during times of market turmoil, while Treasuries are seen as safe havens, which drives the flight to safety. My results indicate that the shift from a predominantly positive to a mostly negative stock-bond return correlation after the late 1990s is largely due to an increase in extreme market stress events, marked by volatility surges.

I also show that the size and value premia are tied to volatility risk, and that a volatility risk premium is present in the Treasury yield curve. The economic rationale behind these findings is rooted in the predictive power of volatility for economic activity and monetary policy, both of which impact equity returns and the yield curve. Furthermore, I link the volatility risk premium observed in the Treasury market to the inverted yield curve pattern often seen at the onset of recessions.

My contribution not only enhances our understanding of investor behavior during times of market stress, but also highlights the importance of considering volatility as a key element in both asset pricing and monetary policy. Notably, my results provide insights into the joint stock-bond price formation and demonstrate that the flight to safety strengthens financial market resilience when needed the most, via stock-bond diversification benefits that increase with volatility. In light of these results, existing yield curve models could be revised to account for volatility. Moreover, my results suggest that central banks have grounds to be concerned with large fluctuations in the financial market, and that volatility can be a valuable instrument in guiding monetary policy during turbulent times. Consequently, volatility should be included among the leading economic indicators.

References

Adrian, T., R.K. Crump and E. Vogt, 2019, Nonlinearity and flight-to-safety in the risk-return tradeoff for stocks and bonds, *Journal of Finance* Forthcoming.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31-56.

Andersen, T.G., T. Bollerslev, F.X. Diebold and P. Labys, 2003, Modeling and forecasting realized volatility, *Econometrica* 71, 579-625.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Arnold, I. J. M., and E. B. Vrugt, 2010, Treasury bond volatility and uncertainty about monetary policy, *The Financial Review* 45, 707-728.

Baele, L., G. Bekaert, and K. Inghelbrecht, 2010, The determinants of stock and bond return comovements, *Review of Financial Studies* 23, 2374-2428.

Baele, L., G. Bekaert, K. Inghelbrecht, and M. Wei, 2020, Flights to safety, *The Review of Financial Studies*, 689-746.

Baker, S. R., N. Bloom, and S. J. Davis, 2016, Measuring economic policy uncertainty, *Quarterly Journal of Economics* 131: 1593–636.

Baker, M. and J. Wurgler, 2012, Comovement and predictability relationships between bonds and the cross-section of stocks, *Review of Asset Pricing Studies* 2, No.1, 57–87.

Bansal, N., R.A. Connolly, and C. Stivers, 2010, Regime-switching in stock index and Treasury futures returns and measures of market stress, *Journal of Futures Markets* 30, 753-779.

Bansal, R., D. Kiku, I. Shaliastovich, and A. Yaron, 2014, Volatility, the macroeconomy, and asset prices, *Journal of Finance*, 69, 2471—511

Barro, R., 2006, Rare disasters and asset markets in the twentieth century, *The Quarterly Journal of Economics* 121, 823–866.

Bauer, M., B. S. Bernanke, and E. Milstein, 2023, Risk appetite and the risk-taking channel of monetary policy, *Journal of Economic Perspectives* 37(1), 77–100.

Baur, D.G. and B.M. Lucey, 2009, Flights and contagion - an empirical analysis of stock-bond correlations, *Journal of Financial Stability* 5, 339-352.

Bauwens, L. and M. Lubrano, 1998, Bayesian inference on GARCH models using the Gibbs sampler, *Econometrics Journal* 1, C23-C46.

Bekaert, G., E. Engstrom, and Y. Xing, 2009, Risk, uncertainty and asset prices, *Journal of Financial Economics* 91, 59-82.

Bekaert, G., M. Hoerova, and M. Lo Duca, 2013, Risk, uncertainty, and monetary policy, *Journal of Monetary Economics* 60(7), 771-788.

Benjamini, Y. and Y. Hochberg, 1995, Controlling the false discovery rate: A practical and powerful approach to multiple testing, *Journal of the Royal Statistical Society, Series B (Methodological)* 57, 289–300.

Berger, D., I. Dew-Becker, and S. Giglio, 2020, Uncertainty shocks as second-moment news shocks, Review of Economic Studies 87(1), 40–76.

Bernanke, B. S., and K. N. Kuttner, 2005, What explains the stock market's reaction to Federal Reserve Policy?, *Journal of Finance* 60, 1221-1257.

Bianchi, F., M. Lettau, and S.C. Ludvigson, 2022, Monetary policy and asset valuation, *Journal of Finance* 77(2), 967–1017.

Bianchi, F., S.C. Ludvigson, and S, Ma, 2023, Monetary-based asset pricing: a mixed-frequency structural approach, *Working Paper.*

Black, F., 1976, Studies of stock price volatility changes, *Proc. Am. Stat. Assoc., Bus. Econ. Stat. Section*, 177-81.

Bollerslev, T., 1986, Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31, 307-27.

Brave, S. A., and R. A. Butters, 2010, Chicago Fed National Activity Index turns ten—Analyzing its first decade of performance, *Chicago Fed Letter, Federal Reserve Bank of Chicago* 273.

Caballero, R.J. and A. Krishnamurthy, 2008, Collective risk management in a flight to quality episode, *Journal of Finance* 63, 2195-2230.

Campbell, J.Y., 1993, Intertemporal asset pricing without consumption data, *American Economic Review* 83, 487–512.

Campbell, J.Y., 1996, Understanding risk and return, *Journal of Political Economy* 104, 298–345.

Campbell, J. R., C. L. Evans, J. D. Fisher, and A. Justiniano, 2012, Macroeconomic effects of Federal Reserve forward guidance, *Brookings Papers on Economic Activity*, 1–80.

Campbell, J. Y., S. Giglio, and C. Polk, 2024, What drives booms and busts in value? Working Paper.

Campbell, J. Y., S. Giglio, C. Polk, and R. Turley, 2018, An intertemporal CAPM with stochastic volatility, *Journal of Financial Economics* 128, 207–233.

Campbell, J.Y., W. Lo and A.C. MacKinley, 1997, *The econometrics of financial markets*, Princeton: Princeton University Press.

Campbell, J.Y., C. Pflueger, and L. M. Viceira, 2020, Macroeconomic drivers of bond and equity risks, *Journal of Political Economy* 128, 3148-3185.

Campbell, J.Y., A. Sunderam, and L.M. Viceira, 2017, Inflation bets or deflation hedges? The changing risks of nominal bonds, *Critical Finance Review* 6, 263-301.

Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52: 57–82.

Chen, J., 2003, Intertemporal CAPM and the cross-section of stock returns, Unpublished manuscript, University of Southern California.

Chen, Z., N. Roussanov, X. Wang, and D. Zou, 2023, Common Risk Factors in the Returns on Stocks, Bonds (and Options), Redux, *Working Paper*.

Cieslak, A., A. Morse, and A. Vissing-Jorgensen, 2015, Stock returns over the FOMC cycle, *Journal of Finance* 74, 2201-2248.

Christiano, L.J., M. Eichenbaum, and C. L. Evans, 2005, Nominal rigidities and the dynamic effects of a shock to monetary policy, *Journal of Political Economy* 113(1), 1-45.

Cieslak, A., and H. Pang, 2021, Common shocks to stocks and bonds, *Journal of Financial Economics*, Forthcoming.

Cieslak, A., A. Morse, and A. Vissing-Jorgensen, 2019, Stock Returns over the FOMC Cycle, *Journal of Finance* 74, 2201–2248.

Cieslak, A., and A. Vissing-Jorgensen, 2021, The economics of the Fed put, *Review of Financial Studies* 34, 4045-4089.

Clarida, R., J. Galí, and M. Gertler 2000, Monetary policy rules and macroeconomic stability: evidence and some theory, *Quarterly Journal of Economics* 115(1), 147–180.

Cochrane, J., 2001, *Asset pricing*, Princeton University Press.

Cogley, T., 2005, Changing beliefs and the term structure of interest rates: cross-equation restrictions with drifting parameters, *Review of Economic Dynamics* 8, 420-451.

Connolly, R., C. Stivers, and L. Sun, 2005, Stock market uncertainty and the stock-bond return relation, *Journal of Financial and Quantitative Analysis* 40, 161-194.

Coval, J. D. and T. Shumway, 2001, Expected Option Returns, *Journal of Finance* 56, 983-1009.

David, A. and P. Veronesi, 2013, What ties return volatilities to fundamentals and price valuations?, *Journal of Political Economy* 121, 682-746.

Engle, R.F., 1982, Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation, *Econometrica* 50, 987-1007.

Engle, R.F., E. Ghysels, and B. Sohn, 2006, On the economic sources of stock market volatility, Unpublished manuscript, NYU and UNC.

Fama, E. F. and K.R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E. F. and K.R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 60, No. 1, 396-425.

Fama, E. F. and K.R. French, 2008, The value premium and the CAPM, *Journal of Finance* 61, No. 5, 2163-2185.

Fama, E. F. and J. MacBeth, 1973, Risk, return, and equilibrium: empirical tests, *Journal of Political Economy* 71, 607-636.

Ferson, E.W. and R.W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425-461.

Ferson,W.E and C.R. Harvey, 1991, The variation of economic risk premiums, *Journal of Political Economy* 99, 385-415.

French, K.R., G.W. Schwert, G.W. and R.F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics*, 19, 3-30.

Gabaix, X., 2012, Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance, *The Quarterly Journal of Economics* 127, 645–700.

Gelfand, A.E. and A.F.M. Smith, 1990, Sampling based approaches to calculating marginal densities, *Journal American Statistical Association* 85, 398-409.

Geman, S. and D. Geman, 1984, Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images, *IEEE Trans. Pattern Anal. Mach. Intell* 6, 721-741.

Glosten, L. R., R. Jagannathan and D.E. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779-801.

Gulko, L., 2002, Decoupling, *Journal of Portfolio Management* 28, 59-66.

Hamilton. J. D. and G. Lin, 1996, Stock market volatility and the business cycle, *Journal of Applied Econometrics*, Vol. 11, No. 5, 573-593.

Harvey, C.R., 1989, Forecasts of economic growth from the bond and stock markets, *Financial Analysts Journal* 45 (5), 38-45.

Harvey, C. R. and A. Siddique, 2000, Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263-1295.

Harvey, C, R., Y. Liu, and H. Zhu, 2016, ... and the cross-section of expected returns, *Review of Financial Studies* 29, 5–68.

Husted, L., J. Rogers, and B. Sun, 2020, Monetary policy uncertainty, *Journal of Monetary Economics*, 115, 20-36.

Jagannathan, R. and Z. Wang, 1996, The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 51, 3-53.

Jegadeesh, N. and S. Titman, 1993, Returns to buying winners and selling losers: implications for the stock market efficiency, *Journal of Finance* 48, No. 1, 65-92.

Jorda, O. and K. D. Salyer, 2003, The response of term rates to monetary policy uncertainty, *Review of Economic Dynamics* 6, 941-962.

Jurado, K., S.C. Ludvigson, and S. Ng, 2015, Measuring Uncertainty, *American Economic Review* 105(3), 1177–1216.

Kelly, B. and H. Jiang, 2014, Tail risk and asset prices, *Review of Financial Studies* 27, 2841-2871.

Kilian, L., and S. Manganelli, 2008, The central banker as a risk manager: estimating the Federal Reserve's Preferences under Greenspan, *Journal of Money, Credit and Banking* 40, No.6, 1103-1129.

Koijen, R.S.J., H. Lustig, and S. Van Nieuwerburgh, 2017, The cross-section and time series of stock and bond returns, *Journal of Monetary Economics*, 88, 50-69.

Laubach, T., and J. C. Williams, 2003, Measuring the natural rate of interest, *Review of Economics and Statistics* 85, 1063–1070.

Leippold, M., and F. H. Matthys, 2022, Economic policy uncertainty and the yield curve, *Review of Finance*, 751-797.

Lettau, M. and J. A. Wachter, 2011, The term structures of equity and interest rates, *Journal of Financial Economics* 101, 90-113.

Lewellen, J., S. Nagel, and J. Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175-194.

Li, H., J. Wang, C. Wu, and Y. He, 2009, Are liquidity and information risks priced in the Treasury bond market?, *Journal of Finance* 64, 467-503.

Li, E. X.N., T. Zha, J. Zhang, and H. Zhou, 2021, Does fiscal policy matter for stock–bond correlation?, *Working paper.*

Lucca, D. O., and E. Moench, 2015, The pre-FOMC announcement drift, *Journal of Finance* 70, 329–371.

