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Predictability of Monetary Policy Surprises and Euro Area Macroeconomic Dynamics

David Worms

DeNederlandscheBank

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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

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Abstract

I document that high-frequency euro area monetary policy surprises – measured as changes in risk-free rates around the Eurosystem's policy announcements – are *not* exogenous to information regarding macroeconomic news and financial market developments that pre-date the announcements. More specifically, around 20% of the variation of surprises can be explained by pre-dated information. I show that the violation of the exogeneity of conventional surprise measures introduces a considerable bias into estimates on the effects of monetary policy on euro area macroeconomic outcomes.

Keywords: High-Frequency Identification, Macro News, Monetary Policy

JEL classifications: E43, E52, E58

*Goethe University Frankfurt & GSEFM, e-mail: worms@finance.uni-frankfurt.de. I am grateful to Gabriele Galati, Timo Haber, Stephen Kho, Sebastian Rast and Maik Schmeling for helpful comments.

1 Introduction

Empirical assessments of the effects of monetary policy are key to policy makers seeking to assess the effectiveness of their measures to inform future decisions, and have shaped a large body of research. However, quantifying the effects of monetary policy is a complex endeavor, primarily since it is complicated by endogeneity between observed financial and macroeconomic variables and measures of policy stance.

To overcome these endogeneity issues, many recent empirical studies rely on high-frequency asset price changes in narrow windows around central bank communication events – e.g., the releases of policy statements and subsequent press conferences – to identify exogenous shifts in monetary policy with respect to short-term rates, e.g., as in Kuttner (2001), Bernanke and Kuttner (2005), and with regard to unconventional policy tools, e.g., as in Gürkaynak et al. (2005), Altavilla et al. (2019), Swanson (2021). This identification implicitly relies on the assumption of full information, with prices reflecting all available information at each point in time. Consequently, all public information that pre-dates the central bank's communication event is assumed to be priced in when the announcement begins, and the news about monetary policy are assumed to be the only driver of asset price changes around policy announcements.

However, recent research challenges the exogeneity of such surprise measures, pointing to the role of macroeconomic expectations in introducing a measurement error. Exogeneity fails to hold, e.g., if there are discrepancies between market expectations and those of the central bank and communicated policy decisions implicitly reveal the central bank's expectations regarding macroeconomic fundamentals, giving rise to surprise measures capturing the so-called *information* or *signalling effects* of monetary policy, as in, e.g., Melosi (2017), Nakamura and Steinsson (2018), Jarociński and Karadi (2020), Andrade and Ferroni (2021). Another strand in the literature documents that high-frequency surprises are correlated with pre-dated information about macroeconomic and financial fundamentals. Bauer and Swanson (2023a,b) show that the predictability of surprises can be explained by a *response-to-news* channel, i.e., markets have imperfect information about systematic monetary policy and the central bank reacts stronger than anticipated to new information, such that surprises partly reflect the central bank's endogenous reaction to incoming data and thus fail to be exogenous.[1] An alternative explanation for the correlation of surprises with pre-dated information is examined by Sastry (2024), highlighting the role of discrepancies about the perceived informativeness of the observed signal between markets and the central bank.

This paper contributes to the latter strand in the literature by examining the exogeneity of changes in interest rates around policy announcements in the euro area with respect to pre-dated information about macroeconomic fundamentals and financial markets. To this end, I use the Euro Area Monetary Policy Database (EA-MPD) by Altavilla et al. (2019) – the standard reference for event-study analyses on the effects of euro area monetary policy – and test for the exogeneity of high-frequency changes in Overnight Index Swap (OIS) rates around European Central Bank (ECB) monetary policy communication events.

I document a considerable degree of *ex-post* predictability of OIS rate changes: pre-dated news about euro area macroeconomic outcomes, preceding financial market developments and OIS surprises of previous announcements explain around 15% of the variation in short-term OIS rate changes and more than 20% of medium-term and long-term OIS rate changes. More specifically, I find that the surprise component of data releases of euro area industrial production and unemployment rate and pre-dated changes in the yield curve slope, the shadow rate, the high-yield option adjusted spread and the equity prices of euro area banks are strong predictors of OIS rate changes, while the magnitude and statistical significance of this correlation varies across maturities of OIS contracts. My results strongly challenge the validity of the exogeneity assumption of euro area monetary policy surprise measures and complement previous US evidence (e.g., Miranda-Agrippino and Ricco (2021), Karnaukh and Vokata (2022), Bauer and Swanson (2023a,b), Swanson (2024), Sastry (2024)). By providing an in-depth assessment of the predictability of monetary policy surprises, this

[1] Jarociński and Karadi (2025) decompose high-frequency changes in US risk-free rates into pure monetary policy shocks, information effects and components related to shifts in perceptions about systemic monetary policy. Their identification relies on the co-movement between risk-free rates, the US stock market, as well as the information embedded in a set of pre-dated predictors.

paper contributes to the scarce literature on the exogeneity of euro area monetary policy surprises. Kerssenfischer and Schmeling (2024) document that high-frequency surprises in 2-year bond yields around ECB announcements are predictable based on the the reaction in the 2-year yield to previous macroeconomic releases and central bank communication events, including earlier euro area macroeconomic news, ECB announcements and Federal Reserve monetary policy announcements, with market reactions to pre-dated news explaining around 13% of surprises around ECB announcements. In contrast, I examine the predictability of policy surprises based on the *actual* surprise component of macroeconomic releases, along with financial market indicators and previous high-frequency policy surprises. In doing so, I assess correlations of high-frequency changes in OIS rates around policy announcements with a broad set of indicators and for surprises across the maturity spectrum. Altavilla et al. (2025) assess the exogeneity of changes in OIS rates and sovereign yields around ECB announcements and policy-makers' speeches with respect to macroeconomic and financial news based on a unified economic surprise index and six-week changes in financial market indicators, covering the change in the yield curve slope, commodity prices, and the stock market. They document that predictive power for surprises is low in general, with mostly single-digit R^2s for surprises around policy meetings and R^2s of below 1% around speeches, and conclude that predictability of high-frequency surprises around communication events is low. My findings, in contrast, suggest that predictability of OIS surprises around policy announcements is considerably higher with a more comprehensive set of predictors, covering, e.g., previous high-frequency monetary policy surprises in addition to macroeconomic news and financial market information.

Building on this insight, I then decompose the monetary policy surprises into a component capturing the correlation with previous information and an adjusted surprise and examine the extent to which the predicted component in surprises leads to biased estimates on the effects of monetary policy at different stages in the transmission. In line with US evidence in Bauer and Swanson (2023b), I document that the impact of the correlation of surprises with pre-dated information on estimates on the immediate, high-frequency effects of monetary policy is negligible. Estimation results on the asset price reactions based on a dynamic framework indicate that the response of some financial market variables in daily frequency is partly driven by the predicted component: the *raw* surprise produces slightly stronger and more persistent reactions of financial conditions and the USD/EUR exchange rate, compared to the adjusted surprise. While the impact of the violation of the exogeneity of surprises on the estimated effects of monetary policy in the early stages of the transmission is rather modest, I document that it introduces a significant bias in the estimated macroeconomic responses to monetary policy shocks. To this end, I use the local projection instrumental variable (LP-IV) methodology as in, e.g., Gertler and Karadi (2015), Ramey (2016) and Stock and Watson (2018) and instrument the monetary policy shock with either the *raw* or the adjusted high-frequency surprise. In line with the literature documenting output and price puzzles, e.g., Sims (1992), Uhlig (2005), Gertler and Karadi (2015), Wu and Xia (2016), a tightening monetary policy shock identified using the *raw* surprise is associated with an increase in economic activity and prices and a decrease in unemployment. In contrast, a monetary policy shock based on the adjusted surprise produces less puzzling macroeconomic reactions, especially with regard to prices and unemployment. I show that this discrepancy arises because the correlation of standard surprises with pre-dated information implies that a tightening monetary policy shock is, in part, associated with expansionary real effects. My findings suggest that conventional euro area surprises do not reflect purely exogenous shifts in monetary policy – challenging the key assumption of high-frequency identification – which distorts the assessment of the effects of monetary policy on real outcomes.

The remainder of the paper is organized as follows. Section 2 describes the data used. Section 3 covers an in-depth analysis of the predictability of surprises. In Section 4, I contrast the estimation results on the effects of monetary policy based on the raw and the adjusted surprises and show that the *ex-post* predictability of surprises introduces a considerable bias into the estimated macroeconomic reactions. Section 5 concludes.

2 Data

For my empirical analysis in Section 3, I use two main data sources: high-frequency monetary policy surprises, which are assumed to capture instantaneous shifts in market expectations about the path of monetary policy in response to policy announcements and a set of pre-dated public signals, covering macroeconomic news and information about financial markets.

2.1 Monetary Policy Surprises

The EA-MPD by Altavilla et al. (2019) constitutes the go-to dataset for analyses that use an event study framework to identify the effects of euro area monetary policy[2]. It covers high-frequency changes in OIS rates and sovereign yields across the maturity spectrum, along with intra-day changes in stock indices and exchange rates, around the Press Release, the subsequent Press Conference, and the entire Monetary Event, covering both elements in the communication timeline of the Eurosystem. Figure A.1 in the appendix illustrates the usual timeline of communication events on Governing Council meeting days. Asset price changes are derived based on the difference between median quotes in ten-minute windows after and prior to the event.

Since OIS changes for medium-term and long-term maturities are available only after August 2011, I follow Altavilla et al. (2019) and proxy the OIS change for these contracts with the Bund yield change with the respective maturity for announcements prior to that date. Given the great coverage of high-frequency changes in risk-free rates in terms of their maturity, I test in Section 3 the exogeneity of surprises to pre-dated information for OIS rates across the maturity spectrum.

2.2 Pre-dated Information

The set of predictors that I use in Section 3 comprises surprise measures of macroeconomic news releases, recent developments in financial variables and previous monetary policy surprises. Table A.1 provides more details on the predictors.

[2]The dataset is publicly accessible via the ECB's website and constantly updated by the authors.

Macroeconomic News. To capture the news component of macroeconomic releases, I employ surprise measures based on survey data on releases of euro area macroeconomic fundamentals from Bloomberg Economic Calenders. The Bloomberg surveys are conducted among professional forecasters and the surprises are computed as the difference between the actual value of the release and the median forecast, divided by the cross-sectional standard deviation of expectations. My set of macroeconomic predictors covers surprises in euro area industrial production, Core CPI and the unemployment rate. Given limited data availability of Bloomberg macro surprises, my sample covers April 2005 to December 2023. In line with Bauer and Swanson (2023a,b) and Swanson (2024), for each ECB announcement, I extract the most recent surprise for the respective macro variable. In case there was no new data release since the last meeting, and for missing values in the time series of surprises, I assume a pre-dated surprise of zero for a given announcement, since there was no news regarding the respective macroeconomic outcome.

Financial News. I complement the set of macroeconomic news with predictors that capture recent movements in financial markets. In particular, I compute changes in the yield curve slope, based on the difference between the 10-year and 3-month yield on euro area sovereign bonds, a common indicator of future macroeconomic fundamentals; the euro area shadow rate, reflecting the overall monetary stance stance without the effective lower bound restriction; the high-yield option-adjusted spread, the yield of below-investment grade corporate bonds over the risk-free rate, which typically serves as a proxy for risk appetite; the Nasdaq Euro Area Bank index, tracking the equity performance of the banking sector; and the Eurostoxx index, reflecting the performance of the broad stock market; from three months before until the day prior to the announcement.

Previous Monetary Policy Surprises. I additionally control for previous surprise components in OIS rates for a given maturity. Conceptually, market participants could change their expectations about future monetary policy decisions based on previous discrepancies between market expectations towards monetary policy and actual policy decisions. Moreover, e.g. Miranda-Agrippino and Ricco (2021) and Swanson (2024) find policy instruments to be serially correlated.

US Data. Motivated by the findings in Kerssenfischer and Schmeling (2024) that euro area surprises are predictable by previous news stemming from the Fed's policy communication events, but not by US macroeconomic news, in Section 3.2 I examine the predictive power of a set of US indicators for OIS changes around ECB policy announcements. In particular, to capture information about US monetary policy, I include the high-frequency change in the 2-year treasury future from the most recent FOMC announcement, retrieved from the Jarociński (2024) data set and the 3-month change in the US shadow rate. With regard to macroeconomic news, I consider the surprise in the nonfarm payroll release (NFP), retrieved from Bloomberg's economic calenders, since Kerssenfischer and Schmeling (2024) find the US employment report to be the most important news release for asset prices and Bauer and Swanson (2023b) show that the NFP surprise is a strong predictor for US short-term policy surprises.

