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Risk Appetite and Monetary Transmission*

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Abstract

We construct a new high-frequency measure of risk appetite shifts around Federal Open Market Committee (FOMC) meetings, the common component of changes in risk-sensitive indicators. Fed policy actions and communication have substantial effects on risk appetite. Interest-rate surprises explain only about one-fifth of the variation in risk appetite, so most policy-induced changes in risk asset prices are orthogonal to the expected rate path. We therefore use both surprises as external instruments in a proxy SVAR with two separately identified shocks. Risk appetite shocks have large and persistent contractionary effects, lowering output and prices while raising unemployment. By contrast, the effects of risk-free rate shocks tend to be small and imprecisely estimated, and some have puzzling signs. Monetary transmission appears to operate primarily through risk appetite and risk asset prices. Estimates relying on interest-rate surprises alone miss most of these effects, for two reasons: the link from interest rates to risk appetite is state-dependent, and Fed communication moves it independently of the expected rate path.

JEL classification: E43, E52, E58

Keywords: monetary policy shocks, risk appetite, external instruments, proxy SVAR, central bank communication

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1 Introduction

Empirical work on monetary transmission relies increasingly on high-frequency identification, using asset price changes around central bank announcements. Policy announcements convey news along multiple dimensions, including surprise rate changes, information about the future policy path, announcements of unconventional policies, signals about the policy reaction function, and possibly information effects.[1] According to the risk-taking channel of monetary policy, central bank announcements affect financial markets not only by changing risk-free interest rates, but also by shifting how investors evaluate and price risk. A growing body of work documents substantial announcement effects on risk appetite and risk premia, only a small share of which is explained by news about the policy path (Cieslak and Schrimpf, 2019; Kroencke, Schmeling and Schrimpf, 2021; Bauer, Bernanke and Milstein, 2023; Boehm and Kroner, 2026*a*; Cieslak and Khorrami, 2026). But while the financial market effects of these "risk appetite shocks" have been widely studied, little is known about their role in monetary transmission. We construct a new high-frequency measure of risk appetite shifts from a wide range of risk assets and use it alongside conventional interest-rate surprises as external instruments in structural VARs. Our results show that risk appetite shocks account for the bulk of the macroeconomic effects of monetary policy, largely subsuming the conventional interest-rate shocks that the literature has focused on.

We first construct RISK, the first principal component of FOMC announcement-window changes in eleven risk-sensitive indicators, covering equity prices, implied volatilities, corporate credit, exchange rates and gold. This common factor accounts for 56% of the total variance across these indicators, and its loadings are consistent with movements in risk appetite. Our measure builds on earlier methods, especially that of Bauer, Bernanke and Milstein (2023), but differs from them in two respects. First, we measure risk shifts in narrow windows around the announcement, which reduces the confounding noise from other news on FOMC days. Second, we do not impose orthogonality to risk-free rate surprises, which lets us investigate the empirical relationship between interest-rate policy and risk appetite. We interpret RISK as a measure of policy-driven shifts in risk appetite, i.e., changes in the willingness of the marginal investor to bear risk, but our conclusions are also consistent with a broader interpretation as a risk premium factor that includes changes in perceived quantities of risk.

We also calculate a conventional monetary policy surprise (MPS) based on risk-free interest rates, following the common approach in the related literature. While MPS and RISK are positively correlated, MPS explains only one-fifth of the variation in RISK, so most of the FOMC-related

[1] See, for example, Gürkaynak, Sack and Swanson (2005); Cieslak and Schrimpf (2019); Jarociński and Karadi (2020); Miranda-Agrippino and Ricco (2021); Swanson (2021); Bauer and Swanson (2023*b*).

movement in risk asset prices is orthogonal to conventional interest-rate surprises, consistent with earlier findings.

A narrative analysis of the largest changes in RISK, including those orthogonal to interest-rate surprises, traces them back to the effects of the Fed's policy actions and communication, with only one instance of possible information effects. For non-policy placebo events, the volatility of RISK is materially lower, and the correlation with interest-rate changes flips sign, indicating that policy news is the dominant driver of changes in RISK around FOMC events. RISK correlates with earlier risk appetite measures, including those of Kroencke, Schmeling and Schrimpf (2021), Bekaert, Engstrom and Xu (2022), and Boehm and Kroner (2026*a*). RISK is also correlated with the estimated Fed information shocks of Jarociński and Karadi (2020), which we reinterpret as capturing shifts in risk appetite and part of monetary transmission. Finally, RISK has broad effects on global financial markets that indicate changes in global risk appetite while leaving international government bond yields largely unchanged.

We then estimate monetary transmission using the proxy SVAR methodology of Stock and Watson (2012, 2018), with MPS and RISK as external instruments. Our goal is to identify the effects of two types of monetary policy shocks: a conventional shock that affects risk-free interest rates, and a separate policy shock to risk appetite and risk premia. Our reduced-form VAR is standard, with monthly U.S. data and a specification similar to Gertler and Karadi (2015) and Bauer and Swanson (2023*b*).

We first estimate the shocks and their impulse responses with separate single-instrument specifications. This approach provides a useful baseline for comparison, and for the case of MPS corresponds to the common practice in earlier work. For the shock identified with MPS alone, we reproduce standard effects in line with Gertler and Karadi (2015), Miranda-Agrippino and Ricco (2021) and others, with a contractionary monetary policy shock leading to a moderate decline in output and prices. For the shock identified with RISK alone, the effects on output, inflation and unemployment are larger, more persistent, and more precisely estimated than those of a risk-free rate shock.

Our main results are from proxy SVARs that combine interest-rate shocks and risk appetite shocks, following Mertens and Ravn (2013) for the joint identification of two shocks with two instruments. The joint identification gives a sharply different picture. RISK shocks generate large and statistically significant macroeconomic effects, consistent with the predictions of standard macroeconomic models: a persistent fall in industrial production, a decline in inflation, and a rise in unemployment. The separate interest-rate shock, by contrast, has small and imprecisely estimated effects: consumer prices respond only modestly after a contractionary shock, while industrial production rises and unemployment falls, the opposite of the textbook responses.

Our findings suggest a reinterpretation of the conventional interest-rate policy shock that has been the focus of much of the literature. The effects estimated with a simple MPS instrument reflect a combination of an interest-rate channel and a risk channel. Once the two are separated, little of the macroeconomic response is attributable to rates alone.

The impulse responses for the MPS and RISK shocks are not directly comparable in magnitude, because their scale depends on the shock normalization. We therefore also report forecast-error variance decompositions, which confirm the dominant role of the RISK shock for monetary transmission. For the single-instrument identification, the shock identified with RISK explains a moderately higher share of the variance in real activity and consumer prices than the shock identified with MPS alone. But in all joint identification schemes, the RISK shock dominates the MPS shock. In our main specification, the former accounts for around 10–40% of the unconditional forecast-error variance of industrial production, consumer prices, and unemployment, while the latter accounts for at most 5%.

Finally, we discuss the economic mechanisms underlying our empirical results, from financial market effects of policy announcements to the importance of asset prices for aggregate demand. A number of well-established channels link interest-rate policy to risk premia. For example, easier monetary policy relaxes intermediary balance-sheet constraints (Adrian and Shin, 2010; He and Krishnamurthy, 2013; Kekre, Lenel and Mainardi, 2024), raises borrower net worth and credit supply (Bernanke and Gertler, 1995; Bernanke, Gertler and Gilchrist, 1999; Borio and Zhu, 2012), and induces reach-for-yield behavior (Hanson and Stein, 2015; Campbell and Sigalov, 2022); all of these channels increase effective risk appetite and risk asset prices. Empirically, much of the variation in risk appetite around monetary policy announcements appears orthogonal to changes in interest rates, and we emphasize two mechanisms that explain such movements. First, the channels linking risk-free rates to risk premia generally feature pronounced non-linearities and state-dependence. We document that the effects of interest-rate surprises on risk appetite indeed vary with the state of the economy and of financial markets in ways that are consistent with theoretical predictions. Linear projections of risk shifts on monetary policy surprises—or even on the entire yield curve as in Boehm and Kroner (2026*a*)—will therefore leave substantial residual variation that on the surface appears unrelated to interest rates. Second, central bank communication can affect risk appetite and risk premia beyond its effects on the expected rate path. Examples include communication about the balance of risks and the policy reaction function (Cieslak and Vissing-Jorgensen, 2021; Haddad, Moreira and Muir, 2025; Bauer, Pflueger and Sunderam, 2024), disagreement between markets and the Fed that generates perceived "policy errors" and a policy risk premium (Caballero and Simsek, 2022, 2024*a*), and announcements of balance sheet policies (Gagnon et al., 2011; Gilchrist et al., 2024).

A different source of orthogonal movements in RISK could be Fed information effects, whereby policy surprises reveal the Fed's private information about the economic outlook, moving beliefs and risk asset prices in the direction opposite to that implied by conventional theories of monetary transmission (Nakamura and Steinsson, 2018). This mechanism would threaten our identification strategy, because it implies reverse causality with news about the future path of the economy affecting current asset prices. But recent empirical literature finds only a minor role for information effects (Karnaukh and Vokata, 2022; Bauer and Swanson, 2023*a*,*b*; Sastry, 2026). Our own narrative analysis of policy events with large orthogonal RISK movements suggests that these are almost always explained by other channels. Evidence of unconventional responses of stock prices (Jarociński and Karadi, 2020) or exchange rates (Gürkaynak et al., 2021) to monetary policy surprises is also consistent with the mechanisms outlined above and does not require information effects as an explanation.

Our paper is related to several strands of the monetary and macro-finance literature. A growing body of empirical work documents that monetary policy affects risk premia in financial markets, going back to Bernanke and Kuttner (2005). The studies by Kroencke, Schmeling and Schrimpf (2021), Bekaert, Engstrom and Xu (2022), Bauer, Bernanke and Milstein (2023), and Boehm and Kroner (2026*a*) are most directly relevant to our paper as they construct measures that aim to capture the shifts in risk appetite or risk premia due to monetary policy announcements. Relatedly, Cieslak and Khorrami (2026) use a new asset pricing non-neutrality test to show that Fed announcements affect risk asset prices in a way that cannot be explained by shifts in Treasury yields alone, pointing to important risk-premium effects. While these studies establish important facts about the effects of monetary policy on risk asset prices, they do not estimate the macroeconomic effects.

Our paper contributes to the body of empirical work on the macroeconomic effects of monetary policy using high-frequency identification of policy shocks, including Gertler and Karadi (2015), Miranda-Agrippino and Ricco (2021), Jarociński and Karadi (2020), Bauer and Swanson (2023*b*), and Swanson (2024), among others. Most of these studies rely on high-frequency interest-rate changes as instruments or proxies for policy shocks; Jarociński and Karadi (2020) additionally use the sign of the joint high-frequency behavior of interest rates and stock prices to separate monetary from central-bank-information shocks. Existing work thus treats the non-rate component of announcement surprises in one of two ways. Miranda-Agrippino and Ricco (2021) purge it, projecting surprises on central-bank forecasts to recover a cleaner monetary instrument, while Jarociński and Karadi (2020) promote it to a separate "information" shock. We take a third approach and measure the risk appetite dimension directly, to estimate its macroeconomic effects. Our findings suggest that this component of monetary policy news is central to monetary transmission.

On the theory side, our results connect to the macro-finance literature on monetary policy and asset prices. Caballero and Simsek (2020, 2022, 2024*b*,*a*) treat the aggregate asset price as the state variable for aggregate demand, so monetary policy works by moving financial conditions and risk premia rather than the risk-free rate itself. Related work quantifies the individual channels, including wealth effects on the consumption of financially constrained households (Kaplan, Moll and Violante, 2018; Auclert, 2019; Chodorow-Reich, Nenov and Simsek, 2021; Auclert et al., 2025) and the response of investment to equity valuations (Christiano, Eichenbaum and Evans, 2005). The evidence for these channels comes mostly from models and micro data. Our proxy SVAR provides aggregate time-series evidence, attributing most of the response of output and prices to the risk appetite shock rather than to the interest-rate shock.

Our findings also connect to the literature on the role of financial and risk shocks in macroeconomic fluctuations (Jermann and Quadrini, 2012; Gilchrist and Zakrajšek, 2012; Christiano, Motto and Rostagno, 2014; Caldara and Herbst, 2019). That work documents large macroeconomic effects of disturbances to credit conditions and to the pricing of risk, which it generally treats as exogenous. Our results are consistent with this evidence and show that monetary policy is itself an important driver of risk appetite.

The paper is structured as follows: Section 2 introduces our new measure RISK and documents its properties. Section 3 reports estimates of the macroeconomic effects of MPS and RISK shocks, with proxy SVAR estimates across different identification schemes. Section 4 discusses the underlying mechanisms and provides some additional results on time- and state-dependence of the effects of interest-rate policy surprises on risk appetite. Section 5 concludes.

2 Risk Appetite Shifts Around FOMC Communication

Conventional monetary policy surprises extracted from risk-free interest rates explain only a modest share of the financial market response to FOMC announcements. A growing literature therefore seeks to measure the component of monetary policy news that operates through risk appetite and risk premia rather than through the expected path of short rates. We first review the most important existing measures and then introduce our own measure of risk appetite shifts.

2.1 Existing measures

Kroencke, Schmeling and Schrimpf (2021) propose the first high-frequency measure of risk appetite shifts around FOMC announcements. Their measure is constructed to be orthogonal to risk-free rate surprises. They extend the factor-based approach of Gürkaynak, Sack and Swanson (2005) by augmenting interest-rate futures and Treasury yields with three intraday risk proxies (the VIX, a

CDS spread index, and a basket of dollar exchange rates). They extract three factors: the first two are rotated to span the target and path factors, while the third is constrained to load only on risk proxies. Orthogonality of the risk shift factor with respect to risk-free rate surprises is built into the factor extraction. Measured over 90-minute windows around 114 FOMC meetings (2006–2019), risk shifts account for roughly 70% of the event-window variation in stock returns, far exceeding the explanatory power of yield-based surprises.

Bekaert, Engstrom and Xu (2022) take a more structural approach, embedding time-varying risk aversion as a latent state variable in a dynamic no-arbitrage model that jointly prices equities and corporate bonds, including credit spreads, the term spread, dividend yields, and realized and option-implied variances.[2] They estimate a monthly risk aversion index and then construct a daily version using linear spanning. Unlike the factor-based approaches, this method does not extract a factor from observed asset prices directly. Instead, the index is the filtered state variable based on a parametric stochastic discount factor, given the model's dynamics and the observed moments. The method does not require the resulting daily risk aversion index to be orthogonal to risk-free rates. Due to the daily frequency, FOMC-day changes inevitably mix policy news with other same-day shocks.

Bauer, Bernanke and Milstein (2023) take a model-free approach, constructing a daily risk appetite index as the first principal component of 14 risk-sensitive indicators spanning equities, volatility, credit spreads, and exchange rates. The resulting factor captures the common variation in the *changes*, or returns, of these risk indicators. On FOMC days, the index is naturally correlated with interest-rate surprises. Indeed, documenting this correlation, and thus the risk-taking channel, is a central focus of the paper. For example, they show that tightening surprises persistently reduce risk appetite. At the same time, interest-rate surprises explain only a modest share of the variation in their risk index on FOMC days, which suggests that monetary policy announcements may move risk appetite independently. A caveat is that the daily index will also pick up other news and noise that are unrelated to monetary policy.

Boehm and Kroner (2026*a*) propose a "Fed non-yield shock" using the heteroskedasticity-based identification of Rigobon (2003). The "excess variance" of S&P 500 futures and 13 dollar exchange rates on FOMC days relative to non-announcement days identifies a latent factor orthogonal to the yield curve. Identification relies on the assumption that FOMC days have a different variance regime than non-FOMC days, while the factor structure linking shocks to asset prices remains the same. The method imposes orthogonality of the shock with respect to the yield curve, and a main focus of the paper is to demonstrate the quantitative importance of this unspanned variation.

[2] Their approach is based on the HARA-utility framework with "bad environment-good environment" fundamentals from Bekaert and Engstrom (2017), which is used to separate risk aversion from macroeconomic uncertainty.

Estimated over a 14-hour window and a long sample (1996–2025), this shock more than doubles the explained variation in risky asset prices compared to interest-rate surprises, and it appears to transmit mainly via risk premia.

While the construction of these measures differs across the papers, they share a common finding: interest-rate policy surprises miss a quantitatively important channel through which monetary policy moves asset prices. The existing proxies differ along three dimensions: the asset prices they rely on, the sampling frequency, and the identification assumptions. Appendix A provides additional details regarding these different approaches. The key takeaway is that the measures reflect a common theme but are constructed with very different methods. As a result, they capture partially overlapping but distinct objects.

2.2 Construction of MPS and RISK

We construct two separate high-frequency policy surprises, based on risk-free rates and risk indicators, respectively. The first is the conventional "monetary policy surprise", or MPS, measured as the first principal component of the changes in near-term interest rates around FOMC communication events. This factor, which is conceptually similar to existing measures of monetary policy surprises such as those in Nakamura and Steinsson (2018) and Acosta et al. (2025), captures common variation in the risk-free interest rates most directly affected by Fed communication. A positive value of MPS indicates a hawkish surprise.

Our second surprise measure is RISK, the common factor of the changes in several risk asset prices and indicators. We include in this calculation a range of assets across several key markets. The breadth of the coverage comes at the cost of some missing values, and we impute the missing observations using standard methods before calculating the first principal component of the balanced panel of risk indicators.[3] Our construction closely follows Bauer, Bernanke and Milstein (2023), who also impute missing observations and take the unrotated first principal component of a broad set of risk-sensitive series, without imposing orthogonality to rate surprises. We differ in the measurement window: we use high-frequency changes around the announcement rather than daily changes. We sign RISK so that a positive value indicates an increase in risk aversion (i.e., equity prices fall, VIX and credit spreads rise), and we scale both MPS and RISK to have unit variance.

[3] We impute missing values separately within each block using an iterative EM-PCA algorithm (Josse and Husson, 2016). The algorithm proceeds as follows: (i) initialize missing entries with column means; (ii) perform PCA (via the truncated SVD) on the completed, standardized data matrix, retaining S components; (iii) replace each missing entry with its fitted value from the rank-S reconstruction, while leaving observed entries unchanged; (iv) iterate steps (ii) and (iii) until convergence. The number of components S is selected automatically via K-fold cross-validation. The algorithm shares the iterative logic of the EM procedure for principal components in Stock and Watson (2002). Unlike Stock and Watson, however, who allow for weakly correlated idiosyncratic errors and embed the EM step in a dynamic factor model, the EM-PCA approach assumes i.i.d. Gaussian errors and operates on a static low-rank model. This is appropriate in our setting, where each FOMC event is treated as an independent cross-sectional observation.

Among the four measures reviewed in Section 2.1, ours is the only one that both (i) measures the Fed's policy communication in a narrow high-frequency window and (ii) leaves the loading on risk-free rate surprises to the data instead of imposing orthogonality. We discuss both features in turn.

First, we measure price changes in narrow event windows around each FOMC announcement rather than over a full trading day. High-frequency identification sharpens the policy signal, because the variation in asset prices is mainly attributable to the policy announcement itself rather than to unrelated same-day moves. As a result, the signal-to-noise ratio is substantially higher than for daily measures, such as that of Bauer, Bernanke and Milstein (2023).