Lutkepohl, H., 1993, Introduction to Multiple Time Series Analysis, 2nd ed., New York: Springer.

Merton, R.C., 1973, An intertemporal asset pricing model, *Econometrica* 41, 867-887.

Moreira, A., and T. Muir, 2017, Volatility-managed portfolios, *Journal of Finance* 72, 1611-1644.

Moreira, A., and T. Muir, 2019, Should Long-Term Investors Time Volatility?, *Journal of Financial Economics* 131, 507-527 .

Nelson, D.B., 1990, Stationarity and persistence in GARCH (1,1) model, *Econometric Theory* 6, 318-334.

Nelson, D.B., 1991, Conditional heteroskedasticity in asset returns: a new approach, *Econometrica*, 59, 347-370.

Petkova, R. and L. Zhang, 2005, Is value riskier than growth?, *Journal of Financial Economics* 78, 187-202.

Rietz, T., 1988, The equity risk premium: A solution, *Journal of Monetary Economics* 22, 117–131.

Rigobon, R. and B. Sack, 2003, Measuring the reaction of monetary policy to the stock market, *Quarterly Journal of Economics* 118 (2), 639-669.

Schwert, G.W., 1989, Why does stock market volatility change over time?, *Journal of Finance* 44, 1115-1153.

Sims, C. A., 1980, Macroeconomics and reality, *Econometrica*, 1–48.

Sinha, A. 2016, Monetary policy uncertainty and investor expectations, *Journal of Macroeconomics* 47, 188-199.

Smets, F., and R. Wouters, 2007, Shocks and frictions in U.S. business cycles: a Bayesian DSGE approach, *American Economic Review* 97(3), 586-606.

Song, D., 2017, Bond market exposures to macroeconomic and monetary policy risks, *Review of Financial Studies* 30, 2761-2817.

Stock, J. and M. Watson, 1999, Forecasting inflation, *Journal of Monetary Economics* 44, 293-335.

Stock, J. and M. Watson, 2001, Vector Autoregressions, *Journal of Economic Perspectives* 15, 101-115.

Stulz, R., 1986, Interest rates and monetary policy uncertainty, *Journal of Monetary Economics* 17, 331-347.

Swanson, E. T., 2018, Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets, *Working paper*.

Tillmann, P., 2019, Monetary policy uncertainty and the response of the yield curve to policy shocks, *Journal of Money, Credit and Banking* 52 (4), 803-833.

Ulrich, M., 2013, Inflation ambiguity and the term structure of U.S. government bonds, *Journal of Monetary Economics* 60, 295-309.

Vayanos, D., 2004, Flight to quality, flight to liquidity, and the pricing of risk, NBER Working paper.

Wachter, J. A., 2013, Can time-varying risk of rare disasters explain aggregate stock market volatility?, *Journal of Finance* 68, 987–1035.

Wright, J. H. , 2011, Term premia and inflation uncertainty: empirical evidence from an international panel dataset, *American Economic Review* 101, 1514-1534.

Wu, J.C., and F.D. Xia, 2016, Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound, *Journal of Money, Credit, and Banking* 48 (2-3), 253-291.

Table 1: Average Excess Returns for the Stock and Treasury Portfolios

This table presents the monthly average excess returns (in percentage points) for 11 Fama maturity-sorted Treasury bond portfolios in Panel A, and 25 (value-weighted) size- and value-sorted portfolios in Panel B. The data span from January 1952 to December 2020. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Average Excess Returns for Treasury Portfolios (%)										
Bond Maturity (in Months)										
1-6	*7-12*	*13-18*	*19-24*	*25-30*	*31-36*	*37-42*	*43-48*	*49-54*	*55-60*	*61-120*
0.03***	0.06***	0.08***	0.09***	0.10***	0.12***	0.13***	0.14***	0.15***	0.12**	0.16***

Panel B) Average Excess Returns for Stock Portfolios (%)					
Size	*Book-to-Market Equity*				
	Lo	*2*	*3*	*4*	*Hi*
S	0.37	0.84***	0.80***	1.00***	1.07***
2	0.56**	0.84***	0.89***	0.90***	1.02***
3	0.66***	0.84***	0.80***	0.93***	0.98***
4	0.71***	0.71***	0.78***	0.85***	0.86***
B	0.64***	0.59***	0.69***	0.55***	0.71***

Table 2: Flight to Safety

This table presents the factor loadings from a 2-factor model that includes the excess market return and unexpected volatility. The test assets are 11 Fama maturity-sorted Treasury portfolios in Panel A, and 25 Fama-French (1992) portfolios sorted on size and book-to-market equity in Panel B. I regress the monthly portfolio excess returns on the two risk factors using an unconditional model specification. Unexpected volatility (UV) is the residual from an AR(1) model applied to the time series of realized stock market volatility. The data span January 1952 to December 2020. I report the R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Factor Loadings in the Treasury Market

Bond Maturity (in Months)										
1-6	*7-12*	*13-18*	*19-24*	*25-30*	*31-36*	*37-42*	*43-48*	*49-54*	*55-60*	*61-120*
					$\widehat{\boldsymbol{\beta}_i^m}$					
0.00***	0.01***	0.02***	0.03***	0.03***	0.03***	0.04***	0.04***	0.04***	0.04***	0.05***
					$\widehat{\boldsymbol{\beta}_i^{UV}}$					
0.01***	0.03***	0.05***	0.06***	0.08***	0.10***	0.11***	0.12***	0.13***	0.15***	0.17***
					$R^2_{adj}(\%)$					
1.85	3.62	3.14	3.41	3.24	3.45	3.44	3.09	2.85	3.18	3.13

Panel B) Factor Loadings in the Stock Market

Size	*Book-to-Market Equity*					*Book-to-Market Equity*				
	Lo	*2*	*3*	*4*	*Hi*	*Lo*	*2*	*3*	*4*	*Hi*
			$\widehat{\boldsymbol{\beta}_i^m}$			$\widehat{\boldsymbol{\beta}_i^{UV}}$				
S	1.33***	1.17***	1.03***	0.97***	0.99***	-0.32***	-0.30***	-0.33***	-0.36***	-0.46***
2	1.33***	1.11***	1.00***	0.97***	1.07***	-0.18**	-0.29***	-0.32***	-0.30***	-0.47***
3	1.26***	1.06***	0.97***	0.95***	1.02***	-0.18***	-0.21***	-0.20***	-0.28***	-0.35***
4	1.18***	1.04***	0.97***	0.96***	1.05***	-0.06	-0.17***	-0.20***	-0.25***	-0.28***
B	1.02***	0.94***	0.86***	0.91***	0.98***	0.14***	0.06**	-0.02	-0.02	-0.10
			$R^2_{adj}(\%)$							
S	60.66	62.78	66.96	65.28	64.20					
2	73.91	76.61	76.52	73.83	71.08					
3	79.32	82.54	80.97	77.34	70.09					
4	84.92	87.42	83.09	78.73	71.74					
B	89.29	88.76	79.03	72.31	62.15					

Table 3: Unconditional Prices of Risk

This table presents the monthly risk prices (expressed in percentage points), estimated using the Fama-MacBeth (1973) procedure, for the unconditional asset pricing model $E(R_i^e) = \lambda_0 + \lambda_m \widehat{\boldsymbol{\beta}_i^m} + \sum_{s=1}^{S} \lambda_s \widehat{\boldsymbol{\beta}_i^s}$, where λ_m is the market price of risk, while λ_s is the price of risk associated with the generic factor s. The left-hand side variable is a vector of monthly excess returns for 36 portfolios (11 maturity-sorted Treasury portfolios plus 25 size- and value-sorted portfolios). The betas represent factor loadings estimated in the corresponding time series models: $R_{i,t}^e = \alpha_i + \sum_{s=1}^{S} \beta_i^s X_{s,t} + \epsilon_{i,t}$. The risk factors include: *UV*, the unexpected volatility, which is the residual from an AR(1) model applied to the time series of realized stock market volatility, *MOM*, the momentum factor of Jegadeesh and Titman (1993), *SMB* and *HML*, the mimicking portfolios for size and book-to-market equity, and *Amih*, the Amihud residual. The data span from January 1952 to December 2020. I report the *multiplicity-adjusted p-values* in parentheses, using the Benjamini and Hochberg (1995) approach. I also report the R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

$\widehat{\lambda}_0$	$\widehat{\lambda}_m$	$\widehat{\lambda}_{UV}$	$\widehat{\lambda}_{SMB}$	$\widehat{\lambda}_{HML}$	$\widehat{\beta}_{MOM}$	$\widehat{\beta}_{Amih}$	$R^2_{adj}(\%)$
0.13***	0.59***						76.45
(0.0004)	*(0.0004)*						
0.20***	0.37**	-0.81***					83.43
(0.0003)	*(0.0178)*	*(0.0012)*					
0.11***	0.49***		0.13	0.29***			89.11
(0.0008)	*(0.0030)*		*(0.1895)*	*(0.0036)*			
0.18***	0.43***	-0.83***	0.16	0.28***			89.88
(0.0005)	*(0.0076)*	*(0.0073)*	*(0.1229)*	*(0.0073)*			
0.06*	0.65***		0.12	0.32***	3.12***		95.23
(0.0636)	*(0.0003)*		*(0.2639)*	*(0.0015)*	*(0.0003)*		
0.13***	0.57***	-1.15***	0.14	0.31***	3.45***		96.33
(0.0003)	*(0.0003)*	*(0.0003)*	*(0.1665)*	*(0.0020)*	*(0.0003)*		
0.13***	0.57***	-1.13***	0.14	0.31***	3.46***	-0.41**	96.35
(0.0004)	*(0.0005)*	*(0.0009)*	*(0.1712)*	*(0.0025)*	*(0.0004)*	*(0.0411)*	

Table 4: Average Returns and Cross-Correlations of Asset Pricing Factors

This table reports the monthly average returns (in percentage points) for the traded factors in Panel A: R_m^e (the excess market return), *MOM* (the momentum factor of Jegadeesh and Titman), *HML* (the mimicking portfolio for book-to-market equity), and *SMB* (the mimicking portfolio for size). It reports in Panel B the cross-correlations between the traded factors and: *UV* (the first unexpected volatility measure which is the residual from an AR(1) model applied to the realized stock market volatility series), UV_2 (the second unexpected volatility measure, which is the difference between predicted and realized volatility), ΔVIX (the month-to-month changes in implied volatility), $\Delta SKEW$ (the month-to-month changes in the *SKEW* index), and Amih (the Amihud residual). The data span from January 1952 to December 2020 (with the exception of *VIX* and *SKEW* series, which are available only from January 1990). I report t-statistics in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Average Returns for the Traded Factors (%)				
	R_m^e	*SMB*	*HML*	*MOM*
Average Return	0.63	0.15	0.25	0.68

Panel B: Cross-correlations									
	R_m^e	*UV*	UV_2	*SMB*	*HML*	*MOM*	ΔVIX	$\Delta SKEW$	*Amih*
R_m^e	1								
UV	-0.40***	1							
UV_2	-0.41***	0.86***	1						
SMB	0.27***	-0.27***	-0.24***	1					
HML	-0.19***	-0.03	-0.04	-0.16***	1				
MOM	-0.15***	0.01	-0.02	-0.05	-0.21***	1			
ΔVIX	-0.13**	0.28***	0.40***	-0.09*	-0.02	0.05	1		
$\Delta SKEW$	0.18***	-0.02	-0.02	-0.04	-0.02	-0.01	-0.10**	1	
Amih	-0.37***	0.47***	0.44***	-0.31***	0.05	0.07*	0.30***	-0.06	1

Table 5: Volatility Risk Premium

This table reports the monthly volatility risk premium (in percentage points) that I find in the yield curve and in the equity premia. For each portfolio, I compute the volatility risk premium as the product between the volatility price of risk and the volatility loading. I estimate the loadings using a 2-factor model specification that controls for market risk. Panel A reports results for 11 Treasury bond portfolios, while Panel B reports results for 25 stock portfolios. The data span from January 1952-December 2020.