3 Predictability of Euro Area Surprises

To empirically test the exogeneity of monetary policy surprise measures, I regress the high-frequency OIS rate changes covered in the EA-MPD on my set of pre-dated macroeconomic and financial predictors, as well as lagged values of the respective OIS surprise. In particular, I estimate:

$$OIS_{m,t} = \alpha + \beta' P^{M}_{t-} + \gamma' P^{F}_{t-} + \delta' P^{OIS}_{t-} + OIS^{\perp}_{m,t} \tag{1}$$

where $OIS_{m,t}$ is the change in OIS rate with maturity m around the Monetary Event, t, i.e., capture the market reactions to both, the press release and the press conference; P_{t-} covers the set of predictors based on information that pre-dates the announcement, indicated by $t-$. In particular, P^{M}_{t-} is the vector of macroeconomic news, covering surprises in the euro area IP, Core CPI and unemployment rate; P^{F}_{t-} is the vector of financial market information, covering the three-month changes in the yield curve slope, the shadow rate, the high-yield option-adjusted spread, the bank equity index and the broad stock market and P_{t-}^{OIS} is the vector of two lags of the respective OIS surprise. $OIS_{m,t}^{\perp}$ is the residual from estimating (1), reflecting an orthogonalized version of the OIS surprise that is adjusted for the correlation with pre-dated macroeconomic and financial information. Note that if the key underlying assumption of identifying exogeneous monetary policy based on high-frequency asset price changes holds, then the OIS rate changes around policy announcements are uncorrelated with the pre-dated predictors, i.e., any pre-dated information does not exhibit predictive power for the surprise measures, given that all intra-day changes are driven solely by the monetary policy announcement.

Table 1 shows the estimation results for selected maturities of OIS surprises. A more comprehensive set of results covering more maturities is covered in Table A.2 in the appendix. To allow for a comparison of the estimated coefficients, I standardize each predictor to have zero mean and unit standard deviation over time prior to estimation. In contrast to the assumption of exogenetiy of surprise measures, Table 1 provides strong evidence that OIS surprises are highly correlated with pre-dated information. R^2s are around 12% to 15% for the changes in short-term OIS rates and around 20% and more for changes in medium and long-term rates. These numbers are comparable in magnitude to those reported in Bauer and Swanson (2023b) and Swanson (2024) for the US.

Most coefficients of pre-dated regressors are statistically significant, with some variation across maturities, indicating that surprises are *ex-post* predictable based on previous public signals. Higher-than-anticipated IP releases are mildly associated with a stronger tightening for medium-term maturities and worse-than-anticipated unemployment releases are associated with a weaker tightening than anticipated. This correlation is highly statistically significant for medium and long-term maturities, while the estimated effects are strongest for OIS rate changes with maturities around two years and then decrease for longer maturities. In contrast, the coefficient of surprises of core CPI releases is not statistically significant for any maturity. In line with the

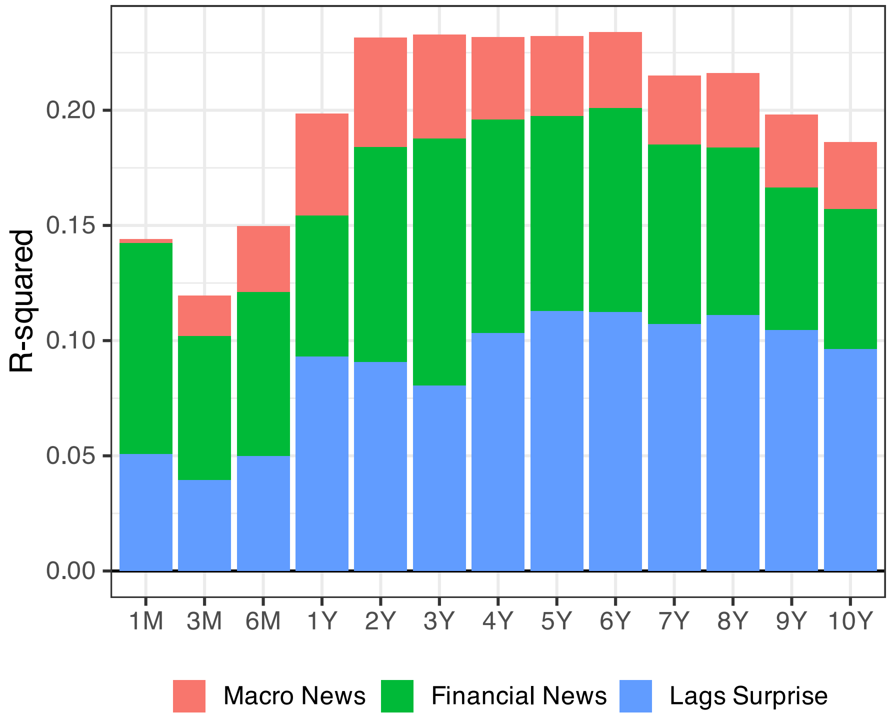
Table 1: Predictability of OIS Surprises by Maturities

	Dependent variable: OIS^m					
	1m	6m	1y	2y	5y	10y
	(1)	(2)	(3)	(4)	(5)	(6)
$EA\ IP$	0.06	0.50**	0.65**	0.73**	0.57**	0.26
	(0.21)	(0.22)	(0.26)	(0.30)	(0.28)	(0.21)
$EA\ CPI$	0.10	−0.22	−0.25	−0.17	−0.09	0.17
	(0.30)	(0.35)	(0.37)	(0.37)	(0.36)	(0.27)
$EA\ Unempl$	−0.10	−0.62*	−1.02***	−1.22***	−0.97***	−0.62**
	(0.32)	(0.34)	(0.37)	(0.37)	(0.34)	(0.25)
$\Delta YCSlope$	0.06	0.25	0.32	0.79*	0.91**	0.70**
	(0.34)	(0.39)	(0.42)	(0.46)	(0.42)	(0.30)
ΔSR	−0.48	−0.52	−0.81*	−1.39**	−1.17**	−0.74**
	(0.30)	(0.39)	(0.49)	(0.59)	(0.54)	(0.36)
$\Delta HYOAS$	0.88*	1.35**	1.49**	1.45**	0.62	0.18
	(0.51)	(0.61)	(0.63)	(0.69)	(0.61)	(0.35)
$\Delta BankEquity$	0.65*	1.01**	1.45**	2.00**	1.80**	0.82
	(0.37)	(0.48)	(0.67)	(0.92)	(0.85)	(0.50)
$\Delta ES50$	−0.46	−0.15	0.13	0.27	0.18	0.12
	(0.53)	(0.57)	(0.61)	(0.65)	(0.56)	(0.42)
$(L)^1$	−0.21*	−0.24**	−0.33***	−0.33**	−0.37***	−0.34***
	(0.12)	(0.10)	(0.12)	(0.13)	(0.12)	(0.10)
$(L)^2$	−0.15	−0.04	−0.03	−0.03	−0.04	−0.04
	(0.11)	(0.09)	(0.13)	(0.11)	(0.09)	(0.09)
Constant	0.37*	0.26	0.15	−0.20	−0.47	−0.24
	(0.22)	(0.28)	(0.33)	(0.36)	(0.32)	(0.23)
Observations	187	187	187	187	187	187
R^2	0.14	0.15	0.20	0.23	0.23	0.19
Adjusted R^2	0.10	0.10	0.15	0.19	0.19	0.14

Note: estimation results for specification (1). OIS rate changes are measured over the Monetary Event window in the EA-MPD by Altavilla et al. (2019); see Sections 2 and 3 for details; robust standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

response-to-news channel proposed by Bauer and Swanson (2023b), these results could be interpreted as suggesting that market participants' conceptions about the central bank's reaction to news related to inflation being fairly accurate, whereas markets underestimate the reaction of the ECB to positive news about economic activity and negative news about unemployment.

Figure 1: Predictive Power by News Category and Maturity



Note: explanatory power of pre-dated information by news category for OIS rate changes across maturities, based on Shapley value decomposition as in, e.g., Mishra (2016), aggregated at the category level.

A recent steepening in the yield curve, potentially indicating higher future economic activity, is associated with a stronger tightening for medium to long-term maturities. An increase in the shadow rate, reflecting an overall tightening in the stance of monetary policy during the past three months, is associated with a weaker tightening with respect to medium and long-term rates, which is in line with US evidence by Swanson (2024). After a widening in the high-yield option-adjusted spread, an indication for an increase in risk-taking, the tightening in short and medium-term rates is stronger than markets anticipated. A strong performance of the banking sector, measured as an increase in equity prices of euro area banks, is associated with a stronger-than-expected tightening across the maturities spectrum. This correlation is most pronounced in magnitude for medium-term maturities, exhibiting a hump-shaped pattern, with weaker correlations observed for short and long-term maturities. There is a very mild and positive correlation between strong stock market performance and tightening surprises for medium and long-term maturities, which is however not statistically significant for any of the maturities. Moreover, OIS surprises are first-order serially correlated, which is in line with the findings in, e.g., Miranda-Agrippino and Ricco (2021) and Swanson (2024) on US monetary policy surprises.

In Figure 1, I illustrate the predictive power by maturity, measured as the R^2s from estimating specification 1, decomposed by category of pre-dated information. Previous macro news explain a relatively small fraction of OIS surprises and predictive power is especially low for the short-term OIS rates. Pre-dated financial market information exhibits higher predictive power, in general. The set of financial predictors explains around half of the variation in short-term surprises and approximately 10% of variation in medium-term OIS rate changes. For longer maturities, the predictive power of financial news decreases. A considerable share of predictive power stems from the autocorrelation of OIS surprises, with its relative contribution increasing for longer maturities.

Overall, my findings suggest that the exogeneity of euro area high-frequency monetary policy surprises does not hold empirically: I document that OIS rate changes are correlated with public signals that pre-date the announcements, which challenges the implicit assumption of event-study analyses that surprise measures capture exogenous shifts in monetary policy.

3.1 Predictive Power in High vs. Low-Uncertainty Regimes

The baseline results in Table 1 show that euro area surprises are correlated with previous information regarding macroeconomic news and financial market developments. I now examine the extent to which my full sample estimation results, indicating *mon-*

etary policy-specific uncertainty among market participants according to the Bauer and Swanson (2023b) *response-to-news* channel, is driven by periods characterized by high *general* levels of uncertainty. To this end, I adjust specification (1) and estimate:

$$OIS_{m,t} = \alpha + \beta' P_{t-} + \gamma'(P_{t-} \times \mathbb{1}_{\{U>75p\}}) + \varepsilon_{m,t} \tag{2}$$

where $OIS_{m,t}$ is again the change in OIS rate with maturity m around the Monetary Event, P_{t-} captures the three sets of pre-dated predictors P^M_{t-}, P^F_{t-} and P^{OIS}_{t-} and $\mathbb{1}_{\{U>75\}}$ is an indicator which is one for announcements in the high uncertainty regime. To distinguish high from low uncertainty states, I use the VSTOXX, a market-based, forward-looking uncertainty indicator that reflects expected stock market volatility and define the two regimes based on the 75th percentile of the distribution of VSTOXX realizations in my sample. The extent to which correlation of surprises with pre-dated information varies across the two uncertainty regimes is reflected in γ.

Table A.3 in the appendix shows the estimation results for specification (2). In general, the baseline results in Table 1 do not seem to be driven by announcements during periods of high levels of uncertainty, with some exceptions: First, the full sample correlation of high-frequency OIS rate changes with the high-yield spread and the equity prices of euro area banks is driven primarily by observations in the high-uncertainty state. Second, Table A.3 provides evidence that the absence of a correlation of OIS surprises with the broad stock market masks that there is a mild tendency that a strong recent performance in the broad stock index is associated with the weaker-than-expected tightening when uncertainty is high and stronger-than-expected tightening when uncertainty is low. Third, Table A.3 indicates that during the periods of elevated uncertainty, positive Core CPI surprises are associated with stronger tightening in long-term rates. Given that for all other predictors, the correlations with OIS surprises are fairly robust across the two uncertainty regimes, Table A.3 illustrates that my baseline results are not driven by announcements in the high-uncertainty state. In particular, the correlation of euro area monetary policy surprises with pre-dated news about economic activity and unemployment holds across both low- and high-uncertainty states.

3.2 Predictive Power of US-related News

In contrast to my projections in specification (1), in which I examine the predictability of policy surprises based on the *actual* surprise component of releases of industrial production, Core CPI and the unemployment rate, along with financial market indicators and previous high-frequency policy surprises, Kerssenfischer and Schmeling (2024) test whether intra-day changes in the 2-year bond yield around a wide array of releases and events – including, e.g., euro area and US macroeconomic news and central bank communication events – help predict high-frequency changes in the 2-year bond yield around ECB monetary policy announcements. They find that the surprise in the 2-year yield around ECB announcements is predictable based on yield reactions to previous macro news, ECB communication events, including, e.g., speeches by policymakers, and Fed policy announcements.

Motivated by their latter finding, I test for spillovers from US-related information on euro area surprises by extending the set of pre-dated predictors for information related to US monetary policy and US macro news. More specifically, I estimate:

$$OIS_{m,t} = \alpha + \beta' P^{M}_{t-} + \gamma' P^{F}_{t-} + \phi' P^{US}_{t-} + \delta' P^{OIS}_{t-} + \varepsilon_{m,t} \tag{3}$$

where P^{US}_{t-} is the additional set of pre-dated predictors, covering the high-frequency change in the 2-year treasury future around the most recent FOMC announcement, the three-month change in the US shadow rate and the surprise component in Bloomberg survey on the release of the nonfarm payroll.

