Flights to Safety, Volatility Risk, and Monetary Policy

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Abstract

I propose a novel explanation for flights to safety in the cross-section of assets, based on volatility risk. Specifically, I document a positive volatility risk premium in equity returns, accompanied by a negative premium in Treasury bond returns, which explains the negative stock-bond return correlation recorded during times of market stress, when volatility rises. Furthermore, using a structural VAR model that interlinks volatility, real economy, and monetary policy with stock and Treasury bond returns, I show that volatility plays a robust role in explaining flights to safety. Financial volatility can therefore be a valuable instrument for guiding central bankers when designing appropriate policies for turbulent times, and it should be included in the set of leading economic indicators.

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Keywords: Volatility, market stress, flights to safety, monetary policy, cross-section of stocks and Treasuries, structural VAR model

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1 Introduction

Times of market stress are characterized by "flights to safety", where investors sell their riskier investments to purchase safer assets. This leads to an increased demand for government backed securities, which are relatively safe as they lack significant default risk, accompanied by a reduced demand for securities issued by private agents. For instance, the 2007-2008 financial market turmoil has spurred investors to flee stocks and seek the safety of the U.S. Treasuries, in an attempt to reduce their stock market risk exposure, which has led to one of the worst periods for holding stocks to coincide with one of the best periods to hold Treasuries. Unsurprisingly, flights to safety translate into a negative stock-bond return correlation, a metric that is otherwise positive, as can be seen in Figure 1 (see also Baele, Bekaert, and Inghelbrecht, 2010; and Campbell, Sunderam, and Viceira 2017). Flights to safety thus highlight the interconnectedness between stocks and Treasuries during times of market stress, when there is a surge in stock market volatility, as illustrated in Figure 2. Therefore, it is natural to examine whether market dynamics such as volatility risk can explain the flight-to-safety phenomenon. From here forth, I refer to realized stock market volatility simply as volatility.

I make the following contributions to the literature. First, I propose a novel explanation for flights to safety in the cross-section of assets, based on volatility risk. Specifically, I document a positive volatility risk premium in equity returns, accompanied by a negative premium in Treasury bond returns, which explains the negative stock-bond return correlation recorded during times of market stress, when volatility rises. Moreover, I relate the volatility risk premium that I find in the Treasury space to the inverted yield curve pattern usually observed at the onset of recessions.

Second, I investigate the economic mechanism that lies behind the effect of volatility on the cross-section of asset returns. In particular, I show that volatility has predictive power for economic activity and monetary policy uncertainty (MPU), which have been shown to affect both equity returns and the yield curve. Furthermore, using a structural vector autoregressive model (SVAR) that interlinks volatility, real economy, and monetary policy with stock and Treasury bond returns, I document that volatility plays a robust role in explaining flights to safety. My findings indicate that volatility can be a valuable instrument for guiding central bankers during times of market stress, and that it should be included in the set of leading economic indicators.

The literature has focused on the flight-to-safety phenomenon for some time, starting with the model in Vayanos (2004), where managers become more risk averse during volatile times, when there is a high probability of withdrawals. In Caballero and Krishnamurthy (2008), Knightian uncertainty is an important ingredient in the flight-to-quality episodes, as it leads agents to drop risky financial claims in favor of safe claims. In turn, this leads to a change in sign in the stock-Treasury bond return correlation, a metric that is highly unstable: while positive most of the time,

it becomes negative during recessions and financial crises, a phenomenon called decoupling. Baele, Bekaert, and Inghelbrecht (2010) attribute the time variation in the stock-Treasury bond return correlation to phenomena like flights to quality (or safety), rather than changing macroeconomic fundamentals. Meanwhile, Gulko (2002) finds that decoupling is associated with steep stock market declines, while Connolly, Stivers, and Sun (2005), and Bansal, Connolly, and Stivers (2010) document that periods of low stock-bond return correlation are associated with higher volatility and higher bond returns. Furthermore, Baele, Bekaert, Inghelbrecht, and Wei (2020) empirically characterize flights to safety as episodes involving large positive bond market returns and large negative stock market returns, negative high-frequency correlations between bond and stock returns, and an elevated market stress, as proxied by a high equity market volatility.

Determining the drivers of flights to safety is a timely topic, as both economists and policy makers have recognized the importance of understanding this phenomenon.[1] My goal is to examine the extent to which volatility risk can explain flight to safety. My approach consists in establishing a link between volatility risk and the returns on stocks and Treasury bonds, followed by an examination of the economic mechanism that lies behind it.

Because financial markets are exposed to common macroeconomic shocks, stocks and bonds should be priced using a common pricing kernel. 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 show that (unexpected) volatility enters the joint pricing kernel with a significant price of risk, ranging between -41bp and -116bp per month, over the period January 1952 to December 2020. Volatility captures macroeconomic shocks that affect prices in a non-linear way.

To understand the negative volatility price of risk, it suffices to look at the most 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 enhance investors' ability to hedge against a deterioration in the investment opportunity set, and investors are willing to pay a premium for getting downside protection.

More importantly, I find a positive volatility risk premium in the equity returns, accompanied by a negative risk premium in the yield curve, which explains the change in sign in the stock-Treasury bond return correlation from positive to negative during times of market stress. The contribution of volatility risk to assets' risk premia gives us insights into the way market participants react during turbulent times, when aggregate risk aversion rises. Investors are willing to pay a premium for holding safe assets (Treasuries), which correlate positively with volatility surprises, and they require a premium for holding risky assets (stocks), which correlate negatively. The economic

[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

explanation is that stocks and bonds have different risk-return profiles, that make them natural hedges for each other during times of heightened volatility.

By uncovering a stock-bond relationship which is based on shared exposure to volatility risk, I provide empirical support for the existence of a unified pricing model for these asset classes. Moreover, I show that asset pricing models tested in the joint markets have good explanatory power, and they provide risk premia estimates that are both economically meaningful (i.e., similar to their realized analogs) and statistically significant, which provides further empirical 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 of returns in an unconditional (conditional) asset pricing model.

An in-depth analysis of the stock market further reveals that most stocks experience a drop in returns during times of heightened volatility, with small-cap stocks being affected the most, while large-cap stocks are immune to volatility shocks (or even pay off in some cases). The relatively greater ability of the latter group to weather volatility surprises, often associated with financial crises, partially accounts for their lower expected returns. For instance, across the book-to-market quintiles, I find a volatility risk premium in small stocks ranging between 3.00% and 4.44% per annum.

Meanwhile, the Treasury market analysis indicates that bonds pay off in times of heightened volatility, which explains why they earn lower expected returns compared to stocks. In addition, volatility loadings increase monotonically with maturity: a long-term bond (i.e., 61-120 months to maturity) has a 1.56% lower volatility risk premium per annum compared to a short-term bond (i.e., 1-6 months to maturity), because it provides more insurance against volatility shocks. These findings are in line with Baker and Wurgler (2012), who show that government bonds comove most strongly with stocks of large, mature firms. Additionally, the volatility risk premium that I find in the yield curve is related to the inverted yield pattern that has been historically documented to occur at the onset of recessions.

Results are robust with respect to the inclusion of classical risk factors in the asset pricing models, and to the methodology used to capture unexpected volatility. Volatility surprises, however computed, are important sources of risk across stocks and Treasuries, and they explain flight to safety in the cross-section of these asset classes.

However, because flights to safety occur during times of market stress, it may be argued that financial variables such as the *VIX* Index (the so-called "Fear Index") and the *SKEW* Index (a tail

risk proxy) can explain this phenomenon.[2,3] I address this concern by examining the link between these indices and flight to safety. I find that, across these financial alternatives, only volatility risk has explanatory power.

Another observation is that both Treasury yields and stock prices respond strongly 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), which itself 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). Furthermore, Campbell, Pflueger, and Viceira (2020) justify the change in sign in the stock-bond return correlation during the early 2000 using the argument that bond returns are affected by inflation and stocks returns by output, and the correlation between inflation and the output gap switched from negative to positive in 2001. Therefore, I examine the role played by volatility in flight to safety while also accounting for the macroeconomic and monetary policy channels.

Note that the asset pricing results indicate a link between volatility risk and the real economy. More specifically, results show that there is a procyclical variation in the volatility price of risk: it is relatively low (i.e., more negative) during recessions and financial crises, when there is a decline in economic growth, and it is relatively high (i.e., less negative) during expansions, when the economy is growing at a faster pace. But more importantly, I also find that volatility is a precursor of economic activity and monetary policy. Using the (change in log of) industrial production, *dlindpr,* and the Chicago Fed National Activity Index, *CFNAI*, for robustness checks, I document that volatility predicts economic activity over the period January 1962-December 2020, and respectively, March 1967-December 2020. An increase in volatility predicts a significantly negative growth in industrial production, with the effect lasting for up to 8 months in the future (although much stronger in the near term). Furthermore, using the monetary policy uncertainty index, *MPU*, 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 volatility predicts *MPU*. An increase in volatility predicts a significant increase in *MPU* for up to ten months in the future, over the period January 1985 - December 2020, again with stronger results in the near term. In addition, I follow Bernanke and Blinder (1992) and use the effective Federal Funds Rate (*FFR*) to proxy for the monetary policy stance. I find that an increase in volatility leads to a decrease in *FFR*,

[2] 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 (2000) document the effect of higher moments in the cross-section of stock returns.

[3] SKEW is based on S&P500 options market data: https://www.cboe.com/us/indices/dashboard/skew/

indicating a more accommodating monetary policy, over the period January 1962-December 2020. And because yields respond immediately to monetary policy, which is preceded by volatility, it is not surprising that volatility has a significant effect in the Treasury market.

In a follow-up exercise, I employ a structural vector autoregressive (SVAR) model specification that interlinks volatility, real activity, and the monetary policy instrument, where I impose some identifying assumptions to determine the extent to which these variables can explain flight to safety. I follow the literature and start with a macro SVAR specification that is a simplified version of Christiano, Eichenbaum, and Evans (2005) that includes a proxy for economic conditions, a measure of inflation, and a proxy for the monetary policy stance. I use the Consumer Price Index for all urban consumers (CPI) to proxy for inflation. I then enhance this model specification by appending volatility to it. I also include in the SVAR model 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*. Because economists and economic policymakers believe that households' and firms' expectations of future inflation are a key determinant of actual inflation, for robustness checks I also consider expected inflation (*EInfl*) in the SVAR model. Also for robustness checks, I repeat my analysis over three subperiods determined by the sign of the stock-bond correlation. Finally, I repeat my analysis by using the monetary policy spread, *MPS*, (i.e., the difference between the real interest rate and the natural interest rate).

Results indicate that volatility shocks have a significant impact on the two asset classes: their effect is positive for *Mktret*, and negative for *Bondret*, which explains the flight-to-safety phenomenon. Meanwhile, both shocks to *dlindpr* and shocks to *CPI* have a significant and negative effect on the *Bondret*, but no effect on *Mktret*, while shocks to *FFR* have a significant and negative effect on both *Bondret* and *Mktret*.

My work is related to three strands of the literature. The first one has focused on flights to safety, where some papers have empirically characterized 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), while other contributions have considered the drivers of the time variability in the stock-bond return correlation (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 complement this literature by providing a novel explanation for flights to safety in the cross-section of stock and Treasury returns based on a financial variable, the volatility risk.

A second strand of the literature has been working towards developing a unified asset pricing model for stocks and bonds. Some examples are 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), and Cieslak and Pang (2021). My

work is distinct from this literature, as I explore the role played by volatility risk in the cross-section of stocks and bonds.