Panel A: Volatility Risk Premium in the Yield Curve (%)										
Bond Maturity (in Months)										
1-6	*7-12*	*13-18*	*19-24*	*25-30*	*31-36*	*37-42*	*43-48*	*49-54*	*55-60*	*61-120*
-0.01	-0.02	-0.04	-0.05	-0.06	-0.08	-0.09	-0.10	-0.11	-0.12	-0.14

Panel B: Volatility Risk Premium in Equities (%)					
Size	*Book-to-Market Equity*				
	Lo	2	3	4	Hi
S	0.26	0.24	0.27	0.29	0.37
2	0.15	0.23	0.26	0.24	0.38
3	0.15	0.17	0.16	0.23	0.28
4	0.05	0.14	0.16	0.20	0.23
B	-0.11	-0.05	0.02	0.02	0.08

Table 6: Conditional Prices of Risk

This table reports factors' monthly conditional risk prices (in percentage points), estimated using the Fama-MacBeth (1973) procedure, for the conditional asset pricing model $E[R^e_{i,t+1}|Z_t] = \lambda_0(Z_t) + \lambda_m(Z_t)\widehat{\beta^m_i(Z_t)} + \sum_{s=1}^{S} \lambda_s(Z_t)\widehat{\beta^s_i(Z_t)}$, where $\lambda_m(Z_t)$ is the conditional market price of risk and $\lambda_s(Z_t)$ is the conditional price of risk associated with the generic factor s. The left-hand side variable is a vector of monthly excess returns for 36 portfolios (11 maturity-sorted Treasury portfolios plus 25 size- and value-sorted portfolios), and the betas represent factors' loadings estimated in the corresponding time series models: $R^e_{i,t+1} = \alpha_i + \sum_{s=1}^{S} \beta^s_i(Z_t)X_{s,t+1} + \epsilon_{i,t+1}$; the conditional betas have the linear functional form $\beta^s_i(Z_t) = b^s_{0i} + B^{s'}_i Z_t$. The risk factors are: *UV*, the unexpected volatility, which is the residual from an AR(1) model applied to the time series of realized stock market volatility, *MOM*, the momentum factor of Jegadeesh and Titman (1993), *HML* and *SMB*, the mimicking portfolios for book-to-market equity and size (zero-investment portfolios), and *Amih*, the Amihud residual. Z_t represents the vector of conditioning variables that enter the information set at time t: the default spread, *DEF* (computed as the difference between the yields of a long-term corporate Baa bond and a long-term corporate Aaa bond), the term spread, *TERM* (computed as the difference between the yields of a ten-year and a one-year government bond), and the dividend yield on the S&P500 value-weighted portfolio, *DY* (computed as the sum of dividends over the last 12 months, divided by the level of the index).The data span from January 1952 to December 2020. I report the *multiplicity-adjusted p-values* in parentheses, using the Benjamini and Hochberg (1995) approach. I report the R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

$\widehat{\lambda}_0$	$\widehat{\lambda}_m$	$\widehat{\lambda}_{UV}$	$\widehat{\lambda}_{SMB}$	$\widehat{\lambda}_{HML}$	$\widehat{\beta}_{MOM}$	$\widehat{\beta}_{Amih}$	$R^2_{adj}(\%)$
0.12***	0.60***						75.72
(0.0003)	*(0.0003)*						
0.14***	0.51**	-0.41**					81.78
(0.0003)	*(0.0027)*	*(0.0347)*					
0.12***	0.46***		0.17	0.27***			90.23
(0.0004)	*(0.0048)*		*(0.1034)*	*(0.0048)*			
0.10***	0.53***	-0.49**	0.18*	0.26**			89.23
(0.0020)	*(0.0020)*	*(0.0171)*	*(0.0857)*	*(0.0158)*			
0.07**	0.59***		0.15	0.27***	1.49***		90.89
(0.0118)	*(0.0005)*		*(0.1564)*	*(0.0097)*	*(0.0005)*		
0.06**	0.61***	-0.55***	0.17*	0.27***	1.68***		92.08
(0.0287)	*(0.0003)*	*(0.0095)*	*(0.0995)*	*(0.0095)*	*(0.0003)*		
0.06**	0.61***	-0.49***	0.17	0.27**	1.62***	-0.11	96.09
(0.0347)	*(0.0004)*	*(0.0205)*	*(0.1157)*	*(0.0152)*	*(0.0004)*	*(0.4118)*	

Table 7: Predicting Monetary Policy Uncertainty with Volatility

This table reports the estimates from a linear regression model where I predict monetary policy uncertainty using volatility. I use the Baker, Bloom, and Davis (2016) monetary policy uncertainty (*MPU)* Index. The data span from January 1985 to December 2020. I report the R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	MPU_{t+1}	MPU_{t+2}	MPU_{t+4}	MPU_{t+6}	MPU_{t+8}	MPU_{t+10}	MPU_{t+12}
*Int (*10^{-2})*	0.86***	0.92***	1.05***	1.07***	1.04***	1.01***	1.13***
*Volat (*10^{-2})*	7.05***	5.53***	2.57**	2.17*	2.72**	3.61***	0.46
R^2_{adj}(%)	9.82	5.95	1.10	0.71	1.26	1.97	-0.20

Table 8: Predicting Economic Activity with Volatility

This table reports the estimates from a monthly linear regression model where I predict economic activity using volatility. In Panel A, I use shocks to industrial production, *dlindpr*, to capture economic activity. In Panal B, I use the Chicago Fed National Activity Index, *CFNAI*, to capture economic activity. The data span from January 1962 to December 2020 in Panel A, and March 1967 to December 2020 in Panel B. I report the R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Growth in Industrial Production (*dlindpr*)

	$dlindpr_{t+1}$	$dlindpr_{t+2}$	$dlindpr_{t+4}$	$dlindpr_{t+6}$	$dlindpr_{t+8}$	$dlindpr_{t+10}$	$dlindpr_{t+12}$
*Int (*100)*	0.74***	0.46***	0.29***	0.36***	0.31**	0.23***	0.24***
*Volat (*100)*	-14.16***	-6.95***	-2.45*	-4.38***	-3.03**	-0.95	-1.16
R^2_{adj}(%)	12.91	3.00	0.25	1.10	0.45	-0.09	-0.07

Panel B: Predicting *CFNAI*

	$CFNAI_{t+1}$	$CFNAI_{t+2}$	$CFNAI_{t+4}$	$CFNAI_{t+6}$	$CFNAI_{t+8}$	$CFNAI_{t+10}$	$CFNAI_{t+12}$
Int	0.69***	0.25***	0.15***	0.21***	0.19***	0.12***	0.08
Volat	-17.41***	-6.22***	-3.91**	-5.42***	-4.70***	-3.16*	-2.15
R^2_{adj}(%)	18.50	2.23	0.78	1.65	1.19	0.37	0.09

Table 9: Flight to Safety - Robustness Checks I

This table presents the factor loadings from a 2-factor model that includes the excess market return and the second measure of unexpected volatility. The test assets are 11 Fama maturity-sorted Treasury portfolios in Panel A, and 25 Fama-French (1992) portfolios sorted on size and book-to-market equity in Panel B. I regress the monthly portfolio excess returns on the two risk factors using an unconditional model specification. UV_2 represents unexpected volatility, and is constructed as the difference between predicted and realized volatility, according to equation (29). The data span from January 1952 to December 2020. I report R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Factor Loadings in the Treasury Market using the 2^{nd} Volatility Measure

Bond Maturity (in Months)										
1-6	*7-12*	*13-18*	*19-24*	*25-30*	*31-36*	*37-42*	*43-48*	*49-54*	*55-60*	*61-120*
					$\widehat{\boldsymbol{\beta}_i^m}$					
0.00***	0.01***	0.02***	0.02***	0.03***	0.03***	0.03***	0.04***	0.04***	0.04***	0.05***
					$\widehat{\boldsymbol{\beta}_i^{UV_2}}$					
0.00***	0.02***	0.03***	0.05***	0.07***	0.08***	0.10***	0.11***	0.11***	0.13***	0.15***
					$R^2_{adj}(\%)$					
0.89	2.58	2.21	2.55	2.56	2.75	2.88	2.75	2.46	2.87	3.07

Panel B: Factor Loadings in the Stock Market using the 2^{nd} Volatility Measure

Size	*Book-to-Market Equity*					*Book-to-Market Equity*				
	L	*2*	*3*	*4*	*Hi*	*Lo*	*2*	*3*	*4*	*Hi*
			$\widehat{\boldsymbol{\beta}_i^m}$					$\widehat{\boldsymbol{\beta}_i^{UV_2}}$		
S	1.35***	1.18***	1.03***	0.98***	0.99***	-0.21**	-0.21***	-0.27***	-0.30***	-0.41***
2	1.33***	1.11***	1.00***	0.97***	1.08***	-0.15**	-0.27***	-0.27***	-0.26***	-0.38***
3	1.26***	1.07***	0.97***	0.96***	1.03***	-0.13**	-0.15***	-0.18***	-0.22***	-0.24***
4	1.19***	1.04***	0.97***	0.96***	1.06***	-0.01	-0.14***	-0.21***	-0.20***	-0.24***
B	1.02***	0.94***	0.85***	0.90***	0.98***	0.14***	0.07***	-0.03	-0.06	-0.11
			$R^2_{adj}(\%)$							
S	60.44	62.55	66.75	65.05	64.00					
2	73.87	76.15	76.34	73.75	70.66					
3	79.23	82.36	80.94	77.09	69.65					
4	84.89	87.36	83.19	78.54	71.63					
B	89.33	88.79	79.04	72.37	62.18					

Table 10: Unconditional Prices of Risk – Robustness Checks II

This table reports the factors' risk premia, estimated using the Fama-MacBeth (1973) procedure, for the unconditional asset pricing model $E(R_i^e) = \lambda_0 + \lambda_m \widehat{\beta_i^m} + \sum_{s=1}^{S} \lambda_s \widehat{\beta_i^s}$,where λ_m is the market price of risk and λ_s is the price of risk associated with the generic factor s. The left-hand side variable is a vector of monthly excess returns for 36 portfolios (11 maturity-sorted Treasury portfolios plus 25 size- and value-sorted portfolios), and the betas represent factors' loadings estimated in the corresponding time series models: $R_{i,t}^e = \alpha_i + \sum_{s=1}^{S} \beta_i^s X_{s,t} + \epsilon_{i,t}$. The risk factors are: UV_2, the second measure of unexpected volatility, which is constructed by taking the difference between realized and predicted volatility according to equation (8), *MOM*, the momentum factor of Jegadeesh and Titman (1993), *HML* and *SMB*, the mimicking portfolios for book-to-market equity and size (zero-investment portfolios), and *Amih*, the Amihud residual. I report results in percentage points, on a monthly basis. The data span from January 1952 to December 2020. I report the *multiplicity-adjusted p-values* in parentheses, using the Benjamini and Hochberg (1995) approach. I report the R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

$\widehat{\lambda}_0$	$\widehat{\lambda}_m$	$\widehat{\lambda}_{UV_2}$	$\widehat{\lambda}_{SMB}$	$\widehat{\lambda}_{HML}$	$\widehat{\beta}_{MOM}$	$\widehat{\beta}_{Amih}$	$R^2_{adj}(\%)$
0.13***	0.59***						76.45
(0.0004)	*(0.0004)*						
0.20***	0.38*	-0.98***					84.22
(0.0003)	*(0.0174)*	*(0.0005)*					
0.11***	0.49***		0.13	0.29***			89.11
(0.0008)	*(0.0030)*		*(0.1895)*	*(0.0036)*			
0.15***	0.46***	-0.65**	0.15	0.29***			89.48
(0.0005)	*(0.0008)*	*(0.0353)*	*(0.1433)*	*(0.0048)*			
0.06*	0.65***		0.12	0.32***	3.12***		95.23
(0.0636)	*(0.0003)*		*(0.2639)*	*(0.0015)*	*(0.0003)*		
0.11***	0.60***	-1.16***	0.14	0.32***	3.51***		96.03
(0.0002)	*(0.0002)*	*(0.0008)*	*(0.1844)*	*(0.0013)*	*(0.0002)*		
0.11***	0.60***	-1.11***	0.13	0.32***	3.53***	-0.43**	96.09
(0.0005)	*(0.0004)*	*(0.0018)*	*(0.1929)*	*(0.0018)*	*(0.0004)*	*(0.0296)*	