Table A.4 and Figure A.2 in the appendix show the estimation result s based on specification (3). In general, euro area surprises seem to be exogenous to previous US news: Table A.4 illustrates that none of the three US-related predictors are correlated with OIS surprises for any maturity. In line with a decrease in adjusted R^2s for most maturities in Table A.4 compared to the baseline results in Table 1, Figure A.2 shows that US news have no predictive power for euro area surprises.

To summarize, in Section 3 I document that euro area monetary policy surprises are highly correlated with pre-dated euro area macroeconomic and financial information. My findings strongly challenge the exogeneity assumption of surprise measures underlying analyses using event-study frameworks to identify monetary policy. I show that the correlation of surprises with previous public signals is not driven by periods of high uncertainty and I do not find evidence for spillover effects of US-based information on euro area surprises. I therefore continue with specification (1) in the next steps of my analysis.

4 Predictability of Surprises and Monetary Policy Effects

The predictability evidence presented in the previous section suggests that surprise measures do not reflect purely exogenous shifts in monetary policy. To evaluate the consequences of the correlation of high-frequency monetary policy surprises with pre-dated information for assessing the effects of monetary policy in different stages of the transmission, I orthogonalize the OIS surprises with respect to the set of pre-dated predictors in specification (1) to decompose *raw* OIS changes into a component that captures the correlation with previous public signals, $OIS^{P}_{m,t}$, and an ortogonalized version of the OIS surprise, $OIS^{\perp}_{m,t}$, derived as the residual of specification (1):

$$OIS^{\perp}_{m,t} = OIS_{m,t} - OIS^{P}_{m,t}, \quad \text{with} \quad OIS^{P}_{m,t} = \widehat{\alpha} + \widehat{\beta}' P^{M}_{t-} + \widehat{\gamma}' P^{F}_{t-} + \widehat{\delta}' P^{OIS}_{t-} \tag{4}$$

Furthermore, for the rest of my analysis, I focus on the use the high-frequency OIS surprise with a maturity of two years as a unified measure of monetary policy, i.e., $m = 2$ years. This is based on the idea that changes in the 2-year maturity capture both, shifts in monetary policy in terms of conventional as well as unconventional measures over the medium term, and is in line with Hanson and Stein (2015) who stress that the 2-year maturity is an appropriate indicator for changes in the future path of monetary policy. Moreover, Table 1 shows that the predictability based on pre-dated information is particularly pronounced for the 2-year OIS surprise.

4.1 Financial Market Reactions to Monetary Policy Surprises

4.1.1 High-Frequency Asset Price Reactions

In line with Bauer and Swanson (2023b), in a first step, I examine the immediate financial market reaction to both the *raw* and adjusted monetary policy surprise. To this end, I regress the high-frequency changes in long-term sovereign bond yields, the stock market and the USD/EUR exchange rate on the surprise measures, respectively, and compare their effects:

$$\Delta y_t = \alpha + \beta\, OIS_t + \varepsilon_t; \text{ with } OIS_t \in \{OIS_{2y,t}, OIS^{\perp}_{2y,t}\} \tag{5}$$

where Δy_t captures the changes of the 10-year sovereign yields, the STOXX50 or the USD/EUR – also retrieved from the EA-MPD by Altavilla et al. (2019) – around the monetary event window. Estimation results for the intra-day asset price reaction to the monetary policy surprises are shown in Table 2.

Table 2: Asset Price Reactions to Raw vs. Adjusted Surprises

	DE 10-year	FR 10-year	IT 10-year	STOXX50	USD/EUR
Raw Surprise:					
β	5.426***	5.907***	6.607***	−0.419***	0.522***
t-stat.	8.95	7.58	4.52	−2.82	6.45
R^2	0.542	0.491	0.207	0.079	0.277
Adjusted Surprise:					
β	5.375***	5.849***	6.344***	−0.342**	0.512***
t-stat.	8.37	7.62	4.37	−2.24	6.14
R^2	0.409	0.370	0.147	0.040	0.204
N	187	187	187	187	187

Note: estimation results on high-frequency financial market reaction to a 10 bps monetary policy surprise, measured as the change in the 2-year OIS rate around the monetary event, based on specification (5). Changes in sovereign bond yields (in bps), the stock market and the USD/EUR exchange rate (in percent) reflect intra-day changes, measured over the monetary event window from the EA-MPD by Altavilla et al. (2019); reported t-statistics are based on robust standard errors; the sample covers all ECB announcements from 04/2005 to 12/2023.

In general, and consistent with US evidence by Bauer and Swanson (2023b), endogeneity of euro area surprises with pre-dated information does not alter their estimated high-frequency effects on financial market variables: in reaction to a 10 bps tightening surprise, measured either as the *raw* or adjusted OIS rate change, sovereign long-term bond yields increase by around 5 to 6 bps, stock prices decrease by approximately .4 % and the Euro appreciates versus the Dollar by around .5 %. The magnitude and statistical significance of the estimated effects are very similar for both surprise measures, with a slightly lower effect in magnitude on stock prices for the adjusted surprise. Overall, Table 2 illustrates that the predicted component in the unadjusted surprise does not introduce a bias in the estimates on the high-frequency reaction of asset prices to monetary policy surprises.

4.1.2 Dynamic Asset Price Reactions

To examine potential discrepancies between the estimated financial market effects of monetary policy based on *raw* versus adjusted surprises beyond the initial market reaction, I use a daily local projection framework and trace the dynamic reactions of financial variables in the weeks after ECB announcements. More specifically, to contrast the estimation results on the financial market responses to the two surprise measures, I estimate:

$$\Delta y_{t+h} = \alpha^{(h)} + \beta^{(h)}\, OIS_{2y,t} + (L)y_t + \varepsilon_t^{(h)}, \tag{6}$$

$$\Delta y_{t+h} = \alpha^{(h)} + \beta_P^{(h)}\, OIS_{2y,t}^{P} + \beta_\perp^{(h)}\, OIS_{2y,t}^{\perp} + (L)y_t + \varepsilon_t^{(h)} \tag{7}$$

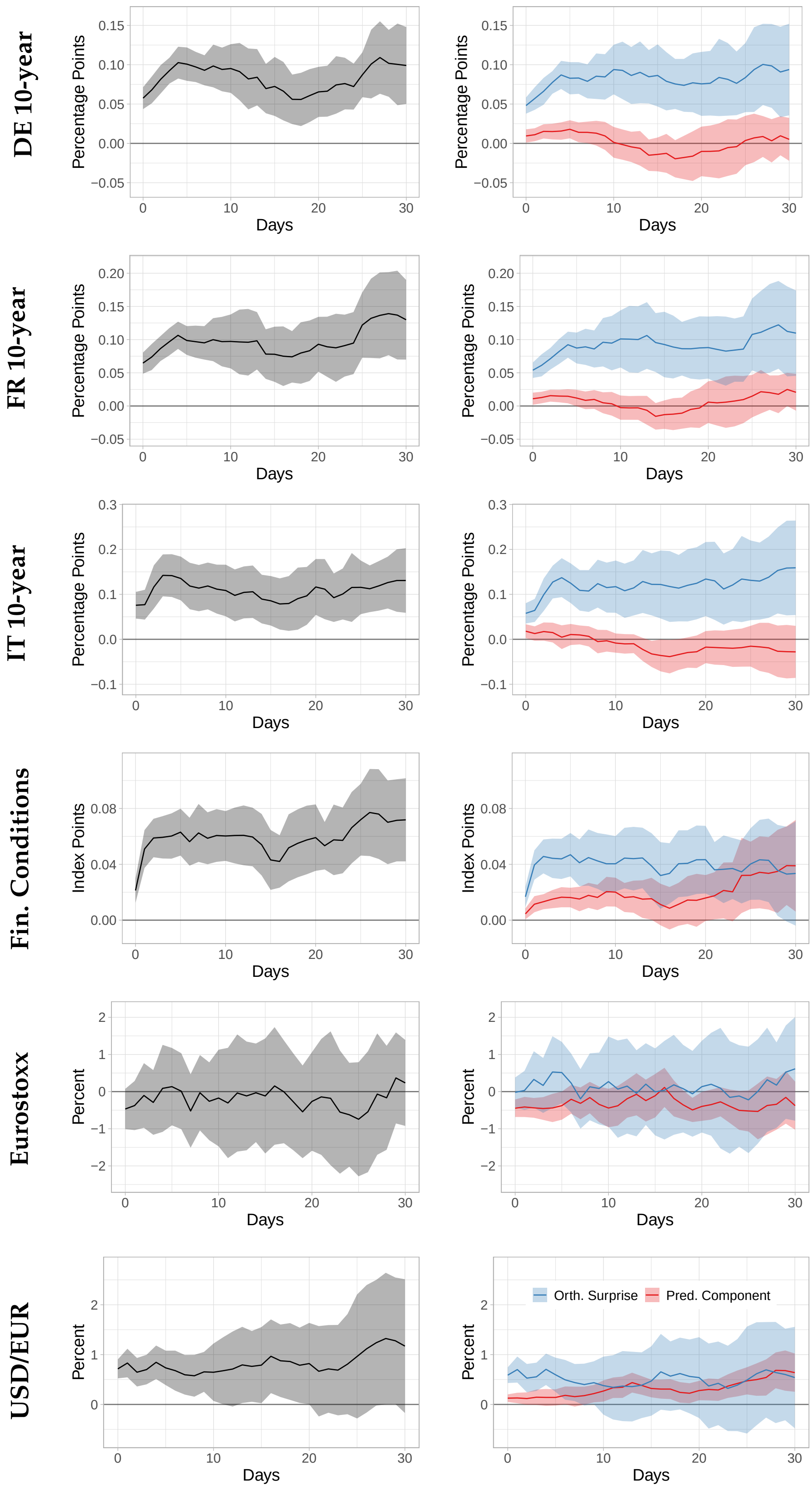
where Δy_{t+h} reflects the cumulative change in financial variable y from the day prior to the announcement to h days after the announcement; $OIS_{2y,t}$ is the unadjusted surprise and $OIS_{2y,t}^{P}$ and $OIS_{2y,t}^{\perp}$ capture the predicted component and the adjusted surprise, respectively, and $(L)y_t$ reflects five lags of variable y. While $\beta^{(h)}$ in specification (6) traces the effect of the *raw* surprise, $\beta_P^{(h)}$ and $\beta_\perp^{(h)}$ in specification (7) decompose the unadjusted reaction into a response to the adjusted component and the predicted component of the surprise. In line with Table 2, I examine the reactions of long-term sovereign bond yields, the Eurostoxx, the USD/EUR exchange rate, and additionally overall financial conditions, proxied with Bloomberg's Financial Conditions Index for the euro area, during the 30 days following the announcement. In line with the previous steps in my analysis, the sample covers 04/2005 to 12/2023.

Figure 2 illustrates the impulse responses for the unadjusted surprise in the left column and for a decomposed surprise in the right column, i.e., the financial reactions to the adjusted surprise and to the predicted part. In reaction to a 10 bps tightening surprise in the unadjusted measure, sovereign bond yields increase by around 5 to 15 bps during the subsequent days. Financial conditions tighten, as indicated by a statistically significant increase in the financial conditions index, and the Euro appreciates versus the Dollar by around one percent on impact. These responses are highly persistent and even seem to intensify over the considered horizon. The statistically significant stock price reaction documented in Table 2, in contrast, exhibits no persistence. The right column of Figure 2 shows that the reactions to the adjusted surprise measure are mostly consistent with the estimation results based on the *raw* surprise: a tightening surprise is associated with increases in bond yields, tighter financial conditions and an increase in the USD/EUR exchange rate. However, the predicted component introduces a mild bias in some of the reactions, which is reflected, e.g., in a slightly weaker initial reaction of long-term rates, and weaker and less persistent reactions in financial conditions and the USD/EUR exchange rate to the adjusted compared to the unadjusted surprise.

More generally, Figure 2 indicates the dynamic financial market reaction to the *raw* surprise is partly driven by the predicted component, which, following Bauer and Swanson (2023b), stems from imperfect information about the central bank's reaction to incoming macroeconomic and financial news. The discrepancy between the responses is relatively mild for most of the variables and the reactions of long-term yields to the predicted component are statistically insignificant for most horizons. Figure A.3 shows that this holds true also for the reaction of risk-free rates across the maturity spectrum and medium-term sovereign bond yields. Still, the reactions of financial conditions and the exchange rate indicate that the predicted component can lead to biased estimates on the effects of monetary policy on some financial variables, both in terms of magnitude and persistence.

Figure 2: Dynamic Reactions to Raw vs. Adjusted Surprises

(a) Raw OIS Surprise (b) Decomposition



Note: Estimation results for LP specifications (6) and (7); the sample covers 04/2005 to 12/2023. The decomposition of responses to the raw OIS surprise is based on rescaling its two components by the ratio of the variance of the raw shock to the variance of the component. Shaded areas denote pointwise 90% confidence bands, based on heteroscedasticity-and autocorrelation robust standard errors with h lags, following Newey and West (1987).