Second, and in contrast to Kroencke, Schmeling and Schrimpf (2021) and Boehm and Kroner (2026*a*), we deliberately do not impose orthogonality of RISK to risk-free rate surprises. Our main reason for this choice is that it allows us to investigate the empirical relationship between interest-rate surprises and risk appetite shifts in order to better understand the risk-taking channel of monetary policy. The economic motivation is that changes in the expected policy path can themselves move risk appetite through a variety of channels, which we discuss below in Section 4.1. Imposing zero correlation would instead assign all of the comovement between rates and risk assets to the rate surprise, which would then absorb part of the risk-taking channel by construction.[4]

Our sample covers all FOMC meetings from January 1996 to September 2025, a total of 245 policy announcements. For each meeting, we measure intraday price changes from 15 minutes before the announcement until the end of the trading day (EOD). This window is much wider than the 30-minute window commonly used since Gürkaynak, Sack and Swanson (2005). It includes the post-meeting press conferences that the Fed Chair has held since Ben Bernanke introduced them in April 2011. The news communicated in these press conferences moves asset prices substantially (Swanson and Jayawickrema, 2024; Acosta et al., 2025). In the classification of Cieslak and Schrimpf (2019), risk-premium news dominates a larger share of Fed press conferences and minutes releases than of the rate decisions themselves. A wider window is also advantageous for measurement, since it allows all of our risk indicators to respond fully to the FOMC news, which need not happen within minutes for the less liquid credit instruments. Appendix B.1 gives further detail on the high-frequency measurement, including the finding that price changes in the morning of an FOMC day are uncorrelated or even negatively correlated with price changes during and after the event.

We consider 16 input series, divided into two blocks: five risk-free rates and eleven risk in-

[4] This choice does not affect the proxy SVAR results in Section 3. Replacing RISK with RISK$^{\perp}$, its component orthogonal to MPS, leaves the space spanned by the two instruments unchanged, and both the Mertens-Ravn and the zero-impact identification use the instruments only through that space. The triangular restriction on the instrument–shock covariance matrix Φ in Appendix C is the exception, since it is stated for a particular pair of instruments rather than for the space they span.

dicators. The risk-free block covers the expected path of risk-free rates over the next two years. Eurodollar futures at horizons of one to four quarters ahead (ED1–ED4) price expectations of three-month USD funding rates and have been the workhorse instrument in the high-frequency monetary policy literature since Gürkaynak, Sack and Swanson (2005). In 2022, we switch to Secured Overnight Financing Rate (SOFR) futures, which have replaced Eurodollar futures as the key money market futures contracts. We also include the 2-year Treasury futures contract, a key benchmark rate that reflects the Fed's expected policy path over a longer horizon than ED1–ED4 alone. Together, these series span the conventional risk-free rate dimension of monetary policy news.

The risk asset block spans four broad asset classes: equities, equity implied volatility, corporate credit, and foreign exchange. We measure the broad U.S. equity market with S&P 500 E-mini and Nasdaq 100 futures, and equity implied volatility with the spot VIX and front-month VIX futures. For corporate credit we use the CDX investment-grade and high-yield credit default swap indices, which price the cost of insurance against default for U.S. corporate debt, together with the corresponding investment-grade and high-yield corporate bond ETFs, which capture price changes in the bond market directly. Three series cover foreign exchange and gold: the U.S. Dollar Index (DXY), gold (XAU), and an FX carry-trade proxy, an equal-weighted portfolio that is long the South African rand (ZAR) and Mexican peso (MXN) and short the Swiss franc (CHF) and Japanese yen (JPY). These four classes let the resulting factor reflect a wide cross-section of risk indicators rather than a single market segment.

We compute log returns for equity indices (S&P 500, Nasdaq), bond ETFs (IG, HY), gold (XAU), the Dollar Index (DXY), and individual exchange rates (CHF, JPY, MXN, ZAR). For the VIX, VIX futures, and CDX credit spreads, we take simple first differences of the level. For money market (Eurodollar/SOFR) futures and bond futures, we calculate the implied interest rate change. All returns and changes are expressed in basis points.[5]

[5] We make a few adjustments before extracting factors. Following the discontinuation of LIBOR-based Eurodollar futures, we splice ED1–ED4 with the corresponding SOFR futures contracts from 2022 onward. We exclude CDX IG and CDX HY observations before 2011 because of limited market liquidity and data quality in the early years of these indices. A few early observations on the VIX and the high-yield ETF are exactly equal to zero and are set to missing to guard against data errors. We also treat one observation on the 2-year government bond future as missing, on September 18, 2007, where the recorded change is roughly 13 times larger in absolute value than the next most extreme reading in the sample and is therefore almost certainly a data error. The value is imputed along with the other missing observations, so MPS for that date rests on the four observed money-market futures, all of which show a large dovish surprise. We then winsorize all series at the 1st and 99th percentiles and restrict the sample to observations from January 1996 onward.

Table 1. Descriptive statistics and loadings

Asset	Mean	Std. Dev.	First Obs.	Loading	Corr(MPS)	Corr(RISK)
Panel A: (Risk-free) Monetary policy shocks (MPS): Explained variance: 76.6%						
ED1	−0.91	5.23	01/1996	0.42	0.82	0.34
ED2	−1.09	5.84	01/1996	0.48	0.93	0.40
ED3	−1.00	8.10	01/1996	0.48	0.93	0.40
ED4	−0.88	8.61	01/1996	0.41	0.81	0.39
Gvt 2y	−0.86	6.13	01/1996	0.45	0.88	0.39
Panel B: Risk shocks (RISK): Explained variance: 56.4%						
SP mini	−0.26	107.03	09/1997	−0.36	−0.28	−0.91
Nasdaq	−1.82	127.22	01/1996	−0.34	−0.20	−0.86
VIX	−30.38	127.44	01/1996	0.32	0.23	0.80
VIX Fut.	2.10	73.92	09/2012	0.35	0.17	0.86
CDX IG	−0.15	1.66	11/2005	0.35	0.41	0.87
CDX HY	−0.24	6.56	11/2005	0.34	0.37	0.86
ETF IG	−15.19	53.09	08/2002	−0.20	−0.39	−0.49
ETF HY	−6.24	50.18	03/2004	−0.29	−0.57	−0.73
Gold	12.34	79.66	01/1996	−0.24	−0.51	−0.61
DXY	−4.02	43.50	01/1996	0.24	0.61	0.59
FX Carry	8.50	43.90	01/1996	−0.21	−0.02	−0.53

This table reports means and standard deviations (based on the imputed data) for all high-frequency asset price changes used in the construction of the risk-free (MPS) factor (Panel A) and the risky asset price (RISK) factor (Panel B). The third row reports the first month with unimputed data for the respective asset. Column "Loading" reports the loading of the asset in the risk-free or risky factor and the last two columns report correlations between high-frequency asset price changes and the two factors, MPS and RISK. The panel headings report the share of explained variance of the respective factor, i.e., the share of explained variance of the first principal component of the imputed data. The full-sample correlation between MPS and RISK is 0.44. The sample period is January 1996 to September 2025.

2.3 Factor loadings and interpretation

Table 1 reports descriptive statistics for the individual asset-price changes, together with the loadings for each series and their correlation with the corresponding factor. Panel A shows results for MPS, and panel B for RISK, with panel headings reporting the share of variance that each factor explains.

Panel A shows uniformly positive loadings of the risk-free rate series (ED1–ED4 and the 2-year government bond future) on MPS. The positive loadings all have a similar magnitude, so MPS corresponds to surprises in the *level* of near-term rates. This first principal component captures 76.6% of the variance of the five input series, and summarizes changes in the expected future rate path.

Panel B reports the loadings of RISK on the eleven risk indicators. The signs of these loadings show that RISK corresponds to an aggregate "risk-off" factor around FOMC communication, with negative changes in risky asset prices and positive changes in risk spreads.

Equities, as captured by the S&P 500 and Nasdaq, load negatively on RISK. Empirically, most of the variation in stock prices reflects risk premium news (Campbell and Shiller, 1988; Cochrane, 2011), so that a positive RISK surprise is one in which investors demand more compensation per unit of risk. Equities are also the most informative single indicator of RISK: the S&P 500 change has the highest correlation with the factor of all eleven risk assets, -0.91, with the Nasdaq close behind at -0.86.

Equity implied volatility, as captured by the spot VIX and front-month VIX futures, loads positively on RISK. Implied variance combines expected physical variance with a variance risk premium (Bollerslev, Tauchen and Zhou, 2009), and monetary easing lowers both components, with the stronger effect on the variance risk premium, the component tied to risk aversion (Bekaert, Hoerova and Lo Duca, 2013). A positive RISK surprise thus indicates that investors pay more for protection against equity variance, which we read as a rise in the price of variance risk.

Credit spreads and bond prices load with opposite signs: positive loadings for credit spreads (CDX indices) and negative loadings for bond ETFs. Credit spreads decompose into a default-loss component and a credit risk premium. Collin-Dufresne, Goldstein and Martin (2001) show that variation in spread changes is largely orthogonal to firm-level fundamentals and is instead dominated by a common factor, which can be interpreted as the price investors charge for bearing credit risk. A positive RISK surprise then means that investors require more compensation for bearing credit risk, which makes default insurance more expensive and lowers corporate bond prices.

The foreign exchange block adds the international dimension of risk appetite. The DXY loads positively on RISK, in line with evidence that safe-haven flows push the dollar up in risk-off episodes (Avdjiev et al., 2019) and that a broad dollar factor behaves as a global risk factor (Verdelhan, 2018). Carry trades load negatively, consistent with high-yielding (low-yielding) currencies depreciating (appreciating) when risk appetite falls (Menkhoff et al., 2012). Gold also loads negatively, so it behaves as a risk-on asset in FOMC windows, like equities, corporate bonds, or FX carry.[6] Since exchange rates are driven largely by discount rates rather than by news about expected fundamentals (Froot and Ramadorai, 2005; Jiang, Krishnamurthy and Lustig, 2021), the FX block picks up shocks to risk premia priced in currencies.

There is strong comovement across the eleven risk indicators. RISK, their first principal component, captures 56.4% of their total variance. That is a sizable common component, especially given that these indicators span equity, options, credit, and FX markets.

[6]This is somewhat surprising given the popular view of gold as a safe-haven asset, but it matches the correlation of gold returns with equity returns observed over the past two decades.

We interpret RISK as a market-wide risk appetite factor, with positive values corresponding to a decline in aggregate risk appetite. Market participants describe such episodes as risk-on and risk-off, in which assets with quite different payoffs move together according to the compensation investors demand for bearing risk.

Cash-flow news is unlikely to be an important driver of the common variation in these eleven risk assets. Payoffs differ substantially across these markets, yet the series move together in a way consistent with shifts in risk appetite. Aggregate asset-price variation in equities, credit and FX is dominated by discount-rate news rather than cash-flow news (Cochrane, 2011; Collin-Dufresne, Goldstein and Martin, 2001; Jiang, Krishnamurthy and Lustig, 2021).[7]

Aggregate risk appetite, the willingness of the marginal investor to bear risk, moves inversely with effective risk aversion and hence with the market-wide price of risk. Risk premia are the equilibrium expected excess returns produced by this price of risk together with an asset's quantity of risk, typically measured by conditional second moments. Just like cash-flow news, changes in the quantity of risk are asset-specific and are unlikely to drive much of the common variation in RISK (Bauer, Bernanke and Milstein, 2023). However, changes in risk perceptions, such as an increase in perceived downside risk to the macroeconomy, could affect the quantity of risk across a range of assets, and in this way affect risk premia without necessarily changing risk appetite. Some of the theoretical channels in Section 4.1, in particular lower perceived uncertainty and tail risk, work through the quantity of risk rather than through risk appetite. Our measure is deliberately model-free, and we make no attempt to disentangle movements in the aggregate price of risk from changes in the perceived quantity of risk. The comovement patterns support the interpretation of RISK as shifts in risk appetite, but our conclusions do not require this distinction. Whether RISK moves risk premia via changes in risk appetite or perceived risk, our estimates show that this risk-taking channel accounts for a large share of the variance of output and prices.

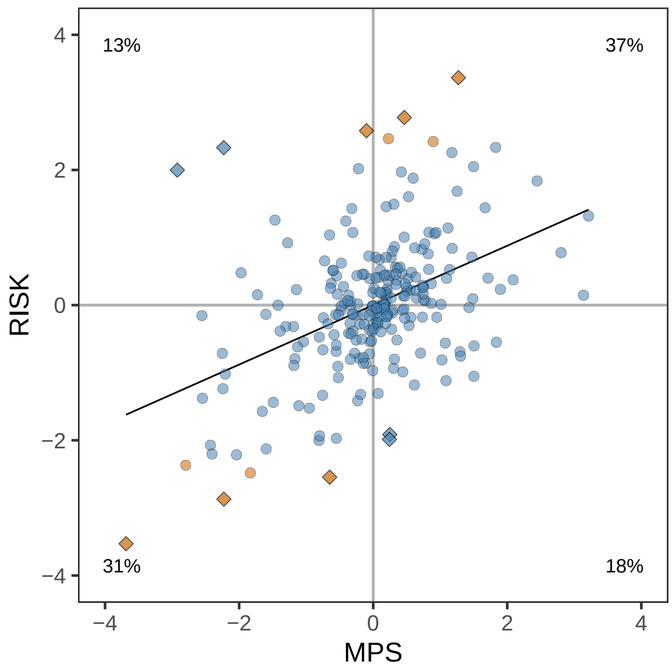
2.4 Understanding RISK surprises

Our two policy surprises MPS and RISK have a strong positive relationship. A linear regression of RISK on MPS yields a positive coefficient of 0.44 with a t-statistic of 5.3 (based on White standard errors). The R^2 is 0.19, and since both series have unit variance, the slope coincides with the correlation of 0.44. Figure 1 plots MPS against RISK, including the regression line.

The regression shows that surprises about the policy path move risk appetite in financial mar-

[7] Risk-free discounting is unlikely to drive the comovement for the same reason. The eleven series differ sharply in their exposure to the expected path of risk-free rates. A change in the policy path moves equity prices and gold directly through discounting, while credit spreads are measured relative to the risk-free curve and implied volatilities are second moments. Yet the credit and volatility series load on RISK about as strongly as equity prices do, while gold, the dollar and the FX carry trade load the least (Table 1).

Figure 1. MPS and RISK surprises



This figure shows a scatterplot of monetary policy surprises (MPS) against risk appetite surprises (RISK) with a regression line from a regression of RISK on a constant and MPS ($R^2 = 0.19$). A positive value of RISK indicates higher risk aversion (lower risk appetite). Both series are scaled to unit variance, so the axes are in standard deviations. The FOMC meetings with the five highest and five lowest values of RISK are highlighted in orange, and the five highest and five lowest values of RISK orthogonalized with respect to MPS are marked with a diamond. The figure reports the percentage of observations that fall within each quadrant. The sample runs from January 1996 to September 2025.

kets. Hawkish surprises lower risk appetite and dovish surprises raise risk appetite. This relationship between interest-rate policy and risk appetite in financial markets is at the core of the risk-taking channel of monetary policy.

But there is also a substantial share of the variation in RISK that is not captured by MPS. About four-fifths of the variation in RISK is left unexplained by the regression.[8] A similar result was documented by Bauer, Bernanke and Milstein (2023), but our intraday RISK measure sharpens this evidence: even over intradaily windows around FOMC announcements and press conferences, which are dominated by monetary news as we demonstrate below, most of the variation in RISK seems unrelated to interest-rate surprises. This variation is captured by RISK$^{\perp}$, the residual from this regression. This large residual variation is one reason we use MPS and RISK as separate instruments in the proxy SVAR of Section 3.

The scatter plot in Figure 1 visualizes the relationship between MPS and RISK, and is our

[8]Regressing RISK on the individual components of MPS (ED1–ED4 and the two-year yield) yields the same R^2 of 0.19. That is, using the term structure of futures rates instead of their first principal component does not help explain a larger share of RISK.

starting point for an analysis of key FOMC events. In the plot, the five highest and lowest realizations of RISK are shown in orange, and the five highest and lowest realizations of RISK$^{\perp}$ are marked with a diamond. The bulk of FOMC events (68%) naturally fall in the lower-left and upper-right quadrants, given the positive correlation between MPS and RISK. For about a third of the observations they move in opposite directions. The largest observations for RISK$^{\perp}$ (diamonds) appear in all four quadrants, several of them near the vertical axis, where the rate surprise is close to zero.

Table 2 lists the fourteen FOMC meetings highlighted in Figure 1, those with the most extreme values of RISK or RISK$^{\perp}$, together with the corresponding values of MPS and a short summary of the policy action and news coverage around each meeting. Panel A collects the risk-off events with positive values for RISK, Panel B the risk-on events with negative values. We assembled the narratives from contemporaneous financial press coverage, reading articles published in the hours and days after each decision and recording the dominant causal explanation that reporters and market participants gave for the market reaction, together with an illustrative verbatim quote.[9] While these narratives are not direct evidence on mechanisms, they show the perceived drivers of the largest moves in risk appetite, and whether these drivers included Fed information effects or instead other effects of the policy decision and its communication.

MPS and RISK move in the same direction for nine of the fourteen events, in line with their positive correlation. For four of these events, a large part of their RISK move is explained by the rate surprise, with RISK$^{\perp}$ less than two standard deviations in absolute value. All four combined a large dovish surprise with a sharp improvement in risk appetite. The sharpest is December 16, 2008, when the Fed cut to the zero bound and pledged to use "all available tools." It produced both the most dovish rate surprise and the largest risk-on move in our sample, and press coverage described a Fed "willing to really go the distance for the market." September 18, 2007, the larger-than-expected 50bp cut at the start of the credit crisis, follows the same pattern, and the VIX fell 23%. At meetings like these, an expansionary policy surprise moves the expected policy path and the price of risk together. But while these moves are in line with, and partly explained by, the statistical relationship between MPS and RISK, the response of RISK to the policy easing is quite a bit stronger than predicted.

For the other ten events, RISK$^{\perp}$ is nearly as large as RISK or larger, meaning that the interest-rate surprise played little or no role in explaining movements in risk appetite. For five of these events, RISK and MPS moved in opposite directions. At four others, a small hawkish surprise came

[9]The narratives come from the Reuters news archive, and the reading was assisted by a large language model, Anthropic's Fable 5. Appendix B.2 gives further detail and plots the time series of RISK with the events from this table marked.