Table 11: VIX Loadings - Robustness Checks III

This table presents the factor loadings from a 2-factor model that includes the excess market return and the month-to-month changes in the implied volatility index, ΔVIX. The test assets are 11 Fama maturity-sorted Treasury portfolios in Panel A, and 25 Fama-French (1992) portfolios sorted on size and book-to-market equity in Panel B. I regress the monthly portfolio excess returns on the two risk factors using an unconditional model specification. The data span from January 1990 to December 2020. I report R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: ΔVIX Loadings in the Treasury Market

Bond Maturity (in Months)										
1-6	*7-12*	*13-18*	*19-24*	*25-30*	*31-36*	*37-42*	*43-48*	*49-54*	*55-60*	*61-120*
					$\widehat{\beta_i^{\Delta VIX}}$					
0.00***	0.01***	0.01***	0.01***	0.02***	0.02***	0.02***	0.03***	0.03***	0.04***	0.05***
					$R^2_{adj}(\%)$					
4.08	3.86	4.34	5.21	5.82	5.48	5.36	5.45	5.85	5.84	5.12

Panel B: ΔVIX Loadings in the Stock Market

Size	*Book-to-Market Equity*					*Book-to-Market Equity*				
	Lo	*2*	*3*	*4*	*Hi*	*Lo*	*2*	*3*	*4*	*Hi*
			$\widehat{\beta_i^{\Delta VIX}}$					$R^2_{adj}(\%)$		
S	-0.10*	-0.05	-0.06*	-0.06	-0.09**	59.46	56.54	65.33	59.55	61.66
2	-0.03	-0.06*	-0.03	-0.02	-0.04	70.95	72.98	72.27	68.68	66.83
3	-0.02	-0.03	-0.04	-0.06**	0.02	74.68	80.22	77.64	72.40	66.22
4	-0.01	-0.04*	-0.06**	-0.06**	0.01	80.77	84.12	77.62	75.69	68.15
B	0.01	0.01	0.00	-0.01	-0.02	89.00	85.97	75.42	66.43	59.13

Table 12: SKEW Loadings - Robustness Checks IV

This table presents the factor loadings from a 2-factor model that includes the excess market return and the month-to-month changes in the implied volatility index, $\Delta SKEW$. The test assets are the 11 Fama maturity-sorted Treasury portfolios in Panel A, and the 25 Fama-French (1992) portfolios sorted on size and book-to-market equity in Panel B. I regress the monthly portfolio excess returns on the two risk factors using an unconditional model specification. The data span from January 1990 to December 2020. I report R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: $\Delta SKEW$ Loadings in the Treasury Market

Bond Maturity (in Months)										
1-6	*7-12*	*13-18*	*19-24*	*25-30*	*31-36*	*37-42*	*43-48*	*49-54*	*55-60*	*61-120*
$\widehat{\beta_i^{\Delta SKEW}}$										
-0.00	0.00	0.00	0.01*	0.01*	0.01*	0.01*	0.01*	0.01	0.01	0.01
$R^2_{adj}(\%)$										
0.01	1.26	2.90	4.33	4.72	4.17	4.21	3.96	3.94	3.90	2.01

Panel B: $\Delta SKEW$ Loadings in the Stock Market

Size	*Book-to-Market Equity*					*Book-to-Market Equity*				
	L	2	3	4	Hi	Lo	2	3	4	Hi
	$\widehat{\beta_i^{\Delta SKEW}}$					$R^2_{adj}(\%)$				
S	-0.09**	-0.07*	-0.06*	-0.04	-0.07**	56.93	56.78	65.43	59.55	61.65
2	-0.05*	-0.02	-0.02	-0.01	-0.03	71.15	72.81	72.26	68.68	66.86
3	-0.04	-0.01	0.00	0.00	-0.03	74.78	80.19	77.49	72.10	66.28
4	-0.02	0.00	0.00	0.00	0.01	80.82	84.00	77.27	75.36	68.15
B	0.02*	0.01	0.00	0.00	0.03	89.07	85.97	75.42	66.41	59.38

Table 13: Volatility Loadings for the Subperiod January 1990 - December 2020 - Robustness Checks V

This table reports the factor loadings from a 2-factor model that includes the excess market return and unexpected volatility. The test assets are 11 Fama maturity-sorted Treasury portfolios in Panel A, and 25 Fama-French (1992) portfolios sorted on size and book-to-market equity in Panel B. I regress the monthly portfolio excess returns on the two risk factors using an unconditional model specification. UV represents unexpected volatility, and is the residual from an AR(1) model applied to the time series of realized stock market volatility. The data span from January 1990 to December 2020. I report R^2_{adj} in percentage points. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Volatility Loadings in the Treasury Market (January 1990-December 2020)

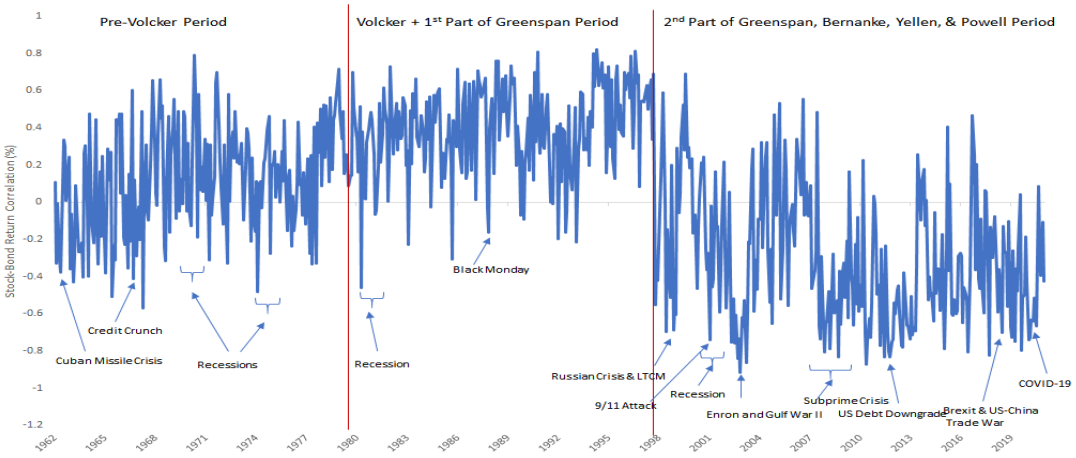
Bond Maturity (in Months)										
1-6	*7-12*	*13-18*	*19-24*	*25-30*	*31-36*	*37-42*	*43-48*	*49-54*	*55-60*	*61-120*
					$\widehat{\boldsymbol{\beta}_i^{UV}}$					
0.01***	0.02***	0.04***	0.05***	0.07***	0.08***	0.09***	0.10***	0.11***	0.11***	0.12***
					$R^2_{adj}(\%)$					
10.47	10.07	8.32	8.76	9.10	8.09	7.53	7.10	6.86	6.47	4.58

Panel B: Volatility Loadings in the Stock Market (January 1990-December 2020)

Size	*Book-to-Market Equity*					*Book-to-Market Equity*				
	L	*2*	*3*	*4*	*Hi*	*Lo*	*2*	*3*	*4*	*Hi*
			$\widehat{\boldsymbol{\beta}_i^{UV}}$					$R^2_{adj}(\%)$		
S	-0.29**	-0.27**	-0.32***	-0.38***	-0.48***	59.53	56.89	66.09	60.83	63.30
2	-0.13	-0.29***	-0.29***	-0.30***	-0.50***	71.02	73.57	73.20	69.75	68.81
3	-0.17*	-0.17**	-0.15***	-0.34***	-0.41***	74.88	80.48	77.81	73.56	67.81
4	-0.05	-0.23***	-0.25***	-0.40***	-0.39***	80.79	84.76	78.09	77.43	69.65
B	0.16***	0.04	-0.08	-0.14*	-0.15	89.43	85.99	75.55	66.66	59.48

Figure 1: Realized Stock-Bond Return Correlation and Stock Market Volatility
Panel A of this figure the monthly correlation between the stock market return and the 10-year Treasury bond return (based on daily data). Results are reported in percentages. The "Pre-Volcker Period" spans January 1962 to July 1979; the "Volcker+1st Part of Greenspan Period" spans August 1979 to September 1997; the "2nd Part of Greenspan, Bernanke, Yellen, & Powell Period" spans October 1997 - December 2020. Panel B plots the monthly realized stock market volatility and the predicted market volatility (based on an Asymmetric-Student GARCH (1,1) model), for the period January 1952 to December 2020.

Panel A: Realized Stock-Bond Return Correlation



Panel B: Stock Market Volatility

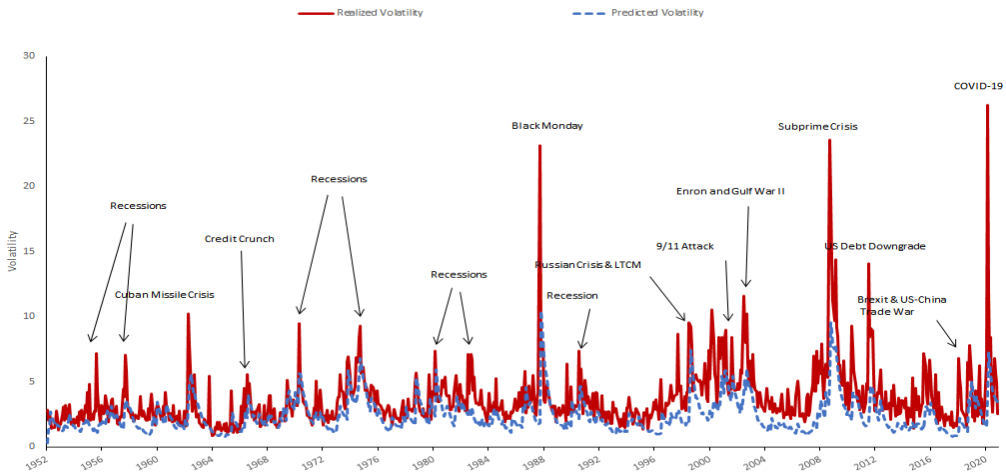
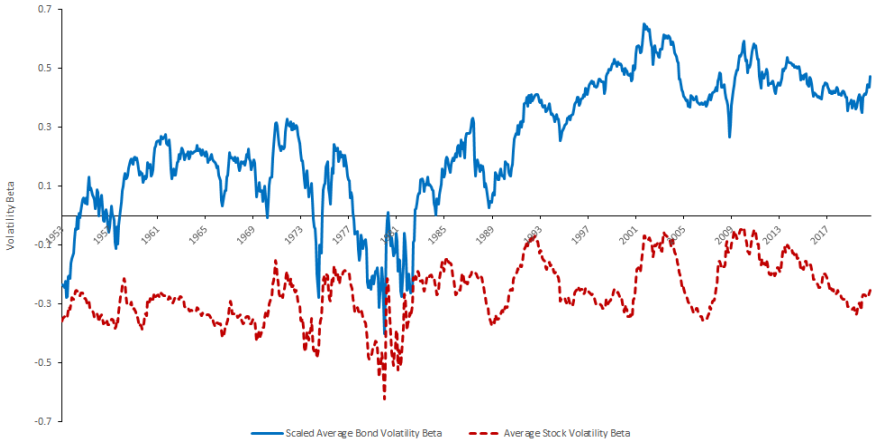


Figure 2: Conditional Volatility Loadings

This figure plots the monthly cross-sectional average conditional volatility loadings on stock and Treasury bond returns in Panel A (the values for bonds are scaled up by a factor of five for better visualization). The loadings are estimated using a two-factor model that inlcudes the excess market return and unexpected volatility. Panel B plots the conditional market price of risk and the scaled volatility price of risk (i.e., the volatility price of risk times 2). The data span from January 1952 to December 2020. For each year, the tick marks correspond to the month of January.