4.2 Macroeconomic Reactions to Monetary Policy Shocks

4.2.1 LP-IV Methodology

Motivated by the findings in Bauer and Swanson (2023b) that predictability of high-frequency surprises leads to biased estimates on the effects of monetary policy on US real outcomes, I now assess whether the bias is evident also for the case of surprises measured around ECB announcements and euro area macroeconomic dynamics.

To this end, I follow the literature that uses the information embedded in high-frequency surprise measures to examine the macroeconomic responses to monetary policy shocks, following, e.g., Gertler and Karadi (2015) and Stock and Watson (2018). In particular, I use a local projections (LP) framework in monthly frequency following Jordà (2005). The set of endogenous variables in the LPs covers industrial production, the harmonized index of consumer prices (HICP), the unemployment rate, the USD/EUR exchange rate and the shadow rate. I incorporate the high-frequency surprises based on the two-stage LP-IV approach and control for 12 lags of the endogenous variables in both stages. The underlying idea is that the external variable, the monetary policy surprise, z_t^{MP}, is a noisy signal of the true but unobserved shock, i.e., the monetary policy shock. In the first stage, I thus project the shadow rate, Y_t^{SR}, on the instrument, z_t^{MP}, where the instrument is based either on the *raw* or the adjusted surprise, $z_t^{MP} \in \{OIS_{2y}, OIS_{2y}^{\perp}\}$, and lags of the endogenous variables Y:

$$Y_t^{SR} = \alpha + A(L)Y_{t-1} + \gamma \, z_t^{MP} + \varepsilon_t^{SR} \tag{8}$$

The second stage then projects the cumulative changes in endogenous variables up to horizon h, Y_{t+h}, on the fitted values of the first stage, $\widehat{Y}_t^{SR}$, while controlling for lagged endogenous values, Y_{t-1}:

$$Y_{t+h} = \alpha^{(h)} + A^{(h)}(L)Y_{t-1} + \theta^{(h)} \, \widehat{Y}_t^{SR} + \varepsilon_t^{(h)} \tag{9}$$

where the horizon-specific macroeconomic reactions to the (instrumented) monetary policy shock for $h = 0, ..., 50$ are captured by $\theta^{(h)}$. Consistent with earlier studies, I construct monthly time series of the instruments by summing over the surprises in each month; for months without an ECB policy announcement, the instrument is zero.

As discussed in detail in Stock and Watson (2018), z_t^{MP} is a valid instrument for a monetary policy shock if the *relevance* and *exogeneity* conditions hold. While the *relevance* of the instrument reflects that it is highly correlated with the "true" monetary policy shock, $E[z_t^{MP} \varepsilon_t^{SR}] \neq 0$, *exogeneity* requires the instrument to be contemporaneously uncorrelated with the shocks other than the monetary policy shock, $E[z_t^{MP} \varepsilon_t^{-SR}] = 0$, where ε_t^{-SR} reflects all shocks apart from the monetary policy shock. As discussed in Stock and Watson (2018), in addition to the contemporaneous *exogeneity*, the dynamic structure of the LP-IV requires the *lead-lag exogeneity* to hold, $E[z_t^{MP} \varepsilon_{t+j}] = 0$, $\forall j \neq 0$, i.e., the instrument needs to be uncorrelated with all past and future shocks.

The first-stage F-statistics for the *raw* and the adjusted instrument, derived as the squared t-statistics for γ in (8), are $F^{raw} = 12.36$ and $F^{\perp} = 12.28$, i.e., both instruments are strong enough to exceed the weak-instrument threshold value of 10, as suggested by Stock and Watson (2012), indicating that the *relevance* condition for the instruments is satisfied. Based on my findings on the correlation with OIS surprises with past macroeconomic and financial information, I expect the *exogeneity* conditions to to hold more reliably for the adjusted version of the instrument.

4.2.2 Macroeconomic Reactions to Raw vs. Adjusted Shocks

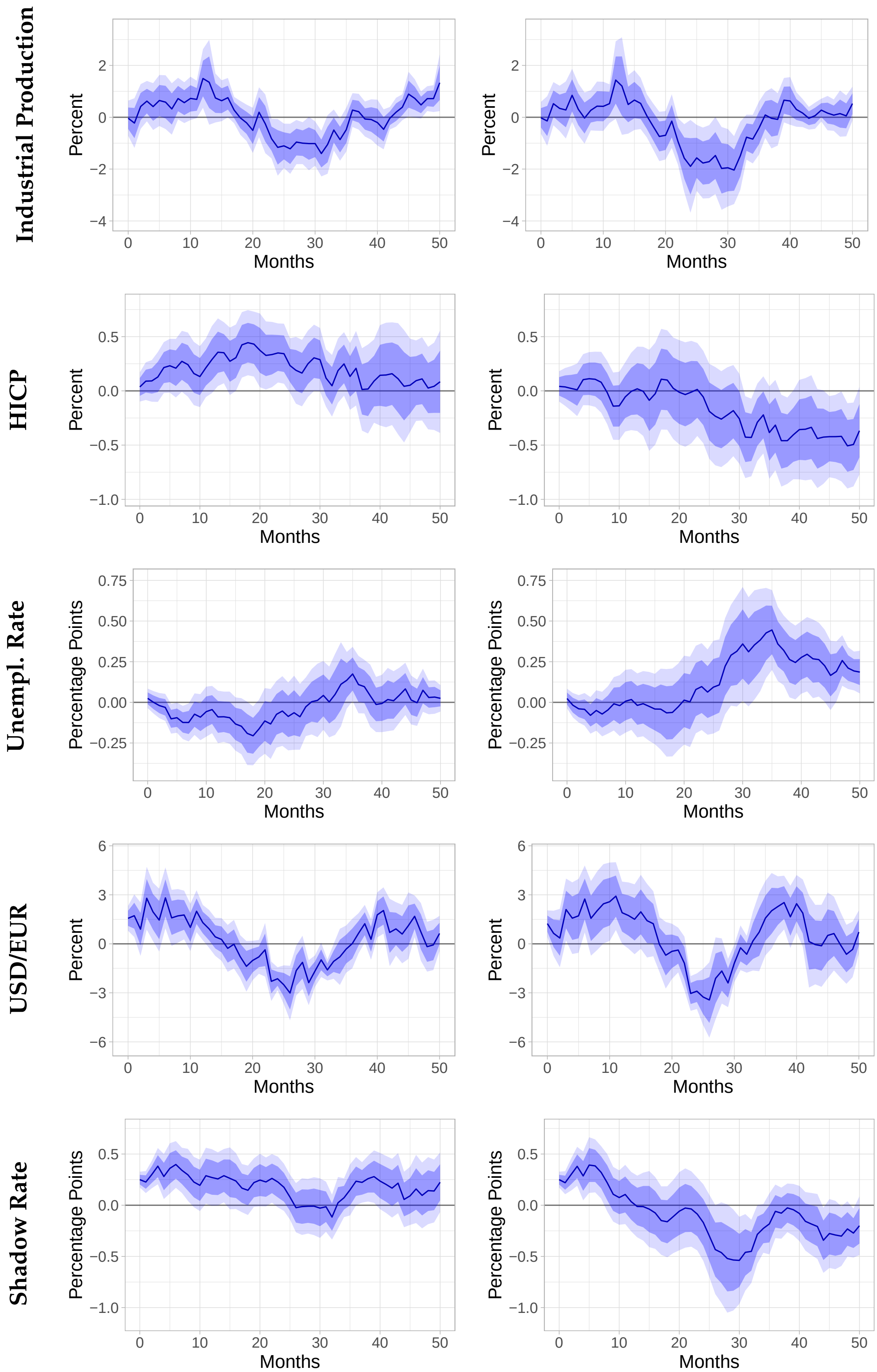
Figure 3 contrasts the macroeconomic reactions to a monetary policy shock identified with the *raw* in the left column versus the adjusted monetary policy surprises as instrument in the right column. For both instruments, the on-impact effect on the shadow rate is normalized to 25 basis points.

In general, the estimated macroeconomic responses to a tightening monetary policy shock, identified using the *raw* surprise, are puzzling: industrial production increases for several months, and turns negative only after around 20 months. The decline in economic activity is around one percent and persists for around 12 months, after which there is again a pick up in industrial production after around four years; the response of the HICP is positive and statistically significant after a few months. More specifically, prices increase persistently for roughly two years with a maximum effect of around .5 percent and the unemployment rate declines for several months. These reactions are in line with the empirical literature documenting output and prize puzzles, e.g., Sims (1992), Uhlig (2005), Gertler and Karadi (2015) and Wu and Xia (2016). Moreover, the Euro appreciates against the Dollar for around one year and the overall policy stance remains more restrictive for around two years, as reflected by the response of the shadow rate.

In contrast, a tightening monetary policy shock that is identified using the adjusted surprise produces macroeconomic reactions that are better aligned with theoretical predictions: the positive response of industrial production in the initial months appears muted and is not statistically significant. After around 20 months, industrial production is estimated to drop more strongly, by around 2%, while the decline in economic activity again persists for around one year. Moreover, with the adjusted instrument, there is no statistically significant increase in industrial production afterwards; the price reaction is clearly negative. The HICP reacts after around two years and declines persistently by around .5 percent; in line with the sluggish reaction in prices, unemployment increases after around two years, with a peak effect of around .5 percentage points after three years, after which the effect slightly fades in magnitude, but is still statistically significant. The reaction of the USD/EUR is mostly consistent with the estimates based on the *raw* instrument, although the confidence bands for the adjusted instrument seem to be slightly larger. The reaction of the shadow rate indicates tighter financial conditions for around a year and is hence less persistent. Figures A.4 and A.5 illustrate that these findings are robust to alternative lag lengths of the endogenous variables and an alternative LP-IV specification, which additionally controls for three lags of the instrument in both stages. For specifications with fewer endogenous lags, the initial increase in prices in response to a tightening monetary policy shock is still evident, also when using the adjusted surprises for identification; however, the

Figure 3: Macroeconomic Responses to Monetary Policy Shocks

(a) Raw Surprise (b) Adjusted Surprise



Note: Estimation results for LP-IV specification (9), in which in the first stage either the raw, or the adjusted 2-year OIS surprise is used as an instrument for the shadow rate and second stage reactions are normalized to increase the shadow rate by .25 percentage points. The sample covers 06/2005 to 12/2023. Dark (light) shaded areas denote pointwise 68% (90%) confidence bands, based on heteroscedasticity- and autocorrelation robust standard errors with h lags, following Newey and West (1987).

effect is attenuated compared to the reaction to the *raw* instrument[3].

In sum, the estimated macroeconomic reactions to monetary policy shocks differ considerably. While the *raw* instrument produces puzzling reactions in economic activity, prices and unemployment, the adjusted instrument yields estimates that are well aligned with theoretical predictions. In particular, adjusting the instrument for the correlation of surprise measures with pre-dated information reverses the sign in the reaction of prices and unemployment and mitigates the puzzling initial reaction in economic activity shortly after a tightening monetary policy shock. Following these lines, and consistent with US evidence in Bauer and Swanson (2023b), my results highlight the necessity to adjust for the correlation of policy surprise measures with pre-dated information when identifying the causal effects of monetary policy on macroeconomic outcomes in the euro area.