Table 2. Extreme RISK surprises

Date	RISK	$\text{RISK}^{\perp}$	MPS	Description
Panel A: Risk-off events				
2024-12-18	3.37	2.81	1.27	25bp cut, but the dot plot halved projected 2025 cuts; the hawkish surprise injected new uncertainty into a market priced for perfection. *"Markets, with high valuations, were pricing in everything being perfect... this basically adds more uncertainty the markets have not priced in."*
2001-09-17	2.78	2.57	0.46	Emergency 50bp cut after 9/11, but fear of recession and war swamped the easing and the Dow fell about 7%. *"The market hates uncertainty and to have this happen is a shock wave."*
2007-12-11	2.58	2.62	-0.10	A 25bp cut fell short of the backstop markets wanted against the credit crunch; fear jumped and investors fled stocks for safety. *"As equities rapidly sank, investors piled into the perceived safety of government debt."*
2018-12-19	2.46	2.36	0.23	25bp hike; Powell's "autopilot" balance-sheet remark dashed hopes that the Fed would backstop a sliding stock market. *"A disappointment for those hoping for a dovish rate hike."*
2013-06-19	2.42	2.03	0.89	Bernanke's taper timeline withdrew the perceived backstop of "accommodation as far as the eye can see" (the "taper tantrum"). *"The stock market has been put on notice... you're on your own."*
2001-03-20	2.33	3.31	-2.23	A dovish third 50bp cut failed to restore confidence; fear of a deepening slump drove investors out of stocks and into safety. *"Treasuries surged as investors sought the safe haven."*
2020-03-03	2.00	3.28	-2.92	A surprise emergency COVID cut was read as a signal of alarm; instead of restoring confidence it fed fear that policy could not offset the virus. *"The Fed's pre-emptive strike... has backfired. The reaction has signaled... that the coronavirus is on par with... the Great Depression."*
Panel B: Risk-on events				
2008-12-16	-3.53	-1.91	-3.69	Cut to the zero bound with a pledge of "all available tools"; the do-whatever-it-takes signal restored confidence and lifted stocks about 5%. *"We've got a Fed that's willing to really go the distance for the market right now."*
2022-05-04	-2.87	-1.89	-2.23	A 50bp hike, but Powell ruled out 75bp, removing the tail risk markets feared. *"The market was really fixated on... whether or not a 75 basis point hike is on the table, and he (Powell) basically pushed back on that."*
2013-09-18	-2.55	-2.26	-0.65	The Fed surprised markets by not tapering; keeping stimulus flowing sent stocks to record highs. *"No taper, the market loves it... off to the races."*
2015-03-18	-2.48	-1.68	-1.83	"Patient" was dropped, but a much lower dot plot and softer forecasts made the net message dovish and eased fear of aggressive hikes. *"If the opposite of a tantrum is a happy dance, then that's just what stock and bond markets performed..."*
2007-09-18	-2.37	-1.14	-2.80	A larger-than-expected 50bp cut at the start of the credit crisis drained fear from the market; the VIX collapsed 23%. *"Tuesday's bold move by the Fed helped to ease market fears about the outlook for the credit markets and the economy."*
2021-12-15	-1.99	-2.09	0.24	An accelerated taper and hawkish dots, yet the as-expected message resolved a large overhang of policy uncertainty. *"Markets breathed a collective sigh of relief."*
2012-09-13	-1.91	-2.02	0.25	Open-ended QE3 flipped markets risk-on across stocks and commodities, and gold jumped. *"The ultimate risk-on stocks... people are getting into them."*

The table lists the FOMC meetings with the most extreme values of RISK or of orthogonalized RISK ($\text{RISK}^{\perp}$, the residual from a regression of RISK on MPS): Panel A collects risk-off events (largest RISK and $\text{RISK}^{\perp}$) and Panel B risk-on events (most negative RISK and $\text{RISK}^{\perp}$). Columns report the FOMC date, the high-frequency RISK surprise, $\text{RISK}^{\perp}$, the corresponding monetary policy surprise (MPS), and a brief description of the policy action and market narrative with an illustrative quote from contemporaneous news coverage. Higher values of RISK indicate greater risk aversion. The sample period is January 1996 to September 2025.

with a large rise in risk aversion. In September 2001 the emergency cut after the September 11 attacks was swamped by fear of recession and war, and the other three are the June 2013 taper tantrum, Powell's "autopilot" remark of December 2018, and the December 2024 dot plot, which markets read as the withdrawal of a perceived Fed backstop or as new policy uncertainty. The tenth event, September 18, 2013, was a surprise inaction, when the Fed did not begin tapering and stocks rose to record highs despite a small rate surprise. Risk appetite moved sharply at several meetings with almost no rate surprise. On December 11, 2007, the Fed cut by 25bp, causing a very small dovish surprise. Yet risk aversion rose sharply, and news coverage attributed the sell-off to a cut that fell short of the backstop markets wanted against the credit crunch, and reported investors leaving equities for Treasuries. On December 15, 2021, the Fed accelerated the taper and raised its rate projections, causing a small hawkish surprise. Although the policy communication was close to expectations, risk aversion fell markedly and coverage described a "collective sigh of relief" as the announcement reduced policy uncertainty. Neither move follows from the interest-rate surprise, and in the second the surprise has the wrong sign.

Our narrative analysis shows that for almost all of the fourteen events, changes in RISK can be explained by the direct effects of the Fed's policy actions and communication on risk appetite and risk perceptions. These include flight-to-safety effects, unconventional monetary policy, policy uncertainty, perceptions about the Fed backstopping asset markets, and fears of tail risk. All of these channels affect risk appetite and risk premia rather than the expected path of the economy. Section 4 takes up these mechanisms.

An alternative explanation for orthogonal or even opposite-sign moves in RISK relies on Fed information effects: markets learn the Fed's own view of the economy, so that a dovish surprise causes a risk-off move because the outlook has deteriorated, and a hawkish surprise causes a risk asset rally because it signals that the outlook has improved. Jarociński and Karadi (2020) classify announcements by the sign of the comovement between interest rates and stock prices, and according to their methodology, the five events in Table 2 where MPS and RISK move in opposite directions would be labeled information shocks. Our narratives generally do not support that reading, with only one exception. On March 3, 2020, the Fed cut 50bp between meetings, which led to a large dovish surprise and the second-largest value for $\text{RISK}^{\perp}$ in the sample. Markets indeed perceived this rate cut as a signal of alarm, in line with a Fed information effect. However, for the other four events the narratives point elsewhere. For example, the 50bp easing of March 20, 2001 was smaller than the 75bp cut many investors expected, and risk asset prices fell as a result of this disappointment rather than on news about the outlook.[10] In December 2007 the issue was

[10] Jarociński and Karadi (2020) open their paper with this event, describing the cut as larger than expected and attributing the fall in stock prices to the pessimistic risk assessment in the statement. But most evidence suggests

again the adequacy of the Fed's backstop, in December 2021 the resolution of policy uncertainty, and in September 2012 the announcement of open-ended QE3 turned markets risk-on across stocks, commodities and gold. Overall, this narrative analysis provides little support for the view that Fed information effects drive the orthogonal variation in RISK.

2.5 Validation: placebo windows and external evidence

An important question is whether our measure of RISK indeed captures shifts in risk appetite due to news about monetary policy. We address it in the following with several validation exercises.

We begin with a placebo exercise to understand how the properties of RISK (and MPS) change between FOMC events and other windows without relevant monetary news. Specifically, we construct placebo event windows that are exactly seven calendar days before each FOMC announcement. We use the same intraday event window, the same input series, and the same construction as for the real FOMC windows, but on days without an FOMC announcement. Details and results are reported in Appendix B.3.

Asset prices are far more volatile around FOMC announcements. Over placebo windows, the volatility is one-fifth to one-half of the FOMC volatility for the risk-free rates and one-quarter to two-thirds for the risk assets, and a bootstrap test rejects equality of the two standard deviations for almost every series. A Rigobon (2003) test strongly rejects equality of the variance-covariance matrix across the two window types. The substantially higher volatilities point to an important role for monetary news in driving asset prices in FOMC windows.

The comovement of interest rates and risk asset prices flips from negative to positive. The correlation between changes in the two-year yield and the S&P 500 is -0.23 in FOMC windows and $+0.20$ in placebo windows, and a similar sign flip holds when we replace the two-year with longer maturities. For MPS and RISK, the correlation is 0.44 around announcements against -0.28 seven days earlier. The sign switch strongly suggests that on placebo days, macroeconomic news dominates, while monetary news is the primary driver of asset prices over FOMC windows. A positive macroeconomic surprise raises the expected rate path and interest rates more broadly, and it raises risk asset prices, so rates rise while risk aversion falls and the MPS–RISK correlation is negative. In the case of monetary news, by contrast, a surprise that raises interest rates tends to increase risk aversion and risk premia, implying a positive correlation between MPS and RISK.

that the cut was in fact smaller than expected. In the words of Federal Reserve Board staff, the reduction "was less than some investors had expected, but the accompanying statement contributed to expectations that an intermeeting ease would follow" (Bluebook, "Monetary Policy Alternatives," May 10, 2001, paragraph 1), and the press reported the disappointment that the Fed had not delivered 75bp (Stevenson, 2001). The surprise change in the target rate was +7bp, while fed funds futures for May through August fell by 6 to 10bp as market participants bet on further easing (Bauer and Swanson, 2023*a*, fn. 37). The disappointment accounts for the fall in stock prices and the promise of further easing for the dovish MPS.

That the MPS–RISK correlation changes sign with the window type also shows that this correlation reflects the content of FOMC news rather than a mechanical feature of how we construct the two surprises.

Our interpretation of comovement follows Cieslak and Schrimpf (2019), who use the sign of the high-frequency stock–yield comovement to separate monetary from non-monetary news in central bank communication. They document the same sign switch between announcement windows and windows without central bank news, using a wide range of interest-rate maturities from three months to thirty years. We find the reversal across the full cross-section of risk assets, in credit and in FX as well as in equities, so RISK measures the risk-premium component of their non-monetary news directly.

Taken together, the results of the placebo analysis indicate that monetary news is the major driver of RISK in our event windows. By contrast, non-monetary news plays a limited role in FOMC windows, which supports the exogeneity condition required for our proxy SVAR analysis below in Section 3. This assumption is standard in the empirical literature using high-frequency identification for monetary policy, but it is important to substantiate it specifically for our new surprise measures.

We now turn to a comparison of RISK with existing measures of FOMC risk shifts and risk appetite. Table 3 reports correlations between RISK, as well as RISK$^{\perp}$, and four alternative risk measures proposed in the literature: the Bauer, Bernanke and Milstein (2023, BBM) risk index, the Bekaert, Engstrom and Xu (2022, BEX) risk aversion measure, the Kroencke, Schmeling and Schrimpf (2021, KSS) FOMC risk shift, and the Boehm and Kroner (2026*a*, BK) Fed non-yield shock. For consistency with RISK and with Table A.1, we sign-normalize each of these four series so that higher values correspond to greater risk aversion. We also report correlations with the Jarociński and Karadi (2020, JK) central bank information shock, even though the JK measure is not designed to capture risk appetite. JK is taken in its raw form, in which a higher value corresponds to higher rates and higher stock prices.

All four risk-aversion measures are positively correlated with RISK and with RISK$^{\perp}$, indicating that they all capture a similar underlying concept. The correlation is highest with KSS, since both measures come from high-frequency event windows and both include credit proxies such as the CDX. We differ in imposing no orthogonality to rate surprises, in using a broader cross-section of eleven risk-sensitive series, and in a window that covers the press conference.

The correlation with the JK measure has the expected negative sign: events with positive information effects have rates and stocks both increasing, corresponding to risk-on events with falling risk aversion and negative values of RISK. However, this correlation also suggests an alternative interpretation of the JK information shocks. These are largely the events at which MPS and RISK

Table 3. Correlations of RISK with other risk (appetite) measures

	BBM (2023)	BEX (2022)	JK (2020)	KSS (2021)	BK (2026)
Corr(RISK)	0.48	0.45	-0.32	0.71	0.45
Corr(RISK$^{\perp}$)	0.47	0.41	-0.43	0.75	0.50
Sample start	01/1996	01/1996	01/1996	01/2006	01/1996
Sample end	05/2022	05/2024	09/2024	12/2019	07/2025
N	217	233	238	114	236

This table reports correlations between RISK and alternative risk measures proposed in the literature: Bauer, Bernanke and Milstein (2023, BBM), Bekaert, Engstrom and Xu (2022, BEX), Jarociński and Karadi (2020, JK) central bank information effects, Kroencke, Schmeling and Schrimpf (2021, KSS) FOMC risk shifts, and Boehm and Kroner (2026*a*, BK) Fed nonyield shocks. For consistency with RISK and with Table A.1, the BBM, BEX, KSS, and BK series are sign-normalized so that higher values correspond to greater risk aversion. The JK central-bank information shock is taken in its raw form, in which a higher value corresponds to higher rates and higher stock prices; we keep JK's native sign because it is not a risk appetite measure. RISK$^{\perp}$ denotes RISK orthogonalized with respect to MPS. We further report the start and end of the joint sample of the respective risk measure and RISK as well as the number of joint observations (N).

move in opposite directions, which is true for about a third of all FOMC meetings in our sample.[11] Restricted to them, the correlation of RISK$^{\perp}$ with the JK information shock is -0.67, against -0.30 at the remaining events.[12] The JK information shock thus picks up much the same variation that we measure directly from the cross-section of risk assets. The comovement across risk assets that RISK captures (Section 2.3) and the narrative evidence in Section 2.4 both suggest that this variation largely reflects shifts in risk premia caused directly by policy actions and communication. Information effects, in which the Fed reveals news about the outlook, are a less plausible source.[13]

FOMC risk appetite shifts have strong effects on international asset prices. Appendix B.4 reports the effects of RISK on risky asset prices around the world, for a cross section of country stock market indices, foreign exchange rates, commodity indices, dividend futures, inflation expectations, and government bond yields. We find that a positive RISK surprise is associated with large and statistically significant declines in most global stock markets, an appreciation of the U.S. dollar against almost all other currencies in our sample, and a significant reduction in benchmark commodity price indices, including energy prices. This pattern is consistent with the global financial cycle documented by Miranda-Agrippino and Rey (2020). In their study of U.S. macroeconomic news, Boehm and Kroner (2026*b*) find similar global effects on stock indices, implied volatilities,

[11] RISK loads on volatility, credit and FX as well as equities, so the two classifications are not identical. They agree at 86% of meetings, and at all fourteen events in Table 2.

[12] This correlation is computed on the 238 FOMC meetings for which the JK series is available, of which 77 have MPS and RISK of opposite sign.

[13] Boehm and Kroner (2026*a*) reach the same conclusion for their Fed non-yield shock, which is identified from excess volatility in stock prices and exchange rates, and constructed to be orthogonal to the yield curve. Regressing it on the JK shocks gives an R^2 of zero, indicating that information effects are unlikely to drive movements in their Fed non-yield shock.

and commodity prices, with the joint behavior of stocks and bond yields indicating investors' risk-taking rather than systematic policy reactions. We also find that dividend futures and market-based inflation compensation (breakeven inflation and inflation swaps), which reflects both expected inflation and an inflation risk premium, point in the same direction: higher RISK is associated with lower dividend futures and lower inflation compensation, with the response most pronounced for Canada and the United States. By contrast, international government bond yields barely respond to RISK. The coefficients have generally small magnitudes and most are not statistically significant. Two-year yields in the major advanced economies, including the United States, move by less than half a basis point, and almost all 10-year responses are below four basis points. This result again highlights that our measure captures a dimension of monetary policy news that is distinct from pure interest-rate effects.

3 Estimates of Monetary Transmission

We now turn to the estimation of monetary transmission that incorporates risk appetite shocks. We use structural vector autoregressions (SVARs) identified with external instruments, or proxy SVARs, following the framework developed by Stock and Watson (2012, 2018) and Mertens and Ravn (2013). Given that we have two external instruments, MPS and RISK, one of the main methodological choices is how to identify multiple shocks with multiple instruments.

3.1 Proxy VAR specification

We start with the specification of the reduced-form VAR,

$$Y_t = \alpha + B(L)\, Y_{t-1} + u_t, \tag{1}$$

where Y_t is a $K \times 1$ vector of endogenous variables, $B(L)$ is a matrix lag polynomial of order p, with coefficient matrices $B_1, \ldots, B_p$, and u_t are serially uncorrelated reduced-form residuals with covariance matrix Ω. We follow the "best practice" VAR in Bauer and Swanson (2023*b*). This is a monthly VAR with $K = 6$ variables: the two-year Treasury yield (Y2), the Gilchrist and Zakrajšek (2012) excess bond premium (EBP), the log of industrial production (IP), the log of the consumer price index (CPI), the log of the Bloomberg Commodity Index (BCOM), and the unemployment rate (UR). The two-year yield and the excess bond premium serve as the "policy variables" and are the primary channels through which the two structural shocks operate: MPS affects the macroeconomy mainly through the risk-free interest rate, while RISK operates through credit spreads and risk premia. The remaining four variables capture real activity, prices, commodity markets, and labor market conditions. We use $p = 12$ monthly lags, and estimate the VAR coefficients α and B_j over a sample from June 1976 to September 2025. The effective estimation sample, after 12 initial lags, starts in June 1977 and contains 580 observations.

To construct the monthly instrument series, we aggregate the high-frequency MPS and RISK surprises described in Section 2 to monthly frequency by summing all FOMC-day surprises within each calendar month. Months without an FOMC meeting receive a value of zero for both instruments. The instrument series are available from January 1996 through September 2025, covering 245 FOMC events that fall in 241 distinct calendar months.[14] A key advantage of the proxy SVAR framework is that the reduced-form VAR dynamics can be estimated over a longer sample than the one for which the instruments are available: the structural identification step uses only the subsample in which the instruments are observed, while the VAR coefficients benefit from the full sample (Stock and Watson, 2018).

Our goal is to identify two separate structural shocks. The first is a conventional interest-rate policy shock that affects risk-free rates. The second is a risk appetite shock that affects risk premia for a broad range of assets, including stock prices and credit spreads. Since we will use MPS and RISK as instruments for these two shocks, we will refer to them as MPS shock and RISK shock, but the reader should keep in mind that the high-frequency instruments are different objects than the structural shocks in the VAR.

To formalize identification via external instruments, first note that the reduced-form innovations are linear combinations of the underlying structural shocks ε_t,

$$u_t = S\,\varepsilon_t, \tag{2}$$

where S is the structural impact matrix and $\text{Var}(\varepsilon_t) = I$, so that $SS' = \Omega$. The identification problem is that there are infinitely many matrices S satisfying this relation. Our goal is to identify the $k = 2$ columns of S corresponding to the two monetary policy shocks just described.

External instruments resolve this identification problem by bringing information from outside the VAR (Stock and Watson, 2018; Bauer and Swanson, 2023*b*). Let z_t denote a $k \times 1$ vector of instruments. Valid instruments must satisfy both an *instrument relevance* condition,

$$E[z_t\,\varepsilon_{1t}'] = \Phi \neq 0, \tag{3}$$

[14] Four months contain two scheduled FOMC meetings; the monthly instrument is the sum of the within-month event-level surprises. Of the 580 effective VAR observations, 241 have nonzero instruments.

where ε_{1t} collects the k policy shocks, and an *instrument exogeneity* condition,

$$E[z_t \, \varepsilon_{2t}'] = 0, \tag{4}$$

where ε_{2t} collects all remaining structural shocks. In our application $k = 2$, with ε_{1t} the rate shock and the risk appetite shock and ε_{2t} the remaining non-policy shocks. The appeal of high-frequency surprises around FOMC announcements is that they have the potential to satisfy both conditions. Asset price changes in narrow event windows are driven by the monetary policy news from the FOMC. If these changes explain at least some portion of the variation in the policy variables, then the instruments satisfy the relevance condition. While weak instrument problems can be detected with available statistical tests, they also simply cause larger confidence intervals, as long as those are correctly calculated. To the extent that asset price changes are only driven by policy news, they are exogenous with respect to other macroeconomic shocks. For high-frequency monetary policy surprises, it is commonly assumed that these provide exogenous instruments for monetary policy shocks. As discussed below in Section 4.4, Fed information effects would violate this exogeneity assumption, but the evidence suggests that information effects are not an important driver of our surprises.[15]

If valid instruments are available, the covariance between the instruments and the VAR residuals satisfies $E[z_t \, u_t'] = \Phi \, S_1'$, where $S_1 = [s_1, \ldots, s_k]$ collects the first k columns of the structural impact matrix S, the impact responses of all VAR variables to the policy shocks. This moment condition identifies S_1 up to the $k \times k$ matrix Φ. With a single instrument for a single shock ($k = 1$), the impact column s_1 is identified up to scale and can be estimated by two-stage least squares (2SLS). This is the case that most recent VAR studies of monetary transmission have focused on, including Gertler and Karadi (2015), Bauer and Swanson (2023*b*), among others. Even in the case of multiple instruments and multiple shocks, it is possible to use the single-instrument approach for each instrument separately. One simply uses one instrument at a time, estimating a specific impact coefficient vector s_1 and calculating the resulting impulse responses. If the multiple instruments are mutually uncorrelated, then the results can be interpreted as representing separate structural

[15] High-frequency monetary policy surprises are partly predictable from economic and financial data released before the FOMC announcement. Bauer and Swanson (2023*b*) show that this predictability can bias proxy SVAR estimates and recommend orthogonalizing the surprises with respect to their predictable component. In our sample MPS is predictable from macroeconomic news released before the announcement, though not from pre-FOMC financial-market data, while for RISK, which loads on risk-sensitive assets rather than interest rates, we find at most marginal evidence of predictability. In additional, unreported analysis we re-estimate the VAR with instruments orthogonalized to three sets of pre-FOMC predictors, including the Bauer and Swanson (2023*b*) controls. The orthogonalized instruments correlate 0.95 to 0.99 with the raw surprises and the RISK responses are essentially unchanged, with industrial production twelve months out falling by 0.18 to 0.24 log points against 0.21 in the baseline. The MPS responses move more but stay well inside their original confidence bands.

shocks; see, for example, Altavilla et al. (2019) and Swanson (2024).[16] For comparability with earlier literature, and to establish a baseline, we will first estimate impulse responses using each individual instrument separately.

When $k = 2$ instruments are used simultaneously to identify $k = 2$ structural shocks, the two impact columns s_1 and s_2 are each identified only up to a linear combination, and one further restriction, in addition to the two scaling restrictions, is needed to separately identify the two shocks. We will use the method of Mertens and Ravn (2013) for our baseline results, and report estimates from alternative methods in the Appendix.

For all specifications, we normalize the MPS shock to produce a 25 basis point increase in the two-year Treasury yield on impact, and the RISK shock to produce a 10 basis point increase in the EBP on impact. These normalizations are arbitrary and we choose them simply to have economically interpretable units. The 25 basis point scaling for the rate shock follows the convention in the literature (Gertler and Karadi, 2015).

3.2 Instrument strength

Before turning to the impulse-response analysis of our VARs, we assess how strongly MPS and RISK are related to the reduced-form residuals. That is, we examine the strength of our external instruments.

With estimates of the residuals u_t in hand, the first stage of our IV estimation is simply to regress the residuals on MPS and RISK. Depending on the precise proxy SVAR specification and identification method, one might consider univariate or multivariate specifications. For simplicity, we report results for the multivariate regression on both instruments. Table 4 reports these first-stage regressions of each reduced-form VAR residual on MPS and RISK, estimated over the 241 months with FOMC meetings.

Each instrument loads primarily on its intended policy variable: MPS is the dominant predictor of the two-year yield residual, while RISK is the dominant predictor of the EBP residual. The impact of these instruments on other variables is modest, indicating that they capture distinct sources of variation around FOMC announcements related to risk-free rates and risk premia, respectively. This is important because identification with multiple instruments requires that the first-stage coefficient matrix has full rank, so that each instrument provides independent information about a distinct structural shock (Stock and Watson, 2018).[17]

[16] Bruns, Lütkepohl and McNeil (2025) show that this one-by-one approach can produce unintentionally correlated structural shocks, even when the proxies are mutually uncorrelated. The joint identification methods we use below avoid this problem by construction.

[17] The condition number of the first-stage coefficient matrix is 1.03, confirming that our instrument configuration is far from the rank-deficient case in which both instruments load on the same shock.

Table 4. Strength of External Instruments

	2y yield	EBP	IP	CPI	BCOM	Unempl.
MPS	0.0389	0.0094	0.0230	-0.0121	-0.3592	-0.0035
	(1.84)	(0.27)	(0.23)	(-0.75)	(-0.86)	(-0.12)
RISK	-0.0093	0.0378	-0.0129	-0.0258	-0.4041	0.0024
	(-0.51)	(1.42)	(-0.17)	(-1.82)	(-1.06)	(0.09)
R^2	0.0293	0.0320	0.0004	0.0300	0.0253	0.0000
Robust F	2.11	1.62	0.03	3.25	2.16	0.01

Each column reports OLS regressions of a reduced-form VAR residual on both instruments (MPS and RISK), using only months with FOMC meetings. The sample covers January 1996 to September 2025 ($N = 241$). Robust t-statistics (HC0) in parentheses. The robust F-statistic tests joint significance of both instruments (Wald statistic divided by $q = 2$).

The robust F-statistics and R^2 values are modest. Such low values raise the concern of weak instruments, but they are common in monthly proxy SVARs, because the signal from high-frequency surprises is small relative to total monthly variation (Mertens and Ravn, 2013; Gertler and Karadi, 2015).

Modest first-stage statistics are less consequential here than they would be in an over-identified setting. Our VAR specifications are just-identified, with as many instruments as structural shocks, and in this case 2SLS is approximately median-unbiased even when the first stage is weak (Angrist and Kolesár, 2024). Weak instruments then show up as imprecision rather than as systematically misleading point estimates. Inference, by contrast, does depend on instrument strength. We report confidence intervals from a wild bootstrap, following Mertens and Ravn (2013) and common practice in the proxy SVAR literature.[18]

3.3 Single-instrument estimation

As a first step, we estimate separate single-instrument proxy SVARs. That is, we first use MPS alone to identify a risk-free rate shock, and then we use RISK alone to identify a risk appetite shock.

This approach treats each shock in isolation, ignoring the correlation between the two instruments. The resulting impulse responses therefore do not correspond to two separate structural shocks, but in general capture two different linear combinations of these shocks. We have several reasons for undertaking this estimation. First, using an instrument like MPS for a monetary policy

[18] Montiel Olea, Stock and Watson (2021, Appendix A.6.2 and A.7) extend the weak-instrument-robust Anderson-Rubin approach to two instruments and two shocks. Their procedure yields a joint confidence region for the responses to both shocks. We do not pursue this route because it does not directly deliver confidence intervals for the individual impulse responses that are our focus.

shock corresponds to the standard approach in monetary VARs. For comparability with earlier work—such as Gertler and Karadi (2015), Bauer and Swanson (2023*b*) and others—this estimation is a helpful exercise in our setting. Second, we also want to compare the estimated effects for MPS and RISK to each other, in order to see what each instrument delivers on its own before imposing additional identifying restrictions to separate them. Lastly, the comparison with the joint-identification estimates will show us how much the correlation between MPS and RISK matters. If the single-instrument IRFs differ substantially from the multi-instrument ones, then this indicates that the joint identification is necessary to really understand these different dimensions of monetary transmission.

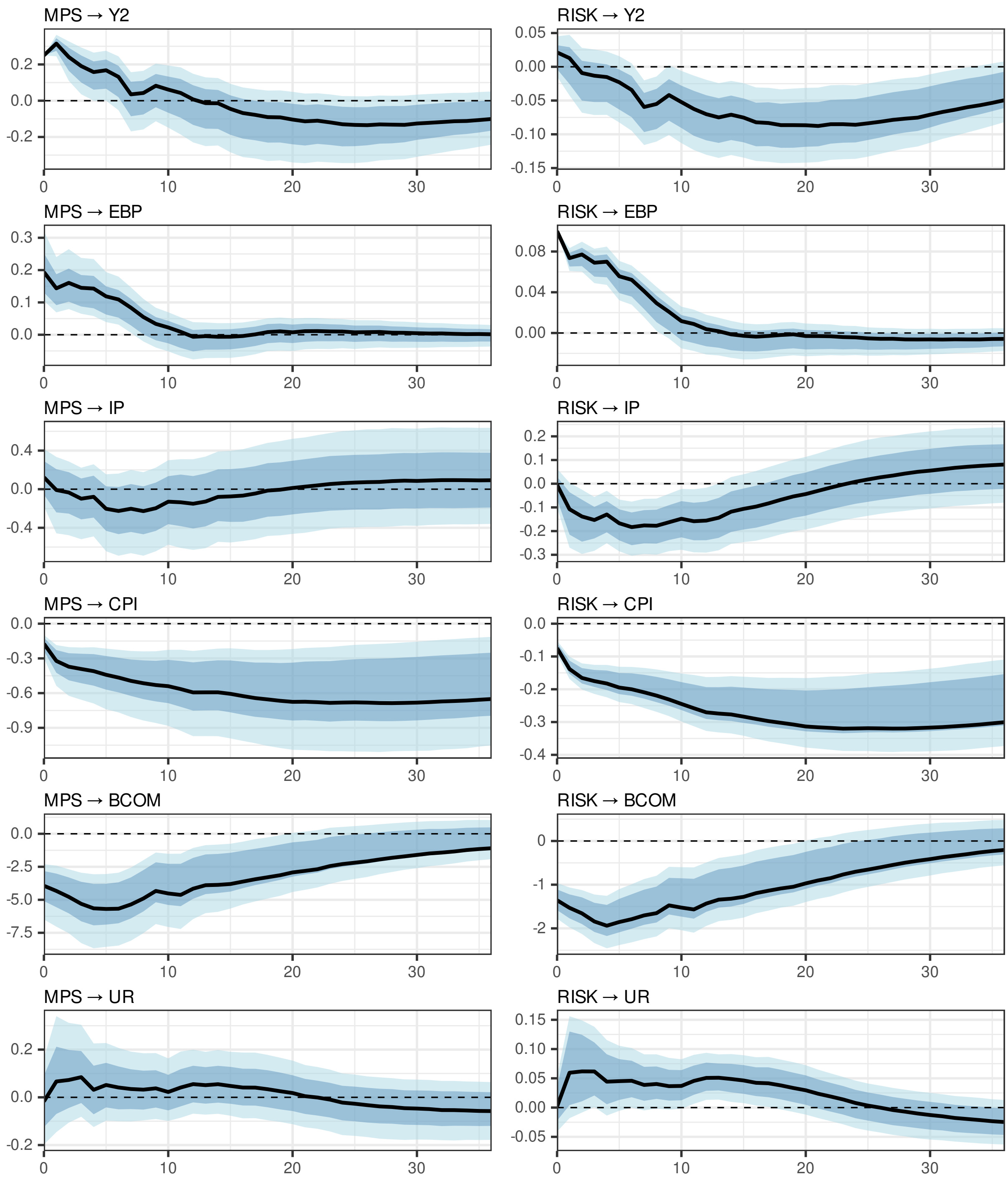
The results, shown in Figure 2, therefore serve as an important benchmark. The estimated effects of the risk-free rate shock, shown in the left panels, are broadly consistent with the extensive earlier literature on the macroeconomic effects of monetary policy shocks. They show that a contractionary monetary policy shock—raising the two-year yield by 25 basis points—leads to a modest decline in industrial production, a gradual fall in consumer prices, and a drop in commodity prices. The effects on unemployment are small and statistically insignificant. Nevertheless, the impulse responses are overall in line with conventional monetary transmission via changes in interest rates. The contractionary shock also raises the excess bond premium, consistent with the important role of credit spreads and risk premia for monetary transmission emphasized by Gertler and Karadi (2015) and others.

The right panels of Figure 2 show the estimates for a structural shock identified using RISK alone. The two-year yield responds gradually and negatively to this shock. This response, which is highly persistent, could reflect an endogenous easing of monetary policy in response to the deteriorating economic conditions. The positive effect of the risk appetite shock on EBP is quite persistent, lasting about one year, consistent with the idea that this shock has substantial and lasting effects on risk premia. The effects of a risk appetite shock on macro variables are stronger than the effects of a risk-free rate shock. In particular, the decline in industrial production is more pronounced and statistically significant. Unemployment also rises, though the response is less precisely estimated. While it is difficult to compare magnitudes, given that the two shocks are normalized differently, the effects of RISK appear to be more persistent and significant than for MPS.

3.4 Joint estimation with MPS and RISK

We now turn to joint estimation that disentangles the two shocks associated with MPS and RISK. In this case, the two impact coefficient vectors s_1 and s_2 are identified only up to a linear combination,

Figure 2. Effects of monetary policy shocks: separate single-instrument estimation



Impulse response functions for monetary policy shocks, identified with separate single-instrument proxy SVARs. Left column: MPS shock. Right column: RISK shock. Shaded areas show 68% (dark blue) and 90% (light blue) confidence intervals. Responses are shown in each variable's own units (Y2 and EBP in basis points; IP, CPI, and BCOM in log points ×100; UR in percentage points) and are not cumulated.

requiring one additional restriction besides the normalizations.

The most common approach is the one developed by Mertens and Ravn (2013), which has subsequently been used in several empirical macroeconomic studies (e.g., Lakdawala, 2019; Känzig, 2021). In this approach, the relative response matrix $\zeta = S_{21}S_{11}^{-1}$, which captures how non-policy variables respond to the two structural shocks relative to the policy variables, and the covariance block $Q = S_{11}S_{11}'$ are recovered from the instrument-residual covariances. Because Q is a 2×2 symmetric matrix, it has three unique elements. Since S_{11} has four free parameters, the rotation between the two shocks remains undetermined. A Cholesky decomposition solves this problem by imposing a zero in either the upper-right or lower-left element of a triangular factor of Q. In the Mertens-Ravn algorithm this factor is not S_{11} itself but $S_{11} - \eta\, S_{21}$, the impact on the policy variables net of the component transmitted through the non-policy shocks, where $\eta = S_{12}S_{22}^{-1}$ collects the loadings of the policy variables on those shocks.

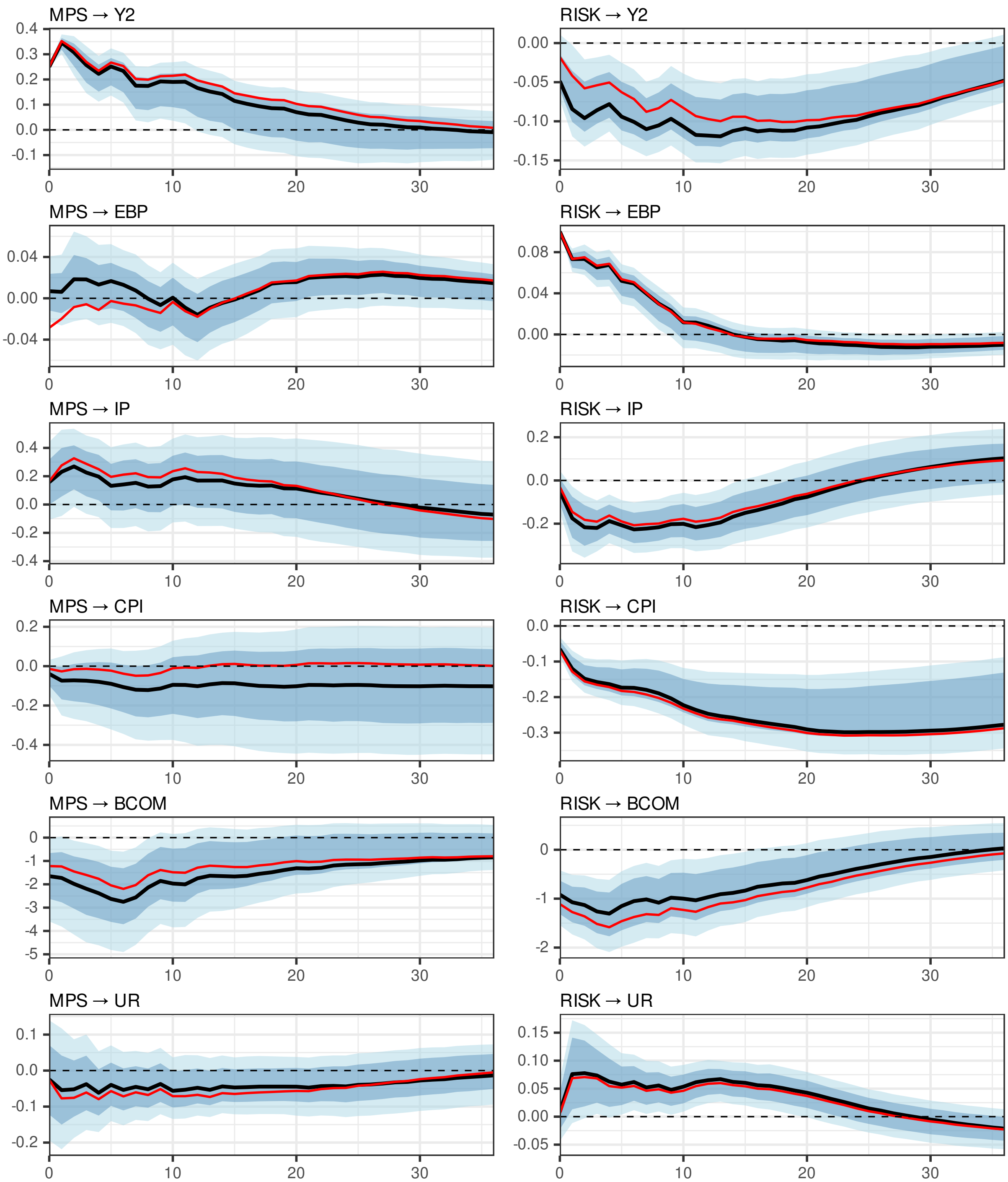
The Cholesky decomposition imposes a causal ordering on the two policy variables, similar to the standard recursive identification but applied only within the 2×2 policy block. If the risk-free rate is ordered first, the RISK shock is restricted to have zero contemporaneous impact on the two-year yield, and to operate through effects on EBP. Intuitively, this ordering attributes all FOMC-induced movement in risk-free rates to MPS, while any contemporaneous change in credit spreads can reflect either shock. If, by contrast, the EBP is ordered first, then the RISK shock is the only shock that directly moves the EBP on impact. Because the two orderings produce very similar impulse responses in our data, the choice is not consequential for our results.[19]

The resulting impulse responses are shown in Figure 3. The black lines and the confidence intervals correspond to the case with the risk-free rate shock ordered first. The red lines show the impulse responses for the alternative ordering with the RISK shock ordered first. The two different identification assumptions lead to very similar estimates of the macroeconomic effects of monetary policy shocks. The main appreciable differences are at very short horizons for the non-targeted policy variable—exactly where the identification restriction is present. Otherwise there are just small differences in the macro responses, mainly for the response of CPI and BCOM to the MPS shock.

The central result of this VAR analysis is a marked difference between the RISK shock and the MPS shock. The former has the expected contractionary and disinflationary effects on macroeconomic variables. Industrial production, consumer and commodity prices decline persistently, the

[19] Because the restriction applies to the impact net of the non-policy component, the restricted shock retains a small contemporaneous effect on the restricted policy variable, transmitted through η. The impulse responses below therefore do not show an exact zero at horizon 0 in the restricted cell: with the risk-free rate ordered first, the impact response of the two-year yield to RISK is -4.9 basis points against the $+25$ basis point normalization for MPS. The restriction rules out a direct effect through the policy channel rather than any contemporaneous comovement. The zero-impact method of Appendix C restricts the impact matrix directly and does deliver an exact zero.

Figure 3. Effects of monetary policy shocks: Mertens-Ravn method



Impulse response functions for monetary policy shocks, identified using Mertens and Ravn (2013) method. Left column: risk-free rate shock. Right column: risk appetite shock. Black lines and shaded areas show point estimates and 68% (dark) and 90% (light) confidence intervals for the ordering with the risk-free rate shock first. Red lines show point estimates for the alternative ordering with the risk appetite shock first. Responses are shown in each variable's own units (Y2 and EBP in basis points; IP, CPI, and BCOM in log points ×100; UR in percentage points) and are not cumulated.

unemployment rate rises, and these effects are statistically significant. This shock also persistently lowers the two-year yield, consistent with expected monetary easing in the future to counteract the deteriorating economic outlook.

By contrast, in this setting the MPS shock no longer produces the conventional contractionary responses. Industrial production rises and the unemployment rate falls, in contrast to the conventional effects of a contractionary shock. The level of consumer prices falls modestly, and the implied decline in inflation is almost completely transitory, in contrast to the common view that policy has persistent effects on inflation. The only conventional response is observed for commodity prices.

These MPS responses differ sharply from the single-instrument estimates in Figure 2. Because MPS and RISK are positively correlated, the single-instrument MPS estimates combine the interest-rate channel with the risk appetite channel, while the joint identification separates the two. The macroeconomic effects of the separately identified MPS shock are then small and imprecisely estimated, and the effects on real activity even switch signs relative to the single-instrument estimates. The difference is clearest for consumer prices: according to the single-instrument estimation, the MPS shock produces a large and persistent decline in CPI, but this response is absorbed by the RISK shock once we identify both shocks jointly. This evidence suggests that the conventional effects estimated with high-frequency interest-rate surprises alone largely reflect transmission through risk appetite and risk premia rather than through risk-free rates.

These results are not unique to the Mertens-Ravn identification method. We also consider two alternative identification approaches: a triangular restriction on the instrument-shock covariance matrix Φ (Lunsford, 2015; Lakdawala, 2019) and zero-impact restrictions on the structural impact matrix (Montiel Olea, Stock and Watson, 2021). Appendix C describes these methods in detail and reports the corresponding impulse responses. The estimates from both alternative approaches are very similar to the results in Figure 3.