Panel A: Average conditional volatility loadings on stocks and Treasuries



Panel B: Conditional market price of risk and volatility price of risk

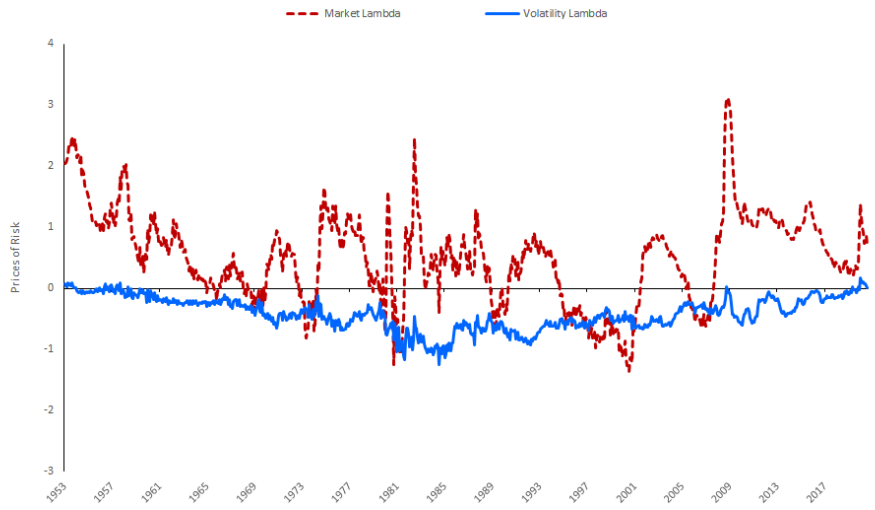
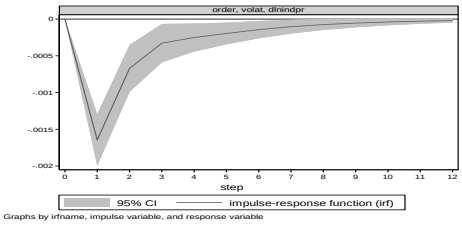
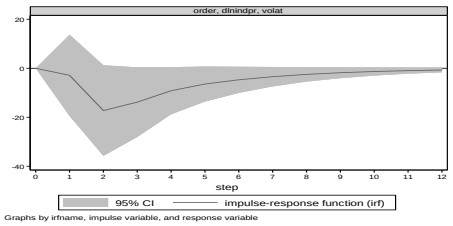


Figure 3: Impulse Response Functions for Volatility and Real Economic Activity
This figure plots the impulse response functions from a VAR(2) model applied to a two-dimensional vector that includes volatility, $Volat$, and either the log industrial production, $dLIndPr$, or the $CFNAI$ index. The gray shaded areas represent 95% confidence intervals from the VAR. The horizontal axis displays the number of months after the shock occured. The data span from January 1962 - December 2020 for Panels A and B, and March 1967 - December 2020 for Panels C and D.

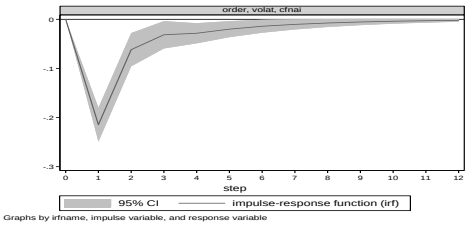
Panel A: Response of *dLIndPr* to *Volat* Shocks



Panel B: Response of *Volat* to *dLIndPr* Shocks



Panel C: Response of *CFNAI* to *Volat* Shocks



Panel D: Response of *Volat* to *CFNAI* Shocks

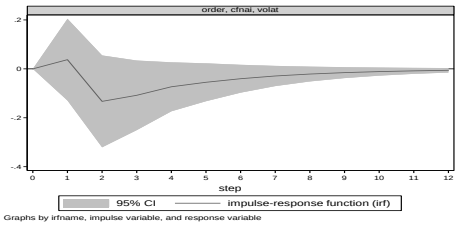
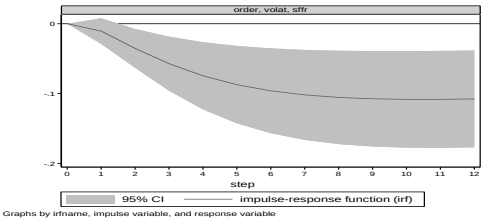
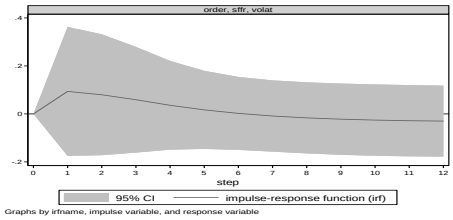


Figure 4: Impulse Response Functions for Volatility and Monetary Policy Stance
This figure plots the impulse response functions from a VAR(2) model applied to a two-dimensional vector that includes volatility, $Volat$, and either the shadow Federal Fund rate, $SFFR$, or its monthly change, $dSFFR$ (used for stationary purposes). The gray shaded areas represent 95% confidence intervals from the VAR. The horizontal axis displays the number of months after the shock occured. The data span from January 1962 - December 2020.

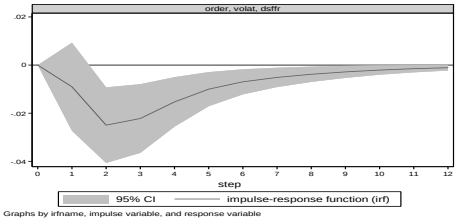
Panel A: Response of *SFFR* to *Volat* Shocks



Panel B: Response of *Volat* to *SFFR* Shocks



Panel C: Response of *dSFFR* to *Volat* Shocks



Panel D: Response of *Volat* to *dSFFR* Shocks

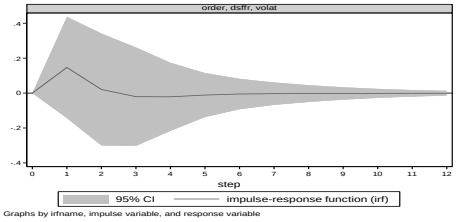
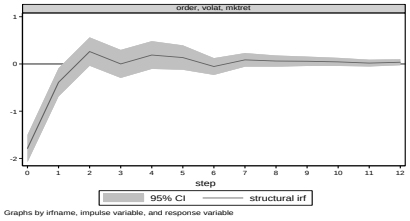


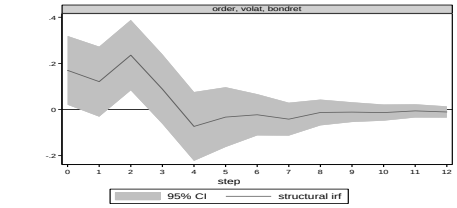
Figure 5: Market and Bond Response to Structural Shocks

This figure plots the SIRFs from an SVAR(5) system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bondret_t)'$. The left column displays the $Mktret$ response to a shock in the other variables, while the right column displays the $Bondret$ response. The gray areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. The data span from January 1962 to December 2020.

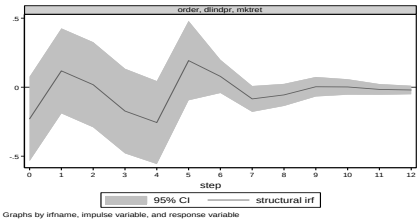
Panel A: Response of *Mktret* to *Volat* Shocks



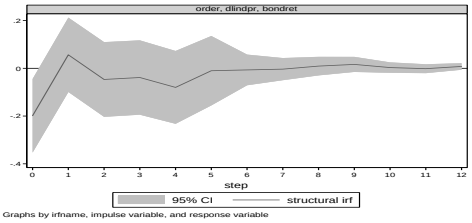
Panel B: Response of *Bondret* to *Volat* Shocks



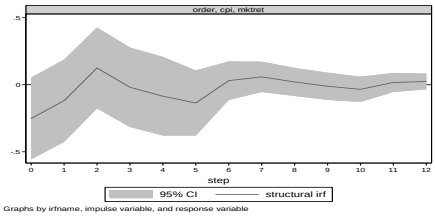
Panel C: Response of *Mktret* to *dlindpr* Shocks



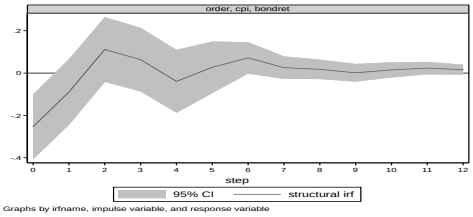
Panel D: Response of *Bondret* to *dlindpr* Shocks



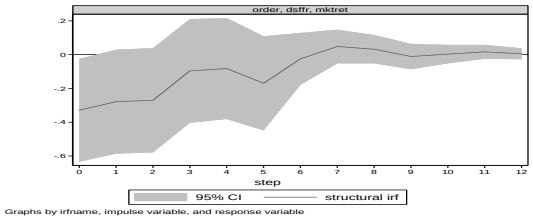
Panel E: Response of *Mktret* to *CPI* Shocks



Panel F: Response of *Bondret* to *CPI* Shocks



Panel G: Response of *Mktret* to *dSFFR* Shocks



Panel H: Response of *Bondret* to *dSFFR* Shocks

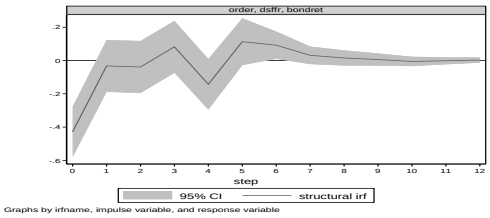
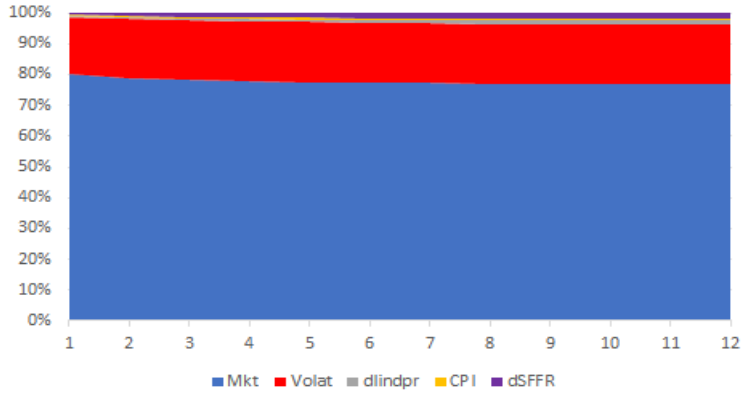


Figure 6: Forecast Error Variance Decompositions

This figure plots the forecast error variance decompositions (FEVD) for the stock market in Panel A, and for the Treasury market in Panel B. The FEVDs are computed based on an SVAR(5) system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bondret_t)'$. The plots show the percentage of variance of the j -step-ahead (with j = 1, 2, ..., 12 months) forecast error in the $Mktret$ (or $Bondret$) due to, going from the bottom to the top, shocks to the $Mktret$ (or $Bondret$) itself (in blue), volatility shocks (in red), business cycle shocks (in gray), inflation shocks (in yellow), and monetary policy shocks (in purple). The data span from January 1962 to December 2020.

Panel A: Forecast Error Variance Decomposition for *Mktret*



Panel B: Forecast Error Variance Decomposition for *Bondret*

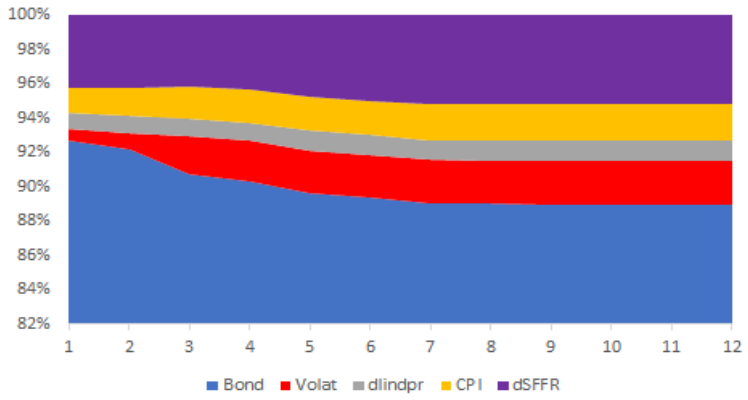
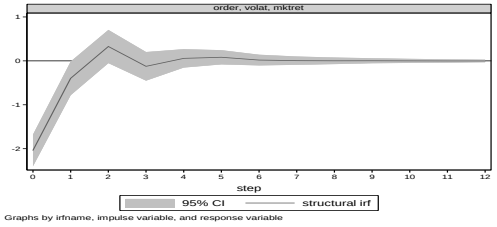
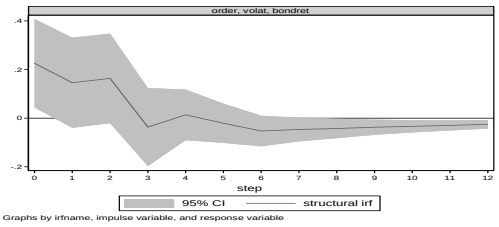


Figure 7: Market and Bond Response to Structural Shocks using Expected Inflation (*EInfl*)
This figure plots the SIRFs from an SVAR(3) system applied to the vector $(dlnindpr_t, EInfl_t, FFR_t, Volat_t, Mktret_t, Bondret_t)'$. The left column displays the $Mktret$ response to a shock in the various variables, while the right column displays the *Bondret* response. The gray areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. The data span from January 1982 to December 2020.