4.2.3 Bias in Macroeconomic Reactions and Predictability of Surprises

To illustrate and further examine the bias in the macroeconomic reactions, I decompose the reaction to the *raw* instrument and contrast the responses to the adjusted surprise and to the predicted component. Given that the predicted component captures the part of surprises that is correlated with pre-dated information – and does not capture exogenous shifts in monetary policy by construction – it does not correspond to a monetary policy shock in the LP-IV framework. I therefore estimate an alternative monthly LP framework:

$$Y_{t+h} = \alpha^{(h)} + A^{(h)}(L)Y_{t-1} + \eta^{(h)}\, z_t^{\perp} + \delta^{(h)}\, z_t^{P} + \varepsilon_t^{(h)} \tag{10}$$

where Y reflects a vector of the same endogenous variables as in (9) and I again control for 12 endogenous lags. In contrast to the LP-IV specification in (8) and (9), I assess the macroeconomic reaction to the two decomposed components of the *raw* surprise measure, with $z_t^{\perp}$ the monthly version of the adjusted surprise measure $OIS_t^{\perp}$ and z_t^{P}

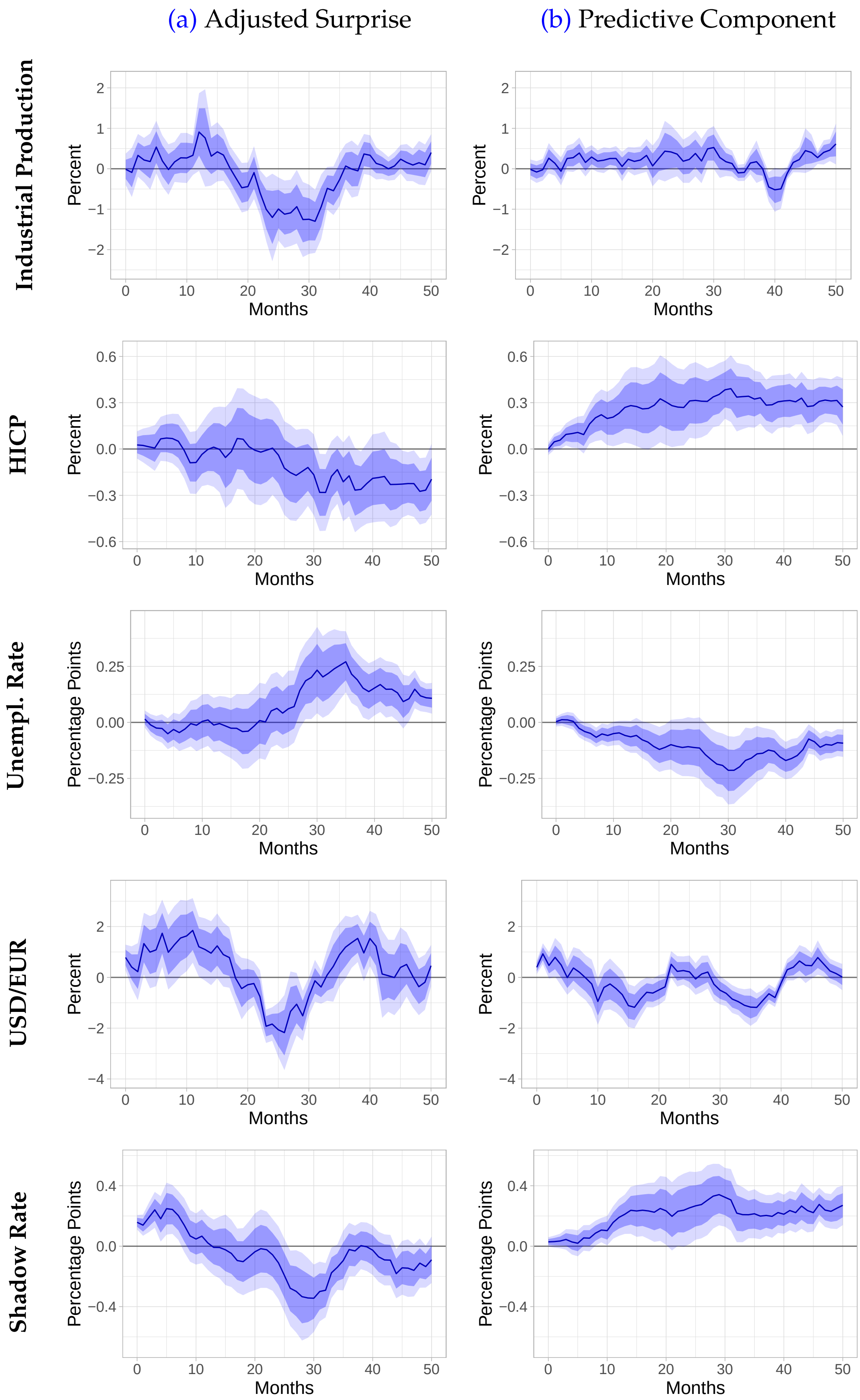
[3] In general, both the *raw* and adjusted surprises satisfy the *relevance* condition of LP-IV for these alternatives specifications with first-stage F-statistics ranging between 11 and 24.

the monthly version of the component capturing the correlation with pre-dated information, OIS_t^P. Since $OIS_t^{\perp}$ and OIS_t^P are orthogonal by construction, I include their monthly versions in the same specification and report estimates on $\eta^{(h)}$ and $\delta^{(h)}$ for $h = 0, ..., 50$ in Figure 4. To ensure that the sum of responses to the decomposed components align with the reactions to the *raw* surprise, I scale both monthly surprises to have the same variance as the unadjusted surprise measure prior to estimation.

While the left column traces the macroeconomic reactions to the adjusted surprise in line with the LP-IV results using the adjusted instrument in Figure 3, the right column illustrates the bias in macroeconomic reactions that is captured by using the unadjusted policy surprise. In line with the *response-to-news* channel in Bauer and Swanson (2023b) and Swanson (2024), this bias stems from the correlation between macroeconomic news and high-frequency surprises: given that a positive high-frequency surprise reflects in part that the ECB reacts more strongly to better-than-anticipated economic news, e.g. in terms of industrial production and unemployment as documented in Table 1, Figure 4 illustrates that estimation results based on the unadjusted surprise suggest that a tightening monetary policy shock is associated with higher economic activity, an increase in prices and lower unemployment[4]. My results indicate that this bias is substantial and induces a statistically significant discrepancy in the estimated macroeconomic reactions to the *raw* versus the adjusted instrument. Figure A.6 in the appendix repeats the estimation of (10) for OIS surprises with shorter and longer-term maturities and illustrates that, the correlation with previous news and information introduces a considerable bias for surprise measures across the maturity spectrum. In line with Swanson (2024), this underscores the importance to adjust surprise measures also when using several factors of monetary policy that reflect exogenous changes in conventional and unconventional measures based on high-frequency changes in risk-free rates with different maturities as in, e.g., Altavilla et al. (2019) and Swanson (2021).

[4]Note that the impulse responses in the right column in Figure 4 are conceptually similar to macro responses to a positive *information effect* or *signalling* shock, in which higher-than-anticipated short-term rates reflect a better-than-anticipated economic outlook by the central bank as in, e.g., Nakamura and Steinsson (2018) and Jarociński and Karadi (2020). However, given that the predictive component captures correlation of surprises with *pre-dated* information, it is not driven by high-frequency changes in asset prices capturing discrepancies between market expectations and those of the central bank.

Figure 4: Bias in Macroeconomic Responses



Note: Estimation results for LP specification (10); the sample covers 06/2005 to 12/2023. The decomposition of responses to the raw OIS surprise is based on rescaling its two components by the ratio of the variance of the raw shock to the variance of the component. Dark (light) shaded areas denote pointwise 68% (90%) confidence bands, based on heteroscedasticity-and autocorrelation robust standard errors with h lags, following Newey and West (1987).

5 Conclusion

In this paper, I document that the common assumption about the exogeneity of high-frequency changes in risk-free rates around monetary policy announcements does not hold empirically: changes in OIS rates around ECB communication events are *ex-post* predictable based on information that pre-dates the announcement. More specifically, pre-dated predictors covering macroeconomic news, financial market information and lagged high-frequency changes explain around 20% of OIS surprises. I show that this finding holds for OIS rates across the maturity spectrum, with predictability being higher in general for medium and long-term maturities. My findings reveal that the correlation of monetary policy surprises with pre-dated information is evident also for the case of the euro area and the ECB, extending earlier evidence by Bauer and Swanson (2023a,b) for the US. In particular, positive news about industrial production are correlated with a stronger tightening and negative news about unemployment are associated with a stronger easing than anticipated. Following the terminology by Bauer and Swanson (2023a,b), a potential mechanism underlying these findings is a *response-to-news* channel, according to which standard surprise measures are contaminated by uncertainty and misconceptions among market participants regarding the central bank's reaction to recent macroeconomic news and financial data.

I then evaluate the bias introduced into estimates on the effects of monetary policy at different stages of the transmission that stems from the predicted component of surprises. In line with Bauer and Swanson (2023b), I find that predictability of surprises does not affect estimates on the immediate, high-frequency reaction of asset prices to monetary policy. In terms of the estimated effects beyond the announcement day, the dynamic financial market reactions to the adjusted surprise are mildly lower in magnitude compared to the reaction to the unadjusted surprise for most variables, including sovereign bond yields and OIS rates. For the USD/EUR exchange rate and financial conditions, however, the discrepancy in the dynamic reactions to the unadjusted versus the adjusted surprise is higher and increases for longer horizons. While the bias seems to be rather modest for most of the considered financial market variables, I document that the violation of the exogeneity of surprises has a much stronger impact on the estimated macroeconomic responses to monetary policy shocks, giving rise to puzzling reactions in economic activity, prices and unemployment. I show that the bias is driven by the predictable component in the *raw* instruments, which implies that tightening shocks are, in part, associated with higher economic activity, an increase in prices, and lower levels of unemployment. Monetary policy shocks that are based on surprises adjusted for the predictable component, accordingly, yield macroeconomic reactions that are better aligned with theoretical predictions: the output puzzle is less pronounced and prices decrease and unemployment rises in response to a tightening monetary policy shock. My findings highlight the relevance of ensuring the exogeneity of surprise measures for empirical assessments of the macroeconomic effects of monetary policy by orthogonalizing high-frequency asset price changes with respect to pre-dated macroeconomic and financial information.

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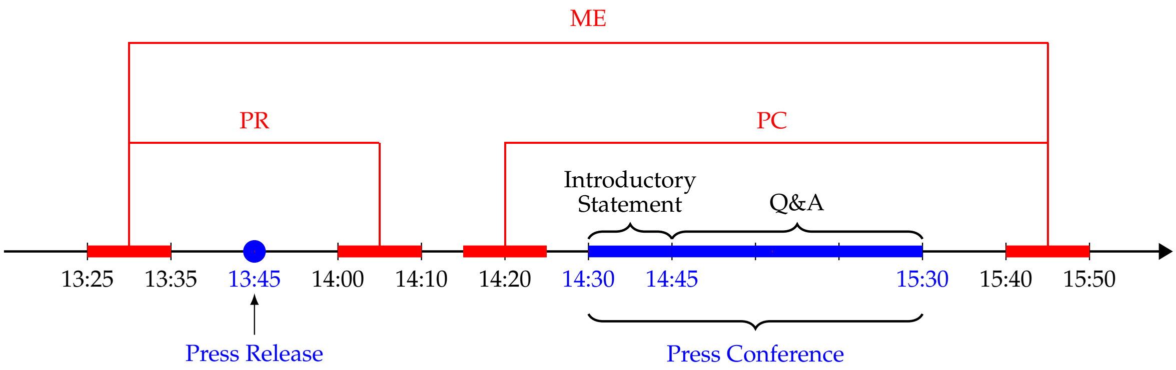
Appendix

Figure A.1: ECB Communication Timeline (until 06/2022)



Note: own representation. The figure illustrates the Eurosystem's standard communication schedule on Governing Council meeting days and demonstrates the methodology underlying the high-frequency dataset EA-MPD provided by Altavilla et al. (2019).

Table A.1: Data Sources of Pre-dated Predictors

	Primary Source	*Secondary Source*	*Ticker*	*Mnemonic*
Macroeconomic Predictors:				
Surprise in Industrial Production MoM Release	Bloomberg	-	-	*EA IP*
Surprise in Core CPI YoY Release	Bloomberg	-	-	*EA CPI*
Surprise in Unemployment Rate Release	Bloomberg	-	-	*EA Unempl*
Financial Predictors (Δ_{3m})*:*				
Change in yield curve slope (10-year - 3-month)	ECB Data Portal	-	YC.B.U2.EUR.4F.G_N_C.SV_C_YM.SR	Δ*YCSlope*
Change in daily shadow rate	Krippner's website	-	-	Δ*SR*
Change in High-Yield Option-Adjusted spread	Ice Data Indices, LLC	FRED	BAMLHE00EHYIOAS	Δ*HYOAS*
Change in equity prices of banking sector	Nasdaq, Inc.	FRED	NASDAQNQEUROZ3010	Δ*BankEquity*
Change in Eurostoxx 50	Bloomberg	-	SX5E	Δ*ES50*
US Predictors:				
High-frequency change in 2-year Treasury future	Jarocinski's website	-	-	*US MPS*
Change in daily US shadow rate (Δ_{3m})	Krippner's website	-	-	Δ*US SR*
Surprise in Non-farm Payroll Release	Bloomberg	-	-	*US NFP*