The third strand of literature has examined the link between monetary policy and financial markets, by focusing on the market reaction 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), or on the impact of monetary policy on asset valuations (see, e.g., Bianchi, Lettau and Ludvigson, 2022). I contribute to this literature by documenting that volatility precedes MPU and it has a direct effect on monetary policy. Moreover, my findings suggest that volatility should be of concern to central bankers during times of market stress.

The remainder of the paper is structured as follows. Section 2 details the data sources. Section 3 documents the role played by volatility in explaining flight to safety. Section 4 examines the connection between volatility, real activity and monetary policy. Section 5 presents a structural model that interlinks all these variables with stocks and 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 analyses.

2 Data Sources

Data come from several sources. I obtain daily value-weighted market returns (used for building the monthly realized volatility) and monthly (value-weighted) returns on 11 Fama maturity-sorted Treasury portfolios for the period January 1952 to December 2020 from the CRSP database in WRDS. The Treasury portfolios are sorted into six-month maturity groups, plus a portfolio comprising maturities between 61 and 120 months: 1-6, 7-12, 13-18,..., 49-54, 55-60, and 61-120 months.[4] I also download from the CRSP database the necessary data to build the Amihud (2002) illiquidity factor, *Amih*, and two state variables used in conditioning tests: the term spread, $TERM$ (i.e., the difference between the yields of a thirty-year and a one-year government bond), and the dividend yield on the S&P500 value-weighted portfolio, DY (i.e., the sum of dividends over the last 12 months, divided by the level of the index).

From the Federal Reserve Bank Reports in WRDS, I download the data needed to construct a third state variable, the default spread, DEF (i.e., the difference between the yields of a long-term

[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.

corporate Baa bond and a long-term corporate Aaa bond).

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

From the Chicago Board Option Exchange (CBOE), I download daily data on the *VIX* and *SKEW* Indices for the period January 1990 - December 2020. I then build a monthly version of these series by considering the last daily value within a month. *VIX* measures market's expectation of 30-day S&P500 volatility implicit in the prices of near-term S&P options, and *SKEW* measures the perceived tail risk in the S&P500 based on the implied volatility of out-of-the-money options.

From the Chicago Fed, I download monthly values for the Chicago Fed National Activity Index, *CFNAI,* for the period January 1985-December 2020. *CFNAI* has been designed to gauge overall economic activity and related inflationary pressure. It 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.

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

From the Federal Reserve Bank of New York, I download monthly data on the natural rate of interest for the period January 1962-December 2020.

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

3 Volatility Risk and Flights to Safety

Flights to safety are characterized by a change in sign in the stock-Treasury bond return correlation from positive to negative during times of market stress. In general, it is expected to have a positive correlation, because both stocks and bonds are major asset classes representing long duration assets (see, e.g., Baele et al., 2010). For instance, the unconditional correlation between the monthly returns on the stock market portfolio and the 10-year Treasury bond equals 10% over my sample period (January 1952 to December 2020). However, the conditional correlation changes signs

through time, as can be seen in Figure 1: while positive most of the time, it becomes negative during recessions and financial crises. The 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). And because volatility also has a strong countercyclical pattern (i.e., it peaks just before or during recessions, and it falls sharply late in recessions or early in recovery periods, as can be seen in Figure 2), it is natural to examine its relation to the flight-to-safety phenomenon.

According to Campbell (1993, 1996), investors want to hedge against changes in forecasts of future volatilities; they are thus concerned with unexpected volatility. Therefore, I start with estimating unexpected volatility. To this end, I use the residual from an AR(1) model applied to the volatility series $Volat_t$ (see, e.g., Engle, 1982), called UV_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):

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

N_t represents the number of trading days in month t.

Figure 2 plots the monthly realized volatility series, $Volat_t$. As expected from a recession and financial crisis proxy, the graph documents increased levels in volatility 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 bond returns, I use the following return generating process:

$$R_{i,t}^e = \alpha_i + \beta_i^m R_{m,t}^e + \beta_i^{UV} UV_t + \epsilon_{i,t}, \qquad i = 1, 2, ..., n. \tag{3}$$

Above, $R_i^e = (R_{b,1}^e, ..., R_{b,11}^e, R_{s,1}^e, ..., R_{s,25}^e)'$ is a vector of excess returns on 11 Treasury bond portfolios and 25 equity portfolios, R_m^e is the excess market return, and n represents the number of test assets.

Panel A of Table 1 reports the monthly average excess returns (in excess of the one-month T-bill rate) for the Treasury portfolios. According to the liquidity preference hypothesis, bond returns should increase with maturity, because long-term bonds are more sensitive to interest rate risk. This monotonic pattern can be observed here, with average bond excess returns increasing with maturity from 3 bp to 16 bp per month, all statistically significant. Meanwhile, Panel B reports the monthly average excess returns for the equity portfolios. Consistent with the 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 dimensions (with the exception of the small-growth portfolio).

I proceed to estimate 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 (outside of market stress episodes), it is not surprising to see positive time-invariable market beta estimates in both spaces. Also, the increasingly monotonic pattern in the market betas recorded in the bond space is in line with the findings in Fama and French (1993): short maturity bonds have a beta close to zero (which was expected, because short-term Treasuries are considered to be riskless assets), while long maturity bonds have a significant (at the 1% level) market beta of 0.05. 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 on the two asset classes. In the bond space, they are all positive and statistically significant (at 1% level). They are also strictly monotonic, increasing from 0.01 for short maturity bonds, to 0.17 for long maturity ones. Meanwhile, in the equity space, volatility loadings are mostly negative. Furthermore, they are strictly monotonic 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 in some cases, holding the market return constant.[5] 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 betas than growth portfolios.

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. Together with the (mostly) negative loadings on stocks, results reveal

[5] This result is in line with the findings in Coval and Shumway (2001).

that stocks and bonds have different risk-return profiles, that make them natural hedges for each other during times of heightened volatility. This explains the shift in demand from stocks to Treasuries during bad times, when volatility rises, which is consistent with flights to safety. Note that, because both stocks and bonds have positive exposure to market risk, this risk factor cannot be used to explain flight to safety.

The above results indicate that stocks and bonds are interconnected via their joint exposure to volatility risk. However, if volatility proxies for common underlying source of macroeconomic risk, then it should be priced across the two financial markets.[6]

To this end, I rely on an asset pricing model that has a linear pricing kernel m:

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

where b_i are factor loadings, and 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, where the equilibrium expected excess returns are linear combinations of the betas of the asset returns with the risk factors (see, e.g., Cochrane, 2001):

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

Above, β_i is a vector of exposures to the risk factors included in the vector f, and λ_i is a vector that contains the corresponding prices of risk.

Because I am interested in the role played by volatility across the two asset classes, I start by employing a two-factor asset pricing model, containing R_m^e and UV. The equilibrium expected excess returns are thus expressed as linear combinations of the betas of the asset returns for the two risk factors:

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

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

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. I estimate the prices of risk (the lambdas) using the second-pass regression outlined in the asset pricing model (12) and the Fama-MacBeth (1973) methodology, by regressing cross-sectionally at each time t, portfolios' excess returns on the beta estimates. Then, I analyze the distribution of the lambda estimates. In order to compare my results with the existing asset pricing literature,

[6] Also, if the test assets in one of the markets have a factor structure (as is the case with 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.

I assume time invariant betas. While doing this exercise, I 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 for the asset pricing tests. The first two rows report the results 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 that includes the market and volatility factors. I highlight three novel findings here. First, according to theory, for the risk factors to form a basis for the space of returns, their risk prices should be close in value to their means (see, e.g., Cochrane, 2001).[7] 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. Second, the two asset pricing models explain a sizable amount of the cross-sectional variation in the asset returns: CAPM by itself has an R^2_{adj} of 76%, and adding the volatility factor to it increases the R^2_{adj} to 83%. Third, 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).

The first 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, and 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. The third finding 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 attempts to reduce this risk exposure. This result is consistent with Merton's (1973) intertemporal asset-pricing model (ICAPM), which suggests using factors that capture unanticipated changes in the opportunity set as hedging instruments, and volatility is clearly related to such changes.

Next, I estimate the volatility premia for the two asset classes. Table 5 documents three additional novel findings. First, there is a negative volatility risk premium in the yield curve, ranging between -12bp (=12*(-0.01)) and -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 of their insurance against volatility shocks, compared to short-term bonds. Third, there is mostly a positive volatility risk premium in equity returns. Additionally, Panel B shows that large-cap

[7] This result refers only to traded factors.

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), over the period January 1952 - December 2020.

Having documented the presence of a volatility risk premium in the term premium, 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 Treasuries reported in Table 2 points to long maturity bonds being better hedges against volatility risk, due to their relatively higher comovement with this risk factor (relative to short maturity bonds). This result implies that long maturity bonds should be in relatively higher demand, and investors should require lower returns for holding them. Why do we then observe higher rates of return on long maturity Treasuries in Table 1?

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. In addition, long term bonds are known to be exposed to interest rate risk. These results imply that long term bonds should have higher expected returns, which is what the unconditional bond returns results indicate in Table 1. In other words, Table 1 points to the usual upward sloping yield curve.

However, there is another factor at play here: the significant exposure of bond returns to volatility risk. The increasing pattern in bonds volatility betas documented in Table 2 translates into a decreasing pattern in the corresponding volatility risk premia that exists in the yield curve, according to Table 5. This result pertains to periods of high volatility, and it suggests a monotonically downward sloping yield curve during such times. And 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 is in line 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 point to investors demanding large-cap and growth stocks during turbulent times, because small-cap and value stocks expose them to larger volatility risk. In accordance 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, and explains, to some extent, 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 turbulent times. 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 the safe assets (Treasury bonds), because they correlate positively with volatility, and they require a premium for holding the risky assets (most stocks), because correlate in a negative fashion. This result explains the negative sign in the stock-bond return correlation that occurs during 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 classical sources of risk. Therefore, I extend the model to account for classical risk factors, by assuming 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 a return generating process:

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

Above, λ_s is the price of risk associated with the generic factor X_s, and λ_0 represents the pricing error. 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 used in the asset pricing exercise, 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 is in line with the results reported in the previous section, where returns of small stocks are more (negatively) affected by volatility risk. There is also a significant correlation of 47% between volatility and aggregate illiquidity, which is in line with the observation that times of heightened volatility tend to coincide with times of low aggregate liquidity. Finally, UV has a significant correlation of 28% with ΔVIX, which was expected because both factors proxy for bad time risk.

The pricing kernel and the expected-return beta model give us a testable implication for the asset pricing models: if factor X_s is priced, its cross-sectional price of risk, λ_s, should be nonzero. Rows 5 - 14 of Table 3 report the prices of risk (i.e., the lambda estimates). 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, and 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 check whether volatility has a pricing effect in the presence of liquidity risk. 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), when the *Amih* factor is also added to the model. Meanwhile, *SMB* has an insignificant price of risk, while *HML*, *MOM* and *Amih* have significant prices of risk. Similarly to the market lambda, 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). When CAPM is augmented with volatility, R^2_{adj} goes up from 76% to 83%. Note that volatility also adds to the explanatory power of the Fama-French (1993) and Carhart (1997) models when included in these models. Results point to an improvement in the fit of each asset pricing model when volatility is included in the model.

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 to a conditional framework. To this end, I use a stochastic discount factor m_{t+1} with time variable coefficients:

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

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, *DIV*, the term spread, *TERM*, and the default spread, *DY,* in the information set.[8] The vector of predetermined instruments is thus $Z_t = (DIV, TERM, DY)_t$.

