

Monetary Policy, Risk-Taking, and the Macroeconomy

Online Appendix

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A Properties of the risk appetite index

In this section, we provide additional details on the daily risk appetite index introduced in Section 4 of the paper.

Table A1 lists metadata for the 14 component variables of the index. We obtain the majority of these series from Bloomberg and FRED, but in several cases supplement with additional historical data. Further details on data transformations and the construction of the index can be found in Section 4 of the paper.

Table A1: Metadata for components of the risk appetite index

<i>Mnemonic</i>	<i>Variable</i>	<i>Start date</i>	<i>End date</i>	<i>Primary source</i>	<i>Secondary source</i>	<i>Ticker</i>
S&P 500	S&P 500 stock index	Mar. 1957	Present	S&P Global	Bloomberg	SPX Index
NASDAQ	NASDAQ composite stock index	Feb. 1971	Present	NASDAQ	Bloomberg	CCMP Index
MOVE	ICE/BofA MOVE index	Apr. 1988	Present	ICE/BofA	Bloomberg	MOVE Index
TYVIX	CBOE 10-year Treasury note volatility ^a	May 1985	May 2020	CBOE	FRED	VXTYN
VIX	CBOE S&P 500 volatility index	Jan. 1990	Present	CBOE	Bloomberg	VIX Index
VRP	Bekaert-Hoerova equity variance risk premium ^b	Jan. 1990	Jan. 2022	Bekaert and Hoerova (2014)	-	-
Baa spread	Moody's Baa corporate bond spread	Jan. 1986	Present	Moody's	FRED	BAA10Y
IG OAS	ICE/BofA US investment-grade corporate option-adjusted spread (OAS)	Jan. 1997	Present	ICE/BofA	FRED	BAMLC0A0CM
HY OAS	ICE/BofA US high-yield corporate OAS	Jan. 1997	Present	ICE/BofA	FRED	BAMLH0A0HYM2
CP spread	3-month commercial paper spread	Apr. 1997	Present	Federal Reserve	Bloomberg	BICLUSSP Index
EM spread	J.P. Morgan emerging markets bond index (EMBI+) spread	Jan. 1998	Present	J.P. Morgan	Bloomberg	JPEMSOSD Index
MBS spread	Bloomberg OAS for US fixed-rate mortgage-backed securities ^c	Aug. 2000	Present	Bloomberg	Bloomberg	LUMSOAS Index
Dollar	US dollar exchange rate versus advanced foreign economies ^d	Mar. 1973	Present	Federal Reserve	FRED	DTWEXBGS
Swiss-Euro	Swiss franc-Euro exchange rate ^e	Jan. 1999	Present	Bloomberg	Bloomberg	EURCHF Curncy

^a The TYVIX is available in FRED from 2003 to 2020. We supplement with historical data from 1985 based on the Treasury Implied Volatility (TIV) measure constructed by Choi et al. (2017).

^b Available on Marie Hoerova's website: <http://mariehoerova.net>

^c The MBS spread is available in Bloomberg from 1988 at the monthly frequency, but we use only daily data from 2000.

^d The US dollar index is available in FRED from 2006. We supplement with historical data from 1973 constructed by Beschwitz et al. (2019), available at <https://www.federalreserve.gov/econres/notes/feds-notes/revisions-to-the-federal-reserve-dollar-indexes-20190115.htm>.

^e For comparability with the US dollar index, we invert the Euro-Swiss franc index, in order to reflect the Swiss franc's role as a safe haven currency.

Table A2 displays summary statistics for the index. We document substantial differences between the behavior of the index on FOMC announcement days relative to the average day, which we interpret as preliminary evidence of the effects of monetary policy on risk appetite. Our index, which is standardized to have zero mean and unit standard deviation over its full history, increases by 0.25 on average on FOMC days, which is statistically significant at the 0.1% level. Additionally, changes on FOMC days are skewed in the positive direction, with a skewness coefficient of 0.54.

Table A2: Summary statistics of the risk appetite index

<i>(A) MPS sample (01/1988-12/2019)</i>				<i>(B) Full sample (01/1988-05/2022)</i>			
	FOMC	Non-FOMC	Total		FOMC	Non-FOMC	Total
<i>N</i>	315	7689	8004	<i>N</i>	335	8272	8607
Mean	0.24	-0.01	0.00	Mean	0.25	-0.01	0.00
<i>t</i> -statistic	4.75	-0.83		<i>t</i> -statistic	4.86	-0.91	
Standard deviation	0.91	0.94	0.94	Standard deviation	0.95	1.00	1.00
Skewness	0.81	-1.16	-1.09	Skewness	0.54	-1.66	-1.58
Kurtosis	7.71	19.60	19.17	Kurtosis	7.57	25.55	24.95

Notes: This table displays summary statistics for the daily risk appetite index on FOMC monetary policy announcement days and all other trading days. Statistics in Panel A are calculated over the Jan. 1988 to Dec. 2019 sample for which [Bauer and Swanson \(2022\)](#) monetary policy surprises are available, while statistics in Panel B are calculated over the full history of the index from Jan. 1988 to May 2022. FOMC announcement dates are from Bauer-Swanson and updated in Panel B to include 20 additional announcements over the 2020-2022 period. In March 2020, we include the 3/3 and 3/23 announcements but exclude Sunday, 3/15, since the market response on 3/16 primarily reflected the onset of the COVID-19 pandemic. *t*-statistics test whether the corresponding sample means are statistically different from zero, based on Huber-White heteroskedasticity-robust standard errors.

To evaluate the plausibility of our index, Table [A3](#) lists the ten largest positive and negative daily movements of the risk appetite index for both all days and FOMC days.