Table A.2: Predictability of OIS Surprises by Maturities

	Dependent variable: ΔOIS^m												
	1m	3m	6m	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$EA\ IP$	0.057	0.314	0.497**	0.647**	0.728**	0.642**	0.635**	0.567**	0.484*	0.421*	0.338	0.295	0.257
	(0.210)	(0.233)	(0.224)	(0.259)	(0.301)	(0.316)	(0.292)	(0.279)	(0.255)	(0.232)	(0.214)	(0.208)	(0.205)
$EA\ CPI$	0.098	−0.182	−0.219	−0.250	−0.169	−0.114	−0.075	−0.087	−0.009	0.083	0.124	0.154	0.174
	(0.305)	(0.300)	(0.350)	(0.368)	(0.370)	(0.340)	(0.367)	(0.356)	(0.327)	(0.303)	(0.283)	(0.274)	(0.268)
$EA\ Unempl$	−0.100	−0.428	−0.616*	−1.018***	−1.219***	−1.106***	−1.014***	−0.969***	−0.874***	−0.761***	−0.732***	−0.678***	−0.617**
	(0.316)	(0.334)	(0.339)	(0.366)	(0.372)	(0.340)	(0.358)	(0.344)	(0.315)	(0.286)	(0.265)	(0.253)	(0.245)
$\Delta YCSlope$	0.064	0.150	0.247	0.322	0.794*	0.765*	0.958**	0.914**	0.948**	0.817**	0.804**	0.712**	0.701**
	(0.338)	(0.380)	(0.394)	(0.425)	(0.456)	(0.398)	(0.447)	(0.423)	(0.389)	(0.361)	(0.340)	(0.320)	(0.299)
ΔSR	−0.481	−0.333	−0.518	−0.815*	−1.385**	−1.485***	−1.351**	−1.171**	−1.161**	−0.975**	−0.850**	−0.772**	−0.736**
	(0.298)	(0.361)	(0.391)	(0.486)	(0.586)	(0.560)	(0.558)	(0.541)	(0.484)	(0.444)	(0.401)	(0.374)	(0.359)
$\Delta HYOAS$	0.877*	0.881	1.346**	1.488**	1.448**	1.272*	0.682	0.617	0.431	0.419	0.313	0.236	0.185
	(0.512)	(0.611)	(0.614)	(0.626)	(0.693)	(0.709)	(0.648)	(0.613)	(0.543)	(0.482)	(0.432)	(0.382)	(0.352)
$\Delta BankEquity$	0.646*	0.758*	1.007**	1.448**	1.999**	2.118**	1.940**	1.801**	1.613**	1.392**	1.171**	0.953*	0.821
	(0.370)	(0.452)	(0.479)	(0.671)	(0.919)	(0.961)	(0.880)	(0.847)	(0.729)	(0.634)	(0.564)	(0.515)	(0.503)
$\Delta ES50$	−0.456	−0.488	−0.155	0.127	0.270	0.174	0.107	0.180	0.025	0.050	0.082	0.074	0.123
	(0.530)	(0.579)	(0.573)	(0.607)	(0.647)	(0.604)	(0.607)	(0.561)	(0.517)	(0.481)	(0.456)	(0.442)	(0.422)
$(L)^1$	−0.207*	−0.176	−0.243**	−0.327***	−0.328**	−0.297**	−0.357***	−0.371***	−0.374***	−0.363***	−0.373***	−0.355***	−0.345***
	(0.123)	(0.122)	(0.102)	(0.115)	(0.130)	(0.127)	(0.118)	(0.116)	(0.105)	(0.103)	(0.102)	(0.103)	(0.097)
$(L)^2$	−0.155	−0.118	−0.039	−0.026	−0.028	0.045	−0.051	−0.043	−0.044	−0.044	−0.054	−0.030	−0.045
	(0.105)	(0.081)	(0.094)	(0.128)	(0.115)	(0.085)	(0.098)	(0.093)	(0.086)	(0.083)	(0.081)	(0.085)	(0.086)
Constant	0.370*	0.262	0.264	0.152	−0.199	−0.335	−0.387	−0.470	−0.377	−0.314	−0.294	−0.261	−0.241
	(0.225)	(0.261)	(0.280)	(0.331)	(0.357)	(0.325)	(0.338)	(0.325)	(0.296)	(0.272)	(0.253)	(0.241)	(0.234)
Observations	187	187	187	187	187	187	187	187	187	187	187	187	187
R^2	0.144	0.119	0.150	0.198	0.231	0.233	0.232	0.232	0.234	0.215	0.216	0.198	0.186
Adjusted R^2	0.095	0.069	0.101	0.153	0.188	0.189	0.188	0.189	0.190	0.171	0.171	0.153	0.140

Note: estimation results for specification (1). OIS rate changes are measured over the Monetary Event window in the EA-MPD by Altavilla et al. (2019); see Sections 2 and 3 for details. robust standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A.3: Predictability of OIS Surprises and in High vs. Low-Uncertainty Regimes

	Dependent variable: ΔOIS^m												
	1m	3m	6m	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
EA IP	0.152	0.193	0.384**	0.485**	0.674**	0.684**	0.637**	0.605**	0.564**	0.504*	0.437*	0.416*	0.405*
	(0.147)	(0.157)	(0.183)	(0.245)	(0.309)	(0.315)	(0.310)	(0.307)	(0.281)	(0.258)	(0.239)	(0.231)	(0.227)
EA CPI	−0.147	−0.372	−0.505*	−0.512	−0.449	−0.372	−0.357	−0.354	−0.282	−0.205	−0.158	−0.114	−0.117
	(0.190)	(0.243)	(0.284)	(0.345)	(0.389)	(0.395)	(0.432)	(0.430)	(0.397)	(0.365)	(0.339)	(0.326)	(0.319)
EA Unempl	−0.134	−0.145	−0.418	−0.718*	−1.020**	−0.963**	−0.978**	−0.999**	−0.988**	−0.917**	−0.900**	−0.873***	−0.893***
	(0.157)	(0.236)	(0.275)	(0.373)	(0.456)	(0.463)	(0.478)	(0.476)	(0.429)	(0.389)	(0.358)	(0.335)	(0.320)
$\Delta YCSlope$	0.120	0.204	0.269	0.546	1.074	0.928	1.286*	1.281**	1.250**	1.181**	1.183**	1.075**	1.031**
	(0.203)	(0.324)	(0.389)	(0.642)	(0.745)	(0.682)	(0.670)	(0.646)	(0.576)	(0.511)	(0.471)	(0.440)	(0.422)
ΔSR	−0.476*	−0.479*	−0.483	−0.686	−0.957	−1.008*	−0.926	−0.868	−0.901	−0.847*	−0.828*	−0.833*	−0.802*
	(0.246)	(0.291)	(0.366)	(0.521)	(0.621)	(0.557)	(0.626)	(0.614)	(0.552)	(0.512)	(0.464)	(0.436)	(0.419)
$\Delta HYOAS$	−0.423*	−0.964*	−0.683	−0.880	−0.978	0.141	−0.846	−0.576	−0.315	−0.161	0.111	0.405	0.536
	(0.252)	(0.567)	(0.768)	(1.173)	(1.289)	(0.809)	(1.250)	(1.147)	(1.008)	(0.874)	(0.748)	(0.671)	(0.663)
$\Delta BankEquity$	0.046	0.091	0.294	0.524	0.837	1.020	0.976	1.020	1.012	0.900	0.799	0.667	0.562
	(0.260)	(0.409)	(0.536)	(0.809)	(1.016)	(0.924)	(0.997)	(0.975)	(0.876)	(0.771)	(0.694)	(0.615)	(0.586)
$\Delta ES50$	0.126	−0.170	0.296	0.814	1.324	1.297*	1.111	1.149	0.944	0.759	0.763	0.721	0.746
	(0.442)	(0.513)	(0.541)	(0.698)	(0.807)	(0.758)	(0.844)	(0.846)	(0.792)	(0.732)	(0.694)	(0.660)	(0.641)
$(L)^1$	−0.129	−0.193*	−0.250**	−0.331**	−0.339**	−0.287*	−0.393**	−0.404**	−0.417***	−0.414***	−0.438***	−0.408***	−0.382***
	(0.132)	(0.112)	(0.122)	(0.156)	(0.173)	(0.171)	(0.160)	(0.157)	(0.146)	(0.139)	(0.133)	(0.130)	(0.123)
$(L)^2$	−0.025	−0.029	−0.013	−0.074	−0.094	0.030	−0.130	−0.118	−0.099	−0.077	−0.074	−0.020	−0.040
	(0.050)	(0.102)	(0.134)	(0.173)	(0.185)	(0.118)	(0.164)	(0.151)	(0.134)	(0.124)	(0.114)	(0.110)	(0.107)
$\mathbb{1}_{\{U>75p\}}$	1.138	1.245	0.663	0.198	−0.023	−0.564	−0.393	−0.582	−0.822	−0.818	−0.889	−1.010	−0.950
	(0.852)	(0.968)	(1.001)	(1.275)	(1.447)	(1.279)	(1.402)	(1.312)	(1.219)	(1.179)	(1.115)	(1.116)	(1.046)
$EA\ IP \times \mathbb{1}_{\{U>75p\}}$	−0.368	0.650	0.724	0.942	0.588	0.204	0.244	0.028	−0.162	−0.177	−0.286	−0.393	−0.538
	(1.144)	(1.119)	(0.924)	(0.949)	(0.971)	(1.002)	(0.897)	(0.835)	(0.776)	(0.720)	(0.668)	(0.631)	(0.613)
$EA\ CPI \times \mathbb{1}_{\{U>75p\}}$	0.996	0.756	1.213	1.281	1.455	1.454	1.485	1.480	1.516	1.479	1.472*	1.437*	1.459*
	(1.059)	(1.024)	(1.191)	(1.287)	(1.271)	(1.119)	(1.126)	(1.045)	(0.955)	(0.900)	(0.835)	(0.811)	(0.773)
$EA\ Unempl \times \mathbb{1}_{\{U>75p\}}$	0.122	−0.804	−0.638	−0.829	−0.577	−0.454	−0.103	0.114	0.351	0.528	0.612	0.691	0.841
	(0.814)	(0.841)	(0.880)	(0.946)	(0.953)	(0.909)	(0.912)	(0.867)	(0.789)	(0.723)	(0.670)	(0.646)	(0.628)
$\Delta YCSlope \times \mathbb{1}_{\{U>75p\}}$	0.242	0.434	0.226	−0.227	−0.662	−0.503	−0.910	−0.927	−0.877	−0.976	−0.954	−0.881	−0.785
	(0.902)	(0.927)	(0.907)	(1.015)	(1.137)	(1.081)	(1.121)	(1.058)	(0.962)	(0.886)	(0.821)	(0.785)	(0.744)
$\Delta SR \times \mathbb{1}_{\{U>75p\}}$	0.592	0.891	0.145	−0.399	−1.443	−1.617	−1.655	−1.321	−1.224	−0.939	−0.664	−0.411	−0.242
	(0.896)	(1.172)	(1.211)	(1.663)	(1.872)	(1.734)	(1.799)	(1.718)	(1.578)	(1.513)	(1.401)	(1.313)	(1.198)
$\Delta HYOAS \times \mathbb{1}_{\{U>75p\}}$	2.412**	3.205**	2.891**	3.077*	2.872	1.091	1.560	1.032	0.349	0.221	−0.245	−0.726	−0.889
	(1.001)	(1.274)	(1.363)	(1.729)	(1.915)	(1.713)	(1.925)	(1.789)	(1.579)	(1.410)	(1.256)	(1.161)	(1.107)
$\Delta BankEquity \times \mathbb{1}_{\{U>75p\}}$	2.030	2.329	2.085	2.425	2.869	2.424	2.252	1.655	1.139	0.968	0.649	0.356	0.272
	(1.265)	(1.511)	(1.353)	(1.519)	(1.936)	(2.303)	(2.085)	(2.032)	(1.830)	(1.619)	(1.459)	(1.332)	(1.293)
$\Delta ES50 \times \mathbb{1}_{\{U>75p\}}$	−1.258	−0.760	−1.111	−1.684	−2.457**	−2.509**	−2.386*	−2.243*	−2.123*	−1.763*	−1.653*	−1.530*	−1.447
	(1.128)	(1.221)	(1.148)	(1.145)	(1.249)	(1.256)	(1.302)	(1.229)	(1.131)	(1.045)	(0.964)	(0.922)	(0.902)
$(L)^1 \times \mathbb{1}_{\{U>75p\}}$	−0.292	−0.117	−0.071	−0.070	−0.003	−0.018	0.130	0.129	0.197	0.236	0.289	0.259	0.212
	(0.293)	(0.232)	(0.222)	(0.238)	(0.239)	(0.279)	(0.240)	(0.229)	(0.212)	(0.212)	(0.207)	(0.216)	(0.208)
$(L)^2 \times \mathbb{1}_{\{U>75p\}}$	−0.285	−0.193	−0.064	0.083	0.127	0.025	0.196	0.188	0.163	0.110	0.085	0.019	0.030
	(0.214)	(0.190)	(0.212)	(0.269)	(0.248)	(0.218)	(0.221)	(0.212)	(0.199)	(0.196)	(0.192)	(0.205)	(0.203)
Constant	−0.002	0.012	−0.019	−0.075	−0.550	−0.518	−0.703	−0.718	−0.590	−0.441	−0.368	−0.246	−0.226
	(0.182)	(0.225)	(0.264)	(0.394)	(0.498)	(0.447)	(0.497)	(0.483)	(0.423)	(0.371)	(0.330)	(0.296)	(0.286)
Observations	187	187	187	187	187	187	187	187	187	187	187	187	187
R^2	0.281	0.250	0.243	0.276	0.312	0.297	0.298	0.291	0.295	0.277	0.283	0.267	0.258
Adjusted R^2	0.190	0.154	0.146	0.184	0.225	0.207	0.209	0.201	0.205	0.185	0.192	0.173	0.163