Similarly to the previous subsection, I start by assuming a return generating process of the form:

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

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

where $\beta_i^m(Z_t)$ and $\beta_i^{UV}(Z_t)$ are the time t conditional market beta and respectively, conditional volatility beta for asset i. The factor $R_{i,t+1}^e$ denotes the time *t+1* excess return on asset i, while $R_{m,t+1}^e$ is the time *t+1* excess return on the market portfolio. Meanwhile, $\lambda_m(Z_t)$ and $\lambda_{UV}(Z_t)$ represent the conditional market and volatility risk prices, respectively

The two conditional betas have the linear functional forms:

$$\beta_i^m(Z_t) = b_{0i}^m + B_i^{m'} Z_t, \tag{11}$$

$$\beta_i^{UV}(Z_t) = b_{0i}^{UV} + B_i^{UV'} Z_t, \tag{12}$$

where $B_i^{m'}$ and $B_i^{UV'}$ are vectors of coefficients corresponding to the conditioning variables included in the vector Z_t.

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

$$R_{i,t+1}^e = \alpha_i + (b_{0i}^m + B_i^{m'} Z_t) R_{m,t+1}^e + (b_{0i}^{UV} + B_i^{UV'} Z_t) UV_{t+1} + \epsilon_{i,t+1}, \qquad i = 1, 2, ..., n. \tag{13}$$

Using the parameter estimates from equation (13), next I construct the fitted betas $\widehat{\beta_i^m(Z_t)}$ and $\widehat{\beta_i^{UV}(Z_t)}$, 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:

$$E_t[R_{i,t+1}^e | Z_t] = \lambda_0(Z_t) + \lambda_m(Z_t)\widehat{\beta_i^m(Z_t)} + \lambda_{UV}(Z_t)\widehat{\beta_i^{UV}(Z_t)}, \qquad i = 1, 2, ..., n. \tag{14}$$

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

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

$$R_{i,t+1}^e = \alpha_i + \sum_{s=1}^{S} \beta_i^s(Z_t) X_{s,t+1} + \epsilon_{i,t+1}, \qquad i = 1, 2, ..., n. \tag{15}$$

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

$$\beta_i^s(Z_t) = b_{0i}^s + B_i^{s'} Z_t. \tag{16}$$

Equilibrium expected excess returns then follow:

$$E_t[R_{i,t+1}^e | Z_t] = \lambda_i'(Z_t)\widehat{\boldsymbol{\beta}_i(Z_t)} = \lambda_0(Z_t) + \sum_{s=1}^{S} \lambda_s(Z_t)\widehat{\beta_i^s(Z_t)}, \qquad i = 1, 2, ..., n. \tag{17}$$

I start by estimating the parameters in equation (13). Next, I build the conditional market and volatility betas as per equations (11) and (12). For each month, I compute the cross-sectional

average conditional volatility beta for both stocks and bonds, and I display these time series in Figure 3. The novel result is that the average conditional volatility beta has, outside the hyper-inflationary period of the 1970s, opposite signs in the two financial markets: it is mostly positive for Treasuries, and it is negative for stocks. This finding indicates again that bonds are safer investments because they provide a hedge against volatility risk, which explains flights to safety.

Next, I evaluate the pricing ability of volatility in a conditional asset pricing context, using equations (14) and (17). Table 6 documents the conditional prices of risk. The first set of rows presents the results for the conditional CAPM. I find that the market return has a significant price of risk of 60 bp per month (*adjusted p-value* = 0.0003), which is, again, close to its realized analog. The conditional CAPM has a good explanatory power in the cross-section of stocks and Treasuries, with an R^2_{adj} of 76%. Meanwhile, volatility is again robustly priced across the two financial markets. Controlling for market risk, volatility has an estimated conditional price of risk of -41 bp per month (*adjusted p-value* = 0.0347). When the *SMB* and *HML* factors are also included in the model, volatility continues to have a significant price of risk of -0.49 bp per month (*adjusted p-value0 = 0.0171*). Volatility further maintains its pricing ability when the *MOM* and *Amih* factors are added to the model, with a price of risk of -55 bp per month (*adjusted p-value* = 0.0095), and -49 bp per month (*adjusted p-value* = 0.0205), respectively.

Figure 4 plots the time series of the conditional market and volatility prices of risk. They represent the fitted values from a regression of each factor' price of risk on the conditioning variables. A visual inspection indicates a procyclical variation in the volatility price of risk, which is relatively low (i.e., more negative) during bad economic times, when there is a decline in economic growth, and it is relatively high (i.e., less negative) during expansions, when the economy is growing at a faster pace. During the former period, income and employment decline, and stock prices tend to fall as companies struggle to sustain profitability, especially the small firms. During the latter period, a healthy and growing economy leads stock prices to often reach all-time highs Meanwhile, there is a countercyclical variation in the market price of risk.

Having documented the role played by volatility during flights to safety, the next step consists of examining the link between volatility and macroeconomic variables that have been shown to affect the returns on the two asset classes studied here.

4 Volatility, Real 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 examine the link between volatility, real

activity, and monetary policy.

4.1 *Volatility and Monetary Policy Uncertainty (MPU)*

Motivated by the existing literature which has shown that uncertainty about monetary policy (or the inflation target) is the main driver of the size of the term premium 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), in the next step I investigate the link between volatility and *MPU*. More precisely, I assess the forecasting power of volatility for *MPU* over the period January 1985 - December 2020 using a linear regression model.

For this exercise, 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 Funds target rate has reached the Zero Lower Bound (ZLB) in the wake of the Great Recession (i.e., starting in December 2008), where it remained until (and including) November 2015. The binding ZLB on short-term interest rates presents a significant problem when employing the variability in the target *FFR* to proxy for *MPU*. To circumvent this problem, I take advantage of recent work that uses 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.[9]

Table 7 indicates that an increase in volatility precedes a significant increase in the *MPU* index for up to ten months in the future, with stronger results in the near term.

4.2 *Volatility and Real Activity*

While the literature has previously related 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 the predictive power of volatility for economic activity using a linear regression model.

The 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 cover similar sources of variation in the economy.[10]

[9] 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.

[10] I use the change in the log industrial production to obtain a stationary variable.

For robustness checks, I use the Chicago Fed National Activity Index, *CFNAI,* which is a monthly index designed to gauge overall economic activity and related inflationary pressure.[11] Figure 1 of the Appendix plots *CFNAI* next to the volatility series. The two series tend to exhibit opposite dynamics during times of market stress, which was expected as the economy tends to experience below trend growth when volatility rises.

Table 8 Panel A reports the results from a linear regression model, where I regress future values for real economic activity on present month volatility. When using *dlindpr* to proxy for real activity, I find that an increase in volatility predicts a significantly negative growth in industrial production over the period January 1962 - December 2020. While the effect of volatility diminishes through time (the R^2_{adj} drops dramatically in the second month), it lasts for up to 8 months in the future. This finding is in line with Berger, Dew-Becker, and Giglio (2020), who find that innovations in realized stock market volatility are robustly followed by economic contractions. For robustness checks, I also use the *CFNAI* Index. Panel B of Table 8 shows that an increase in volatility predicts a significantly negative *CFNAI* for up to ten months in the future, which translates into an economic growth below trend over the period March 1967 - December 2020. Again, the result is stronger in the near term.

However, to better capture the dynamics between volatility and economic activity, I need to estimate impulse response functions (IRFs). To this end, I rely on a vector autoregressive system (VAR) specification.

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 checking for stationarity in the variables of interest, and based on the information criteria, I select a VAR(2) model to capture the dynamics between monthly volatility (captured by $F_{1,t}$) and the real activity proxy (the latter is captured by $F_{2,t}$). After I run the VAR, I visually examine the relation between the two variables based on the IRFs, where I shock one variable by one unit standard deviation, and I trace the time series impact in the other variable.

[11] 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.

Figure 5 plots the IRFs for *Volat* and *dlindpr* in Panels A and B, and for *Volat* and *CFNAI* in Panels C and D. The graphs capture the response, through time, of one of the variables included in the vector F_t to a shock in the other variable, while the gray shaded areas represent 95% confidence intervals from the VAR. Panel A shows that a positive shock to volatility leads to a significantly negative growth in industrial production over the following seven months. Meanwhile, Panel B indicates that the effect is unidirectional: a shock to industrial production does not have a significant effect on future volatility, as the corresponding IRF stays very close to zero at all horizons. The IRFs displayed in Panels C and D of Figure 5 show that results are robust, by documenting a unidirectional effect from *Volat* shocks to *CFNAI* in the near future (i.e., over the next six months).

4.3 *Volatility and Monetary Policy Stance*

In this subsection I investigate the relation between volatility and the monetary policy stance. The Federal Reserve's traditional policy instrument is the target Federal Funds Rate. The Federal Open Market Committee (FOMC) meets eight times per year to determine the Federal Funds target rate, which further influences the effective Federal Funds Rate via the open market operations. In line with existing research, I consider the effective Federal Funds Rate as the indicator for the US monetary policy stance. However, because my sample includes the ZLB period, I start with the FFR for the period January 1962 to December 1989, and I append to it the shadow interest rate from Wu and Xia (2016) for the period January 1990 to December 2020. I denote the final series by *SFFR* (i.e., shadow *FFR*). Note that this series is not stationary. However, to be consistent with the literature, I use *SFFR* for the first set of tests. In addition, I apply the differencing operator to obtain a stationary series, labeled *dSSFR,* which I use for additional tests. Finally, to capture the dynamics between volatility and monetary policy, I rely again on a VAR(2) model.

Figure 6 plots the corresponding IRFs. The plots displayed in 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, a shock to *dSFFR* does not have a significant effect on future volatility.

These results imply that the stock market leads monetary policy, with increases in volatility leading to a more accommodating monetary policy. This is in line with Rigobon and Sack (2003), who document that stock market movements have a significant impact on the determination of monetary policy. They are also consistent with Cieslack and Vissing-Jorgensen (2021), who find that negative stock market returns, which coincide with high unexpected volatility (as indicated by Figure 2 and Table 4), precede monetary policy accommodation by the Federal Reserve.

Overall, this section shows that an increase in volatility is associated with a statistically significant decline in future industrial production, and an accommodating future monetary policy. Additionally, volatility precedes monetary policy uncertainty.

While these results establish a link between volatility and macroeconomic variables, it is important to assess the role played by volatility in the flight-to-safety phenomenon in the presence of macroeconomic and monetary policy variables. To this end, I construct a structural model that interlinks volatility, real activity, and traditional monetary policy instruments, with stocks and Treasury bond returns.

5 Structural Model

The purpose of the structural model is to integrate the above findings in a macro-finance model, while at the same time assessing the robustness of volatility in explaining flights to safety in the presence of potential macroeconomic drivers of this phenomenon. To this end, I employ a structural vector autoregressive (SVAR) model.

I collect all the variables of interest in a vector Y_t. I start by describing the dynamic behavior of Y_t using the following VAR specification:[12]

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

where Y_t is a vector of K variables, each modeled as a function of p lags of those variables, 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 $E(u_t u_s') = 0_k \; \forall \; t \neq s$.

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

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

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

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

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 I use a recursive scheme for identification. Because the most commonly used identification method in macroeconomics imposes alternative sets of recursive zero restrictions on the contemporaneous coefficients, I follow the literature and 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 was introduced by Sims (1980) and 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 $E(e_t e_s') = 0_k \ \forall \ t \neq s$.