The three largest “risk-off” days over the full sample (Panel A) occurred at the onset of the COVID-19 pandemic in March 2020 amidst large stock market declines, increases in volatility, and widening credit spreads. Other dates with large declines in risk appetite include the U.S. credit downgrade on 8/8/2011 and various events during the 2007-08 financial crisis, including the Lehman bankruptcy on 9/15/2008, the failure of the TARP vote in Congress on 9/29/2008, and NBER’s formal declaration of a recession on 12/1/2008. As mentioned in the paper, many of the largest “risk-on” days (Panel B) are reversals of these risk-off shocks. Some also reflect specific policy responses, such as Treasury’s proposal of the TARP program on 9/19/2008, its announcement of bank capital injections on 10/14/2008, and Congress’s announcement of pandemic emergency aid on 3/13/2020.

Panels C and D of Table [A3](#) restrict to FOMC announcement days. The largest risk-off FOMC day was 1/27/2021, which occurred during a resurgence of the COVID-19 pandemic, while the largest risk-on days followed the Fed’s unscheduled 50bp rate cut on 1/3/2001 and its 75bp rate cut on 3/18/2008. Notably, there are few FOMC announcement days at the tails of the distribution of the index over all days. This suggests that even the most impactful monetary policy announcements may not affect risk appetite to the same extent as other macroeconomic, financial, or geopolitical shocks ([Baker et al., 2016](#); [Caldara and Iacoviello, 2022](#)).¹

Table [A4](#) displays correlations between the risk appetite index and a broad range of alternative indicators constructed using various methodologies. For daily indicators, we compute correlations with both our daily index and its cumulated (levels) version. For lower-frequency indicators, we compute relative to the average of our cumulated index over the corresponding period. Overall, we find that our index is strongly correlated with alternative indicators of risk and financial conditions, and moderately correlated with measures of economic conditions, consumer and investor sentiment, and uncertainty.

¹However, if the effects of monetary policy on risk appetite operate with a lag (as documented in Section 4 of the paper), movements on FOMC days alone may not capture the full extent of the market’s response to policy announcements.

Table A3: Largest daily movements in the risk appetite index

<i>(A) Largest risk-off days</i>							
	Date	Risk index	S&P 500	VIX	Baa spread	HY OAS	Dollar
1	3/16/2020	-14.03	-12.77	24.86	0.08	1.07	-0.40
2	3/12/2020	-12.15	-9.99	21.57	0.21	0.81	1.58
3	3/9/2020	-11.42	-7.90	12.52	0.38	1.04	-0.60
4	10/15/2008	-9.41	-9.47	14.12	0.16	0.64	0.84
5	8/8/2011	-9.29	-6.90	16.00	0.11	0.60	-0.26
6	10/22/2008	-8.41	-6.30	16.54	0.00	0.18	1.74
7	12/1/2008	-8.29	-9.35	13.23	0.02	0.42	0.34
8	9/15/2008	-8.22	-4.83	6.04	0.23	0.51	-0.06
9	9/29/2008	-8.03	-9.20	11.98	0.13	0.50	0.85
10	11/20/2008	-7.68	-6.95	6.60	0.19	0.87	1.53
<i>(B) Largest risk-on days</i>							
	Date	Risk index	S&P 500	VIX	Baa spread	HY OAS	Dollar
8598	9/1/1998	5.04	3.79	-7.80	0.03	0.06	-1.33
8599	1/3/2001	5.06	4.89	-3.39	-0.16	-0.23	-0.13
8600	3/24/2020	5.22	8.97	0.08	-0.12	-0.32	-0.59
8601	5/10/2010	6.00	4.30	-12.11	-0.02	-0.22	-0.91
8602	3/26/2020	6.07	6.05	-2.95	-0.09	-0.82	-1.95
8603	9/19/2008	6.85	3.95	-1.03	-0.02	-0.62	-0.49
8604	10/20/2008	7.12	4.66	-17.36	0.07	-0.19	1.01
8605	3/13/2020	7.62	8.88	-17.64	0.10	-0.11	0.62
8606	10/28/2008	8.50	10.25	-13.10	-0.01	-0.14	0.14
8607	10/14/2008	11.01	10.42	-14.82	-0.08	-0.86	-1.35
<i>(C) Largest risk-off FOMC days</i>							
	Date	Risk index	S&P 500	VIX	Baa spread	HY OAS	Dollar
50	1/27/2021	-3.90	-2.60	14.19	0.00	0.11	0.41
131	10/8/2008	-2.57	-1.14	3.85	-0.06	0.33	0.42
139	6/26/2002	-2.52	-0.27	0.58	0.09	0.79	-0.94
162	5/20/1988	-2.38	0.18	.	-0.05	.	0.02
165	12/11/2007	-2.36	-2.56	2.85	0.04	0.13	0.11
184	1/22/2008	-2.27	-1.11	3.83	0.11	0.35	-0.13
193	9/16/2008	-2.24	1.74	-1.40	0.02	0.24	0.27
273	2/4/1994	-1.89	-2.29	4.50	-0.08	.	0.63
347	3/15/2011	-1.64	-1.13	3.19	0.03	0.16	0.22
408	11/12/1997	-1.51	-1.66	1.21	0.01	0.02	0.57
<i>(D) Largest risk-on FOMC days</i>							
	Date	Risk index	S&P 500	VIX	Baa spread	HY OAS	Dollar
8532	12/17/2014	2.59	2.01	-4.13	0.00	-0.23	0.46
8541	9/18/2007	2.68	2.88	-6.13	0.01	-0.06	-0.18
8547	8/21/1991	2.73	2.90	-3.24	-0.01	.	-1.21
8556	8/9/2011	2.98	4.63	-12.94	0.13	0.35	-0.03
8572	3/16/2022	3.23	2.21	-3.16	-0.13	-0.25	-0.25
8574	12/16/2008	3.30	5.01	-4.39	0.01	-0.38	-0.88
8578	1/28/2009	3.39	3.30	-2.59	0.02	-0.36	-0.90
8580	3/11/2008	3.58	3.65	-3.02	-0.04	-0.13	0.26
8582	3/18/2008	3.69	4.15	-6.45	-0.11	-0.23	-0.09
8599	1/3/2001	5.06	4.89	-3.39	-0.16	-0.23	-0.13