3.5 Quantitative importance: variance decompositions

The impulse-response estimates suggest that risk appetite shocks lead to strong macroeconomic effects, while the effects of interest-rate shocks are more modest, barely statistically significant, and often puzzling in terms of their sign. But the magnitudes of these estimated dynamic responses are difficult to interpret because they depend on the normalization of the effects. To better understand the quantitative importance of the two different shocks, we carry out forecast error variance decompositions, which reveal the contribution of each structural shock to the variance of each macroeconomic variable across forecast horizons.

Table 5 reports the forecast error variance decompositions for our main identification methods.

Table 5. Forecast error variance decomposition

	MPS shock					RISK shock				
	1	6	12	36	∞	1	6	12	36	∞
Panel A: Single-instrument										
Y2	25.0	13.2	8.4	8.3	8.9	1.4	0.5	3.3	16.4	15.6
EBP	30.1	30.4	26.3	21.6	20.2	60.7	56.4	48.9	40.4	38.3
IP	0.9	0.6	1.2	0.6	7.7	0.0	6.3	8.1	4.5	11.9
CPI	30.4	42.6	43.2	40.9	23.7	42.6	63.1	63.4	65.7	37.4
BCOM	35.7	44.9	44.1	40.8	26.4	32.1	39.9	37.8	33.9	21.8
UR	0.1	1.0	1.0	1.3	2.4	0.0	5.4	6.4	6.7	7.5
Panel B: Mertens–Ravn (risk-free rate shock ordered first)										
Y2	74.0	57.6	49.7	32.8	25.4	8.6	15.9	24.4	40.3	32.9
EBP	0.1	0.8	0.7	3.4	3.6	72.6	63.9	55.5	47.8	46.0
IP	4.3	6.4	4.8	2.8	3.8	1.3	15.8	17.4	9.7	13.7
CPI	4.6	5.1	5.5	3.2	2.1	38.7	60.0	59.9	66.9	37.5
BCOM	18.6	24.0	25.2	24.8	18.0	17.6	21.5	19.3	16.7	11.7
UR	0.4	1.8	2.8	3.7	2.8	0.1	10.5	13.2	13.6	12.9
Panel C: Mertens–Ravn (risk appetite shock ordered first)										
Y2	81.5	67.9	62.0	44.7	33.9	1.1	5.6	12.1	28.4	24.4
EBP	2.1	1.0	1.1	4.7	5.2	70.6	63.6	55.2	46.5	44.4
IP	5.2	10.8	8.8	5.0	4.1	0.5	11.4	13.3	7.4	13.3
CPI	0.6	0.4	0.6	0.1	0.1	42.7	64.7	64.8	69.9	39.5
BCOM	11.1	14.6	16.0	16.4	13.1	25.0	30.9	28.5	25.1	16.6
UR	0.4	3.9	5.7	6.7	5.0	0.1	8.4	10.3	10.6	10.7

Entries show the percentage of forecast error variance at horizon h (months) explained by each shock. Panel A uses separate single-instrument proxy SVARs. Panels B and C use Mertens–Ravn identification with the Cholesky ordering stated in each panel heading, applied to the policy-block impact net of non-policy shocks, $S_{11} - \eta S_{21}$. "Risk-free rate shock ordered first" restricts the direct impact of the risk appetite shock on the two-year yield to zero; "risk appetite shock ordered first" restricts the direct impact of the risk-free rate shock on the EBP. VAR sample: 1977:06–2025:09 (T = 580 after p = 12 lags), of which 241 months have nonzero instruments. H = 36 month horizon. Table C.1 in Appendix C reports analogous results for Lunsford–Lakdawala and zero-impact identification.

Panel A shows that for the single-instrument estimation, the share of variance explained by RISK is substantially higher for IP, CPI and UR, while for BCOM both shocks contribute similarly. In interpreting the results in this first panel, the reader should keep in mind that these are not separate structural shocks, but simply two different versions of monetary policy shocks with partly overlapping contributions.

For Panels B and C, the two shocks are orthogonal by construction. The RISK shock explains a much larger portion of the variance in industrial production, consumer prices, and the unemployment rate, the key macroeconomic outcome variables. Its contribution to the unconditional variance of these variables is around 10–40%, while the MPS shock explains at most 5%. The MPS shock matters mainly for the two-year yield and commodity prices.[20]

Together, the impulse responses and the variance decompositions show that the risk appetite shock accounts for most of the macroeconomic effects of monetary policy. This finding implies that the pure interest-rate policy shock plays a more limited role in the transmission of monetary policy to key macroeconomic aggregates than earlier estimates suggest.

4 Understanding the Mechanism

We now turn to the economic mechanisms that can rationalize our empirical results. Two broad questions guide our discussion: How can monetary policy announcements affect risk appetite, either via shifts in interest-rate policy or directly via other types of communication? And why do asset prices and risk appetite matter for monetary transmission, above and beyond the risk-free interest rates controlled by a central bank? We provide theory-based answers to these questions, synthesizing important earlier work in the monetary and macro-finance literature. In addition, we document new evidence for state-dependent effects of monetary policy surprises on risk appetite that is consistent with existing theoretical models of the risk-taking channel. We also discuss Fed information effects, which would threaten our identification strategy but receive little support in our analysis and in other recent work. Both theories and evidence further support the view that accounting for changes in risk appetite is paramount for understanding monetary transmission.

4.1 Interest rates and risk appetite

The first of our guiding questions arises from the results in Section 2, which establish that monetary policy announcements cause substantial volatility in risk appetite. These movements (captured by RISK) are correlated with changes in risk-free rates (captured by MPS), and we begin our discussion by reviewing the main mechanisms that explain this correlation, that is, the direct effects of interest-rate policy on risk appetite and risk premia. This correlation is far from perfect, however, and a substantial share of the variation in RISK is orthogonal to MPS. Below, in Sections 4.2 and 4.3, we explain several reasons for this orthogonal RISK variation, including the role of state dependence and central bank communication.

The literature on the "risk-taking channel" of monetary policy has established a range of mech-

[20] In Appendix C, we show that these variance decomposition results are also robust to alternative identification approaches. Plagborg-Møller and Wolf (2022) show that variance decompositions based on external instruments are only interval-identified, with the estimated share a lower bound on the true contribution of the shock. The shares we report for the MPS and RISK shocks therefore understate their true importance, and our comparison rests on the pattern across the two shocks rather than on the precise level of any single share.

anisms that connect interest rates to risk appetite and risk premia. Here we review the most important ones, without any claim to comprehensiveness, focusing on how monetary easing increases risk appetite and thereby lowers risk premia.

- **Intermediary balance sheets and leverage.** By increasing asset values and reducing funding costs, monetary easing relaxes the balance-sheet and leverage constraints of financial intermediaries. With greater capacity to absorb risk, intermediaries expand their risky asset holdings, compressing risk premia (Adrian and Shin, 2010; He and Krishnamurthy, 2013; Adrian and Boyarchenko, 2018; Drechsler, Savov and Schnabl, 2018; Kekre, Lenel and Mainardi, 2024).

- **Credit channel and financial accelerator.** Lower interest rates improve borrower net worth and relax collateral constraints. The resulting increase in credit supply amplifies risk-taking in financial markets (Bernanke, Gertler and Gilchrist, 1999; Borio and Zhu, 2012; Bruno and Shin, 2015). Whereas the intermediary channel works through the balance sheets of lenders, this channel works through the balance sheets of borrowers.

- **Reaching for yield.** Many investors target certain nominal returns, either due to behavioral anchoring or institutional constraints (e.g., defined-benefit pensions and insurance liabilities). In response to lower interest rates, they accept greater portfolio risk to meet their objective and thus exhibit effectively higher risk appetite (Stein, 2012; Hanson and Stein, 2015; Becker and Ivashina, 2015; Campbell and Sigalov, 2022).

- **Uncertainty and tail risk.** Monetary easing tends to lower the perceived uncertainty about the future rate path (Bauer, Lakdawala and Mueller, 2021) and the option-implied likelihood of tail events in equity and other asset markets (Hattori, Schrimpf and Sushko, 2016). Both effects reduce the quantity of risk that investors bear, thereby lowering risk premia.[21]

- **Habits and consumption.** In the presence of consumption habits, changes in the economic outlook and, in particular, expected consumption affect the risk appetite of households (Campbell and Cochrane, 1999). Monetary easing raises expected consumption relative to its habit level, which lowers effective risk aversion and risk premia (Pflueger and Rinaldi, 2022). More generally, changes in interest-rate policy that improve the consumption outlook can increase risk appetite in consumption-based frameworks.

- **Heterogeneous agents and redistribution.** Monetary easing redistributes wealth toward agents with higher risk tolerance, such as leveraged borrowers or equity holders (Kekre and

[21] As noted in Section 2.3, our empirical analysis using RISK cannot perfectly distinguish between price and quantity of risk.

Lenel, 2022). This kind of redistribution—a composition effect—raises the wealth-weighted average willingness to bear risk, even though the risk appetite of individual agents has not changed.

These channels connect interest-rate policy to risk appetite and risk premia and can rationalize the empirical connection between changes in interest rates and risk appetite. The positive correlation between MPS and RISK we documented in Section 2 is consistent with earlier evidence of the effects of monetary policy on stock prices and risk premia, including Bernanke and Kuttner (2005), Bauer and Swanson (2023*b*), Bauer, Bernanke and Milstein (2023), among others.

This discussion is closely related to the model of monetary policy, asset prices, and risk premia developed by Caballero and Simsek (2024*a*). In their framework, the connection between conventional interest-rate policy and asset prices is captured with a link from risk-free interest rates to perceived asset return volatility. This reduced-form link from interest rates to risk premia is a convenient modeling shortcut. Taken literally, it works exclusively via changes in the perceived quantity of risk rather than changes in risk appetite. But this link can be viewed as a stand-in for most of the theoretical channels described above; in this way, Caballero and Simsek provide a helpful organizing framework that encompasses a broad range of mechanisms developed in the theoretical macro-finance literature.

4.2 Time variation and state dependence

While various mechanisms can explain the empirical link from interest rates to risk appetite, it is less obvious why and how monetary policy can move risk appetite *independently* of changes in interest-rate policy. The variation in RISK that is orthogonal to MPS suggests that these mechanisms should be quantitatively important: As noted in Section 2.4, MPS explains about 20% of RISK in a linear regression, meaning that 80% of the variation remains unexplained. Some portion of this unexplained variation is likely due to idiosyncratic factors and news that are unrelated to monetary policy. But FOMC communication is a major source of news for financial markets during the intraday window over which we calculate RISK, and this calls for an explanation of its effects on RISK$^{\perp}$.

Two different channels, which we discuss in turn in this and the next subsection, can explain this variation in RISK$^{\perp}$. First, the effects of interest-rate surprises on risk appetite and risk premia are characterized by important non-linearities, time variation and state-dependence, which inflate the residual in a linear regression of RISK on MPS. Second, central bank communication can generate truly orthogonal shocks to risk appetite that are independent of interest-rate policy.

The residual variation in RISK is the result of a full-sample, linear regression, but the effects of interest-rate policy on risk appetite and risk premia are neither constant nor linear. The time variation and state dependence of these effects have not been appreciated by the literature on monetary transmission, despite their important role for explaining seemingly orthogonal variation.[22] Most of the theoretical mechanisms discussed above in Section 4.1 imply non-linear or state-dependent linkages, as the following examples show:

- The strength of the channel via intermediary balance sheets and leverage is inherently state-dependent. Some theories predict that the same rate change has modest effects on risk premia when intermediaries are well capitalized but large effects when capital is scarce (He and Krishnamurthy, 2013). Kekre, Lenel and Mainardi (2024) develop a segmented-markets model in which arbitrageur wealth is an endogenous state variable governing the price of risk, and show, in the model and in the data, that the effects of monetary policy on term premia are amplified when measures of intermediation capacity are low.

- During calm economic times, low volatility loosens risk-management constraints and intermediaries endogenously build up leverage (Adrian and Shin, 2010; Brunnermeier and Sannikov, 2014; Adrian and Boyarchenko, 2018), so that a subsequent policy surprise triggers larger portfolio rebalancing and bigger movements in risk premia. The prediction is the opposite from the previous one, as amplification occurs when balance-sheet capacity is ample. Which of the two forces dominates is an empirical question.[23]

- Reach-for-yield effects are stronger at lower rate levels (Campbell and Sigalov, 2022).

- In habit models, effective risk aversion is a nonlinear function of the surplus consumption ratio (Campbell and Cochrane, 1999), so the same easing surprise moves risk aversion and risk premia much more in recessions, when surplus consumption is low, than in expansions (Pflueger and Rinaldi, 2022).

- With heterogeneous intermediaries, the composition of risk-taking itself changes with the level of rates; at very low rates, further easing disproportionately expands the balance sheets of the most aggressive intermediaries, so that effects on risk premia diminish or even reverse (Coimbra and Rey, 2024).

[22] Knox and Vissing-Jorgensen (2025) are an exception. They point out that the coefficient in event-study regressions of stock returns on FOMC surprises "is unlikely to be constant—or even to have the same sign—across FOMC announcements" (p. 275).

[23] Brunnermeier and Sannikov (2014) call this the "volatility paradox." As volatility and exogenous risk fall, intermediaries lever up, capital buffers weaken, and endogenous crisis risk remains. While they emphasize the crisis proneness of a calm financial system, the mechanism also implies that risk premia respond more strongly to policy surprises during calm times.

We now establish some empirical evidence on the time-varying relationship between MPS and RISK. Our results confirm that the strength of the connection between interest-rate policy and risk premia varies over time and depends on the business cycle and credit cycle in ways that are consistent with some of the above-mentioned theoretical channels.

Figure 4 plots the regression coefficient from a rolling 3-year regression of RISK on MPS, together with the corresponding R^2. There is clear evidence of time-variation in the sensitivity of RISK to MPS. There are two periods (around 2001–2004 and 2020–2023) when the R^2 essentially drops to zero and the two shocks are uncorrelated. In contrast, the three-year period leading up to 2015 has the largest slope estimate, about four times higher than its unconditional average, whereas the period leading up to 2007/08 has the largest R^2 of 0.75. Toward the end of the sample, we also observe again a tight relationship between MPS and RISK, with a high slope and R^2.

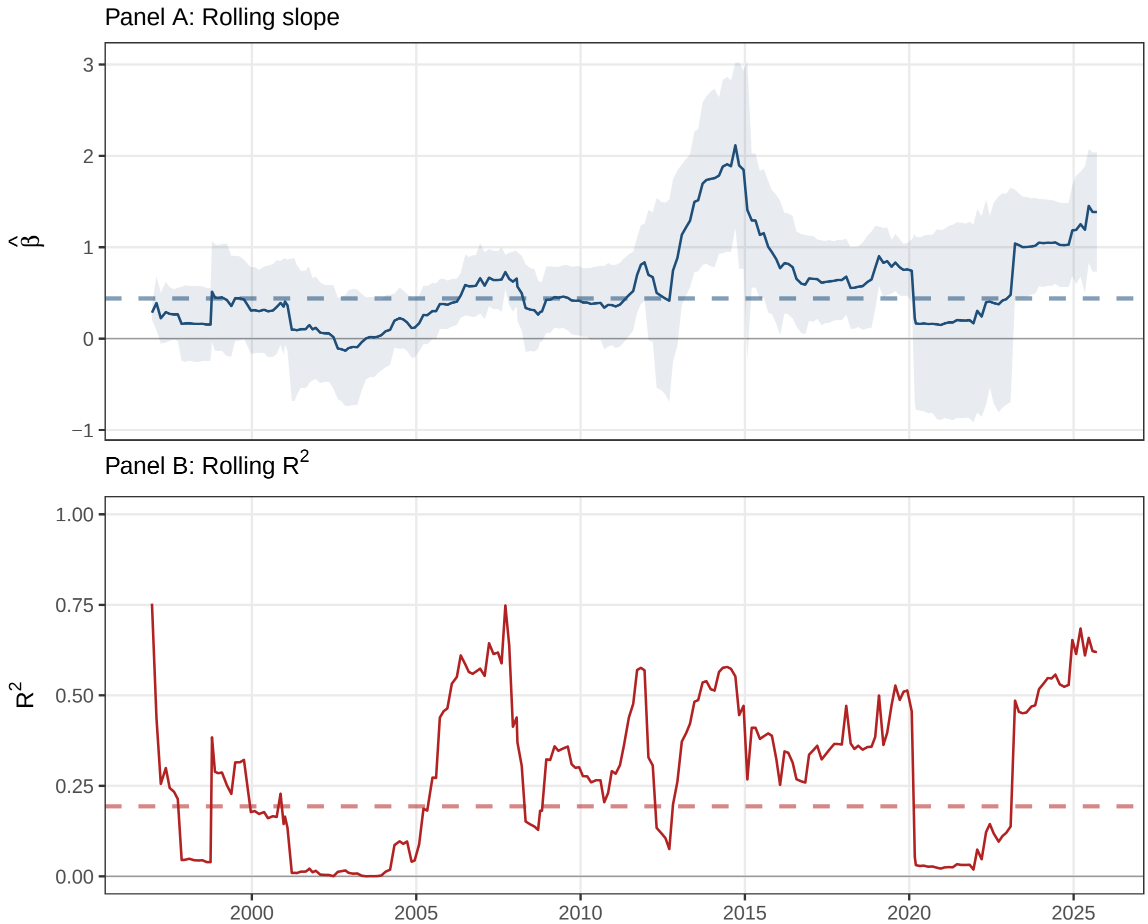
To better understand the economic drivers of this time-varying correlation between MPS and RISK, Table 6 reports estimates of state-dependent regressions of RISK on MPS. For each candidate state variable, we split the sample into quartiles and estimate a separate regression within the subsamples where the state variable takes values in the lowest and highest quartile. The results show strong evidence of state dependence.

Consistent with non-linear reaching-for-yield effects, lower yield levels are associated with a higher sensitivity of RISK to MPS. The slope of RISK on MPS is roughly twice as large when the 2-year Treasury yield is low as when this yield is high, and the difference between the coefficients across the two sub-samples is statistically significant at the one-percent level. The same pattern emerges, roughly as strongly, when we use the effective fed funds rate as the state variable, although here the slope difference is not statistically significant.

The sub-sample regressions also show very clearly that monetary policy surprises have larger effects on RISK during times of low volatility and risk premia. In particular, the regression slope is significantly larger during periods when the VIX and the EBP are low, compared to the periods when these measures are elevated. In both cases, the R^2 is also several times larger for the bottom-quartile compared to the top-quartile sample, indicating that MPS explains a much larger share of RISK during calm times. Similar to the reach-for-yield estimates, this pattern matches the leverage channel, in which calm financial conditions let intermediaries build leverage, so that a given policy surprise moves risk premia more. The rolling estimates in Figure 4 also show this pattern, with the strongest effects during the low-volatility phase in the run-up before the Great Financial Crisis, and the weakest effects during the 2001 and 2020 stress episodes.

Measures of intermediary balance-sheet capacity yield similar state dependence. We use the He, Kelly and Manela (2017) intermediary capital ratio, detrended using a rolling three-year mean

Figure 4. Rolling regression of RISK on MPS



The figure plots, for a trailing 3-year calendar window of FOMC events, the slope coefficient $\hat{\beta}_t$ (Panel A) and the R^2 (Panel B) of a regression of RISK on MPS within the window. The number of FOMC events in each window varies between 8 and 28, with a median of 25. The shaded blue band around $\hat{\beta}_t$ in Panel A is the 99% HC1 confidence interval. The thick dashed horizontal lines mark the corresponding full-sample value in each panel ($\beta = 0.44$ in Panel A; $R^2 = 0.19$ in Panel B). The sample runs from January 1996 to September 2025 (245 FOMC events).

so that it captures whether dealer capital is being rebuilt or depleted.[24] The sensitivity of RISK to MPS is more than three times as large when this capital is high relative to trend as when capital is scarce, and the difference is significant at the one-percent level. The R^2 rises fourfold across the two subsamples. This state dependence lines up with the same logic: when intermediaries have rebuilt capital and can absorb risk, a given policy surprise moves risk premia by more. Using the Adrian, Etula and Muir (2014) broker-dealer leverage ratio leads to a similar result. Broker-dealer leverage is procyclical, rising in good times when funding constraints are relaxed, so in the

[24] The level of the ratio trends down before 2008 and up afterwards, so quartiles of the level compare the pre- and post-crisis regimes rather than constrained and unconstrained states. Trailing means of two to five years, log deviations, and 12-month changes all deliver the results reported here.