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 to be the Cholesky decomposition of Σ is equivalent to imposing a recursive structure for the corresponding dynamic structural equation model. I obtain identification by placing 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, to ensure a just-identified model and therefore, just -identified IRFs. $\widetilde{B}$ is assumed to be a diagonal matrix. The ordering of the recursive structure is the same as the ordering imposed in the Cholesky decomposition. Note that the orthogonality assumption applies to the contemporaneous covariances between the elements of the e_t vector. As said, the model still 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. They are captured in the vector Y_t. To stay comparable to the literature, I start with a macro SVAR specification that is a simplified version of Christiano, Eichenbaum, and Evans (2005). It includes a subset of variables whose dynamic relationships have been extensively studied by the macroeconomic literature: a proxy for economic activity, a measure of inflation (or expected inflation), and a proxy for the monetary policy stance. I use the (changes in the log of) industrial production, *dlindpr,* to capture economic activity. The *dlindpr* variable is a proxy for the output gap in the Phillips curve. For inflation, I use the *CPI* rate. I

follow Bernanke and Blinder (1992) and use the effective Federal Funds Rate, *FFR*, to capture the monetary policy stance. To make sure that I have only stationary variables in the SVAR model, I employ the *dSFFR* variable.

My approach consists of running SVARs on the data. As mentioned above, I use a recursive scheme for identification on the SVARs in order to back out empirical impulse responses of stock return and bond return to various shocks in the model, in an attempt to identify the extent to which the various variables of interest can explain flight to safety. 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): the 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 the economic conditions to be purely exogenous, and I order them first. Moreover, Taylor (1993) observed that inflation and the output gap tend to drive the short-term Federal Funds Rate set by the Fed.[13] While the Taylor rule represents one type of 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 could be motivated by sluggish responses of inflation and real activity to shocks to the policy variable. In turn, this motivates the ordering of real activity and inflation proxies before the Federal Funds Rate in the SVAR model.[14]

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 citations on page 22). Therefore, I include the return on the market portfolio, *Mkt*, which replaces the real profits variable in Christiano, Eichenbaum, and Evans (2005), and the 1-year Treasury bond return, *Bond,* below the macroeconomic variables in the SVAR model. And because the previous sections document a significant contemporaneous effect of volatility on stocks and Treasuries, as well as a significant effect on future business activity and monetary policy, I include volatility before *Mkt* and *Bond* in the SVAR model, but after the macroeconomic and monetary policy variables.[15] In sum, I collect the variables of interest in the vector

[13] 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).

[14] 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).

[15] 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.

$Y_t = (dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bond_t)'$. I consider alternative SVARs as part of an extensive series of robustness checks discussed in the next section.

This structural model specification allows for the possibility of a reaction in monetary policy and financial variables to business cycle fluctuations, while financial volatility represents 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 exhibit a faster response to changes in the economy when compared to monetary policy variables, due to decision lags on the part of policymakers or other adjustment costs. This ordering also allows for testing whether flights to safety can be explained by the contemporaneous response of market and bond returns to alternative shocks, such as economic shocks, changes in inflation, or monetary policy surprises.

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

5.1 *Structural Impulse Response Functions*

After I run the SVARs, I examine the structural impulse response functions (SIRFs). They are displayed in Figure 7, where the gray shaded areas represent 95% confidence intervals from the SVAR. The SIRFs corresponding to the response of the market return (*Mkt*) to a structural shock in the variables included in the vector Y_t are displayed in the left column, while those corresponding to the response of the Treasury return (*Bond*) are displayed in the right column.

Panels A and B show the response of *Mktret* and *Bondret* to a structural shock in *Volat* that occurs now. While the effect is short lived, the SIRFs indicate that a positive volatility shock leads to a fall in the market return by around 1.8% on impact, and an increase in the Treasury bond return by around 0.18%. The opposite sign in of the effect of volatility on the two asset returns explains flight to safety.

The SIRFs displayed in Panels C and D of Figure 7 capture the response of *Mktret* and *Bondret* to a shock in industrial production (*dlindpr*). The graphs show that a shock to the real activity proxy leads to a contemporaneous drop in *Bondret* by about 0.2%. However, it has an insignificant effect on *Mktret*.

The SIRFs displayed in Panels E and F of Figure 7 capture 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. The SIRFs show empirically that a positive *CPI* shock has indeed a significantly negative effect on bond returns of about 0.25% at impact. However, the *CPI* shock has no significant contemporaneous effect on market returns (or at any time horizon).

The SIRFs displayed in Panels G and H capture the response of the two asset returns to a shock to the monetary policy instrument (*dSFFR*). Monetary policy is an important determinant for the

rate of inflation. And because the *CPI* shock has a significantly (negative) contemporaneous effect only on bond returns, I expect a similar result for *dSFFR.* The SIRFs show empirically that this is the case here, with a positive *dSFFR* shock having a significantly negative effect on *Bondret* on impact of about 0.4%. However, *dSFFR* also has a contemporaneous effect on *Mktret*: a positive *dSFFR* shock leads to a drop in *Mktret* of about 0.05%. Because the effect of the *dSFFR* shock has a similar sign on the two asset returns, *dSFFR* cannot explain flight to safety. Note that the complete set of SIRFs for the SVAR model are displayed in Figure 2 of the Appendix.[16]

5.2 *Structural Forecast Error Variance Decomposition*

Next, I examine the variance decompositions. Figure 8 Panel A displays the time series of the percentage of variance of the j-step-ahead (with $j = 1, 2, ..., 12$ months) forecast error in the *Mktret* due to shocks to the *Mktret* itself (in blue), volatility shocks (in red), business cycle shocks (in gray), inflation shocks (in yellow), and monetary policy shocks (in purple). Results show that shocks to volatility explain a significant and economically larger amount of the forecast error variance in the stock returns when compared to the business cycle, inflation and monetary policy proxies, despite volatility being placed below them in the structural model.

Meanwhile, Panel B of the same figure displays the time series of the percentage of variance of the j-step-ahead forecast error in the *Bondret* due to shocks to the various variables included in the SVAR model. The plot shows that shocks to volatility explain a significant and economically important amount of the forecast error variance in the Treasury bond returns, which is larger than the one explained by the business cycle. The amount of 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*, which is impressive for a stock market variable.

Based on the results documented in this section, I conclude that volatility plays a robust role in explaining flight to safety. It can be argued that volatility is the channel through which real activity and monetary policy affect stock and bond returns.

6 Robustness Checks

In this section I perform a series of robustness checks. While Subsection 3.1.1 presents results that support the robust pricing effect of volatility in the presence of classical risk factors, I now ensure that the role played by volatility in explaining flights to safety holds when using an alternative methodology for capturing its shock. In addition, I test whether alternative financial and

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

macroeconomic variables can explain flights to safety. Finally, I perform a sub-period analysis for the structural model.

6.1 *Using a Second Measure of Unexpected Volatility*

This section ensures that the above results are not a by-product of the way I measure unexpected volatility. To this end, I build a second unexpected volatility factor, based on the difference between predicted and realized volatility. I predict volatility using a model that captures some stylized facts, such as: *i)* volatility increases after a drop in stock prices (see, e.g., Black, 1976; Nelson, 1990, 1991); *ii)* it is persistent (see, e.g., Schwert, 1989; French, Schwert, and Stambaugh, 1987); *iii)* there is usually leptokurtosis in returns; *iv)* negative shocks to returns drive up volatility, called the leverage effect (see, e.g., Black, 1976); and *v)* there is usually a positive autocorrelation of order one in an index' return series (see, e.g., Campbell, Lo and MacKinley, 1997). 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:

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

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

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

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

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

Here, h_t represents the conditional variance of market returns. The model described by the system of equations (24)-(28) accommodates the asymmetry in the news impact curve (see Appendix A.1 for more details on this model), and 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 $Griddy - Gibbs\ sampler$, which is a very popular $Markov\ Chain\ Monte\ Carlo$ method, and I report the results in Table 9 (see Appendix A.2 for details on the estimation).[17]

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

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

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

Figure 2 plots predicted volatility next to realized volatility. The two series track each other closely, a result that is due to the $GARCH$ predicting equation being a weighted average of past squared returns, with slowly declining weights. Meanwhile, Table 9 presents the posterior estimates from the system of equations (24)-(28), where the significant posterior estimates for θ^{-} and ϕ support the previously documented leverage and volatility clustering effects, respectively. Panel B of Table 4 reports the correlation of this new (unexpected) volatility factor with the other risk factors. Similarly to the first volatility measure, UV_2 has a significantly negative correlation with the *SMB* factor (-24%), and significantly positive correlations with the ΔVIX and *Amih* factors (40% and 44%, respectively).

Panel A of Table 10 presents the factor loadings from equation (3) for the Treasury market. Similarly to the results reported in Section 3, market betas are all significantly positive across Treasury bonds, with short maturity bonds having a market beta close to zero, and long maturity bonds having a market beta of 0.05. Meanwhile, volatility loadings on Treasuries are again all significantly positive and strictly increasing in bond maturity: short maturity bonds have a volatility beta close to zero, while long maturity bonds have a volatility beta of 0.15. As for the stock market, Panel B shows that the majority of volatility betas are again significantly negative, and monotonically increasing in both the size and the value dimensions. As before, large firms are not affected by volatility risk (or are paying off in a couple of cases).

I report the asset pricing results for the second measure of (unexpected) volatility in Table 11. I find a significant price of risk for UV_2 across the various model specifications, that ranges between -65 bp per month (*adjusted p-value* = 0.0353) and -116 bp per month (*adjusted p-value* = 0.0008). The volatility pricing effect in the joint markets is further robust when controlling for the *SMB*, *HML, MOM* and *Amih* factors. As before, augmenting the classical asset pricing models with volatility leads to a slightly higher explanatory power.

In summary, these results show that the flight-to-safety phenomenon is robustly captured by (unexpected) volatility, and that it is not simply due to the way I measure volatility shocks.

Next, I consider two potential alternatives for capturing the flight-to-safety episodes: the implied volatility index, *VIX*, which is a measure of 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 the *VIX* index to proxy for turbulent times. *VIX* measures the market's expectation of 30-day S&P500 volatility implicit in the prices of near-term S&P options. I follow Ang et al. (2006) and I build the innovations in the *VIX* index, denoted by ΔVIX, using the month-to-month changes in implied volatility.

To test whether *VIX* captures the flight-to-safety phenomenon, I perform the time series regres-

sion 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 the one documented for realized volatility. Meanwhile, Panel B shows that only a third of the ΔVIX betas estimates are statistically significant (half of them at 5% level, and the other half at 10% level) in the stock market.

6.3 *Using the Skewness Index, SKEW*

Another potential alternative for capturing the flight-to-safety phenomenon is the *SKEW* index. *SKEW* measures the perceived tail risk in the S&P500 based on the implied volatility of out-of-the-money options. Similarly to the implied volatility index, I build the month-to-month changes in the tail risk index, denoted by $\Delta SKEW$.

Table 13 reports the results when running the time series model in equation (3) by replacing UV with $\Delta SKEW$. I find that only half of the $\Delta SKEW$ betas are statistically significant (at the 10% level) in the Treasury market; they vary from 0 to 0.01. Meanwhile, most of the $\Delta SKEW$ betas are statistically insignificant in the stock market.

6.3.1 *Volatility Results for the Most Recent Period (January 1990-December 2020)*

To address a possible concern that the results for the *VIX* and *SKEW* indices are simply due to a lack of power in the statistical tests, as these indices are available only over a shorter time period, I reassess the role played by realized volatility over the most recent period, which starts in January 1990. Table 14 reports the results. I find that all Treasury bonds have significant (at the 1% level) volatility betas, that increase strictly monotonically from 0.01 to 0.12. Meanwhile, most volatility betas are significant and negative in the stock space. They are again more negative for small firms in the size dimension, and for value firms in the book-to-market dimension. These results are in line with the findings documented in Table 2, and they indicate that realized volatility continues to capture the flight-to-safety phenomenon over the most recent period, January 1990 - December 2020.

6.4 *Using Expected Inflation in the Structural Model*

In this subsection I perform robustness checks by testing alternative macroeconomic variables. Specifically, economists and economic policymakers believe that households' and firms' expectations of future inflation are a key determinant of actual inflation. For instance, in his October 25, 2010 speech, former Fed chairman Ben Bernanke mentioned inflation expectations as one of the objectives

of monetary policy.[18] Because the financial market is an important channel for the expectations of economic agents, in this exercise I assess the role played by volatility in flight to safety in the presence of inflation expectations. To analyze the contemporaneous effect of expected inflation on the stock and bond returns, I use the short-run inflation expectation measure developed by Haubrich, Pennachi, and Ritchken (2012), where expectations are extracted using a term structure model of the interest rates. I denote it by *EInfl*.[19] Because the *EInfl* series is available only starting with January 1982, I perform this exercise over the period January 1982-December 2020.

I consider an alternative SVAR model, where I replace CPI with *EInfl*, and I run SVARs on the data using the vector $Y_t = (dlindpr_t, EInfl_t, dSFFR_t, Volat_t, Mktret_t, Bond_t)'$. The SIRFs displayed in Figure 9 indicate that a shock to *EInfl* does not have a significant effect on either *Mktret* or *Bondret* on impact (see Panels E and F). It has a positive impact on *Bondret* a month later. Meanwhile, a volatility shock has again significant and opposite effects on the two asset returns (see Panels A and B), which is consistent with flights to safety. The complete set of SIRFs are displayed in Figure 3 of the Appendix.

6.5 *Sub-Period Analysis for the Structural Model*

In this subsection I repeat the SVAR analysis by splitting the sample period into three subperiods, with the cutoff points being based on previous economic results, as well as on the examination of the time series dynamics of the stock-bond correlation series. The first subperiod ends before Volcker's appointment as Fed chairman, because of evidence that monetary and macroeconomic dynamics changed after that time, with the interest rate policy becoming much more sensitive to changes in expected inflation during Volcker's appointment (see, e.g., Clarida, Gali, and Gertler, 1999). This subperiod is labeled as the "Pre-Volcker Period" in Figure 1, and it covers January 1962 to July 1979. During this time, the stock-bond correlation has an average value of 12%, with a 95% confidence interval of (8%, 16%). The second period covers August 1979 to September 1997, and is labeled "Volcker & 1^{st} Part of Greenspan Period" in Figure 1. This period ends in September 1997, because the correlation drops in the following month by more than 3 standard deviations from the previous period's mean; it also stays in mostly negative territory after that, signaling a new regime. During this second period, the stock-bond correlation has an average value of 39%, with a 95% C.I. of (36%, 43%). The third period covers October 1997 - December 2020, and is labeled "2^{nd} Part of Greenspan, Bernanke, Yellen, & Powell Period" in the same figure. During this period, the stock-bond correlation has an average value of -30%, with a 95% C.I. of (-35%, -0.26%). Given the very low correlation recorded during the first sub-period, I don't expect to find much of a volatility effect in that case. Nonetheless, for completeness, I report the results

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

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

for all three subperiods for the vector $Y_t = (dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bond_t)'$.

Figure 10 plots the SIRFs. As expected, Panels A and B indicate that a positive volatility shock implies a fall in *Mktret* by around 1.2% on impact, but has no significant effect on *Bondret* over the earlier sub-period. During the second sub-sample period, a positive volatility shock implies 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 time period, a positive volatility shock implies 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 signed contemporaneous volatility effect on the two asset classes recorded over the two most recent time periods explains flight to safety, with the volatility effect becoming stronger through time. Finally, note that the complete set of SIRFs for the three sub-periods are displayed in Figures 4-6 of the Appendix.

6.6 *Using Monetary Policy Spread in the Structural Model*

In this subsection I perform another set of robustness checks, where I use another proxy for the monetary policy stance. Specifically, I follow Bianchi, Lettau, and Ludvigson (2022) and build a variable, labeled *MPS*, which is defined as the difference between the real interest rate and the natural rate of interest from Laubach and Williams (2003). Next, I consider an alternative SVAR model, where I replace $dSFFR$ 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 the real interest rate, $RFRR$, and the natural interest rate, $RSTAR$, in Panel A. It plots the monetary policy spread, MPS, in Panel B.

Figure 11 plots the SIRFs for an SVAR(5) model applied to the new vector Y. They indicate that my findings are robust: a structural volatility shock has significant and opposite effects on the two asset returns on arrival (see Panels A and B), which is consistent with flights to safety. The complete set of SIRFs for this model specification are displayed in Figure 8 of the Appendix.

In sum, 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 power in the statistical tests. The *VIX* results may be due to this series being an expectation of future volatility. In addition, the (squared) *VIX* includes both the equity variance premium and the conditional variance, which may complicate things when trying to capture the flight-to-safety phenomenon. Meanwhile, the macroeconomic and the monetary policy variables cannot individually explain the negative correlation between stocks and Treasury bonds returns, which is characteristic of flights to safety. Only volatility risk has a significant and opposite signed effect on the two financial markets.

7 Conclusion

I contribute to the literature on flights to safety by showing that volatility risk plays an important role in explaining this phenomenon. Events historically associated with financial crises attest to the interdependence between stocks and Treasuries, with both asset classes being sensitive to unexpected shifts in volatility. While (most) stocks have negative correlations with volatility surprises, Treasuries have positive correlations, which makes the former assets relatively riskier and the latter relatively safer during turbulent times. This translates into a positive volatility risk premium in equity returns, accompanied by a negative premium in the yield curve, and explains the negative stock-Treasury bond correlation recorded during flight-to-safety episodes. It also explains why investors turn to Treasuries as a safe haven for their investments during bad times, when volatility rises, while they flee the stock market. In addition, the mostly negative stock-bond return correlation recorded during the most recent time period (i.e., starting in the late 1990s) is due to the large number of times when financial markets experienced extreme stress, when there is a surge in volatility.

In addition, I find that the size and value premia have been tied to volatility risk, and that a volatility risk premium exists in the Treasury yield curve. The explanation behind the latter results rests on the findings documenting the predictive role of volatility for MPU and monetary policy. Furthermore, using a structural model that interlinks financial volatility, real activity, and monetary policy, I also show that volatility can robustly explain flight to safety.

My work has important implications for the literature and for policymakers. Notably, my results help us understand the joint stock-bond price formation, while they also show that flights to safety enhance the resiliency of financial markets when needed the most, via the stock-bond diversification benefits, which increase with stock market volatility. In light of my findings, existing yield curve models could be recast to include volatility. Also, my results indicate that central banks have grounds to be concerned with large fluctuations in the financial market, and that volatility can be a valuable instrument for guiding policymakers when designing appropriate policies for turbulent times.

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

This table reports 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. Data cover the period 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: Flights to Safety

This table reports factors' 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. Data cover the period 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: Factors' 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) Factors' 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 reports factors' monthly risk prices (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), 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*, 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. Data cover the period 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.

$\widehat{\lambda}_0$	$\widehat{\lambda}_m$	$\widehat{\lambda}_{UV}$	$\widehat{\lambda}_{SMB}$	$\widehat{\lambda}_{HML}$	$\widehat{\beta}_{MOM}$	$\widehat{\beta}_{Amih}$	$R^2_{adj}(\%)$
0.13***	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). Data cover the period 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. Data cover the period 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). Data cover the period 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. Data cover the period 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. Data cover the period 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: 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

Table 10: Flights to Safety - Robustness Checks I

This table reports 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 (see Eq. (7) in Subsection 3.1). Data cover the period 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: Factors' 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: Factors' 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 11: 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. Data cover the period 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 12: VIX Loadings - Robustness Checks III

This table reports the factor loadings from a 2-factor model that includes the excess market return and 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. Data cover the period 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 13: SKEW Loadings - Robustness Checks IV

This table reports the factor loadings from a 2-factor model that includes the excess market return and 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. Data cover the period 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 14: 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. Data cover the period 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 Correlations

This figure presents the monthly realized correlation between the stock market return and the 10-year Treasury bond return (based on daily data). Results are reported in percentages. Data cover the period January 1962 to December 2020. The "Pre-Volcker Period" covers January 1962 to July 1979; the "Volcker + 1^{st} Part of Greenspan Period" covers August 1979 to September 1997; the "2^{nd} Part of Greenspan , Bernanke, Yellen, & Powell Period" covers October 1997 - December 2020.

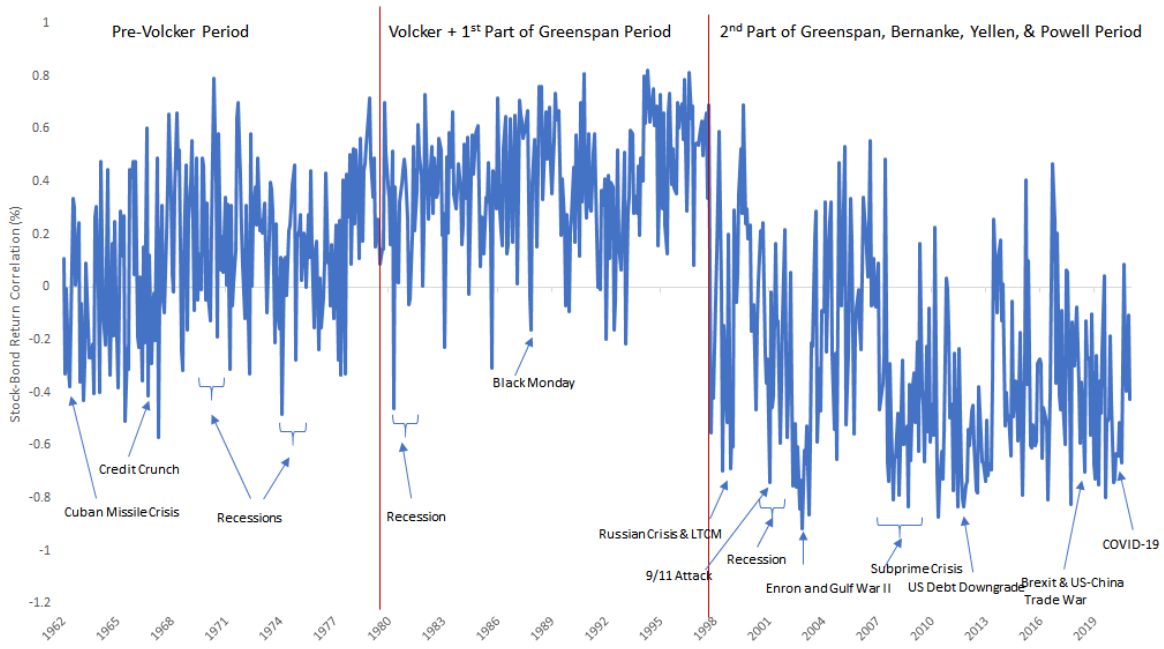


Figure 2: Stock Market Volatility

This figure presents the monthly realized stock market volatility, computed as the sum of squared daily market returns, and the predicted market volatility, which is based on the estimates of an Asymmetric-Student GARCH (1,1) model applied to the monthly stock market returns. Results are reported on a monthly basis. For each year, the tick marks correspond to the month of January. Data cover the period January 1952 to December 2020.

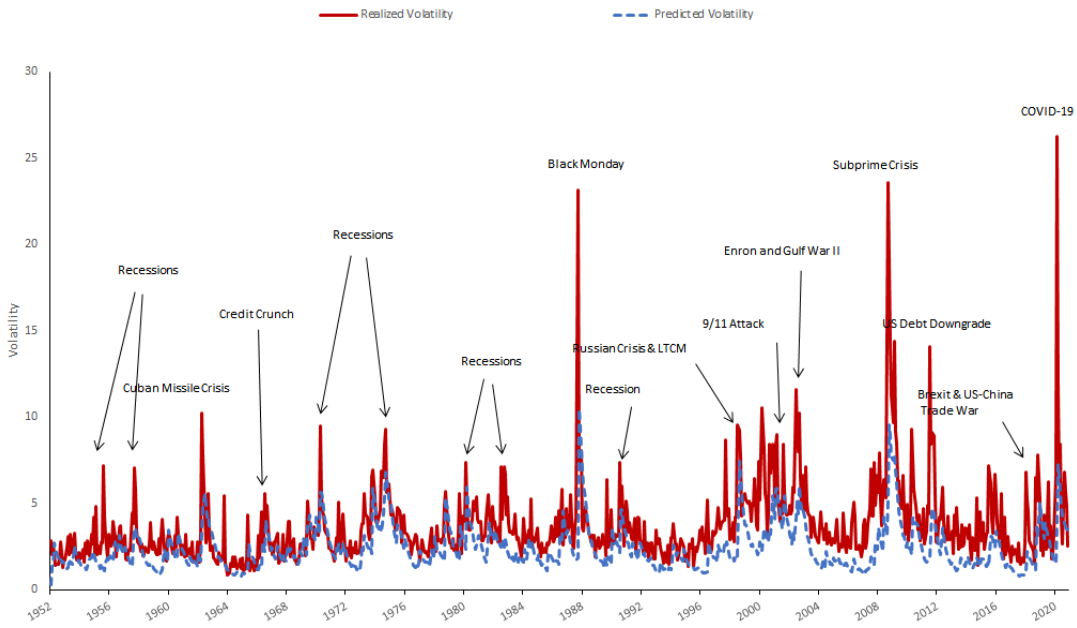


Figure 3: Conditional Volatility Loadings

This figure plots the monthly cross-sectional average conditional volatility loadings on the space of stock returns and Treasury bond returns. The average volatility beta for bonds is scaled up by a factor of five for better visualization. I estimate the conditional betas at a monthly frequency using a two-factor model with excess market return and unexpected volatility as risk factors (see Subsection 3.3 for details). I report the results for the period January 1952 to December 2020. For each year, the tick marks correspond to the month of January.

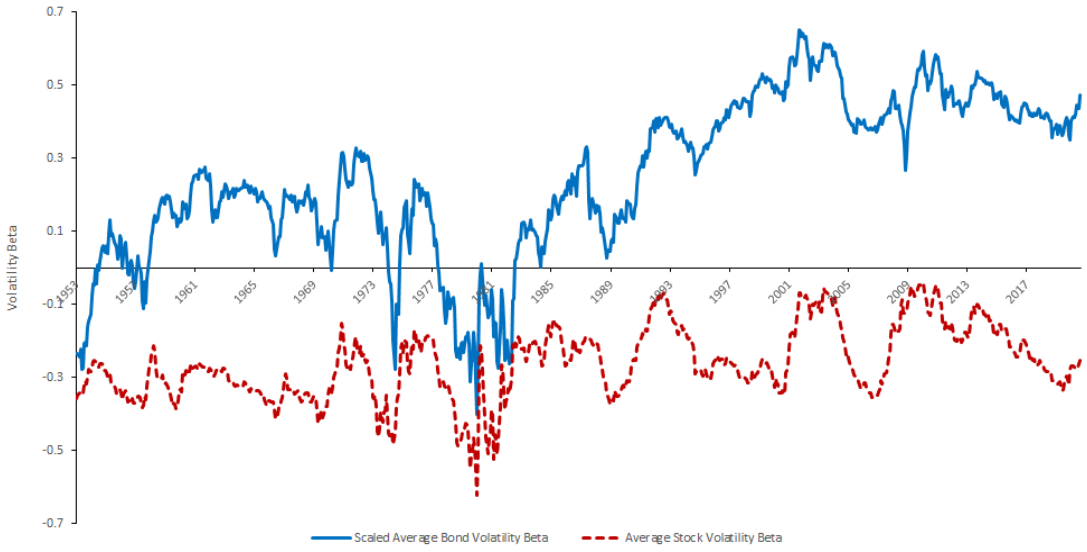


Figure 4: Conditional Prices of Risk

This figure plots the conditional market price of risk and the scaled volatility price of risk (i.e., the lambdas in the conditional asset pricing model). The scaled volatility lambda is the volatility price of risk times 2. I estimate the conditional lambdas on a monthly frequency using a two-factor model with excess market return and unexpected volatility as risk factors (see Subsection 3.3 for details). I report the results for the period January 1952 to December 2020. For each year, the tick marks correspond to the month of January.

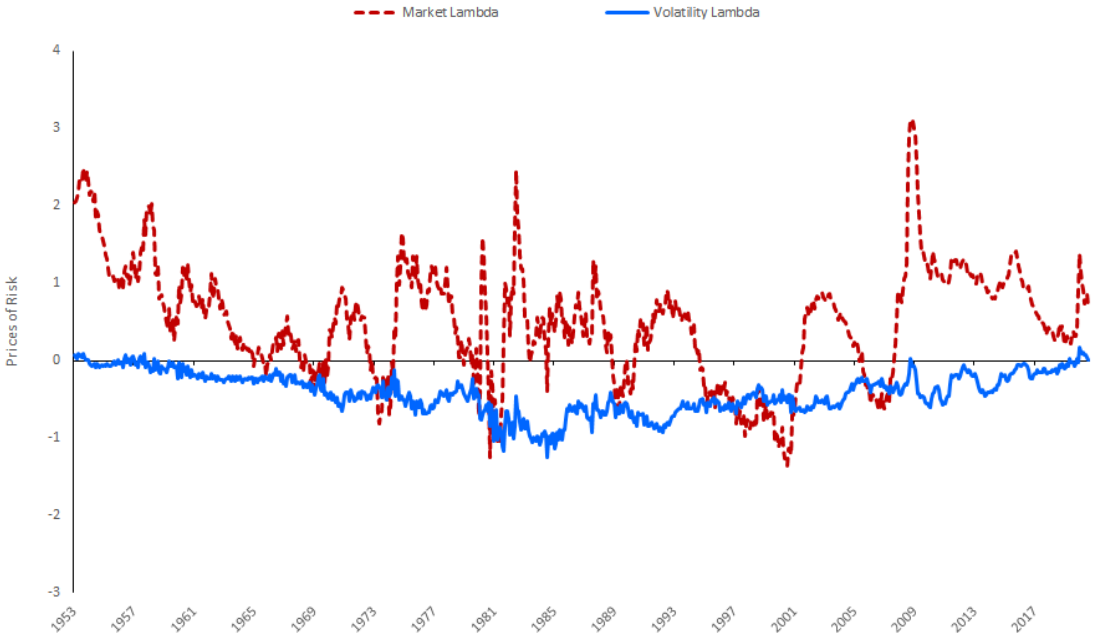
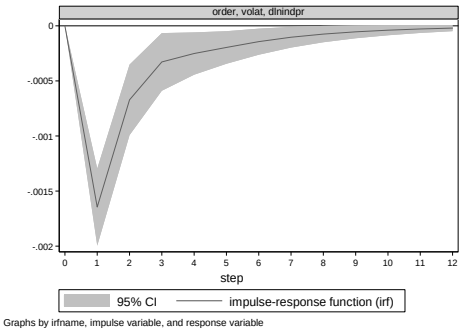
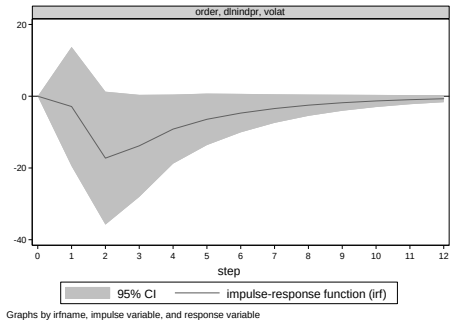


Figure 5: Impulse Response Functions for Volatility and Real Economic Activity
This figure plots the impulse response functions from a VAR(2) model applied to a two-dimensional vector that includes volatility, $Volat$, and either the log industrial production, $dLIndPr$, or the $CFNAI$ index. The gray shaded areas represent 95% confidence intervals from the VAR. The horizontal axis displays the number of months after the shock occured. Data cover the period January 1962 - December 2020 for Panels A and B, and March 1967 - December 2020 for Panels C and D.

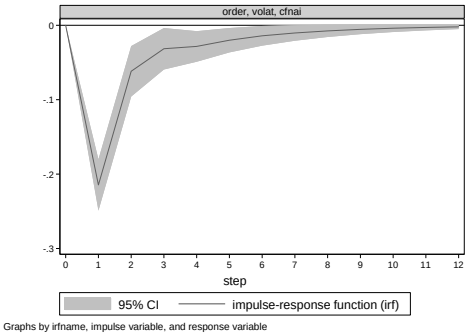
Panel A: Response of *dLIndPr* to *Volat* Shocks



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



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



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

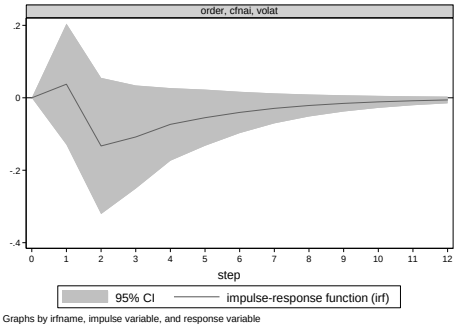
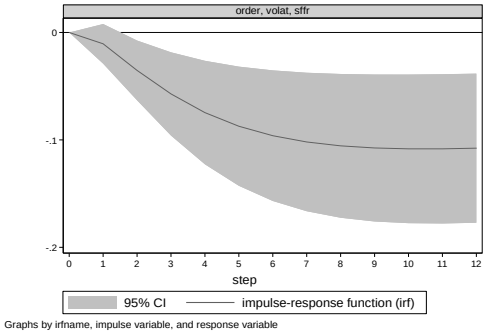
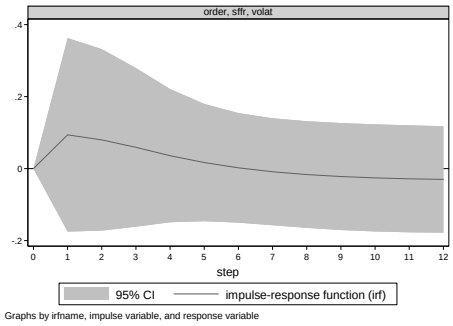


Figure 6: Impulse Response Functions for Volatility and Monetary Policy Stance
This figure plots the impulse response functions from a VAR(2) model applied to a two-dimensional vector that includes volatility, $Volat$, and either the shadow Federal Fund rate, $SFFR$,or its monthly change, $dSFFR$. The gray shaded areas represent 95% confidence intervals from the VAR. The horizontal axis displays the number of months after the shock occured. Data cover the period January 1962 - December 2020.

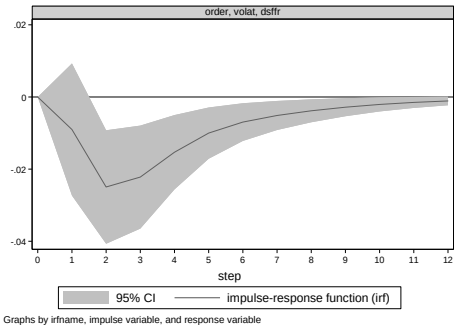
Panel A: Response of *SFFR* to *Volat* Shocks



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



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



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

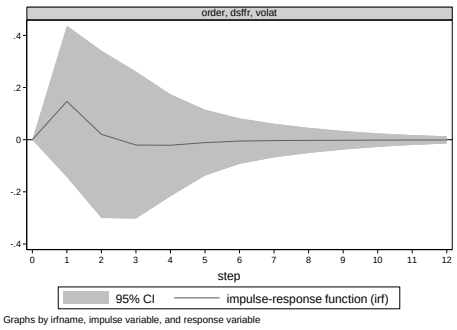
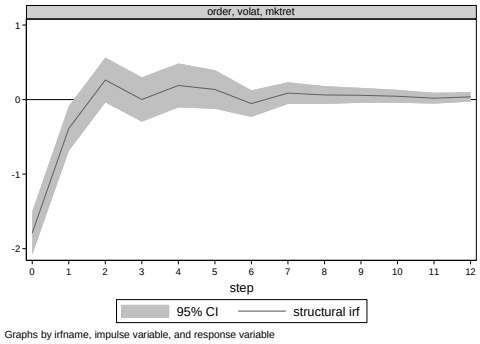


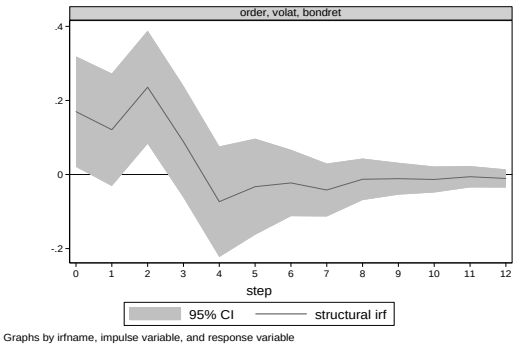
Figure 7: Market and Bond Response to Structural Shocks

This figure plots the structural impulse response functions (SIRFs) from an SVAR(5) system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bondret_t)'$. 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 10-year Treasury 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. Data cover the period January 1962 - December 2020.

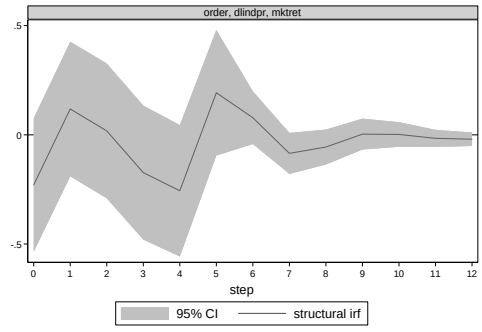
Panel A: Response of *Mktret* to *Volat* Shocks



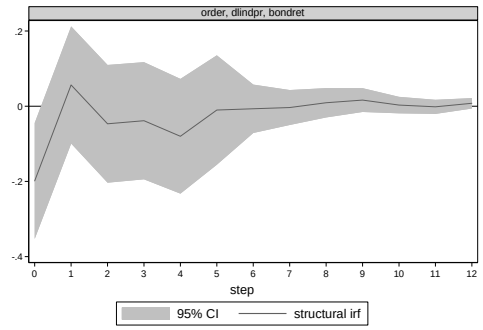
Panel B: Response of *Bondret* to *Volat* Shocks



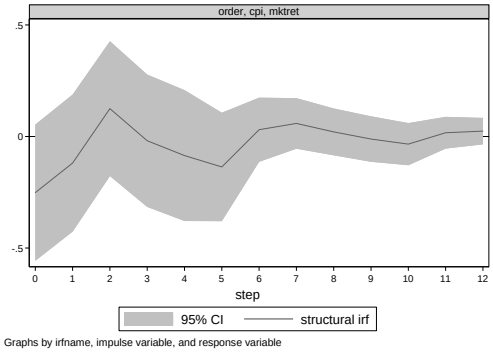
Panel C: Response of *Mktret* to *dlindpr* Shocks



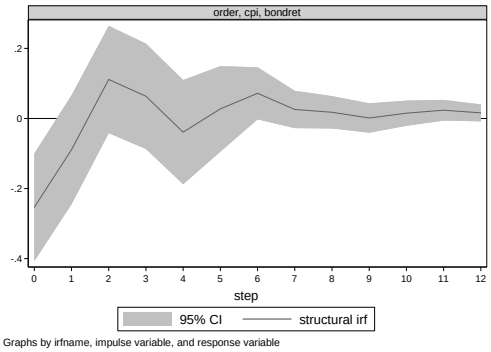
Panel D: Response of *Bondret* to *dlindpr* Shocks



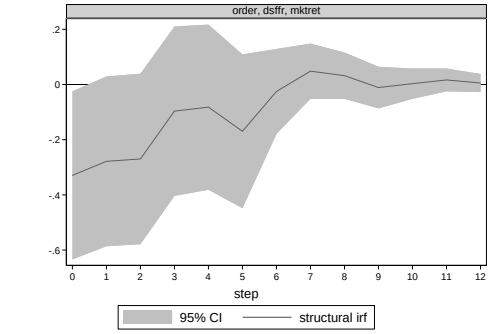
Panel E: Response of *Mktret* to *CPI* Shocks



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



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



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

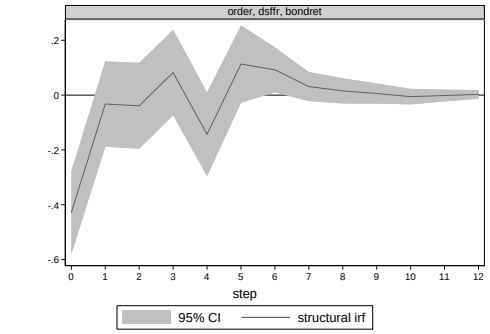
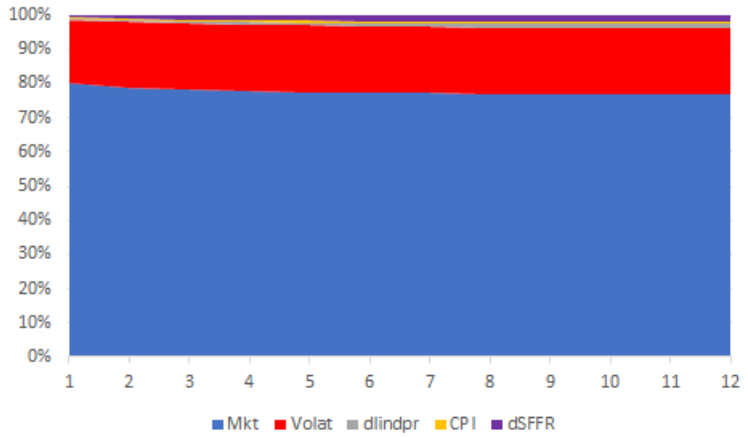


Figure 8: Forecast Error Variance Decompositions

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). Data cover the period January 1962 - December 2020.

Panel A: Forecast Error Variance Decomposition for *Mktret*



Panel B: Forecast Error Variance Decomposition for *Bondret*

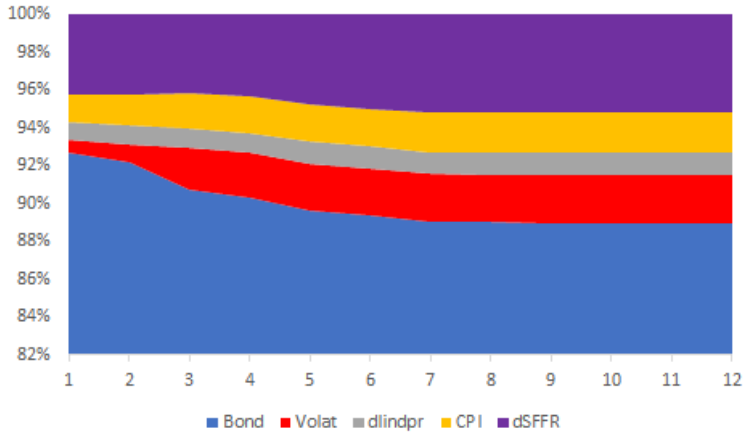
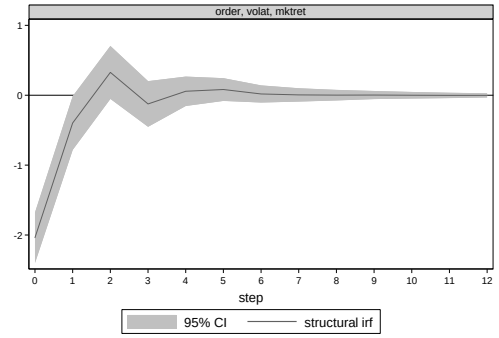
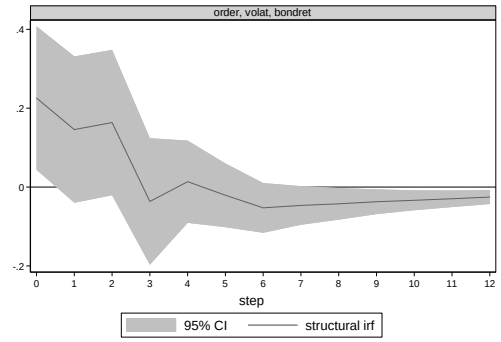


Figure 9: Market and Bond Response to Structural Shocks using Expected Inflation (*EInfl*)
This figure plots the SIRFs from an SVAR(3) system applied to the vector $(dlnindpr_t, EInfl_t, FFR_t, Volat_t, Mktret_t, Bondret_t)'$. In the left column it displays the market return response to a shock in the 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. Data cover the period January 1982 - December 2020.

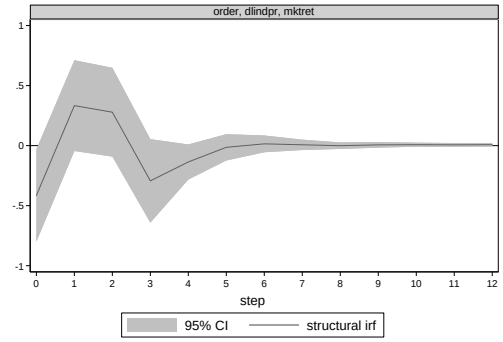
Panel A: Response of *Mktret* to *Volat* Shocks



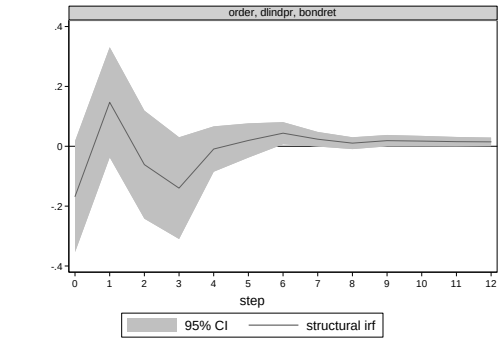
Panel B: Response of *Bondret* to *Volat* Shocks



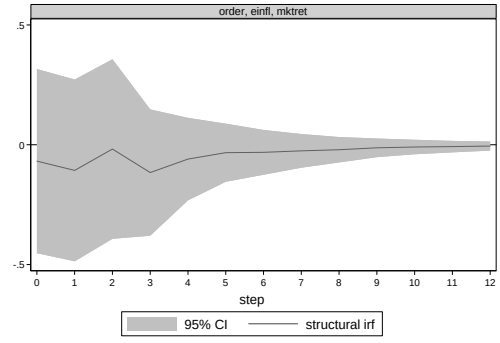
Panel C: Response of *Mktret* to *dlindpr* Shocks



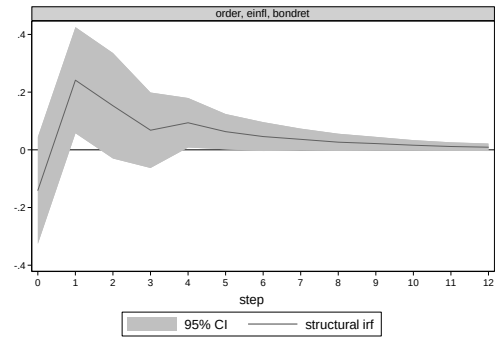
Panel D: Response of *Bondret* to *dlnindpr* Shocks



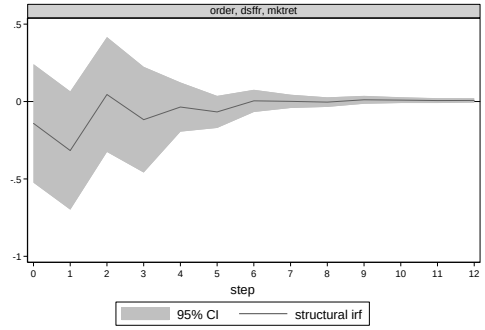
Panel E: Response of *Mktret* to *EInfl* Shocks



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



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



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

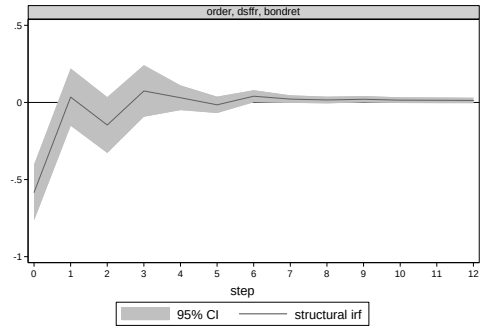
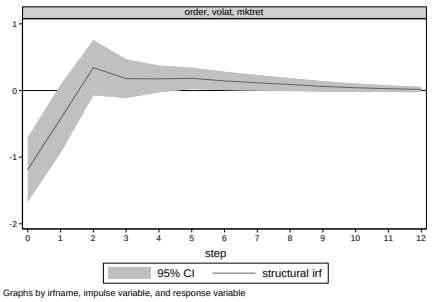
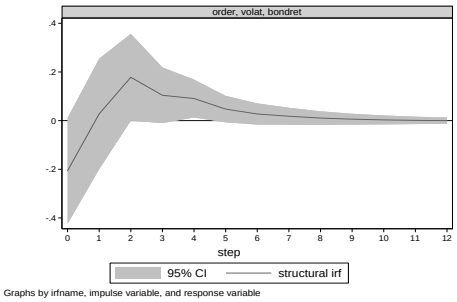


Figure 10: Market and Bond Response to Structural Shocks in Volatility over Three Subperiods
This figure plots the SIRFs from an SVAR system applied to the vector $(dlindpr_t, CPI_t, dSFFR_t, Volat_t, Mktret_t, Bondret_t)'$. The gray shaded areas represent 95% confidence intervals from the SVAR. The horizontal axis displays the number of months after the shock occured. The "Pre-Volcker Period" covers January 1962 to July 1979 in Panels A and B; the "Volcker + 1^{st} Part of Greenspan Period" covers August 1979 to September 1997 in Panels C and D; the "2^{nd} Part of Greenspan, Bernanke, Yellen, & Powell Period" covers October 1997 - 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.

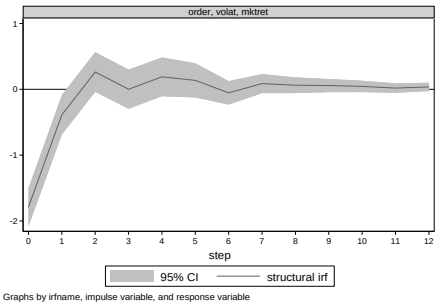
Panel A: Response of *Mktret* to *Volat* Shocks (Pre-Volcker)



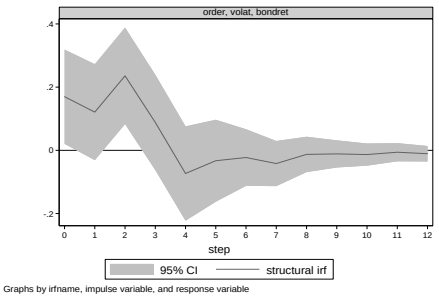
Panel B: Response of *Bondret* to *Volat* Shocks (Pre-Volcker)



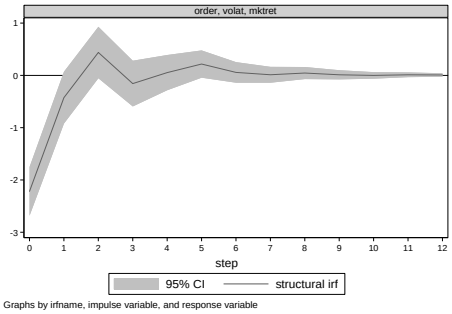
Panel C: Response of *Mktret* to *Volat* Shocks (Volcker + 1^{st} Part of Greenspan)



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)

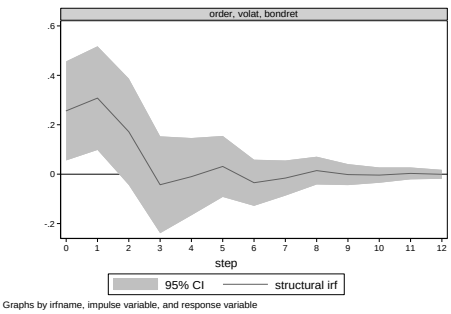
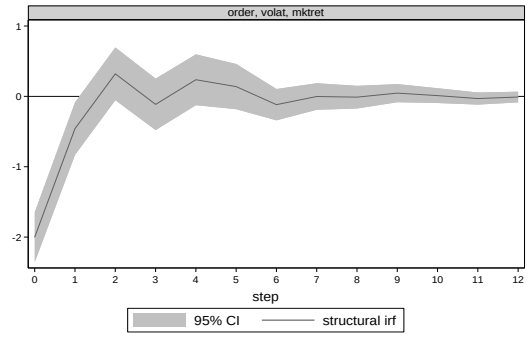
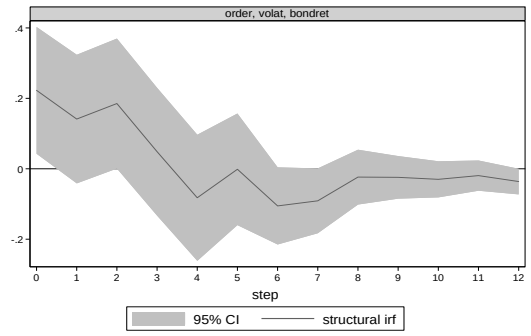


Figure 11: Market and Bond Response to Structural Shocks using Monetary Policy Spread
This figure plots the SIRFs from an SVAR(5) system applied to the vector $(dlnindpr_t, CPI_t, MPS_t, Volat_t, Mktret_t, Bondret_t)'$. In the left column it displays the market return response to a shock in the macroeconomic 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. Data cover the period January 1982 - December 2020.

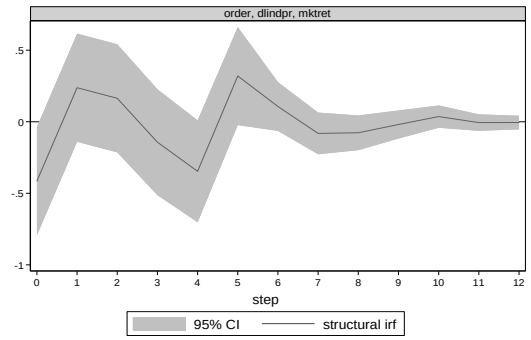
Panel A: Response of *Mktret* to *Volat* Shocks



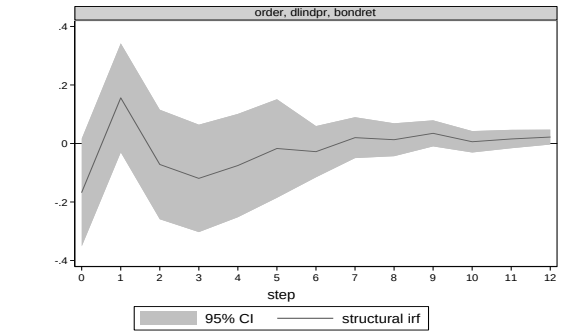
Panel B: Response of *Bondret* to *Volat* Shocks



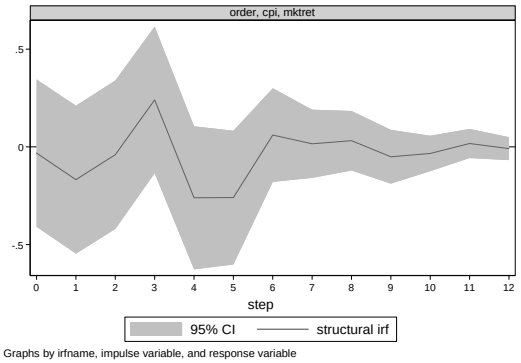
Panel C: Response of *Mktret* to *dlindpr* Shocks



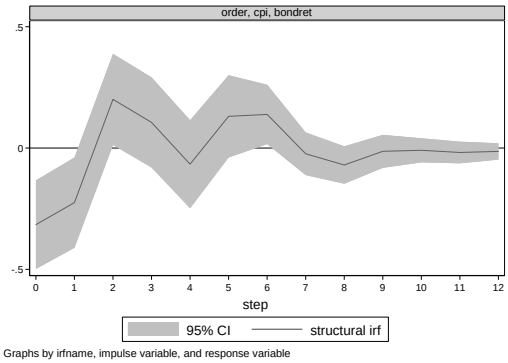
Panel D: Response of *Bondret* to *dlnindpr* Shocks



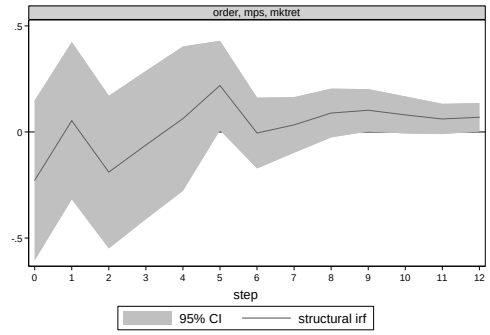
Panel E: Response of *Mktret* to *CPI* Shocks



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



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



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