Notes: This table displays the largest single-day movements in the risk appetite index, along with the selected daily measures of financial risk shown in Table 1 of the paper. The Risk index and VIX are measured as daily changes in index points, the S&P 500 and Dollar as daily log returns, and the Baa spread and HY OAS as daily changes in percentage points. The leftmost column in all panels shows each day's rank among all daily movements (from smallest to largest) from Jan. 1988 to May 2022. Panels C and D restrict to only dates of FOMC announcements, taken from [Bauer and Swanson \(2022\)](#) and extended to 2020-22 as described in Table A2.

Table A4: Correlations of risk appetite index with alternative measures

Measure	Frequency	Start date	End date	Correlation with risk index		
				Levels	Differences	Obs.
<i>Risk</i>						
Bekaert et al. (2013) risk component of VIX	Monthly	Jan. 1990	Jan. 2022	-0.47	-	385
Bekaert et al. (2022) risk aversion	Daily	Jun. 1986	Jun. 2022	-0.60	-0.53	8592
Chicago Fed NFCI, risk subindex	Weekly	Jan. 1971	Present	-0.60	-	1728
Datta et al. (2017) global risk-on/risk-off index	Daily	Jan. 2000	Present	0.87	0.88	5606
Gilchrist-Zakrajšek (2012) excess bond premium	Monthly	Jan. 1973	Mar. 2022	-0.64	-	411
Miranda-Agrippino et al. (2020) global financial cycle	Monthly	Jan. 1990	Apr. 2019	0.50	-	376
Pflueger et al. (2020) price of volatile stocks	Quarterly	Jul. 1950	Jul. 2021	0.79	-	134
Westpac risk aversion index	Daily	Apr. 1998	Present	-0.11	-0.51	5981
<i>Economic conditions</i>						
Aruoba-Diebold-Scotti business conditions index	Daily	Mar. 1960	Present	0.32	0.10	8607
Brave-Butters-Kelly business cycle index	Monthly	Jan. 1960	Present	0.49	-	413
Chicago Fed national activity index	Monthly	Mar. 1967	Present	0.31	-	413
Citi economic surprise index	Daily	Jan. 2003	Present	0.18	0.05	4838
Conference Board business cycle coincident index	Monthly	Feb. 1959	Present	0.64	-	413
Ludvigson-Ng (2009) first macro factor	Monthly	Mar. 1960	Dec. 2021	-0.59	-	408
New York Fed weekly economic index	Weekly	Jan. 2008	Present	0.58	-	750
<i>Financial conditions</i>						
Bloomberg financial conditions index	Daily	Jan. 1990	Present	0.80	0.72	8108
Chicago Fed NFCI	Weekly	Jan. 1971	Present	-0.67	-	1728
Goldman Sachs financial conditions index	Daily	Sep. 1982	Present	-0.42	-0.79	8607
Kansas City Fed financial stress index	Monthly	Jan. 1990	Present	-0.74	-	389
St. Louis Fed financial stress index	Weekly	Jan. 1994	Present	-0.70	-	1429
U.S. Treasury OFR financial stress index	Daily	Jan. 2000	Present	-0.61	-0.87	5596
<i>Sentiment</i>						
Baker-Wurgler (2006) sentiment index	Monthly	Jul. 1965	Dec. 2018	0.36	-	372
Conference Board consumer confidence index	Monthly	Feb. 1967	Present	0.56	-	413
San Francisco Fed news sentiment index	Daily	Jan. 1980	Present	0.69	0.03	8607
Societe Generale sentiment index	Daily	May 2000	Present	0.07	0.44	5524
State Street investor confidence index	Monthly	Jul. 1998	Present	0.37	-	287
University of Michigan consumer sentiment index	Monthly	Jan. 1978	Present	0.59	-	413
<i>Uncertainty</i>						
Baker et al. (2016) economic policy uncertainty	Daily	Jan. 1985	Present	-0.38	-0.01	8607
Bauer et al. (2022) monetary policy uncertainty	Daily	Jan. 1990	Sep. 2020	0.16	-0.16	7692
Bekaert et al. (2013) uncertainty component of VIX	Monthly	Jan. 1990	Jan. 2022	-0.61	-	385
Bekaert et al. (2022) 1-mo uncertainty	Daily	Jun. 1986	Jun. 2022	-0.87	-0.65	8592
Caldaro-Iacoviello (2022) geopolitical risk index	Daily	Jan. 1985	Present	-0.12	0.00	8607
Husted et al. (2020) monetary policy uncertainty	Monthly	Jan. 1985	Sep. 2021	-0.10	-	413
Jurado et al. (2015) 1-mo macro uncertainty	Monthly	Jul. 1960	Dec. 2021	-0.50	-	408
Ludvigson et al. (2021) 1-yr financial uncertainty	Monthly	Mar. 1960	Dec. 2021	-0.51	-	408
Scotti (2016) uncertainty	Daily	May 2003	Apr. 2021	-0.08	0.00	4493

Source: Authors' websites, Bloomberg, FRED.

Note: The levels column shows the correlations between each indicator and our cumulated index. For lower-frequency indicators, we average our cumulated index over the corresponding period. The differences column shows the correlations between our daily index and the daily first differences of the indicators. Our index is signed such that an increase corresponds to an increase in risk appetite (a decrease in the price of risk). All other series retain their original signs and units. Correlations are calculated over the period for which both series are jointly available. Our index runs from Jan. 1988 to May 2022.

B Additional event-study results

In this section, we extend the event-study results in Sections 3 and 4 of the paper to better understand the responses of financial variables and our risk appetite index to monetary policy surprises.

Table B1 shows the within-day responses of the nine component variables of the risk appetite index not shown in Section 3 of the paper to the Bauer and Swanson (2022) monetary policy surprise (MPS), the Gürkaynak et al. (2005) target and path factors, and the Nakamura and Steinsson (2018) surprise. In Figure B1, we evaluate the dynamic responses of these variables by regressing their multi-day changes on MPS.

In line with our results in Section 3, we find that the remaining nine variables respond in the expected direction to a surprise monetary policy tightening, with declines in equity indices, increases in measures of stock and bond market volatility, and wider credit spreads.² We also document a persistent drift in the responses of several of these variables in the weeks following FOMC announcements.

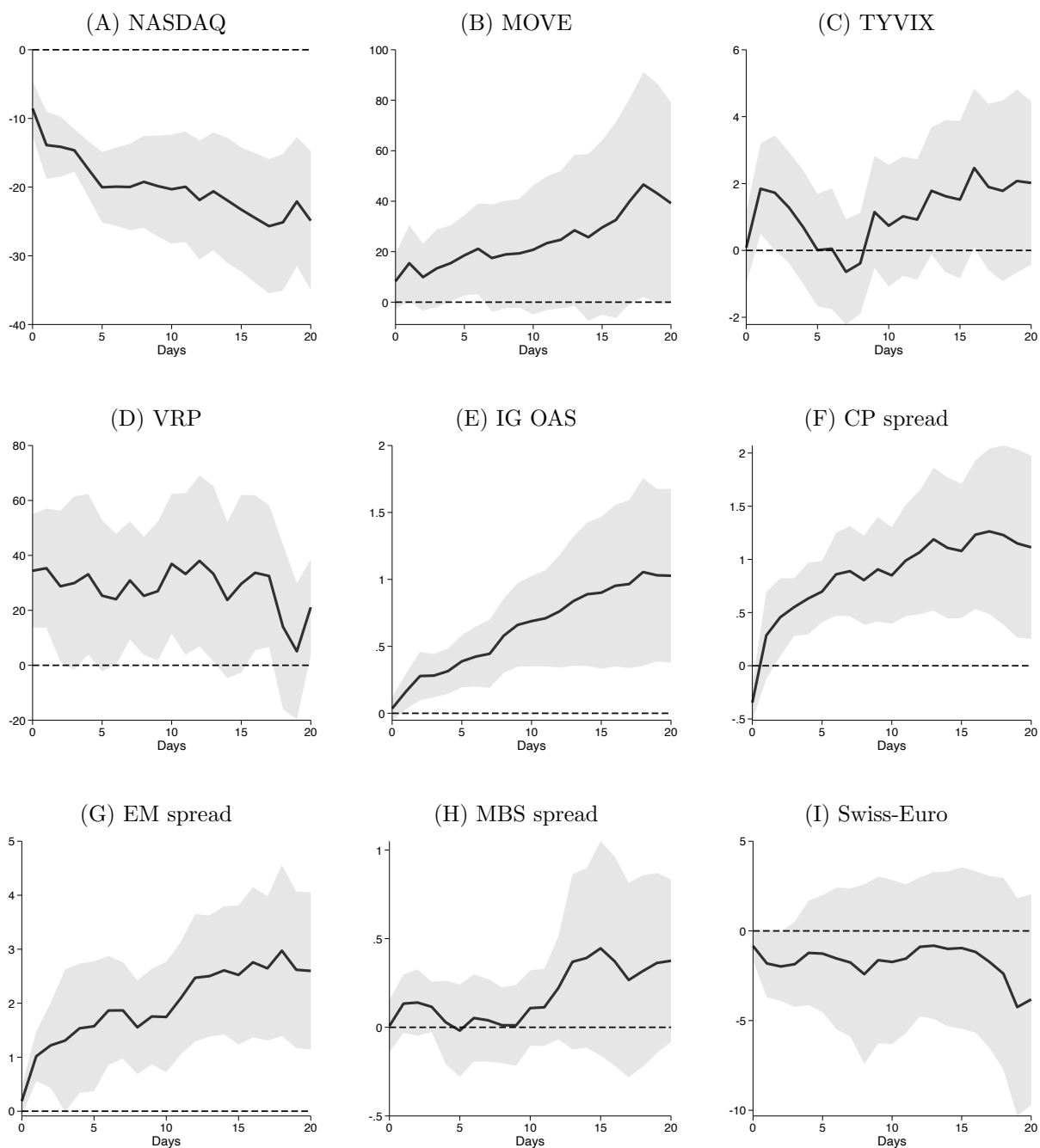
Table B1: Within-day asset price responses to a surprise monetary tightening

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NASDAQ	MOVE	TYVIX	VRP	IG OAS	CP spread	EM spread	MBS spread	Swiss-Euro
<i>(A) Bauer-Swanson (2022)</i>									
MPS	-8.55 (-3.49)	8.28 (1.25)	0.08 (0.13)	34.41 (2.74)	0.04 (0.67)	-0.35 (-3.43)	0.19 (1.11)	0.01 (0.09)	-0.84 (-1.65)
<i>N</i>	315	311	315	267	193	191	185	164	176
<i>R</i> ²	0.11	0.01	0.00	0.05	0.00	0.10	0.01	0.00	0.01
<i>(B) Gürkaynak-Sack-Swanson (2005)</i>									
Target factor	-7.70 (-2.09)	-7.03 (-1.29)	-0.84 (-1.31)	29.77 (1.96)	0.05 (0.74)	-0.43 (-4.75)	0.25 (1.32)	0.09 (1.58)	-0.72 (-1.28)
Path factor	-3.51 (-1.34)	21.59 (3.43)	0.79 (2.29)	17.74 (1.27)	-0.02 (-0.43)	-0.06 (-0.66)	-0.02 (-0.13)	-0.10 (-1.37)	-0.64 (-1.26)
<i>N</i>	259	259	259	259	188	186	180	159	171
<i>R</i> ²	0.12	0.07	0.04	0.05	0.01	0.18	0.02	0.06	0.02
<i>(C) Nakamura-Steinsson (2018)</i>									
NS surprise	-13.07 (-2.92)	6.83 (0.62)	-0.53 (-0.54)	53.71 (2.65)	0.05 (0.62)	-0.61 (-4.45)	0.30 (1.17)	0.04 (0.30)	-1.47 (-1.69)
<i>N</i>	259	259	259	259	188	186	180	159	171
<i>R</i> ²	0.11	0.00	0.00	0.05	0.00	0.14	0.01	0.00	0.02