Table 6. State-dependent slope of RISK on MPS: lower vs. upper quartile

	Q1 (lower 25%)		Q4 (upper 25%)		Diff.
State variable S_{t-1}	$\hat{\beta}$ (t)	R^2	$\hat{\beta}$ (t)	R^2	p-val
Reach for yield					
2-year Treasury yield (%)	1.03^{***}	0.47	0.47^{***}	0.20	0.00^{***}
	(8.29)		(3.47)		
Effective fed funds rate (%)	0.78^{***}	0.23	0.37^{*}	0.14	0.17
	(3.46)		(1.92)		
Volatility paradox / pro-cyclical leverage					
VIX	0.85^{***}	0.65	0.42^{***}	0.18	0.02^{**}
	(10.04)		(2.72)		
Excess bond premium (%)	0.60^{***}	0.35	0.25	0.07	0.09^{*}
	(4.60)		(1.52)		
Intermediary balance sheet constraints					
Intermediary capital ratio (detrended)	0.29^{**}	0.13	1.07^{***}	0.51	0.00^{***}
	(2.08)		(6.43)		
Broker-dealer leverage growth	0.29	0.09	0.61^{***}	0.48	0.12
	(1.57)		(5.63)		
Business cycle					
Nonfarm payrolls, 12m growth (%)	0.23^{*}	0.10	0.60^{***}	0.31	0.05^{**}
	(1.69)		(4.65)		
Real GDP, 4-quarter growth (%)	0.40^{***}	0.18	0.52^{***}	0.28	0.53
	(2.99)		(4.02)		

Slope $\hat{\beta}$, HC1 t-statistic in parentheses, and R^2 from regressions of RISK on MPS within the lower (Q1) and upper (Q4) quartile of each state variable S_{t-1}, with the p-value of a test of equal slopes in the last column. Significance: * 10%, ** 5%, *** 1%. Each S_{t-1} is the most recently released observation strictly before the FOMC date: the prior day's close for daily series, the latest print for monthly series, and the end of the last completed quarter for quarterly series (Z.1 leverage, real GDP). The intermediary capital ratio is detrended by subtracting its mean over the preceding three years, so positive values indicate dealer capital above its recent average. Broker-dealer leverage growth is the quarterly log change in the Z.1 leverage ratio, the pricing factor of Adrian, Etula and Muir (2014), for which positive values indicate expanding dealer balance sheets. The sample runs from January 1996 to September 2025 (245 FOMC events, 61 or 62 per bin); the capital-ratio row starts in March 2000 (211 events, 53 per bin), when three years of daily data first become available. Sources: FRED (DGS2, DFF, VIXCLS, PAYEMS, GDPC1, BOGZ1FL664090005Q, BOGZ1FL664190005Q), Gilchrist and Zakrajšek (2012) excess bond premium, and the He, Kelly and Manela (2017) capital ratio from `https://zhiguohe.net`.

mapping of Adrian, Etula and Muir it is low leverage that signals tight constraints. We use the growth rate of leverage, which is the object they use as a pricing factor. While the difference in coefficients between the two quartiles is not significant, the coefficient is about twice as large and highly significant when dealer leverage has been expanding, and indistinguishable from zero when leverage is contracting. Both measures of intermediary capacity indicate that risk appetite responds more strongly to interest-rate surprises during times when dealers have the balance-sheet capacity to take on risk, corresponding to calm economic times.

The slope is larger in expansion phases than in recessionary phases. This is evident from the sample splits based on employment growth and real GDP growth. In both cases, high-growth observations have a higher and strongly significant RISK-response to interest-rate surprises. The difference in the estimated sensitivity for low-growth and high-growth periods is statistically significant at the five-percent level for employment growth. These results suggest that risk appetite reacts more strongly to monetary policy shocks in "good times" when the economy is improving.

In sum, our evidence shows strong time variation and state dependence of the effects of monetary policy surprises on risk premia and risk appetite. The direction is consistent across state variables: the sensitivity of risk appetite to interest-rate surprises is highest when rates, volatility and credit spreads are low, when intermediaries have rebuilt capital and expanded leverage, and when the economy is growing. The sign of this state dependence is tangential to our main point. Our argument requires only that the Fed's interest-rate policies affect risk appetite and risk premia in ways that a linear relationship between monetary policy surprises and risk asset returns does not capture. This complexity contributes to the variation in RISK$^{\perp}$, and equally to the FOMC risk shifts of Kroencke, Schmeling and Schrimpf (2021) and the Fed "non-yield" shock of Boehm and Kroner (2026*a*).

4.3 Communication and risk appetite

Central bank communication can also directly affect risk appetite—without changing the path of interest rates—via several different channels. Some of these mechanisms are discussed in Boehm and Kroner (2026*a*), whose "non-yield" shock is the close conceptual counterpart of RISK$^{\perp}$: variation in risk premia that is unspanned by the yield curve, i.e., movements in risky asset prices that cannot be attributed to changes in the expected path of policy rates.

First, central banks can change perceptions about the balance of risks and uncertainty, thereby directly affecting risk premia and asset prices. By communicating certain contingency plans they could effectively take certain tail risks off the table, for example by signaling a tendency for a Fed put that would prevent large negative stock returns (Cieslak and Vissing-Jorgensen, 2021) or by making other conditional policy promises (Haddad, Moreira and Muir, 2025). Boehm and Kroner point to the same channel, arguing that the Fed can credibly promise a more decisive policy response in adverse states of the world. Relatedly, a central bank can communicate about its policy reaction function via qualitative statements or quantitative projections. Changes in the perceived reaction function also shift the balance of risks, and thus affect asset prices (Bauer, Pflueger and Sunderam, 2024).

A separate incomplete information mechanism is based on persistent differences in economic expectations between the Fed and financial market participants. If the Fed's communication reveals disagreement about the economic outlook relative to market expectations, then markets may price in future "policy errors" and generate a policy risk premium (Caballero and Simsek, 2022, 2024*a*). This mechanism links risk premia to the *disagreement* about the rate path, not the rate path itself.

Another mechanism explains transitory movements in asset prices due to rebalancing flows. Even if the monetary policy decision is fully anticipated and there are no surprises, the announcement can still trigger portfolio rebalancing across heterogeneous investors and generate transitory price pressure in risky assets. Evidence on flow-driven returns around FOMC announcements in Kroencke, Schmeling and Schrimpf (2021) provides support for this mechanism.

Announcements of central bank asset purchase programs and other extraordinary policy measures can also affect risk premia in financial markets above and beyond any effects on the expected policy path. A large empirical literature documents risk premium effects of the Fed's bond purchases on term premia, credit spreads, and beyond (Gagnon et al., 2011; D'Amico and King, 2013; Gilchrist et al., 2024). Many theoretical contributions model the risk premium effects of asset purchases (e.g. Gertler and Karadi, 2013; Vayanos and Vila, 2021; Caballero and Simsek, 2021). It is well established that announcements of central bank asset purchase programs can affect risk premia across markets.

Taken together, two reasons explain why the effects of monetary policy on asset markets are not fully captured with common statistical models based on interest-rate changes. First, interest-rate policy affects risk appetite, risk premia and asset prices in non-linear, time-varying and state-dependent ways. Second, monetary policy communication can directly affect risk asset prices without changing the policy rate path.

4.4 Fed information effects

Fed information effects are another potential mechanism that can decouple movements in risk asset prices and risk premia from interest-rate surprises around monetary policy announcements. According to this theory, monetary policy actions or communication can reveal information about the economic outlook that directly changes private sector expectations. Romer and Romer (2000) show that the Fed's inflation forecasts contain information beyond that of commercial forecasters, and that forecasters revise their own predictions when policy moves, which they suggest explains why long rates rise when policy tightens. Nakamura and Steinsson (2018) take this logic to high-frequency announcement windows. For example, monetary easing or a downward revision in the central bank's projections of future real activity could cause forecasters and investors to become more pessimistic, thereby raising risk premia and lowering risk appetite. As discussed in Section 2, Jarociński and Karadi (2020) identify such information shocks from the sign of the stock market response to the interest-rate surprise. Boehm and Kroner (2026*a*) also explain how information effects can cause movements in risk asset prices that are not attributable to the expected rate path.

If information effects drive an important share of the variation in our surprises, this would challenge the causal interpretation of our proxy SVAR estimates as the macroeconomic effects of monetary policy. The reason is reverse causality: an expected future economic development, possibly caused by other structural shocks, is signaled by the Fed and causes risk appetite to change. Both policy surprises, and especially the orthogonal movements in RISK, would be affected by such a shock. Information effects, in other words, are a threat to our identification strategy.

The empirical importance of information effects is debated in the literature. Nakamura and Steinsson (2018) and Jarociński and Karadi (2020) provide the most prominent evidence in favor. Yet much of the recent evidence is unfavorable: several studies find that information effects play only a minor role for the response of forecasts and asset prices to monetary policy (Bauer and Swanson, 2023*a*,*b*; Karnaukh and Vokata, 2022; Bu, Rogers and Wu, 2021; Sastry, 2026; Swanson, Wang and Wu, 2026).[25]

The evidence for information effects now largely rests on the puzzling response of the stock market and other risk assets to interest-rate policy surprises (Jarociński and Karadi, 2020; Jarociński, 2022; Gürkaynak et al., 2021). But our discussion above in Sections 4.2 and 4.3 has demonstrated that various other economic channels can decouple asset prices from the conventional monetary policy surprises. Our state-dependence results are a case in point: the sensitivity of risk appetite to interest-rate surprises varies with the economic and financial environment, so a classification based on the sign of the stock market response will label some events as information shocks even though they reflect ordinary policy news arriving in a different state. More generally, these channels can generate orthogonal movements in risk appetite without any information effects, and so offer a reinterpretation of the evidence in the papers mentioned above.

Our own narrative evidence in Section 2.4 speaks to this question for the events with the largest movements in risk appetite. Of the fourteen events, only one had news coverage consistent with the Fed signaling news about the economic outlook, while all others had narratives unrelated to information effects. The narratives cover only the largest realizations of RISK, but these are precisely the events that carry most of the identifying variation and that any information-effects

[25] The information-effects hypothesis has been challenged in earlier work as well. Faust, Swanson and Wright (2004) find that, aside from industrial production, policy surprises do not systematically improve forecasts of subsequent macro data releases, nor lead the private sector to revise its forecasts. Relatedly, Hoesch, Rossi and Sekhposyan (2023) compare the accuracy of Fed and private-sector forecasts and find that the forecasting advantage documented by Romer and Romer (2000) has largely disappeared in recent decades.

account would have to rationalize. Beyond the extreme observations, the correlation evidence in Section 2.5 points in the same direction: the JK information shock picks up much the same variation as $\mathrm{RISK}^{\perp}$, and that variation lines up with risk-premium narratives rather than growth outlook news. Overall, there is little evidence that information effects are an important driver of our policy surprises.

4.5 How asset prices affect macroeconomic outcomes

Changes in asset prices affect consumption and investment above and beyond the effects of changes in interest rates. Several strands of macroeconomic theory give asset prices a central role in monetary transmission, through the following channels:

- Rising asset prices increase household consumption via wealth effects. The quantitative importance of these effects is especially large in heterogeneous-agent New Keynesian (HANK) models, because some households face financial constraints and thus have high marginal propensity to consume out of asset wealth (Auclert, 2019; Kaplan, Moll and Violante, 2018; Auclert et al., 2025). Chodorow-Reich, Nenov and Simsek (2021) estimate this channel using regional variation in stock market wealth, and find sizable effects on local employment and consumption.

- Equity valuations directly affect Tobin's Q and firm investment. This Q-theory channel is standard in New Keynesian models with investment (Christiano, Eichenbaum and Evans, 2005).

- From the borrower's perspective, higher risk appetite and asset valuations improve balance sheets, lowering the cost of debt financing and stimulating borrowing and investment. This channel operates through the financial accelerator (Bernanke, Gertler and Gilchrist, 1999) and intermediary balance-sheet mechanisms (Adrian and Shin, 2010; Gertler and Karadi, 2015).

- Changes in house prices underlie several channels of monetary transmission. Housing wealth effects on consumption are especially important, given the broader distribution of homeownership than stock market participation. House prices also matter through collateral constraints: rising home values relax borrowing constraints for homeowners, supporting consumption and residential investment.

The central role of asset prices for monetary transmission is the fundamental premise of Caballero and Simsek (2020, 2022, 2024*b*,*a*). This work unifies the above-mentioned channels by treating the aggregate asset price—corresponding to broad financial conditions—as the key state variable for aggregate demand. It provides a coherent theoretical foundation for the role of asset prices for monetary transmission.

This section has established the economic mechanisms underlying the important role of risk appetite for monetary transmission. The basic idea is relatively simple and worth re-stating: Monetary policy affects asset prices—including equity prices, credit spreads, and other risk asset prices—in ways that are not captured by conventional high-frequency measures of "monetary policy surprises." These measures rely exclusively on interest-rate changes which span only a small share of the variation in risk asset prices due to non-linearities, state dependence, and central bank communication. Because not just interest rates but various risk asset prices matter for aggregate demand and monetary transmission, it is important to account for the policy-induced changes in risk appetite in the estimation of the macroeconomic effects of monetary policy. If, by contrast, only interest-rate surprises are used in such estimation, then much of the policy effects transmitted via asset prices would be ignored. Consistent with this logic, our SVAR estimates in Section 3 show that the RISK shock has large effects on EBP, real activity, and prices, without any appreciable near-term response of the risk-free interest rate.

5 Conclusion

We construct a new high-frequency measure of risk appetite shifts around FOMC announcements, and use it alongside conventional interest-rate surprises to estimate the effects of risk appetite shifts on financial markets and on macroeconomic aggregates. Our event-study analysis documents that the link between interest-rate surprises and risk appetite shifts, commonly ascribed to the risk-taking channel of monetary policy, is time-varying and state-dependent. This is part of the reason why interest-rate surprises explain only about one-fifth of the variation in risk appetite around policy announcements. Central bank communication, including signals about the policy reaction function, can generate further movements in risk appetite and asset prices independently of changes in interest rates.

Our main empirical results come from a proxy SVAR that uses both conventional monetary policy surprises and risk appetite shifts as external instruments for two separate policy shocks. Risk appetite shocks have large and persistent contractionary effects, lowering output and prices while raising unemployment. The pure interest-rate shock produces small and imprecise responses, some with puzzling signs. Variance decompositions confirm that risk appetite shocks account for a far larger share of macroeconomic fluctuations. These results are robust across several identification methods.

Our findings imply that the prevailing approach to estimating monetary transmission, using interest-rate surprises as the sole external instrument, overstates the role of the standard interest-rate channel. Because rate surprises are correlated with risk appetite shifts, single-instrument estimates combine the two structural responses and attribute both to changes in rates. Empirical work on monetary policy should explicitly incorporate risk appetite alongside interest rates, both in the measurement of policy shocks and in the identification of their macroeconomic effects.

Our results also have implications for the conduct of policy. Because changes in risk appetite and risk asset prices are of first-order importance for monetary transmission, policy tools that directly affect risk premia are likely to be especially effective, including asset purchases, the tone and content of communication, signals about the policy reaction function, and conditional policy promises. The evidence on state dependence implies that the effectiveness of policy depends on how tightly it can control risk asset prices, which varies over time with the financial and economic environment. Strong and state-dependent effects of policy on risk premia carry financial-stability consequences that are not easily separated from monetary transmission. More broadly, monetary policy reaches the macroeconomy in large part through the prices of risk assets, so risk premia deserve at least as much attention in policy deliberations as the expected path of interest rates.

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Appendix

A Existing Risk Appetite Measures

Table A.1 summarizes the four existing risk appetite measures discussed in Section 2.1: Kroencke, Schmeling and Schrimpf (2021, KSS), Bekaert, Engstrom and Xu (2022, BEX), Bauer, Bernanke and Milstein (2023, BBM), and Boehm and Kroner (2026*a*, BK). The comparison focuses on the dimensions most relevant for our purposes. Panel A shows that the measures sort along two characteristics: frequency (daily for BBM and BEX; high-frequency for KSS and BK) and orthogonalization to risk-free rate surprises (imposed by construction for KSS and BK; left free for BBM and BEX). No existing measure combines a strict announcement-window identification with a risk-free-rate loading that is determined by the data rather than by assumption. Panel B reports descriptive statistics and correlations with MPS on the FOMC-day subsample. Panel C shows that the measures agree on direction but disagree substantially on magnitude: pairwise correlations range from 0.13 (BEX with BK) to 0.75 (BBM with BEX, both daily and sharing much of their sample), with the two high-frequency measures (KSS and BK) correlated at 0.48.

Table A.1. Overview: Existing measures of risk appetite

	KSS (2021)	BEX (2022)	BBM (2023)	BK (2026)
Panel A: Basic information				
Construction	Rotated PCA (3rd factor)	No-arbitrage model	Daily PCA, 14 indicators	Het.-based identification
Ingredients	Rates, VIX, CDX, FX basket	Equity & bond moments	Equities, vol, credit, FX	S&P 500 + 13 FX rates
Sample start	01/2006	06/1986	01/1988	01/1996
Sample end	12/2019	05/2024	05/2022	07/2025
Frequency	High-frequency	Daily	Daily	High-frequency
Availability	FOMC days	All days	All days	FOMC days
Orthogonal to MPS?	Yes	No	No	Yes
Panel B: Descriptive statistics on FOMC-day subsample				
Mean	-0.24	-0.01	-0.27	0.02
Std. dev.	1.00	0.06	1.07	0.96
N	114	233	217	236
Corr. with MPS	0.17	0.19	0.13	0.03
Panel C: Pairwise correlation matrix (FOMC-day joint sample)				
KSS (2021)	1.00	0.24	0.38	0.48
BEX (2022)		1.00	0.75	0.13
BBM (2023)			1.00	0.21
BK (2026)				1.00

All series are sign-normalized so that higher values correspond to greater risk aversion. Panel B includes the correlation of each series with MPS, which is signed so that higher values correspond to a contractionary surprise. Panel C correlations are computed on each pair's joint FOMC-day sample.

B Additional Results: MPS and RISK

B.1 High-frequency versus daily measurement

Does it matter whether we measure risk appetite shifts in a narrow announcement window or over the full trading day? At daily frequency, a broader cross-section of risk-sensitive assets becomes available for the factor extraction, since many such assets are not traded or quoted at higher frequencies. But daily measurement also picks up unrelated price movements from non-FOMC news released earlier in the day, potentially diluting the announcement signal.

To assess this, we decompose daily asset price changes for the assets in Table 1. Let Δp denote the change from the EOD price on the day before an FOMC meeting to the EOD price on the meeting day. We split it into:

$$\Delta p = \Delta^{-} p + \Delta^{+} p \tag{5}$$

where $\Delta^{-} p$ is the change from the previous day's EOD price up to 15 minutes before the FOMC statement and $\Delta^{+} p$ is the price change from 15 minutes before the statement until the EOD price of the FOMC day. A simple variance decomposition then implies:

$$1 = \frac{Var[\Delta^{-} p] + Var[\Delta^{+} p] + 2Cov[\Delta^{-} p, \Delta^{+} p]}{Var[\Delta p]}. \tag{6}$$

Figure B.1 plots this decomposition for each individual asset as well as for the two factors, MPS and RISK.

The results in this figure show that the pre-statement window accounts for about half of the total variance in daily asset price changes on average across assets. Pre-statement and post-statement price changes are only weakly correlated on average and even *negatively* correlated for several of the assets. Daily measurement thus mixes two largely unrelated sources of variation, only one of which is plausibly driven by the FOMC announcement. Using high-frequency price changes therefore sharpens the measurement of monetary policy surprises and risk appetite shifts substantially.[26]

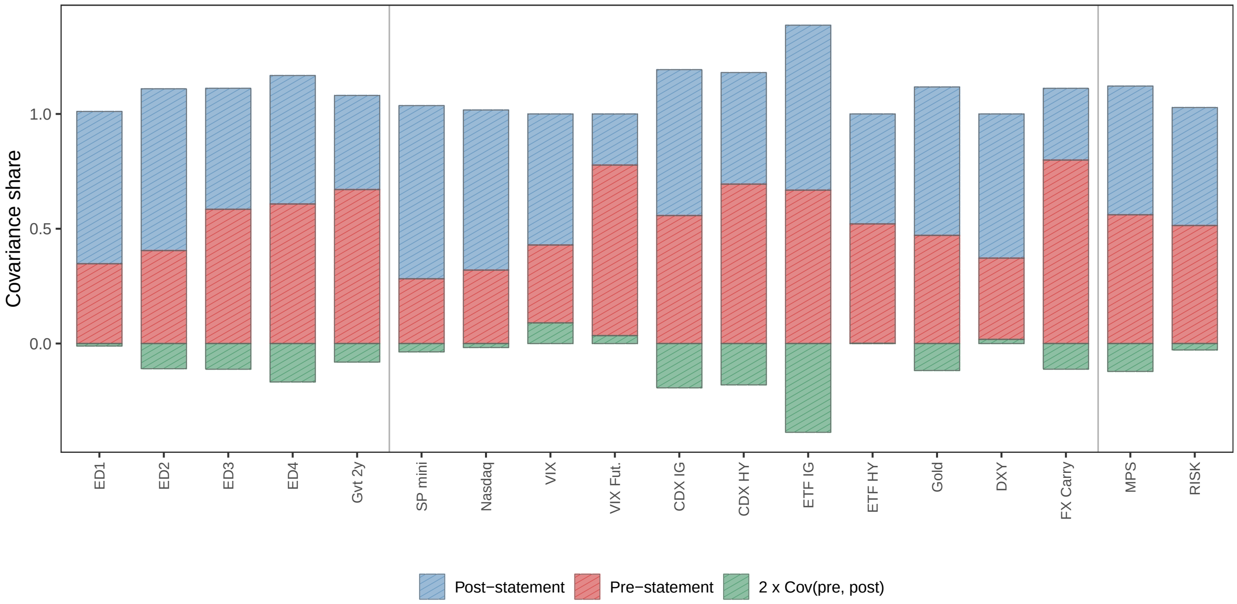
B.2 Time-series variation in RISK

Figure B.2 plots the high-frequency RISK series across the 245 FOMC events in our sample. The events with the most extreme values of RISK or RISK$^{\perp}$ are highlighted with a dot and the corresponding meeting date; these are the fourteen events listed in Table 2.

We draw the narratives in Table 2 from the Reuters news archive, using all articles published in the hours and days after each of these fourteen decisions. For each event we record the dominant causal explanation that reporters and market participants gave for the market reaction, together with a verbatim quote and the article's Reuters item ID, headline, and publication timestamp. Where the coverage explains the move by growth, inflation, or the policy path rather than by a change in the willingness to bear risk, the narrative says so. We checked every quote against the archived article.

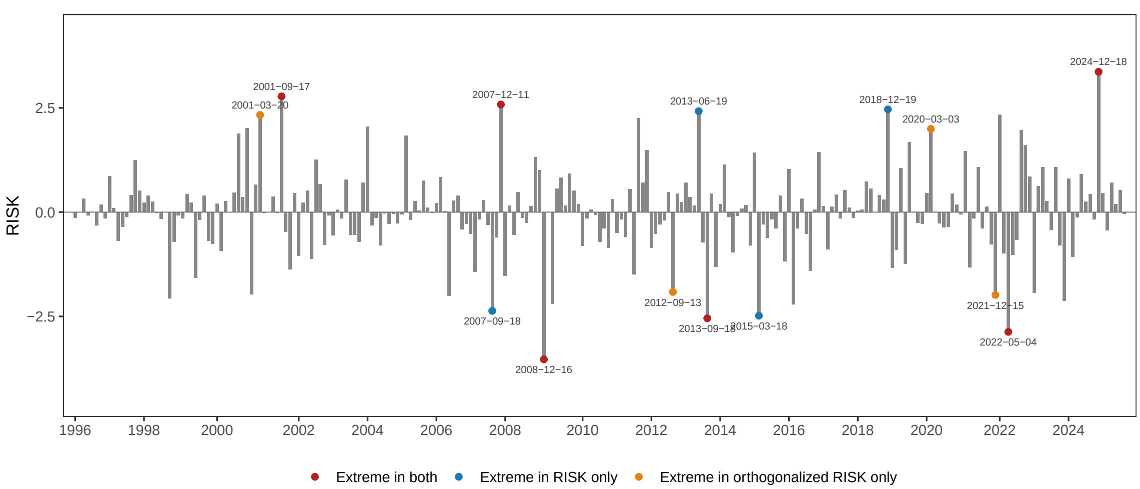
[26] This finding corroborates Gürkaynak, Sack and Swanson (2005), who advocated narrow announcement windows in this literature precisely to isolate the announcement signal from unrelated variation on the same day. An important example are the releases of U.S. macroeconomic data. Many of these news releases are at 8:30 AM (Faust and Wright, 2018) and so precede the FOMC statement.

Figure B.1. Asset price changes and shocks: variance decomposition



This figure plots results for a simple variance decomposition of daily asset price changes on FOMC days. For each asset and for the two factors MPS and RISK, the figure decomposes the variance of the daily FOMC-day price change Δp (close of the day before an FOMC meeting to the close of the FOMC day) into three components: the share due to the pre-announcement window $\Delta^{-}p$ (previous-day EOD to 15 minutes before the statement, red), the share due to the post-announcement window $\Delta^{+}p$ (15 minutes before the statement to the FOMC-day EOD, blue), and twice the covariance between the two windows (green). The sample runs from January 1996 to September 2025.

Figure B.2. RISK over time



Time series of the high-frequency RISK shock across the 245 FOMC events from January 1996 to September 2025. Dots mark the fourteen events listed in Table 2: the five most extreme realizations, positive and negative, of RISK and of orthogonalized RISK (RISK$^{\perp}$), with the corresponding FOMC meeting date printed next to each marker. Colors distinguish events that are extreme in RISK only (blue), in RISK$^{\perp}$ only (orange), or in both (red). The six events extreme in both are 2001-09-17, 2007-12-11, 2008-12-16, 2013-09-18, 2022-05-04, and 2024-12-18.

B.3 Placebo tests

This appendix reports the exhibits and econometric details for the placebo exercise described in Section 2.5. Table B.1 reports the volatility and covariance results discussed there. Table B.2 compares the factor loadings, explained variance, and factor correlation of MPS and RISK estimated on the FOMC and placebo windows. Figure B.3 plots the placebo MPS and RISK factors against each other. The remainder of this appendix gives the econometric details behind the tests reported in Table B.1.

Samples. All statistics use the observed, winsorized high-frequency changes (not the imputed series), so that the real-versus-placebo comparison is not affected by the imputation step and the two legs are treated symmetrically. The data form a matched panel of the $n = 245$ FOMC events for which a placebo window (the same intraday window measured seven calendar days earlier) exists, each row holding both the FOMC and the placebo change vector for one event. A window seven calendar days ahead of the announcement falls inside the FOMC's pre-meeting blackout period, which begins on the second Saturday preceding the meeting, so the placebo windows contain no Fed communication rather than merely no announcement. The Committee codified this rule in its 2011 communications policy and followed a similar convention before then. Volatilities (Panels A and B) and the correlation/covariance statistics use each series' or pair's non-missing observations. The block covariance tests (Panel C) use pairwise-complete observations, so each covariance entry is formed from the events where that pair is jointly observed, and series with short samples (CDX from 2011, the credit ETFs) contribute fewer pairs. Panel E is the exception, where the correlation of MPS and RISK uses the imputed, unit-variance factors, so all n events enter.

Bootstrap. Inference is by a paired-event case bootstrap with $B = 5{,}000$ replications. Each replication resamples the n events with replacement. Each draw selects a whole event, it carries that event's FOMC vector of asset price changes, placebo vector of asset price changes, and (potential) missing data in some of the series. This setup preserves the FOMC-placebo pairing and the cross-sectional dependence within each window. Every statistic is recomputed on each resampled panel. For a scalar difference $\hat{\theta}$ (a volatility log-ratio in Panels A and B, a correlation or covariance difference in Panels D and E), the reported p-value is the two-sided percentile p-value

$$p = 2\,\min\Big(\tfrac{1}{B}\textstyle\sum_b \mathbf{1}\{\theta^b \le 0\},\ \tfrac{1}{B}\sum_b \mathbf{1}\{\theta^b \ge 0\}\Big), \tag{7}$$

twice the smaller tail mass of the bootstrap distribution under the null $\theta = 0$. The volatility test uses $\hat{\theta} = \log(\hat{\sigma}^P/\hat{\sigma}^F)$, and Panels D and E use the FOMC-minus-placebo difference of the relevant correlation or covariance, with both legs evaluated on the same resampled events.

Heteroskedasticity (Rigobon) tests. The columns $p^{\text{Het}}_{2y,\cdot}$ and Panel C test whether the reduced-form covariance matrix is the same on FOMC and placebo windows. This is the second-moment shift that identification through heteroskedasticity (Rigobon, 2003) exploits. With stable structural loadings, a change in the relative variances of the structural shocks across regimes moves the reduced-form covariances, so rejecting equality means the FOMC window carries covariation that the placebo window lacks. Collecting the distinct entries of a covariance matrix by the half-vectorization $\text{vech}(\cdot)$, let $\hat{d} = \text{vech}(\hat{\Sigma}^F) - \text{vech}(\hat{\Sigma}^P)$ be the FOMC-minus-placebo difference. For the bivariate test $\hat{\Sigma}^F, \hat{\Sigma}^P$ are the 2×2 covariance matrices of one series and the two-year future (the common anchor). With $\hat{V}$ the bootstrap covariance of $\hat{d}$, the statistic is the Mahalanobis distance $W = \hat{d}'\hat{V}^{-1}\hat{d}$, and $p^{\text{Het}}_{2y,\cdot}$ is the bootstrap probability that a recentered draw $d^b - \hat{d}$ lies farther from the origin (in the $\hat{V}$ metric) than $\hat{d}$. Panel C applies the same null to the full covariance matrix of a block (risk-free, risky, all sixteen series). Since that matrix has up to 136 distinct entries, we replace the Wald form by the omnibus statistic

$$T = \sum_m \left(\frac{\hat{d}_m}{\hat{s}_m}\right)^2, \tag{8}$$

the sum of the squared (co)variance differences, each studentized by its bootstrap standard error $\hat{s}_m$, with a bootstrap p-value. T is the value in the "Statistic" column. Because the entries use pairwise-complete data, short-sample series enter with larger $\hat{s}_m$ and are down-weighted.

Term structure of rate surprises. The sign switch in the comovement of rates and risk assets is not confined to the short end of the yield curve. In additional, unreported analysis we regress RISK on the term structure of risk-free rate surprises—the four Eurodollar/SOFR quarterly futures and the two-, five-, and ten-year government-bond futures—in multivariate and univariate form and on both window types. In the univariate specifications, ten-year yield changes correlate positively and significantly with RISK in FOMC windows but negatively and significantly in placebo windows, mirroring the pattern at the two-year maturity.

B.4 RISK and international asset returns

This appendix reports cross-country estimates of the effects of RISK on asset returns. We estimate standard event-study regressions of the form

$$\Delta y_{i,t} = \alpha + \beta\, MPS_t + \gamma\, RISK_t + e_{i,t},$$

where $\Delta y_{i,t}$ is the two-day change in asset price i, measured from the close of the day before an FOMC meeting to the close of the day after the meeting. Following Boehm and Kroner (2026*a*), we use two-day windows to accommodate time-zone shifts in trading hours and to allow for slower price discovery in the less-liquid emerging markets in our sample. Table B.3 reports the estimated RISK coefficients $\hat{\gamma}$ across all series: country stock market indices, exchange rates against the US dollar, 2-year and 10-year government bond yields, dividend futures, inflation expectations, and broad commodity indices.

Table B.1. Volatility and covariance around FOMC and placebo events

Asset	N	FOMC	Placebo	P/F	$p_{\Delta\sigma}$	$p^{\text{Het}}_{2y,\cdot}$
Panel A: Risk-free instrument volatilities						
ED1	238	5.23	0.98	0.19	(0.00)	(0.00)
ED2	211	5.97	1.49	0.25	(0.00)	(0.00)
ED3	241	8.16	2.79	0.34	(0.00)	(0.00)
ED4	230	8.86	4.88	0.55	(0.00)	(0.00)
Gvt 2y	213	6.20	2.20	0.36	(0.00)	–
Panel B: Risk-asset volatilities						
SP mini	229	110.31	57.36	0.52	(0.00)	(0.00)
Nasdaq	236	129.56	73.99	0.57	(0.00)	(0.00)
VIX	215	131.67	81.73	0.62	(0.00)	(0.00)
VIX Fut.	106	75.03	48.22	0.64	(0.00)	(0.00)
CDX IG	106	2.01	2.31	1.15	(0.55)	(0.00)
CDX HY	106	7.95	5.48	0.69	(0.00)	(0.00)
ETF IG	189	59.92	33.82	0.56	(0.00)	(0.00)
ETF HY	149	60.74	37.38	0.62	(0.00)	(0.00)
Gold	231	81.90	27.11	0.33	(0.00)	(0.00)
DXY	242	43.77	11.95	0.27	(0.00)	(0.00)
FX Carry	227	45.53	26.28	0.58	(0.00)	(0.00)
Panel C: Joint covariance-equality (Rigobon) tests						
Block			Statistic	p		
Risk-free block (5 instr.)			514.42	(0.00)		
Risk-asset block (11 instr.)			981.20	(0.00)		
All instruments (16 instr.)			2107.42	(0.00)		
Panel D: Joint behavior of Gvt 2y and SP mini						
	N	FOMC	Placebo	p		
Correlation ρ	203	-0.23	0.20	(0.00)		
Covariance (bp^2)	203	-153.70	22.79	(0.01)		
Panel E: Correlation of MPS and RISK						
	N	FOMC	Placebo	p		
Correlation ρ	245	0.44	-0.28	(0.00)		

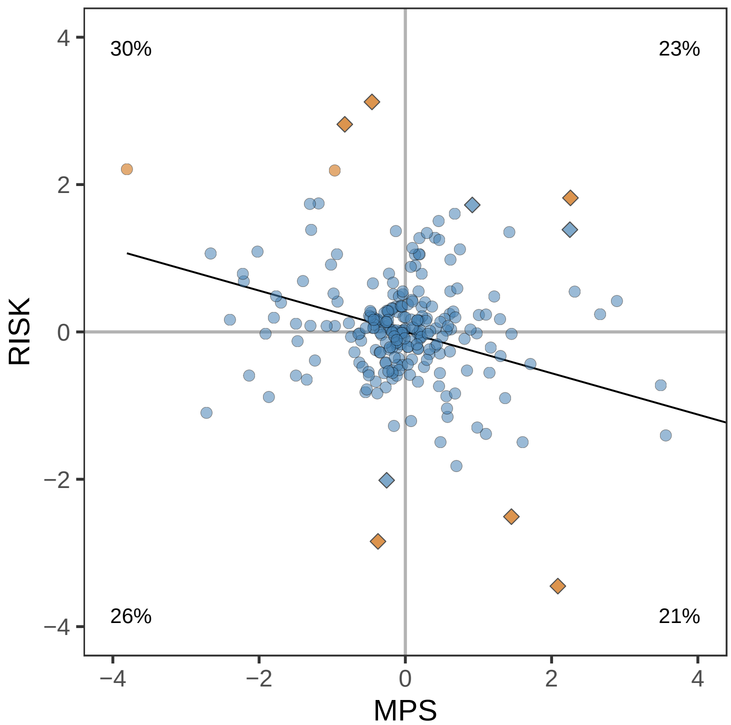
Panels A and B report standard deviations (basis points) of asset price changes for FOMC windows (F) and placebo windows (P, 7 days before an FOMC event). Volatilities are computed on the observed (not imputed), winsorized data and N is the number of FOMC-day observations. P/F reports the ratio of placebo to the FOMC window volatilities. Inference is based on a paired bootstrap with 5000 replications with replacement of the 245 rows of the paired (FOMC, placebo) events (i.e., we resample all 245 events even if one or both of the series have missing data). $p_{\Delta\sigma}$ is the two-sided p-value for the null of equal FOMC- and placebo-window volatility (statistic $\log(\sigma_{\text{P}}/\sigma_{\text{F}})$). $p^{\text{Het}}_{2y,\cdot}$ is a bootstrap Wald p-value for the null that the covariance matrix of the series and the Gvt 2y future is identical across the two regimes following Rigobon (2003). Panel C reports results for the same Rigobon (2003) test but applied to blocks of risk-free and risk-sensitive series. Block covariances use pairwise-complete observations, so series with fewer observations are down-weighted accordingly. Panel D reports the correlation and covariance of 2-year government yields and the SP mini, and the (bootstrap) p-value for a test that the correlation/covariance are equal in the FOMC sample and the placebo sample. Panel E reports the correlation of MPS and RISK (based on the imputed data) for FOMC events and placebo events. The sample period is January 1996 to September 2025.

Table B.2. Factor loadings and correlations: FOMC versus placebo

	FOMC			Placebo (−7d)		
Asset	Loading	Cor(MPS)	Cor(RISK)	Loading	Cor(MPS)	Cor(RISK)
Panel A: MPS, explained var. FOMC 76.6%, placebo 62.6%						
ED1	0.42	0.82	0.34	0.41	0.73	−0.20
ED2	0.48	0.93	0.40	0.50	0.89	−0.16
ED3	0.48	0.93	0.40	0.47	0.83	−0.34
ED4	0.41	0.81	0.39	0.38	0.67	−0.21
Gvt 2y	0.45	0.88	0.39	0.47	0.83	−0.21
Panel B: RISK, explained var. FOMC 56.4%, placebo 42.9%						
SP mini	−0.36	−0.28	−0.91	−0.30	0.33	−0.65
Nasdaq	−0.34	−0.20	−0.86	−0.27	0.38	−0.58
VIX	0.32	0.23	0.80	0.34	−0.38	0.74
VIX Fut.	0.35	0.17	0.86	0.18	−0.35	0.39
CDX IG	0.35	0.41	0.87	0.31	0.00	0.68
CDX HY	0.34	0.37	0.86	0.37	−0.10	0.80
ETF IG	−0.20	−0.39	−0.49	−0.30	−0.07	−0.64
ETF HY	−0.29	−0.57	−0.73	−0.39	0.12	−0.84
Gold	−0.24	−0.51	−0.61	−0.27	0.09	−0.59
DXY	0.24	0.61	0.59	−0.01	0.02	−0.02
FX Carry	−0.21	−0.02	−0.53	−0.38	0.34	−0.83

MPS and RISK are extracted exactly as in the paper, namely the first principal component of the imputed, standardized risk-free block (Panel A) and risky block (Panel B), with sign conventions MPS positive = hawkish and RISK positive = risk-off. "Loading" is the series' weight in the first principal component. Cor(MPS) and Cor(RISK) are the correlations of the series' price change with the two factors. "Explained var." is the share of block variance captured by the first principal component. The FOMC columns are estimated on the FOMC windows and reproduce the paper's Table 1, the placebo columns use the placebo windows (7 days before each FOMC). The two-factor correlation is $\rho = 0.44$ on the FOMC windows and $\rho = -0.28$ on the placebo windows.