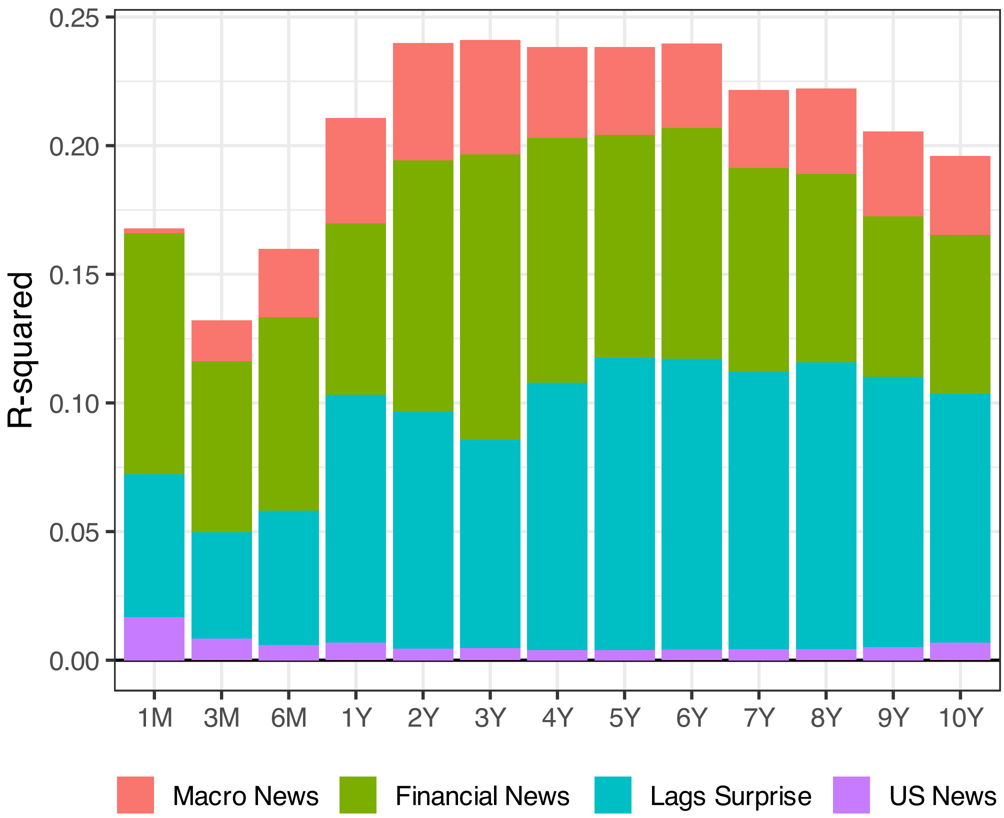
Note: estimation results for specification (2). Distinction between high and low-uncertainty states based on cut-off of 75th percentile of VSTOXX distribution over time, which results in 52 announcements in the high-uncertainty state; robust standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A.4: Predictability of OIS Surprises by US News

	Dependent variable: ΔOIS^m												
	1m	3m	6m	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
EA IP	0.077	0.307	0.486**	0.622**	0.686**	0.597*	0.599**	0.534*	0.461*	0.400*	0.329	0.295	0.260
	(0.207)	(0.232)	(0.225)	(0.257)	(0.301)	(0.316)	(0.293)	(0.281)	(0.258)	(0.236)	(0.218)	(0.212)	(0.209)
EA CPI	0.141	−0.133	−0.166	−0.181	−0.124	−0.098	−0.058	−0.079	−0.015	0.075	0.106	0.128	0.139
	(0.327)	(0.315)	(0.364)	(0.372)	(0.376)	(0.348)	(0.377)	(0.367)	(0.337)	(0.310)	(0.289)	(0.277)	(0.271)
EA Unempl	−0.061	−0.369	−0.553	−0.933**	−1.162***	−1.082***	−0.991***	−0.959***	−0.880***	−0.769***	−0.754***	−0.710***	−0.659***
	(0.362)	(0.359)	(0.368)	(0.390)	(0.394)	(0.354)	(0.371)	(0.354)	(0.322)	(0.291)	(0.267)	(0.251)	(0.245)
$\Delta YCSlope$	0.057	0.100	0.190	0.237	0.724	0.716*	0.915**	0.883**	0.934**	0.806**	0.809**	0.732**	0.729**
	(0.372)	(0.405)	(0.421)	(0.450)	(0.471)	(0.402)	(0.449)	(0.424)	(0.387)	(0.358)	(0.337)	(0.316)	(0.296)
ΔSR	−0.439	−0.360	−0.561	−0.901*	−1.519***	−1.628***	−1.454***	−1.254**	−1.214**	−1.024**	−0.864**	−0.755**	−0.715*
	(0.304)	(0.355)	(0.392)	(0.484)	(0.582)	(0.567)	(0.550)	(0.533)	(0.479)	(0.443)	(0.403)	(0.382)	(0.372)
$\Delta HYOAS$	0.949*	0.959	1.421**	1.578**	1.501**	1.287*	0.703	0.629	0.429	0.415	0.300	0.216	0.151
	(0.517)	(0.615)	(0.622)	(0.632)	(0.694)	(0.692)	(0.639)	(0.606)	(0.536)	(0.480)	(0.433)	(0.384)	(0.354)
$\Delta BankEquity$	0.701*	0.829*	1.070**	1.539**	2.066**	2.146**	1.978**	1.833**	1.628**	1.403**	1.170**	0.943*	0.794
	(0.377)	(0.464)	(0.491)	(0.692)	(0.931)	(0.942)	(0.882)	(0.849)	(0.729)	(0.635)	(0.566)	(0.519)	(0.502)
$\Delta ES50$	−0.490	−0.587	−0.261	−0.039	0.126	0.080	0.019	0.114	−0.007	0.024	0.088	0.109	0.178
	(0.544)	(0.598)	(0.588)	(0.617)	(0.665)	(0.611)	(0.633)	(0.591)	(0.544)	(0.508)	(0.480)	(0.463)	(0.437)
US MPS	−0.138	−0.264	−0.230	−0.313	−0.216	−0.023	−0.137	−0.129	−0.092	−0.075	−0.051	−0.035	0.023
	(0.227)	(0.243)	(0.278)	(0.374)	(0.425)	(0.425)	(0.393)	(0.381)	(0.352)	(0.324)	(0.306)	(0.297)	(0.286)
$\Delta US\ SR$	−0.023	0.222	0.261	0.441	0.465	0.372	0.325	0.264	0.163	0.142	0.041	−0.047	−0.085
	(0.363)	(0.349)	(0.354)	(0.407)	(0.420)	(0.417)	(0.404)	(0.390)	(0.353)	(0.328)	(0.301)	(0.284)	(0.280)
US NFP	0.414	0.252	0.251	0.248	−0.027	−0.209	−0.179	−0.221	−0.256	−0.249	−0.250	−0.252	−0.300
	(0.262)	(0.285)	(0.290)	(0.322)	(0.351)	(0.329)	(0.322)	(0.306)	(0.280)	(0.256)	(0.237)	(0.227)	(0.223)
$(L)^1$	−0.230*	−0.188	−0.259**	−0.346***	−0.340**	−0.305**	−0.364***	−0.378***	−0.379***	−0.369***	−0.377***	−0.358***	−0.348***
	(0.132)	(0.125)	(0.106)	(0.121)	(0.137)	(0.132)	(0.122)	(0.119)	(0.108)	(0.107)	(0.106)	(0.106)	(0.100)
$(L)^2$	−0.168	−0.125	−0.051	−0.044	−0.042	0.035	−0.060	−0.053	−0.052	−0.051	−0.058	−0.032	−0.044
	(0.110)	(0.085)	(0.095)	(0.129)	(0.116)	(0.085)	(0.100)	(0.095)	(0.088)	(0.084)	(0.083)	(0.085)	(0.087)
Constant	0.375*	0.263	0.268	0.154	−0.201	−0.336	−0.389	−0.473	−0.378	−0.314	−0.294	−0.260	−0.240
	(0.228)	(0.265)	(0.284)	(0.336)	(0.363)	(0.329)	(0.343)	(0.330)	(0.301)	(0.277)	(0.257)	(0.245)	(0.237)
Observations	187	187	187	187	187	187	187	187	187	187	187	187	187
R^2	0.162	0.130	0.158	0.208	0.237	0.238	0.236	0.236	0.238	0.220	0.221	0.204	0.194
Adjusted R^2	0.099	0.065	0.095	0.148	0.179	0.181	0.178	0.179	0.181	0.161	0.162	0.144	0.134

Note: estimation results for specification (3). OIS rate changes are measured over the Monetary Event window in the EA-MPD by Altavilla et al. (2019); see Sections 2 and 3 for details. robust standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

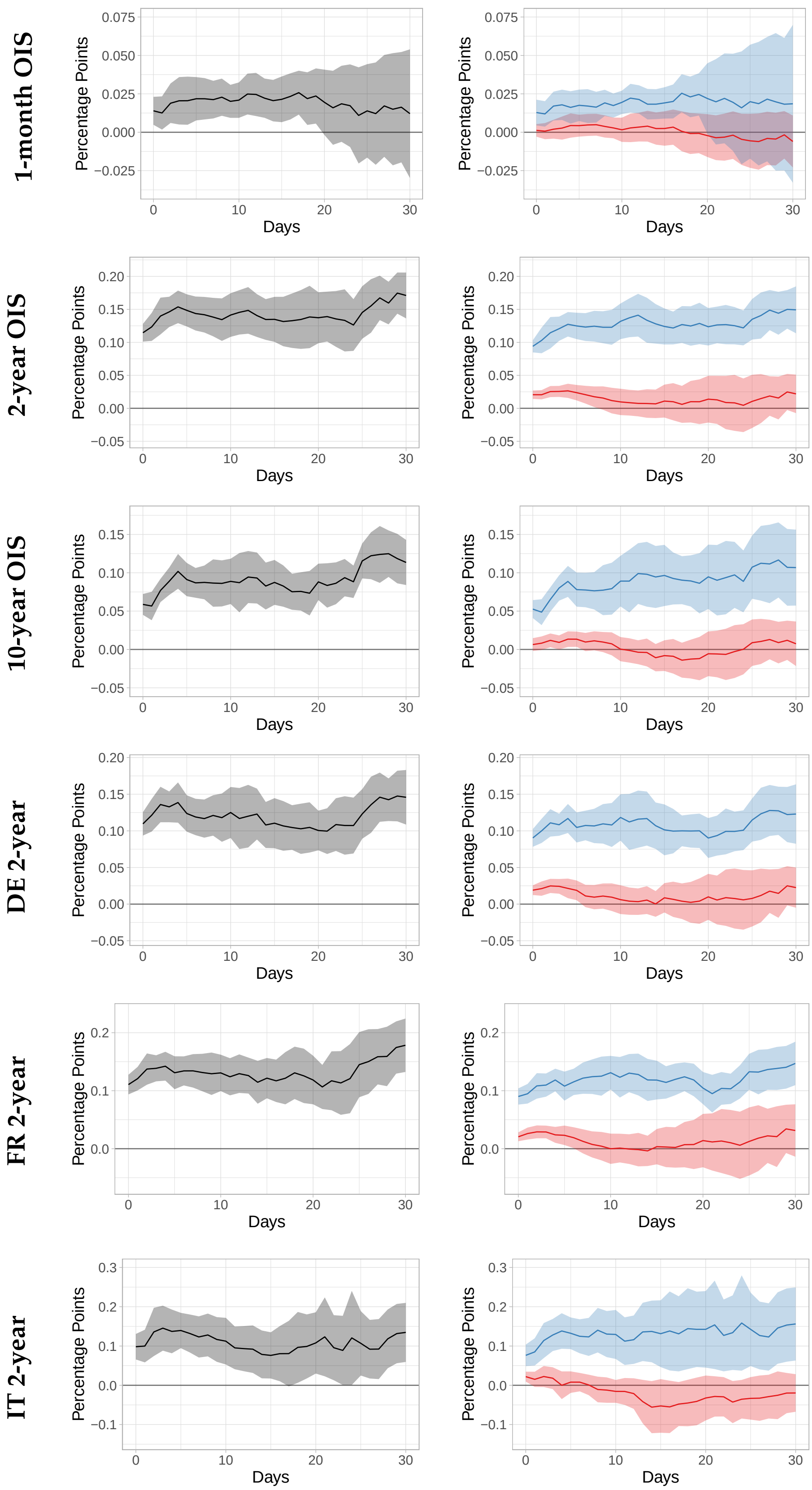
Figure A.2: R^2 with US News



Note: explanatory power of pre-dated information by news category for OIS rate changes across maturities, based on Shapley value decomposition as in, e.g., Mishra (2016), aggregated at the category level.