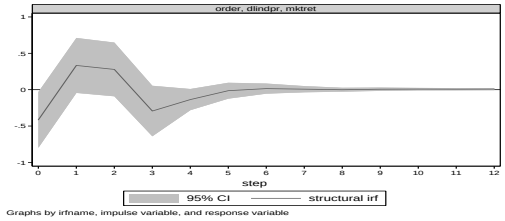
Panel A: Response of *Mktret* to *Volat* Shocks



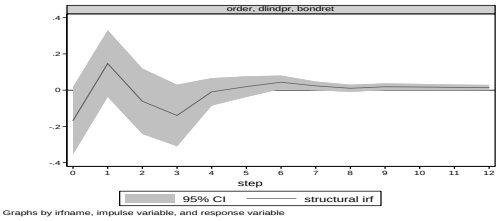
Panel B: Response of *Bondret* to *Volat* Shocks



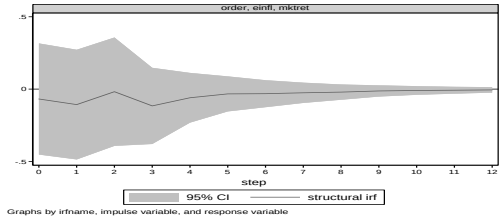
Panel C: Response of *Mktret* to *dlindpr* Shocks



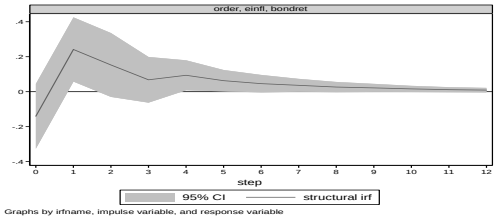
Panel D: Response of *Bondret* to *dlnindpr* Shocks



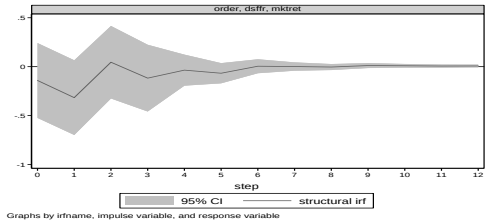
Panel E: Response of *Mktret* to *EInfl* Shocks



Panel F: Response of *Bondret* to *EInfl* Shocks



Panel G: Response of *Mktret* to *dSFFR* Shocks



Panel H: Response of *Bondret* to *dSFFR* Shocks

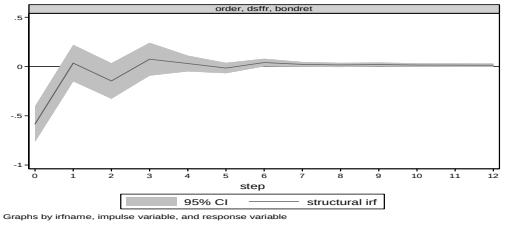
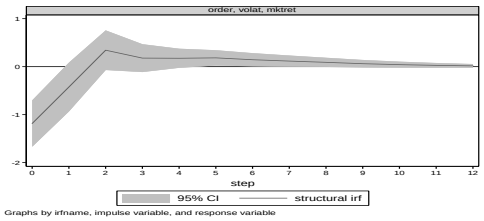
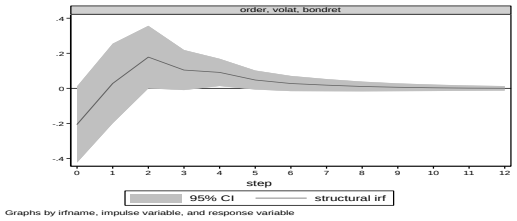


Figure 8: Market and Bond Response to Structural Shocks in Volatility over Three Subperiods
This figure plots the SIRFs from an SVAR system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bondret_t)'$. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. The "Pre-Volcker Period" spans January 1962 to July 1979 in Panels A and B; the "Volcker + 1^{st} Part of Greenspan Period" spans August 1979 to September 1997 in Panels C and D; the "2^{nd} Part of Greenspan, Bernanke, Yellen, & Powell Period" spans October 1997 to December 2020 in Panels E and F. I use an SVAR(2) model for the first subperiod, an SVAR(5) for the second one, and an SVAR(3) for the third one.

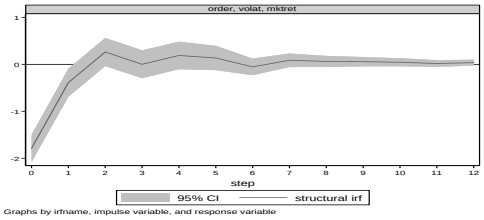
Panel A: Response of *Mktret* to *Volat* Shocks (Pre-Volcker)



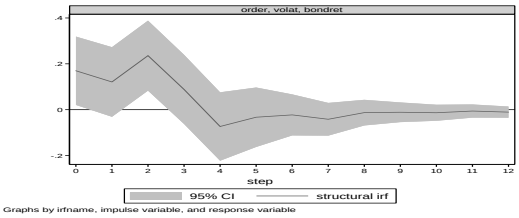
Panel B: Response of *Bondret* to *Volat* Shocks (Pre-Volcker)



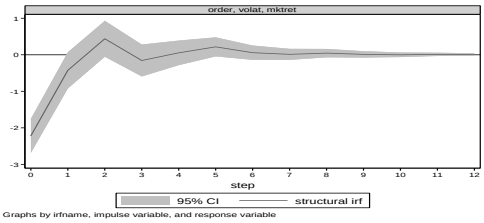
Panel C: Response of *Mktret* to *Volat* Shocks (Volcker + 1^{st} Part of Greenspan)



Panel D: Response of *Bondret* to *Volat* Shocks (Volcker + 1^{st} Part of Greenspan)



Panel E: Response of *Mktret* to *Volat* Shocks (2^{nd} Part of Greenspan, Bernanke, Yellen, & Powell)



Panel F: Response of *Bondret* to *Volat* Shocks (2^{nd} Part of Greenspan, Bernanke, Yellen, & Powell)

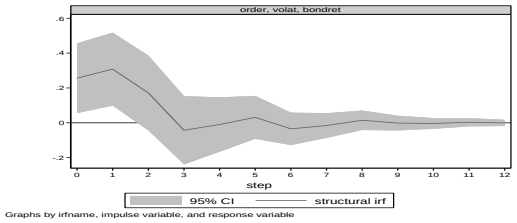
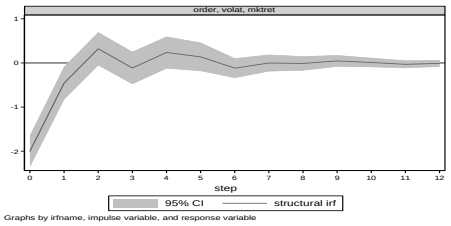
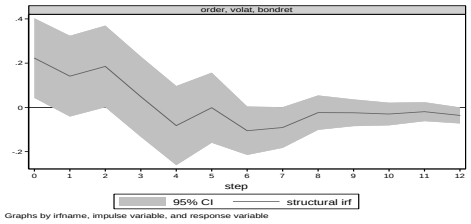


Figure 9: Market and Bond Response to Structural Shocks using Monetary Policy Spread
This figure plots the SIRFs from an SVAR(5) system applied to the vector $(dlnindpr_t, CPI_t, MPS_t, Volat_t, Mktret_t, Bondret_t)'$. In the left column it displays the market return response to a shock in the macroeconomic or financial variables included in the SVAR model, while in the right column it displays the bond return response to these variables. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. The data span from January 1982 to December 2020.

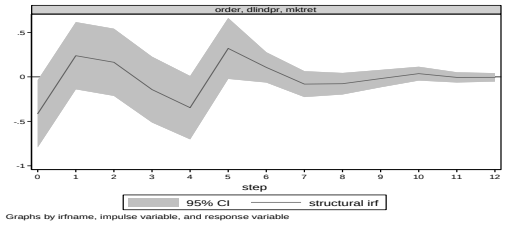
Panel A: Response of *Mktret* to *Volat* Shocks



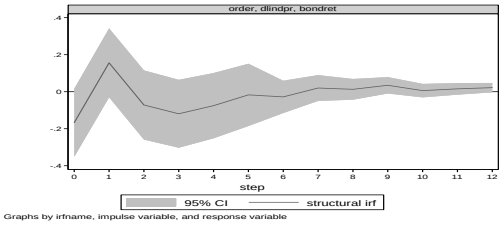
Panel B: Response of *Bondret* to *Volat* Shocks



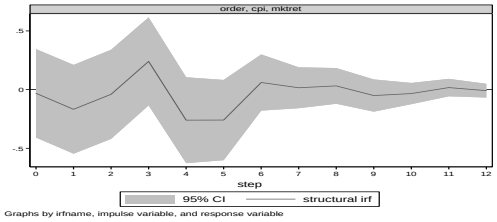
Panel C: Response of *Mktret* to *dlindpr* Shocks



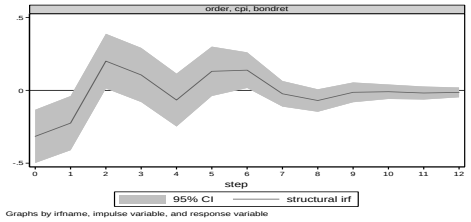
Panel D: Response of *Bondret* to *dlnindpr* Shocks



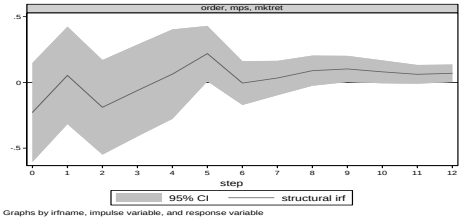
Panel E: Response of *Mktret* to *CPI* Shocks



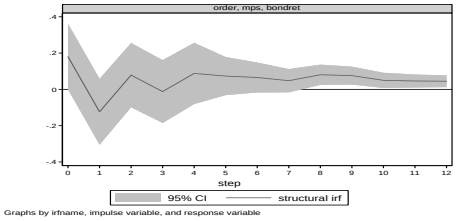
Panel F: Response of *Bondret* to *CPI* Shocks



Panel G: Response of *Mktret* to *MPS* Shocks



Panel H: Response of *Bondret* to *MPS* Shocks



NOT FOR PUBLICATION

Online Appendix: "Flights to Safety, Volatility Risk, and Monetary Policy"

By Claudia E. Moise

A.1 The Asymmetric Volatility Model

The model used in this study is the *GJR model* of Glosten, Jagannathan and Runkle (1993), which is designed to introduce asymmetry into the model:

$$\begin{array}{c} R_{m,t} = \mu + \rho R_{m,t-1} + \eta_t \\ \eta_t = \varepsilon_t \sqrt{h_t}, \\ \varepsilon_t / I_{t-1} \sim Student\ (\upsilon), \qquad t = 1, ..., T. \\ h_t = \alpha + \phi h_{t-1} + \theta^+ \eta_{t-1}^{2+} + \theta^- \eta_{t-1}^{2-}, \\ \eta_t^{2+} = \eta_t^2 1_{\{\eta_t > 0\}},\ \eta_t^{2-} = \eta_t^2 1_{\{\eta_t < 0\}} \end{array} \tag{A1.1}$$

The distribution of $R_{m,t}$ is *Student* with mean zero and variance $h_t^{1/2}\upsilon/(\upsilon - 2)$ given past information I_{t-1} and assuming $\upsilon > 2$. The ε_t sequence is independent and the initial variance is a known constant. Let γ denote the parameter vector in this model, with $\gamma = (\mu, \rho, \alpha, \theta^+, \theta^-, \phi, \upsilon)$. The posterior density for a sample of T observations is given by

$$\varphi(\gamma/R) \propto \varphi(\gamma) l(\gamma/R), \tag{A1.2}$$

with the likelihood function given by

$$l(\gamma/R) \propto \prod_{t=1}^{T} \frac{\Gamma(\frac{\upsilon+1}{2})}{\Gamma(\frac{\upsilon}{2})} (\upsilon h_t^{1/2})^{-1/2} \left[1 + \frac{R_t^2}{\upsilon h_t^{1/2}} \right]^{-\frac{\upsilon+1}{\upsilon}}, \tag{A1.3}$$

where the prior density, $\varphi(\gamma)$, needs to respect the positivity restrictions on the parameters and the condition $\phi < 1$. Integrability of the posterior density depends in part on the integrability of the prior density. Given an integrable (or proper) prior and a non-pathological likelihood, the posterior will also be integrable. Examining the likelihood function (A3) it can be seen that, if $h_t^{1/2}$ is strictly positive, since the *Student* density is finite and positive, no pathology appears. However, the posterior density of υ is not integrable if one were to use a flat prior (see Bauwens and Lubrano (1998)). For the posterior density of υ to be integrable, the prior information must be such that the posterior is forced to go to zero quickly enough in the tail. The prior at the right tail should be at least $O(\upsilon^{1+d})$, with d being small and positive, e.g. $1/\upsilon^2$ (improper prior obtained by being flat on $1/\upsilon$). This prior must be truncated to the interval (m, ∞), with m being small and positive, to avoid causing problems at the left tail. This approach avoids the problem of $l(\gamma/R)/\upsilon^2$ approaching infinity as υ approaches zero. Therefore, for a proper prior for υ, I use a $half - right\ Cauchy$ centered at 0:

$$\varphi(\upsilon) \propto (1 + \upsilon^2)^{-1} \quad (\upsilon > 0). \tag{A1.4}$$

For the rest of the parameters in the model I use a uniform prior.

A.2 The Griddy-Gibbs Sampler

The *Gibbs sampler* of Geman and Geman (1984) and Gelfand and Smith (1990) is a very popular $MCMC$ method. Let $\theta_1,\ \theta_2,\ ...\theta_n$ be a set of parameters that need to be estimated, X the available data, and M the model entertained. Suppose that the conditional distributions of each parameter given the others, $f_i(\theta_i/\theta_{j\neq i}, X, M)$ are known, but the likelihood function of the model is hard to obtain. What I do is to draw a random number from each of these conditional distributions. For instance, if $n = 3$, let's consider $\theta_{2,0}$ and $\theta_{3,0}$ two arbitrary starting values of θ_2 and θ_3. Then

1. I draw a random sample $f_1(\theta_1/\theta_{2,0}, \theta_{3,0}, X, M)$, call it $\theta_{1,1}$;
2. I draw a random sample $f_2(\theta_2/\theta_{3,0}, \theta_{1,1}, X, M)$, call it $\theta_{2,1}$;
3. I draw a random sample $f_3(\theta_3/\theta_{2,1}, \theta_{1,1}, X, M)$, call it $\theta_{3,1}$.

This is a *Gibbs iteration*. The iteration can be repeated for n times, with n sufficiently large such that $m < n$ initial random draws can be discarded. I get the *Gibbs sample* this way, $(\theta_{1,m+1}, \theta_{2,m+1}, \theta_{3,m+1}), ...(\theta_{1,n}, \theta_{2,n}, \theta_{3,n})$, which can be used to obtain the point estimates and the variances of the three parameters.

In the case when the conditional posterior distributions of the parameters don't have closed-form expressions, the *Gibbs sampler* implementation can become complicated. But Ritter and Tanner (1992) have a method to obtain draws in this case. It is called the $Griddy-Gibbs\ sampler$:

1. I choose a grid of points from a properly selected interval of θ_i, say $\theta_{i1} \leq \theta_{i2} \leq ... \leq \theta_{im}$. I evaluate the conditional posterior density function to obtain $w_j = f(\theta_{ij}/\theta_{lk\neq ij}, X, M)$ for $j = 1, ...m$;

2. I use $w_1, ..., w_m$ to obtain an approximation to the inverse cumulative distribution function of $f(\theta_{ij}/\theta_{lk\neq ij}, X, M)$;

3. I draw a $Uniform(0, 1)$ random variate and I transform the observation via the approximate inverse CDF to obtain a random draw for θ_i.

The usual *Gibbs sampler* cannot be applied to the $GARCH$ model even if the error term is (conditionally) normal. It requires analytical knowledge of the full conditional posterior densities. Regression models with $GARCH$ errors do not contain this knowledge. To handle this, I apply a unidimensional deterministic integration rule to each coordinate of the posterior density in combination with the *Gibbs sampler*, as described by Bauwens and Lubrano (1998). The random draws of the joint posterior are then obtained by evaluating and inverting the full conditional densities.

I keep 5000 draws in the $Griddy-Gibbs\ sampler$ and I consider the 1000 initial draws as the burn-in sample. The grid I do the search over is similar to the one used by Bauwens and Lubrano (1998): $\mu \times \rho \times \alpha \times \phi \times \theta^+ \times \theta^- \times \upsilon \in (-0.60, 0.94) \times (0.00, 0.40) \times (0.01, 0.90) \times (0.35, 0.95) \times$

$(0.00001, 0.50) \times (0.01, 0.70) \times (0.01, 30)$. I report the posterior estimates in Table B1. The extent to which a volatility shock today feeds through into the next period$'$s volatility is equal to 0.75. The leverage hypothesis of Black (1976) is also supported by the results, with only the coefficient for the negative shocks to returns being precisely estimated.

References

Bauwens, L. and M. Lubrano, 1998, Bayesian inference on GARCH models using the Gibbs sampler, *Econometrics Journal* 1, C23-C46.

Gelfand, A.E. and A.F.M. Smith, 1990, Sampling based approaches to calculating marginal densities, *Journal American Statistical Association* 85, 398-409.

Geman, S. and D. Geman, 1984, Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images, *IEEE Trans. Pattern Anal. Mach. Intell* 6, 721-741.

Glosten, L. R., R. Jagannathan and D.E. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779-801.

Ritter, C. and M.A. Tanner, 1992, Facilitating the Gibbs sampler: the Gibbs stopper and the Griddy-Gibbs sampler, *Journal of American Statistical Association* 87, 861-8.

Table 1: Posterior Estimates for the Asymmetric Student-GARCH(1,1) Model

This table reports the posterior estimates and the corresponding standard errors from the model:

$$
\begin{aligned}
&R_{m,t} = \mu + \rho R_{m,t-1} + \eta_{t,} \\
&\eta_t = \varepsilon_t \sqrt{h_t}, \\
&h_t = \alpha + \phi h_{t-1} + \theta^{+} \eta_{t-1}^{2+} + \theta^{-} \eta_{t-1}^{2-}, \\
&\eta_t^{2+} = \eta_t^2 1_{\{\eta_t > 0\}}, \quad \eta_t^{2-} = \eta_t^2 1_{\{\eta_t < 0\},} \\
&\varepsilon_t / I_{t-1} \sim Student(\upsilon), t = 1, ..., T.
\end{aligned}
$$

The R_t represents the monthly time series of returns on the stock market portfolio for the period January 1952 to December 2020. I compute the results using a Griddy-Gibbs sampling algorithm, where I keep 5000 draws and I consider the initial 1000 draws as the burn-in sample. I use a flat prior on finite intervals for all parameters except for the prior on υ, which is half-Cauchy.

	Estimate	Std Err
μ	0.212	0.02
ρ	0.035	0.03
α	0.102	0.04
θ^{+}	0.027	0.02
ϕ	0.730	0.06
υ	10.541	3.75
θ^{-}	0.208	0.06

Figure 1: Realized Stock Market Volatility and Economic Activity

This figure plots the monthly stock market volatility series, using the continuous line, next to the monthly scaled $CFNAI$ index (i.e., the index value times 2), using the dashed line. $CFNAI$ represents a measure of economic activity. Data cover the period May 1967 to December 2020. For each year, the tick marks correspond to the month of January.

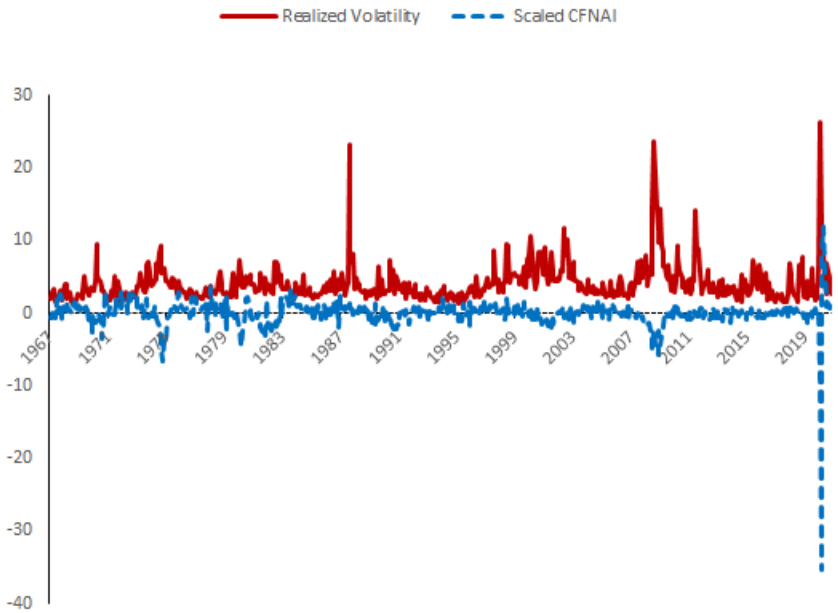


Figure 2: Structural Impulse Response Functions (SIRFs) over the Period 1962-2020
This figure plots the structural impulse response functions from an SVAR(5) system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, V_t, Mktret_t, Bondret_t)'$. The first row shows the effect of a one-standard-deviation impulse to the *Bondret* on the other variables. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. Data cover the period January 1962 - December 2020.

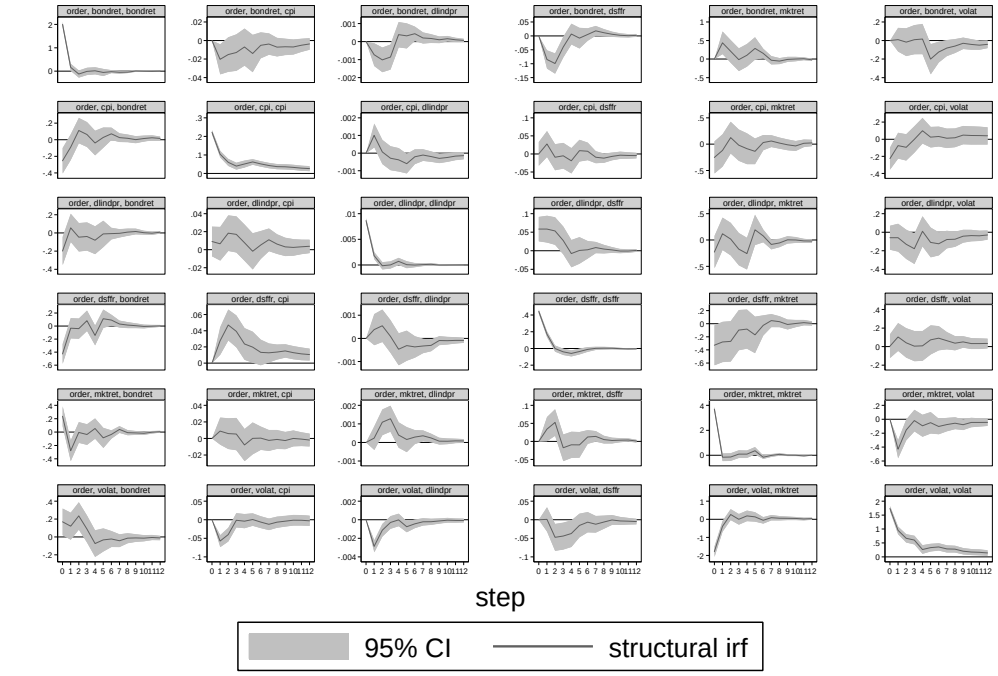


Figure 3: SIRFs for an SVAR with Expected Inflation (EInfl)

This figure plots the SIRFs from an SVAR(3) system applied to the vector $(dlnindpr_t, EInfl_t, FFR_t, V_t, Mkt_t, Bond_t)'$. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. Data cover the period January 1982 - December 2020.