Figure B.3. Placebo MPS vs. placebo RISK



Scatterplot of placebo MPS against placebo RISK, with a regression line from a regression of placebo RISK on a constant and placebo MPS ($R^2 = 0.08$). Both factors are extracted from the placebo windows (7 days before each FOMC) exactly as in the paper. A positive value of RISK indicates higher risk aversion. The placebo events with the five highest and five lowest values of RISK are highlighted in orange, and the five highest and five lowest values of RISK orthogonalized with respect to MPS are marked with a diamond. The figure reports the percentage of observations that fall within each quadrant. The placebo factor correlation is $\rho = -0.28$, compared with $\rho = 0.44$ on the FOMC windows in Figure 1.

Table B.3. RISK shocks and international asset returns

	Country instruments				Inflation & dividend futures		Commodities	
Country	Stocks	FX	2y Yield	10y Yield	Name	$\hat{\gamma}$	Name	$\hat{\gamma}$
AUS	−44.58***	38.30***	0.29	0.69	*Inflation expectations*		Gold	−53.66***
BEL	−36.12***		−0.53	0.99**	CAN 2Y	−2.19**	Silver	−82.59***
CAN	−64.38***	24.79***	0.08	0.74	CAN 5Y	−2.73***	GSCI Prec. Met.	−55.96***
CHE	−25.17**	30.63***	0.61	0.36	CAN 10Y	−1.97***	WTI Oil	−59.79*
CZE	−16.39	26.10***	0.64	0.59	EUR 2Y	−0.26	Brent Oil	−74.63***
DEU	−34.03**		0.27	0.47	EUR 5Y	−0.41	GSCI Energy	−49.61**
DNK	−43.76**	27.62***	0.05	0.63	EUR 10Y	−0.27	GSCI Ind. Met.	−46.08***
ESP	−38.30**				GBR 2Y	−0.44	Ag. & Livest.	−14.83
EUR		27.85***			GBR 5Y	−0.15	GSCI	−41.07**
FRA	−34.05**		0.20	0.68	GBR 10Y	−0.14		
GBR	−27.93**	21.49***	0.39	1.08*	USA 2Y	−4.04***		
HKG	−62.62***	0.69*	1.78*	1.32*	USA 5Y	−2.70***		
ISL			−0.85	0.30	USA 10Y	−1.86***		
ISR	−51.34***	29.06***			*Dividend futures*			
ITA	−24.29*		0.65	1.59*	CAN 1Y	−8.42**		
JPN	−51.06***	12.50*	−0.15	−0.32	CAN 2Y	−15.07*		
KOR	−25.85	17.71*	0.90**	1.21**	CAN 3Y	−19.23**		
NLD	−25.38*		0.44	0.76	CAN 4Y	−14.59*		
NOR	−37.28**	34.93***	−0.44	−0.57	CAN 5Y	−13.90		
NZL	−6.86	39.45***	0.77	0.60	CAN 6Y	−25.85**		
SGP	−40.32***	19.19***	0.22	0.82	CAN 7Y	−24.51*		
SWE	−56.04***	37.90***	0.85	2.18	CAN 8Y	−24.89		
TWN	−32.73**	11.25***	0.30	0.21	EUR 1Y	−2.40		
USA	−89.19***		0.42	0.79	EUR 2Y	8.40		
ARG	−69.46***	−70.90			EUR 3Y	−3.73		
BRA	−73.10***	34.76***	0.07	0.59	EUR 4Y	−10.52		
CHL	−56.81***	30.32***			EUR 5Y	−14.19		
CHN	−15.38	5.02***	1.37	0.98*	EUR 6Y	−16.73		
COL	−25.20	22.67***		3.55	EUR 7Y	−18.32		
EGY	−35.50**	−11.97	4.93**	3.30	EUR 8Y	−33.45*		
IDN	−42.01**	20.97**		−0.56	JPN 1Y	−1.78		
IND	−33.82**	19.75***	0.95	1.30	JPN 2Y	−16.77***		
MAR	1.25	17.08***	−0.33	0.04	JPN 3Y	−25.31***		
MEX	−95.25***	32.69***	2.30***	0.69	JPN 4Y	−30.07***		
NGA	3.19	13.39	0.87	13.64**	JPN 5Y	−29.06**		
POL	−32.42*	23.97***	−0.02	1.77**	JPN 6Y	−35.35***		
RUS	−27.54	32.26***	0.31	0.51	JPN 7Y	−35.23***		
SAU	−1.06	0.04			JPN 8Y	−30.57***		
THA	−36.16**	16.56***	0.84*	1.61*				
TUN	−6.50	19.05***						
TUR	−64.60***	10.75	−1.74	0.63				
ZAF	−50.45***	38.11***	1.21*	2.16**				

Each cell reports the OLS coefficient $\hat{\gamma}$ from the regression $\Delta y_{i,t} = \alpha + \beta MPS_t + \gamma RISK_t + e_{i,t}$, where $\Delta y_{i,t}$ is the two-day change in asset price i from the close of the day before an FOMC meeting to the close of the day after the meeting. Country stock indices, FX rates (FC/USD), commodity indices, and dividend futures are in log returns; bond yields and inflation expectations are in simple differences. Coefficients on stocks, FX, bond yields, dividend futures, and commodities are scaled to basis points; inflation expectations are in basis points (1bp = 0.01%). Stars denote heteroscedasticity-robust significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "Inflation expectations" for the US are based on breakeven inflation rates; for CAN, EUR, GBR we use inflation swaps. Both are measures of market-based inflation compensation, which reflects expected inflation and an inflation risk premium. Empty cells indicate that the series is unavailable for the country or has fewer than ten FOMC-day observations. The sample covers FOMC meetings from January 31, 1996 to July 30, 2025 (244 events).

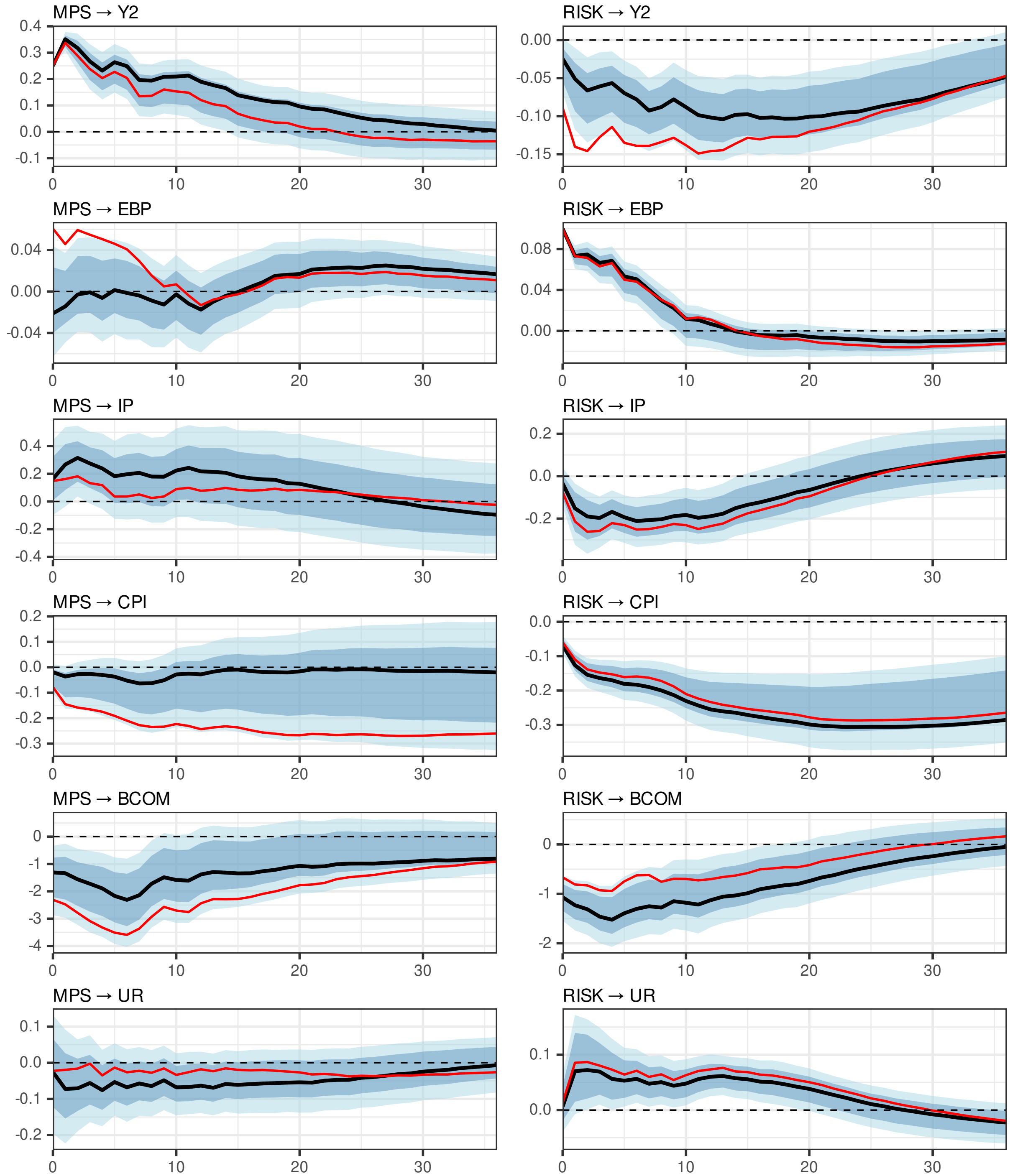
C Additional VAR Results

This appendix presents impulse response estimates and forecast error variance decompositions from two alternative identification approaches for the joint estimation with MPS and RISK. Both yield results that are qualitatively similar to the Mertens-Ravn estimates reported in Section 3.

One alternative to Mertens-Ravn is an approach that applies a Cholesky decomposition not to the structural covariance block Q but to the instrument–shock covariance matrix Φ. Lunsford (2015) proposes this type of restriction in the single-instrument setting, and Lakdawala (2019) extends it to the two-instrument case. Setting the upper-right element of Φ to zero implies that the RISK instrument is uncorrelated with the MPS structural shock—a restriction on the statistical relationship between instruments and shocks rather than on the economic impact of shocks on observables. The resulting impulse responses, shown in Figure C.1, are broadly similar to the Mertens-Ravn estimates, although the RISK shock effects on real activity and prices are somewhat attenuated. This similarity is reassuring: the two methods impose different types of restrictions yet yield qualitatively consistent conclusions about the transmission of risk appetite shocks.

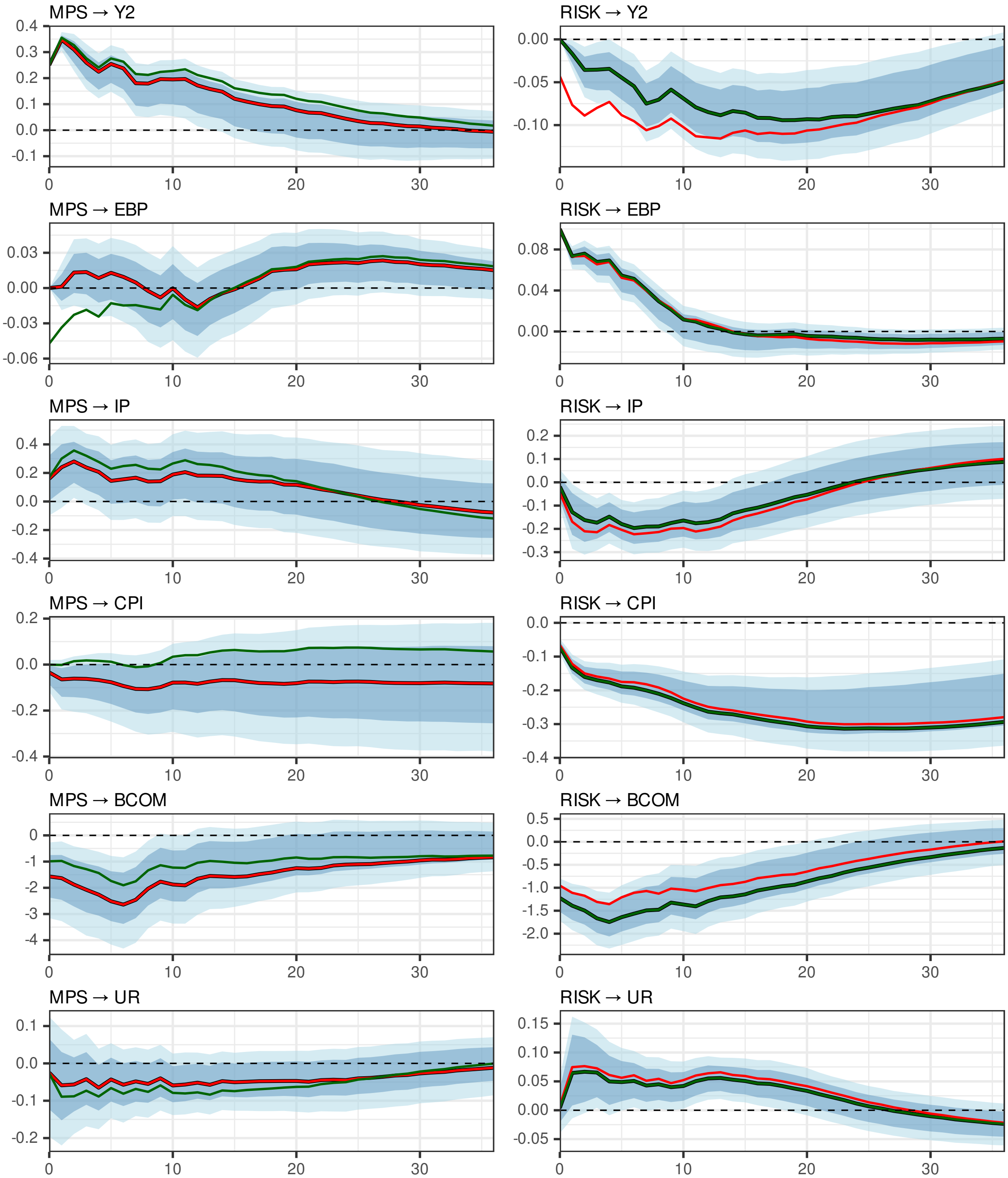
Our second alternative method is to impose zero-impact restrictions directly on the structural impact matrix, following the approach in Appendix A.7 of Montiel Olea, Stock and Watson (2021). Either of the following restrictions alone is sufficient to exactly identify the system: (i) MPS has zero contemporaneous impact on the EBP, or (ii) RISK has zero contemporaneous impact on the two-year yield. The first assigns all instantaneous credit spread movements around FOMC announcements to the risk appetite channel; the second ensures that the RISK shock does not move the risk-free rate on impact. We impose both restrictions simultaneously, which over-identifies the system. The identifying assumptions are economically motivated: MPS captures the conventional interest-rate channel of monetary policy, while RISK captures changes in risk appetite that are orthogonal to the policy rate path. The resulting impulse responses, shown in Figure C.2, are similar to the Mertens-Ravn estimates but somewhat sharper, reflecting the additional identifying information. The figure also shows the estimates with each restriction imposed on its own, which are close to the over-identified estimates. Table C.1 reports variance decompositions for both alternative methods, imposing the zero-impact restrictions one at a time so that the two structural shocks are orthogonal and their variance shares are additive.

Figure C.1. Effects of monetary policy shocks: Lunsford/Lakdawala method



Impulse response functions for monetary policy shocks, identified using a triangular restriction on the instrument-shock covariance matrix Φ (Lunsford, 2015; Lakdawala, 2019). Left column: risk-free rate shock. Right column: risk appetite shock. Black lines and shaded areas show point estimates and 68% (dark) and 90% (light) confidence intervals for the ordering with the risk-free rate shock first. Red lines show point estimates for the alternative ordering with the risk appetite shock first. Responses are shown in each variable's own units (Y2 and EBP in basis points; IP, CPI, and BCOM in log points $\times 100$; UR in percentage points) and are not cumulated.

Figure C.2. Effects of monetary policy shocks: zero-impact constraints



Impulse response functions for monetary policy shocks, identified using zero-impact constraints. Left column: risk-free rate shock. Right column: risk appetite shock. Black lines and shaded areas show point estimates and 68% (dark) and 90% (light) confidence intervals for the specification with both zero-impact restrictions imposed simultaneously. Red and green lines show point estimates for each restriction imposed individually (zero EBP response to MPS, and zero yield response to RISK, respectively). Responses are shown in each variable's own units (Y2 and EBP in basis points; IP, CPI, and BCOM in log points ×100; UR in percentage points) and are not cumulated.

Table C.1. Forecast error variance decomposition: alternative identification methods

	MPS shock					RISK shock				
	1	6	12	36	∞	1	6	12	36	∞
Panel A: Lunsford–Lakdawala, risk-free rate shock ordered first										
Y2	80.4	66.1	59.6	42.2	32.1	2.2	7.4	14.4	30.9	26.2
EBP	1.2	0.5	0.6	4.1	4.5	71.6	64.1	55.7	47.1	45.1
IP	5.0	9.8	7.9	4.5	4.0	0.6	12.4	14.3	7.9	13.5
CPI	1.2	0.9	1.2	0.3	0.2	42.1	64.1	64.2	69.8	39.4
BCOM	12.7	16.6	18.0	18.2	14.2	23.5	28.9	26.5	23.3	15.5
UR	0.4	3.4	5.0	6.0	4.5	0.1	8.9	11.0	11.3	11.2
Panel B: Lunsford–Lakdawala, risk appetite shock ordered first										
Y2	56.5	39.5	31.1	18.9	15.7	26.1	34.0	42.9	54.2	42.6
EBP	6.7	8.4	7.2	7.3	7.0	66.1	56.3	49.1	43.9	42.6
IP	2.9	2.2	1.2	0.8	4.6	2.7	20.0	21.0	11.7	12.9
CPI	13.8	17.9	18.5	14.9	8.9	29.5	47.2	46.9	55.2	30.7
BCOM	27.7	35.4	36.0	34.3	23.2	8.4	10.1	8.6	7.3	6.4
UR	0.2	0.3	0.5	1.2	1.3	0.3	12.0	15.5	16.1	14.4
Panel C: Zero-impact, zero EBP response to MPS										
Y2	75.9	59.9	52.2	35.1	27.0	6.7	13.6	21.8	38.1	31.3
EBP	0.0	0.4	0.4	3.3	3.6	72.8	64.2	55.8	47.9	46.0
IP	4.5	7.2	5.5	3.1	3.8	1.1	15.0	16.7	9.3	13.7
CPI	3.6	3.8	4.2	2.1	1.4	39.7	61.2	61.2	67.9	38.2
BCOM	17.1	22.2	23.5	23.3	17.1	19.0	23.3	21.0	18.3	12.6
UR	0.4	2.2	3.3	4.2	3.1	0.1	10.1	12.7	13.1	12.6
Panel D: Zero-impact, zero yield response to RISK										
Y2	82.6	71.4	67.1	50.9	38.4	0.0	2.1	7.0	22.3	19.9
EBP	5.9	3.6	3.3	7.1	7.6	66.8	61.1	53.0	44.1	42.0
IP	5.5	13.3	11.3	6.4	4.7	0.2	8.9	10.8	6.0	12.8
CPI	0.0	0.2	0.2	1.1	0.5	43.3	64.9	65.2	69.0	39.1
BCOM	7.4	10.0	11.3	12.0	10.5	28.7	35.6	33.2	29.5	19.2
UR	0.5	5.3	7.5	8.6	6.5	0.0	7.0	8.5	8.7	9.2

Entries show the percentage of forecast error variance at horizon h (months) explained by each shock. Panels A and B use Lunsford (2015); Lakdawala (2019) identification with a triangular restriction on the instrument–shock covariance matrix Φ: "risk-free rate shock ordered first" sets the upper-right element of Φ to zero (RISK instrument uncorrelated with MPS shock), and "risk appetite shock ordered first" sets the lower-left element to zero (MPS instrument uncorrelated with RISK shock). Panels C and D use zero-impact restrictions on the structural impact matrix following Montiel Olea, Stock and Watson (2021), imposing one restriction at a time. See notes to Table 5 for further details on the VAR specification.