Notes: Regressions are estimated at the daily frequency, with monetary policy surprises calculated over the 30-minute windows surrounding FOMC announcements. The NASDAQ and Swiss-Euro exchange rate are measured as daily log returns, the MOVE, TYVIX, and VRP as daily changes in index points, and the IG OAS, CP spread, EM spread, and MBS spread as daily changes in percentage points. Sample periods are determined jointly by the availability of the policy surprises and asset prices. For the policy surprises, MPS are available from Jan. 1988 to Dec. 2019, while the target and path factors and the NS surprise are available from Jan. 1990 to Jun. 2019. Start and end dates for the asset prices are listed in Table A1. Huber-White heteroskedasticity-robust t-statistics are in parentheses.

²The only variable that does not respond as expected is the Swiss Franc-Euro exchange rate. However, the results for that variable are insignificant, suggesting that it is largely unresponsive to changes in U.S. monetary policy. We justify its inclusion in the risk appetite index by its negative comovement with the index across all days, shown in Table 2 of the paper.

Figure B1: Cumulative asset price responses to a surprise monetary tightening



Notes: Plots show the estimated slope coefficients from regressions of the cumulative changes in asset prices over 0-20 trading days, with the FOMC announcement occurring on day 0, on the [Bauer and Swanson \(2022\)](#) monetary policy surprise measure. The NASDAQ and Swiss-Euro exchange rate are measured as daily log returns, the MOVE, TYVIX, and VRP as daily changes in index points, and the IG OAS, CP spread, EM spread, and MBS spread as daily changes in percentage points. Sample periods are the same as Panel A of Table B1. Shading depicts 90% confidence intervals based on Huber-White heteroskedasticity-robust standard errors.

Table B2 shows the magnitude and statistical significance of the drift in the responses of selected financial variables and the risk appetite index to monetary policy surprises. The dependent variables in Panel A are the differences between the 20-day and FOMC-day responses of the variables to policy surprises, while the dependent variables in Panel B are the differences between the 20-day and 5-day responses.

As discussed in the paper, we find a significant degree of post-FOMC drift, especially for the two credit spreads and the risk appetite index. For most variables, including the index, a large proportion of this drift occurs over the first 5 trading days following the FOMC meeting, as evidenced by the smaller magnitudes and significance of the results in Panel B. However, over 40% of the 20-day response of the risk appetite index to MPS occurs during days 6-20, suggesting that conventional event-study methods using daily or even weekly changes in the prices of risky assets following FOMC announcements may not capture the entire financial market response to policy surprises.

In Figure B2, we test the extent to which our main event-study result, the response of the risk appetite index to MPS, depends on the state of the economy or the conduct of monetary policy. We introduce indicator variables denoting the sign of MPS, whether the economy is in a recession, and whether the output gap, unemployment gap, stance of monetary policy, and level of risk are above or below their median from Jan. 1988 to Dec. 2019. The plots show how the cumulative response of the risk appetite index to MPS differs based on the value of these indicator variables.³

Across most specifications, the response of the index to MPS does not exhibit strong evidence of state-dependence, with a few exceptions. Panel B shows a larger response of risk appetite to MPS during NBER-dated recessions, and Panel F shows a larger response during periods when the level of risk is below its median. However, these differences are not statistically significant, and we view our findings as inconclusive.⁴ A full analysis of time variation in the strength of the risk-taking channel would be a promising area for future research, but is beyond the scope of this paper.

³In addition to the plots in Figure B2, we also tested the robustness of our results to different subsamples, finding roughly similar results across sample periods.

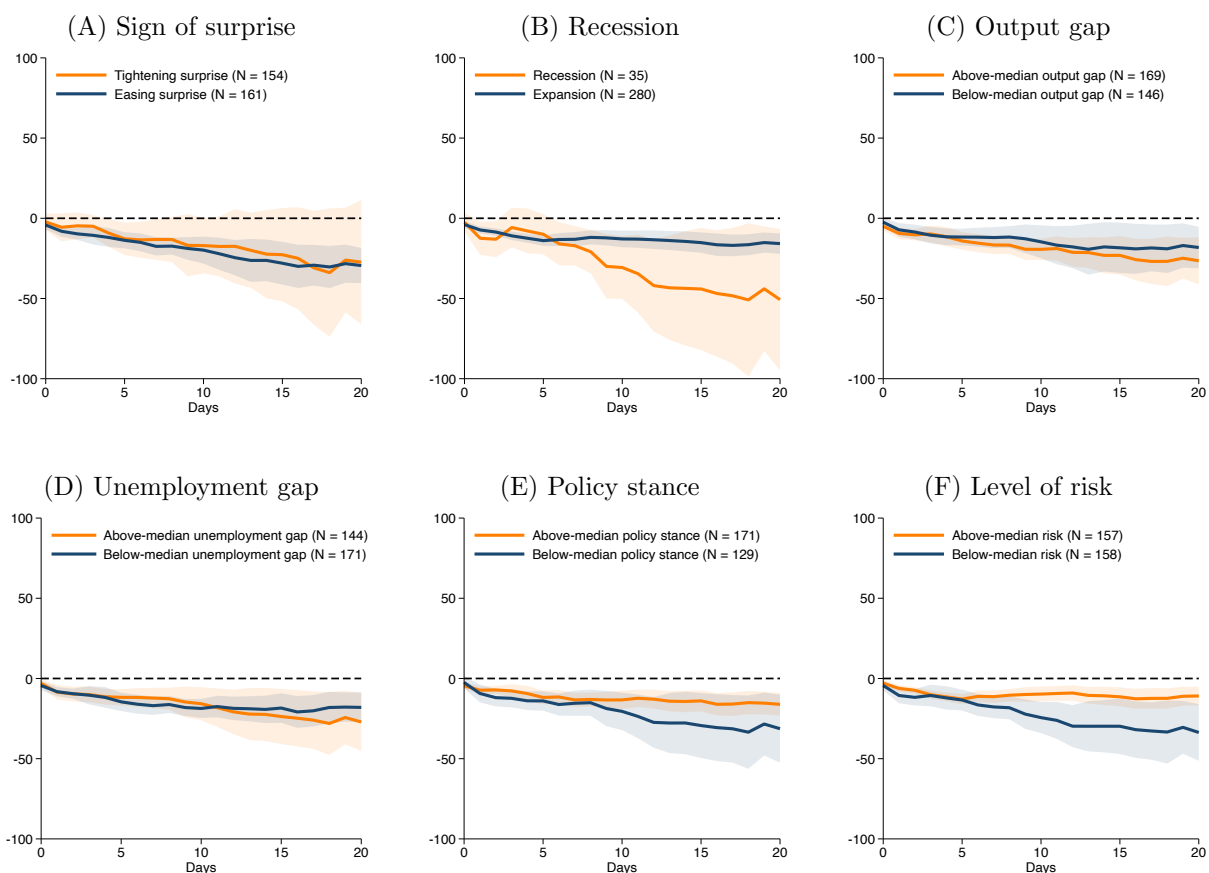
⁴We estimated state-dependence local projections specifications interacting these indicator variables with MPS, using a similar methodology to Bauer et al. (2022b). The only interaction term that was statistically significant at the 5% level was the interaction between MPS and the level of risk (Panel F), and this term only became significant several weeks after an FOMC announcement.

Table B2: Significance of drift results

	(1)	(2)	(3)	(4)	(5)	(6)
	S&P 500	VIX	Baa spread	HY OAS	Dollar	Risk index
<i>(A) 20-day response minus same-day response</i>						
MPS	-8.35 (-1.82)	9.76 (2.09)	0.63 (3.63)	4.63 (2.81)	1.25 (0.74)	-19.26 (-3.47)
<i>N</i>	315	267	315	193	315	315
<i>R</i> ²	0.01	0.02	0.04	0.11	0.00	0.06
Target factor	-10.23 (-2.21)	11.01 (2.01)	0.49 (2.48)	3.22 (2.17)	-0.53 (-0.36)	-17.16 (-2.68)
Path factor	-1.30 (-0.30)	1.67 (0.46)	0.32 (1.71)	2.75 (1.94)	1.52 (0.81)	-11.34 (-2.23)
<i>N</i>	259	259	259	188	259	259
<i>R</i> ²	0.03	0.03	0.04	0.09	0.00	0.07
NS surprise	-14.81 (-1.99)	16.16 (2.20)	0.90 (3.18)	6.44 (2.50)	0.44 (0.17)	-31.79 (-3.45)
<i>N</i>	259	259	259	188	259	259
<i>R</i> ²	0.02	0.02	0.04	0.09	0.00	0.07
<i>(B) 20-day response minus 5-day response</i>						
MPS	-2.43 (-0.66)	2.99 (0.62)	0.38 (2.37)	2.97 (2.35)	0.33 (0.19)	-9.71 (-1.87)
<i>N</i>	315	267	315	193	315	315
<i>R</i> ²	0.00	0.00	0.02	0.06	0.00	0.02
Target factor	-7.32 (-1.80)	9.21 (1.88)	0.37 (2.12)	2.40 (1.87)	-0.03 (-0.02)	-12.57 (-2.07)
Path factor	3.71 (1.14)	-6.84 (-1.78)	0.07 (0.46)	1.33 (1.35)	-0.30 (-0.17)	-1.01 (-0.23)
<i>N</i>	259	259	259	188	259	259
<i>R</i> ²	0.02	0.03	0.03	0.06	0.00	0.03
NS surprise	-7.08 (-1.17)	7.27 (0.97)	0.55 (2.16)	4.19 (2.12)	-0.27 (-0.10)	-17.76 (-2.05)
<i>N</i>	259	259	259	188	259	259
<i>R</i> ²	0.01	0.00	0.02	0.06	0.00	0.03

Notes: This table shows the estimated coefficients from the regressions $y_{t+20} - y_t = \alpha + \beta mps_t + \epsilon_t$ (Panel A) and $y_{t+20} - y_{t+5} = \alpha + \beta mps_t + \epsilon_t$ (Panel B), where t denotes the day of FOMC announcements, y the corresponding asset prices, and mps_t the monetary policy surprise calculated over the 30-minute window surrounding FOMC announcements. The S&P 500 and Dollar are measured as daily log returns, the VIX and Risk index as daily changes in index points, and the Baa spread and HY OAS as daily changes in percentage points. Sample periods are determined jointly by the availability of the policy surprises and asset prices. For the policy surprises, MPS are available from Jan. 1988 to Dec. 2019, while the target and path factors and the NS surprise are available from Jan. 1990 to Jun. 2019. Start and end dates for the asset prices are listed in Table A1. Huber-White heteroskedasticity-robust t-statistics are in parentheses.

Figure B2: State-dependence of the response of risk appetite to monetary policy surprises



Notes: Plots show the estimated slope coefficients from regressions of the cumulative changes in the risk appetite index over 0-20 trading days, with the FOMC announcement on day 0, on the [Bauer and Swanson \(2022\)](#) monetary policy surprise measure. Each figure displays two lines, showing the responses of the risk appetite index restricting to subsamples with each value of the corresponding indicator variables. The sample period for the regressions and median calculations is Jan. 1988 to Dec. 2019, except for the policy stance variable, which ends in Mar. 2018.

Panel A delineates positive and negative values of MPS (tightening and easing surprises). Panel B delineates NBER-dated recessions and expansions (USRECD in FRED). Panel C delineates above and below-median values of the output gap, constructed as $(Y - Y^*)/Y^*$, with Y as the level of real GDP (GDPC1) and Y^* as the CBO's estimate of the potential level of real GDP (GDPPOT) during the quarter of the FOMC meeting. Panel D delineates above and below-median values of the unemployment gap, defined as the difference between the unemployment rate (UNRATE) and the CBO's estimate of the non-cyclical rate of unemployment (NROU) in the month of the FOMC meeting. Panel E delineates above and below-median values of the stance of monetary policy, defined as the daily nominal two-year Treasury yield less the [Bauer and Rudebusch \(2020\)](#) estimate of the equilibrium real interest rate in the quarter of the FOMC meeting and the potential rate of inflation from the Fed Board's FRB/US model in the month of the FOMC meeting. Panel F delineates above and below-median values of the one-day lagged level of the risk appetite index, constructed as the cumulative sum of the daily index.

C Details for SVAR estimation

C.1 First-stage regressions and instrument relevance

Table C1 shows estimates of “first-stage” regressions of the external-instruments SVAR: the VAR residuals are regressed on our two monthly instrument series, MPS and RISK, over the sample period when the instruments are available, January 1988 to December 2019. For ease of interpretability, RISK is signed so that an increase corresponds to an increase in risk aversion (“risk-off”) and divided by 10 (so that both instruments have similar standard deviations). The main regressions of interest are the first two, for the VAR residuals of the two-year yield and the excess bond premium. MPS is strongly significant for the yield residual, whereas none of the instruments is statistically significant for the EBP residual at conventional significance levels. The robust F -statistics generally do not exceed the threshold of ten suggested by [Stock et al. \(2002\)](#), suggesting that the external instruments may suffer from a weak instruments problem.

Table C1: Instrument regressions

Residual	MPS	RISK	R^2	F -stat.	Robust F
y2	0.53 (2.95)	0.03 (0.18)	0.026	5.15	4.84
ebp	0.09 (0.45)	0.23 (1.30)	0.011	2.15	1.43
ip	0.02 (0.04)	-0.04 (0.11)	0	0.01	0.01
cpi	-0.07 (0.58)	-0.13 (1.22)	0.005	0.86	1.27

Notes: Regressions of VAR residuals on instruments MPS and RISK. Numbers in parentheses are t -statistics, which are calculated using Huber-White heteroskedasticity-robust standard errors. Robust F -statistic is equal to the heteroskedasticity-robust Wald statistic divided by two. Sample period: 1988:01 to 2019:12. Number of observations: 383.

These estimates may raise some concerns about instrument relevance for our SVAR. However, a newly emerging perspective on weak instruments in exactly identified systems, as in most SVAR applications, suggests that may in fact be little reason for such concerns: [Angrist and Kolesár \(2021\)](#) document that the use of weak instruments in just-identified systems does not introduce noticeable bias, which had been the overwhelming concern about weak instruments. One interpretation of these findings is that in case an instrument in a just-identified system is truly weak, this will not lead to bias but simply show up as less precise estimates in the second stage. In any event, we hope that future research will use other external instruments for changes in risk appetite—ideally with higher relevance for reduced-form VAR residuals—in order to revisit and assess our findings of a strong risk-taking channel in the monetary transmission.

C.2 Identification under zero-impact restrictions

Here we provide details of our identification procedure. We generally follow the setup and notation of [Montiel Olea et al. \(2021\)](#), and we refer the reader to that paper for a complete description. In Section A.7 of their online appendix, they provide some derivations for identification in the case of two instruments, but our identifying restrictions differ slightly from theirs.

Our goal is to identify the first two columns of the impact matrix Θ_0 which links the reduced form

residuals η_t to the structural shocks ε_t ,

$$\eta_t = \Theta_0 \varepsilon_t.$$

There are $N = 4$ shocks. Denote these first two columns as $\Theta_{0,1}$ and $\Theta_{0,2}$. They capture the impact effects of the risk-free rate shock and the risk-taking shock, respectively. The matrix that combines these two columns is denoted as $\Theta_{0,1:2}$.

The starting point of the estimation is the empirical relationship between the residuals and the two instruments in the $T \times 2$ matrix z_t . This relationship is captured by the $N \times 2$ matrix

$$\Gamma = E(\eta_t z_t') = \Theta_{0,1:2} \Phi,$$

where $\Phi = E(\varepsilon_{1:2,t} z_t')$ captures the relationship between the two instruments and the two structural shocks. We estimate Γ as the sample covariance matrix between the VAR residuals and our two instruments.

The baseline identification strategy in our paper is to impose four restrictions. We denote by e_i the i th column of the $N \times N$ identity matrix.

- The impact effect of the risk-free rate shock on EBP, the second variable in the VAR, is zero, i.e., $e_2' \Theta_{0,1} = 0$.
- The impact effect of the risk-taking shock on the two-year yield, the first variable in the VAR, is zero, i.e., $e_1' \Theta_{0,2} = 0$.
- The ‘‘own’’ impact effects of the shocks are normalized to be constants, $k_1 = 0.25$ and $k_2 = 0.1$, that is, $e_1' \Theta_{0,1} = k_1$ and $e_2' \Theta_{0,2} = k_2$.

To use these restrictions in the estimation we combine them as follows

$$[e_1, e_2]' \Gamma = [e_1, e_2]' [\Theta_{0,1}, \Theta_{0,2}] \Phi = \begin{pmatrix} k_1 & 0 \\ 0 & k_2 \end{pmatrix} \Phi,$$

where the first equality uses the definition of Γ , and the second inequality uses the restrictions specified above. Using the assumed invertibility of Φ it is then straightforward to obtain the impact matrix $\Theta_{0,1:2}$ as

$$\Theta_{0,1:2} = \Gamma \Phi^{-1} = \Gamma ([e_1, e_2]' \Gamma)^{-1} \begin{pmatrix} k_1 & 0 \\ 0 & k_2 \end{pmatrix}$$

An SVAR with two external instruments for two shocks requires three additional restrictions for identification, thus we have imposed one more restriction than necessary. We have also considered exactly identified systems, similar to [Montiel Olea et al. \(2021\)](#). First, consider the case where we only impose $e_2' \Theta_{0,1} = 0$ but not $e_1' \Theta_{0,2} = 0$. We obtain

$$[e_1, e_2]' \Gamma = \begin{pmatrix} k_1 & e_1' \Theta_{0,2} \\ 0 & k_2 \end{pmatrix} \Phi \quad \Rightarrow \quad \Theta_{0,1} = \Gamma ([e_1, e_2]' \Gamma)^{-1} \begin{pmatrix} k_1 \\ 0 \end{pmatrix}.$$

To obtain $\Theta_{0,2}$ we use the fact that $\Theta_{0,1}' \Sigma^{-1} \Theta_{0,2} = 0$, where $\Sigma = E(\eta_t \eta_t')$ is the residual covariance matrix.⁵

⁵The result $\Theta_{0,i}' \Sigma^{-1} \Theta_{0,j} = 0$ for all $i \neq j$ is due to the orthogonality of the structural shocks: $\Theta_0' \Sigma^{-1} \Theta_0$ is diagonal, since it equals the inverse of the diagonal matrix $E(\varepsilon_t \varepsilon_t')$.

Using this fact we have

$$[\Sigma^{-1}\Theta_{0,1}, e_2]'\Gamma = \begin{pmatrix} \Theta_{0,1} & \Sigma^{-1}\Theta_{0,1} & 0 \\ 0 & & k_2 \end{pmatrix} \Phi \Rightarrow \Theta_{0,2} = \Gamma ([\Sigma^{-1}\Theta_{0,1}, e_2]'\Gamma)^{-1} \begin{pmatrix} 0 \\ k_2 \end{pmatrix}.$$

For the alternative identification assumptions, where we impose $e_1'\Theta_{0,2} = 0$ but not $e_2'\Theta_{0,1} = 0$, similar calculations yield the result

$$\Theta_{0,2} = \Gamma ([e_1, e_2]'\Gamma)^{-1} \begin{pmatrix} 0 \\ k_2 \end{pmatrix} \quad \text{and} \quad \Theta_{0,1} = \Gamma ([e_1, \Sigma^{-1}\Theta_{0,2}]'\Gamma)^{-1} \begin{pmatrix} k_1 \\ 0 \end{pmatrix}.$$

Empirically, we found the results for these two exactly-identified systems to be very similar to the baseline results for the system with one overidentifying restriction.

C.3 Forecast error variance decompositions

Here we provide some details on the calculations of our forecast error variance decompositions (FEVDs). We want to calculate the fraction of the h -step ahead forecast error variance of the i th variable in the VAR, $Y_{i,t+h}$, that is due to the j th structural shock, $\varepsilon_{j,t}$.

The forecast error variance of $Y_{i,t+h}$, that is, the denominator of the FEVD, is given by this standard result:

$$Var_t(Y_{i,t+h}) = e_i' \left(\sum_{k=0}^{h-1} C_k \Sigma C_k' \right) e_i,$$

where C_k is the k th moving average coefficient matrix, i.e., the reduced-form impulse response at horizon k (note that $C_0 = I_N$).

The part of $Var_t(Y_{i,t+h})$ due to $\varepsilon_{j,t}$, that is, the numerator of the FEVD, is

$$Var_t(Y_{i,t+h}(\varepsilon_j)) = \sum_{k=0}^{h-1} \Theta_{k,ij}^2 \sigma_j^2,$$

where $\Theta_{k,ij}$ is the structural impulse response of variable i to shock j at horizon k , i.e., the (i, j) -element of $\Theta_k = C_k \Theta_0$. The variance of the j th structural shock, $\sigma_j^2 = Var(\varepsilon_{j,t})$, is not normalized to one, since we have followed the “unit effect” normalization of [Stock and Watson \(2018\)](#) and [Montiel Olea et al. \(2021\)](#). We can obtain it for each of the $r = 2$ structural shocks of interest using

$$D_{1:r,1:r} = \Phi (\Gamma' \Sigma^{-1} \Gamma)^{-1} \Phi',$$

the diagonal covariance matrix of the first r structural shocks.⁶ All that is needed is an estimate of Φ , which we can obtain as follows:

$$[e_1, e_2]'\Gamma = [e_1, e_2]'\Theta_{0,1:2}\Phi \Rightarrow \Phi = ([e_1, e_2]'\Theta_{0,1:2})^{-1} [e_1, e_2]'\Gamma.$$

⁶This relationship follows from equations (A.9)–(A.11) in Section A.6 of the Online Appendix of [Montiel Olea et al. \(2021\)](#).

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