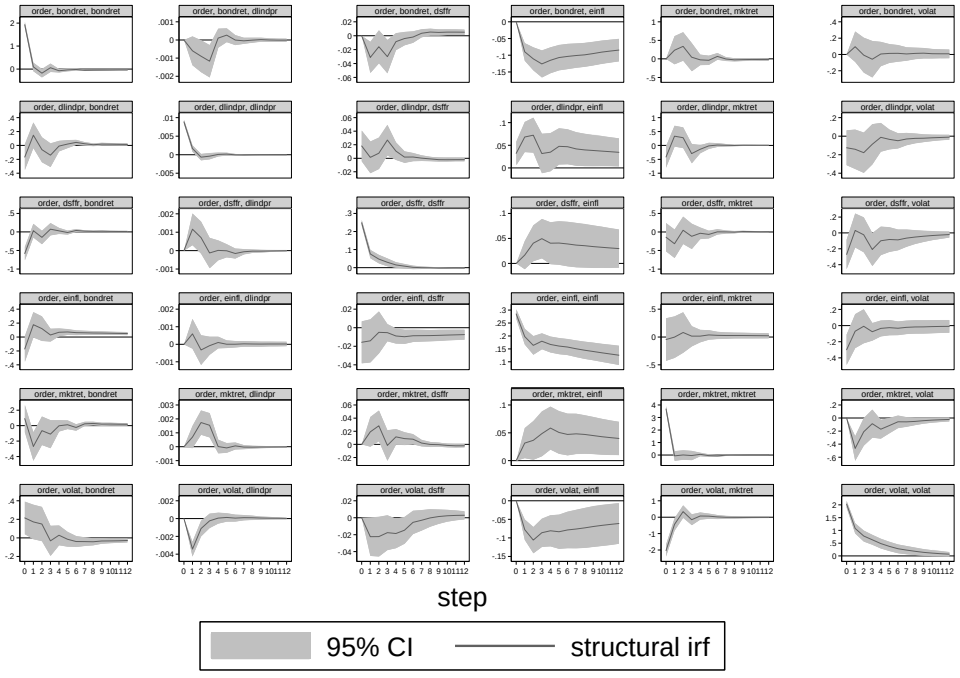


Figure 4: Structural Impulse Response Functions (SIRFs) for the Period January 1962-July 1979
This figure plots the structural impulse response functions (SIRFs) from an SVAR(2) system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, V_t, Mktret_t, Bondret_t)'$. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. Data cover the period January 1962-July 1979.

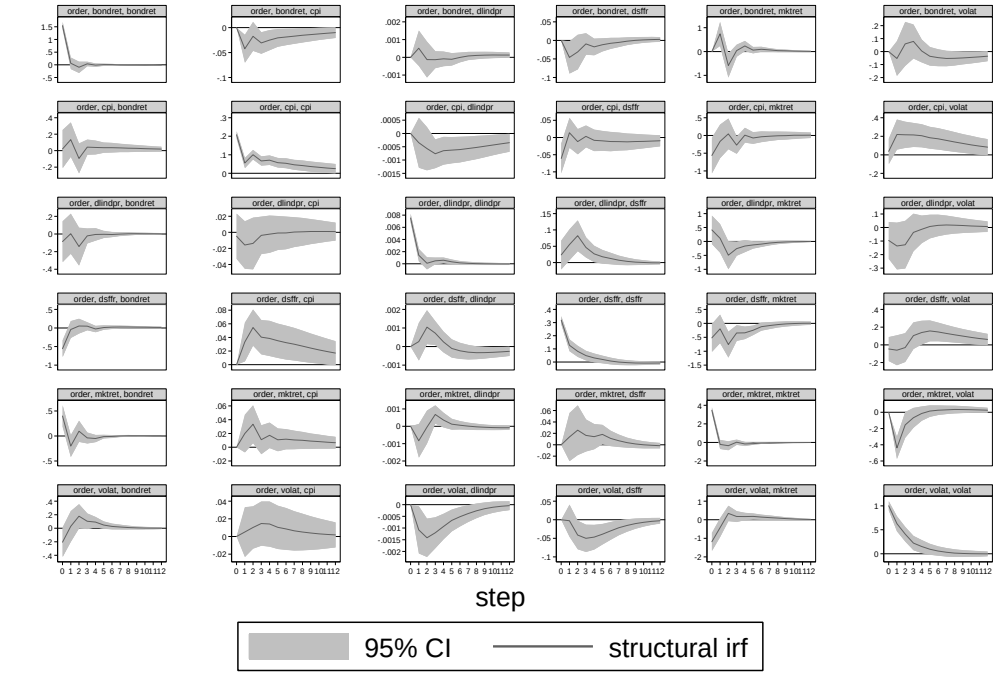


Figure 5: SIRFs for the Period August 1979 - September 1997

This figure plots the SIRFs from an SVAR(5) system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, V_t, Mkt_t, Bond_t)'$. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. Data cover the period August 1979 - September 1997.

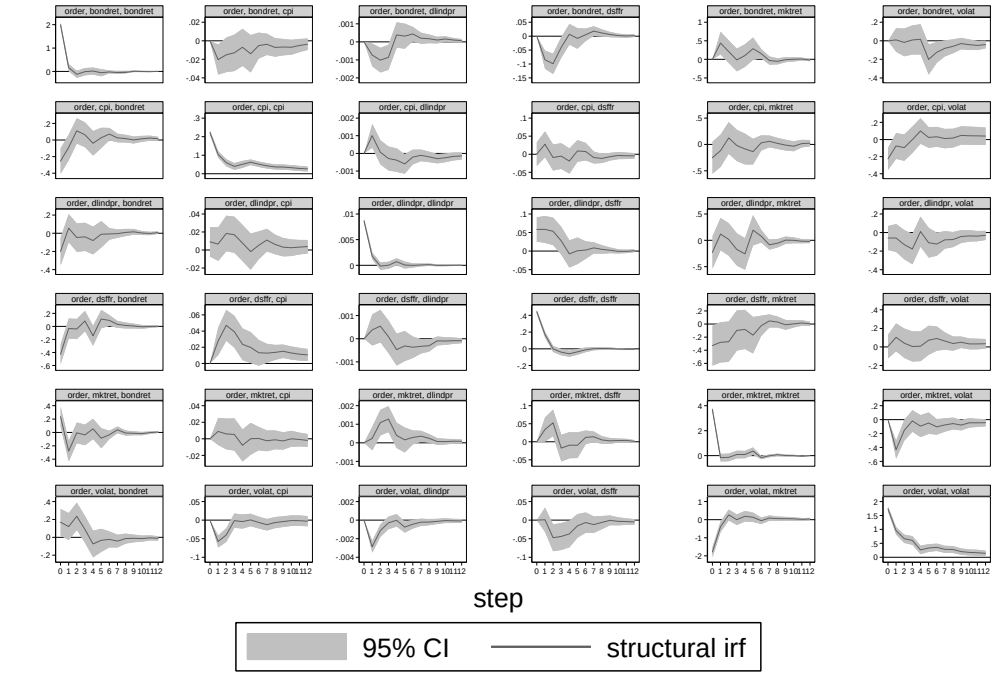


Figure 6: SIRFs for the Period August 1997-December 2020

This figure plots the SIRFs from an SVAR(3) system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, V_t, Mkt_t, Bond_t)'$. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. Data cover the period August 1997-Decemebr 2020.

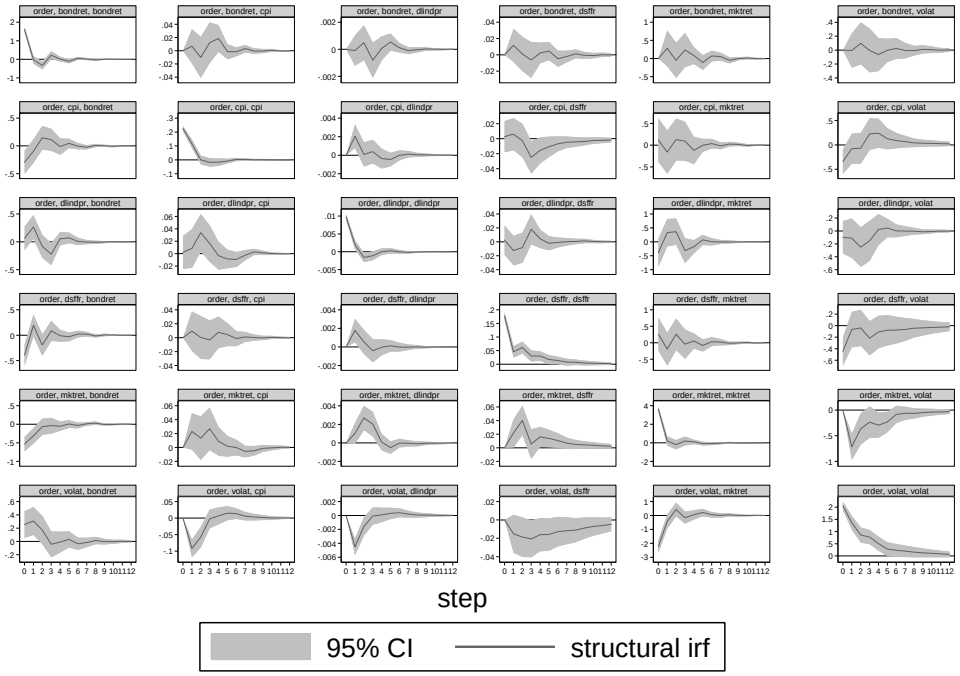
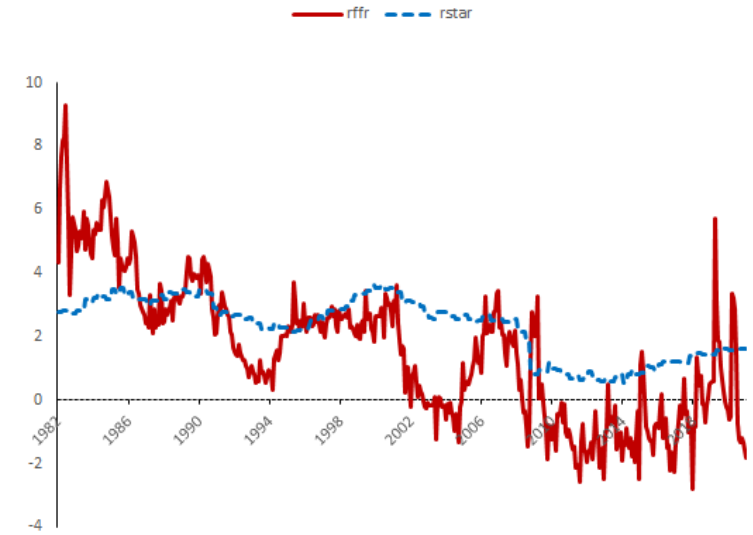


Figure 7: Real Interest rate and Monetary Policy Spread

This figure plots the real interest rate, $rfffr$, and the natural interest rate, $rstar$, in Panel A. It plots the monetary policy spread, mps, in Panel B, defined as the difference between the former and the latter variables. Data cover the period January 1982 - December 2020. For each year, the tick marks correspond to the month of January.

Panel A: Real Interest Rate and the Natural Interest Rate



Panel B: Monetary Policy Spread

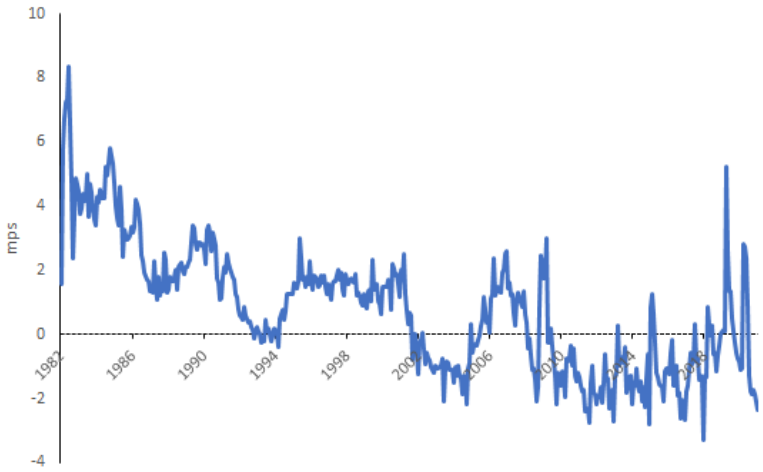


Figure 8: SIRFs for an SVAR with Monetary Policy Spread

This figure plots the SIRFs from an SVAR(5) system applied to the vector $(dlindpr_t, CPI_t, MPS_t, V_t, Mkt_t, Bond_t)'$. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. Data cover the period January 1982 - December 2020.