Figure A.3: LPs: Dynamic Reactions of Alternative Financial Variables

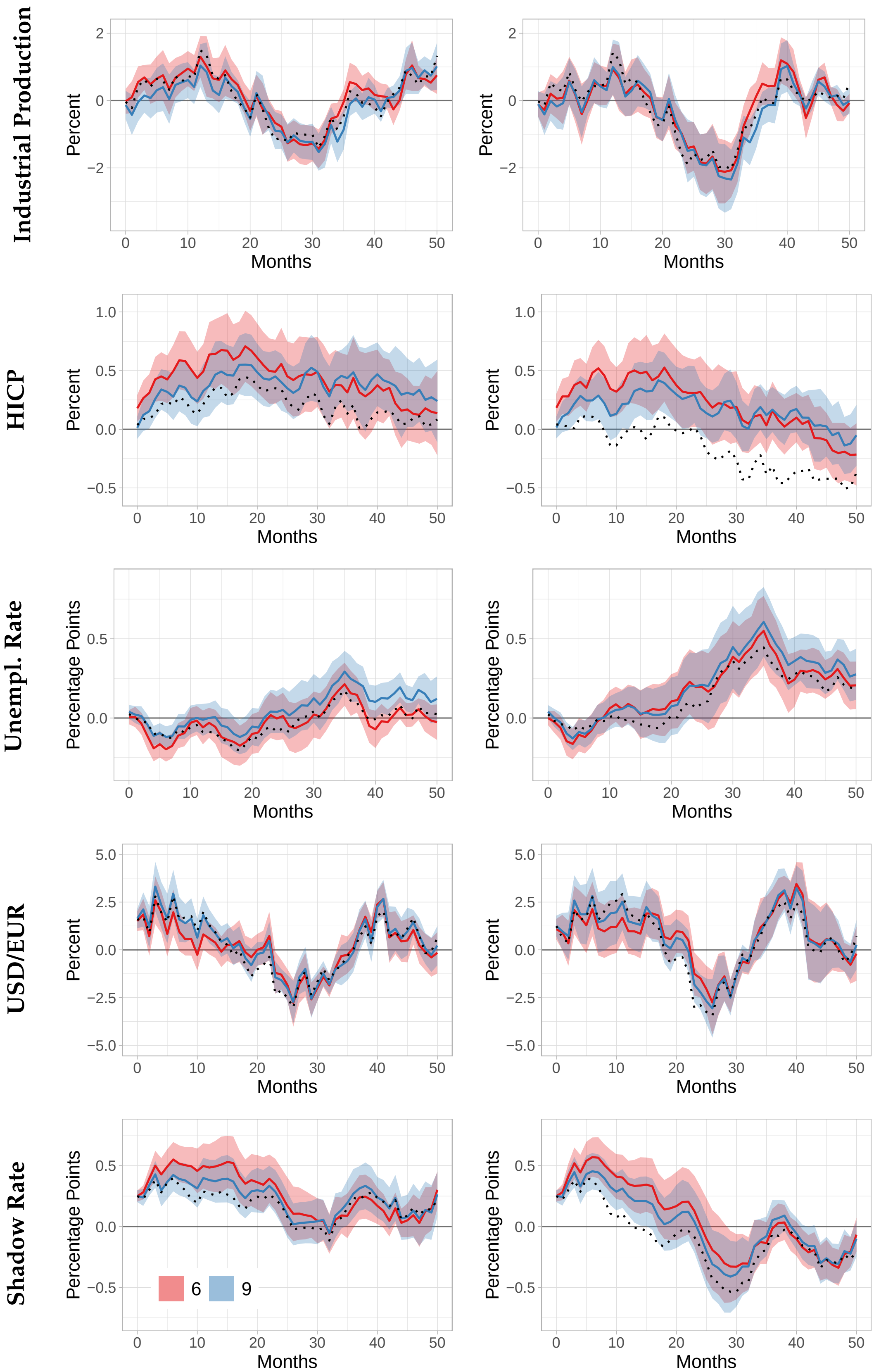
(a) Raw OIS Surprise (b) Decomposition



Note: Estimation results for LP specifications (6) and (7); the sample covers 04/2005 to 12/2023. The decomposition of responses to the raw OIS surprise is based on rescaling its two components by the ratio of the variance of the raw shock to the variance of the component. Shaded areas denote pointwise 90% confidence bands, based on heteroscedasticity-and autocorrelation robust standard errors with h lags, following Newey and West (1987).

Figure A.4: LP-IV: Alternative Endogenous Lags

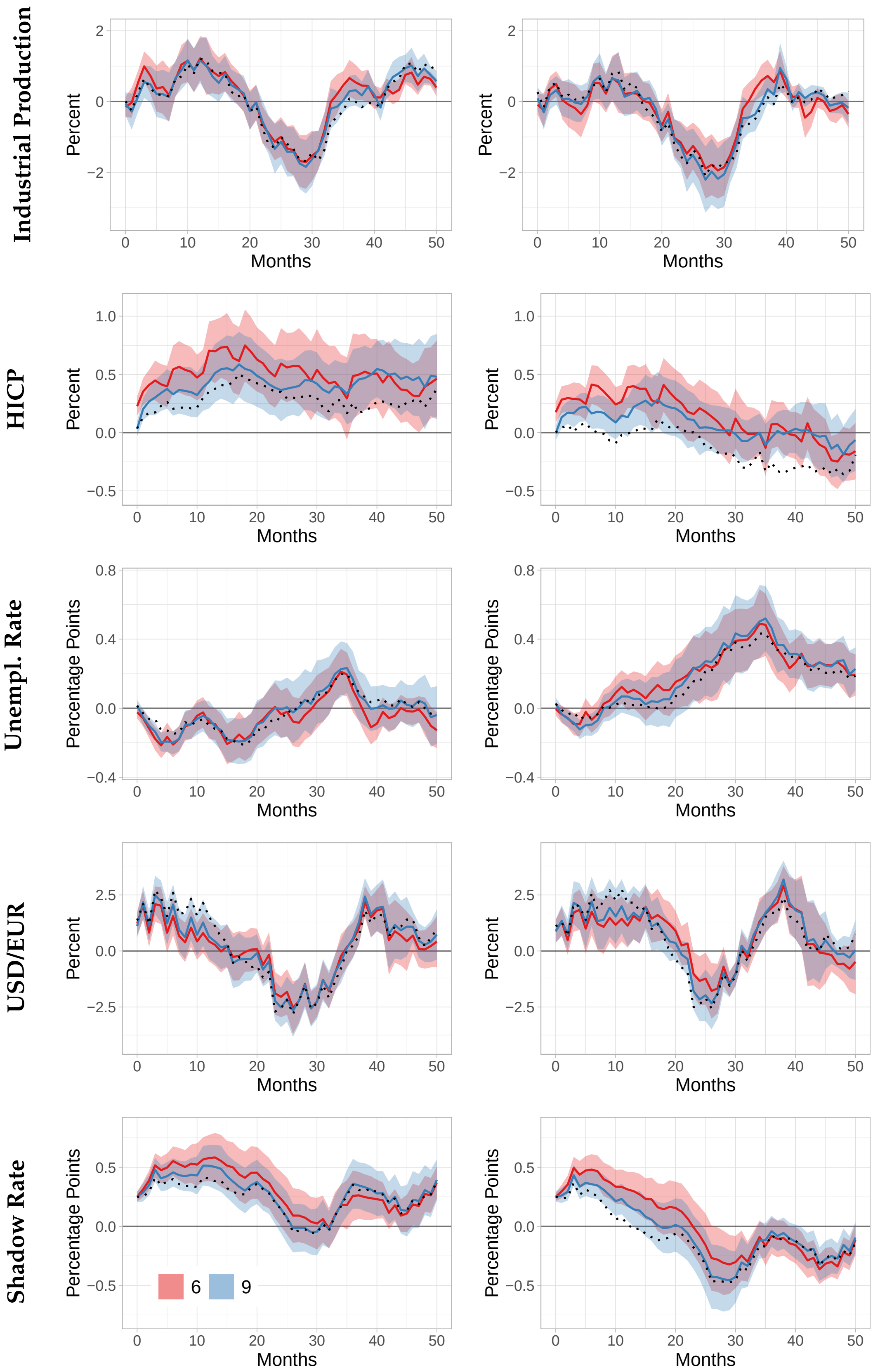
(a) Raw Surprise (b) Adjusted Surprise



Note: Note: Estimation results for LP-IV specification (9) for alternative lag lengths of endogenous variables; six endogenous lags in red and nine endogenous lags in blue, the dotted black line indicates the baseline estimates based on twelve lags. Second stage reactions are normalized to increase the shadow rate by .25 percentage points. The sample covers 06/2005 to 12/2023. Shaded areas denote pointwise 68% confidence bands, based on heteroscedasticity-and autocorrelation robust standard errors with h lags, following Newey and West (1987).

Figure A.5: LP-IV: Alternative Endogenous and Exogenous Lags

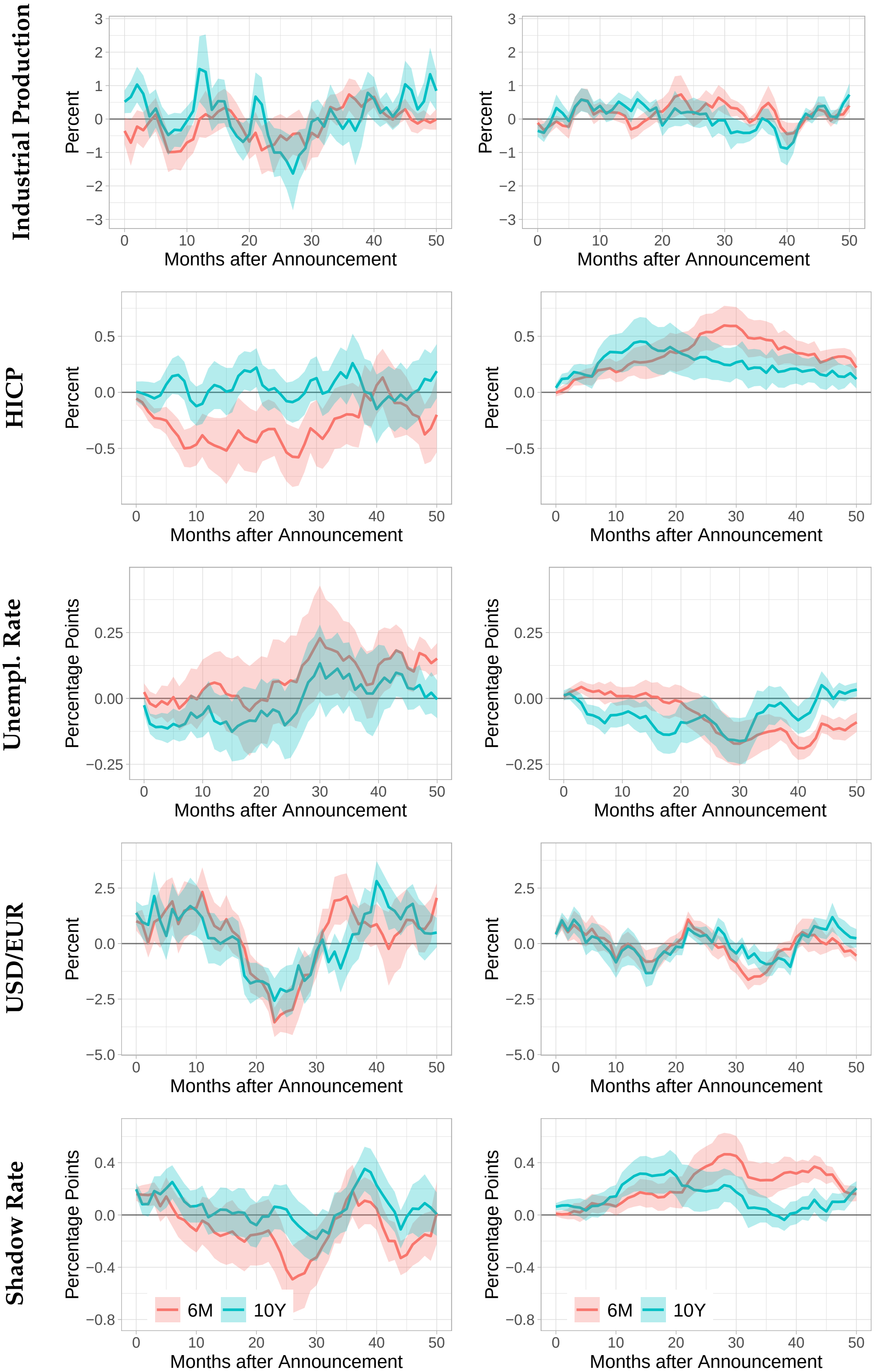
(a) Raw Surprise | (b) Adjusted Surprise



Note: Estimation results for an extended LP-IV specification (9), which additionally controls for three lags of the instrument and is based on alternative lag lengths of endogenous variables; six endogenous lags in red and nine endogenous lags in blue, the dotted black line indicates the baseline estimates based on twelve lags. Second stage reactions are normalized to increase the shadow rate by .25 percentage points. The sample covers 06/2005 to 12/2023. Shaded areas denote pointwise 68% confidence bands, based on heteroscedasticity-and autocorrelation robust standard errors with h lags, following Newey and West (1987).

Figure A.6: LPs: Bias in Macroeconomic Responses - Alternative Maturities

(a) Adjusted Surprise (b) Predictive Component



Note: Estimation results for LP specification (10), for which the instruments z_t are based on OIS surprises with alternative maturities; the sample covers 06/2005 to 12/2023. The decomposition of responses to the raw OIS surprise is based on rescaling its two components by the ratio of the variance of the raw shock to the variance of the component. Dark (light) shaded areas denote pointwise 68% (90%) confidence bands, based on heteroscedasticity-and autocorrelation robust standard errors with h lags, following Newey and West (1987).

DeNederlandscheBank
EUROSYSTEEM

De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl