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# The Predictability of Global Monetary Policy Surprises

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**Abstract:**
Markets systematically misprice interest rate changes around central bank announcements. I show that the strongest predictor of this mispricing is recent change in global interest rates. More specifically, a 1 percentage point increase in global short-term interest rates in the 15 days before a central bank meeting is associated with a 12 basis point surprise increase in short-term rates at that meeting. I demonstrate that this is the result of markets underreacting to signals coming from the global interest rate cycle.

**JEL Classifications:** E43, E52, E58
**Keywords:** Monetary policy surprise, central bank, global interest rate cycle, predictability

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# 1 Introduction

Short-term interest rates are a crucial economic measure. They have a large impact on macroeconomic outcomes (Woodford, 2003; Christiano, Eichenbaum, and Evans, 2005). They made up 78 percent of the notional outstanding of global over-the-counter derivatives at the end of 2024, according to data from the Bank for International Settlements. And they play a large role in driving other asset prices, including bond prices, stock prices, and exchange rates (Bernanke and Kuttner, 2005; Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018). Central banks exert control over short-term interest rates through mechanisms such as paying interest on reserves. As a result, monetary policy announcements regarding interest rate decisions are key moments in the financial calendar. Despite this importance, however, surprise changes to short-term interest rates around central bank announcements—commonly termed "monetary policy surprises"—have been shown to be predictable using information available before the announcements (Cieslak, 2018; Schmeling, Schrimpf, and Steffensen, 2022; Bauer and Swanson, 2023a; Sastry, 2022). This is notable given the profit opportunity this predictability presents in such an important market.

This paper investigates the predictability of monetary policy surprises in an international context, offering both new evidence and perspective. I first show that monetary policy surprises across nine countries/zones co-move together and with the global interest rate cycle. Second, I show that recent change in global interest rates more strongly predicts monetary policy surprises than other proposed predictors, including recent asset price changes and economic news. Third, I show that this predictability results from markets underreacting to signals from global interest rates.

To investigate this question, I construct a data set with monetary policy surprises across nine central banks—covering Australia, Canada, the euro zone, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, and the United States—and around 2,000 announcements. To identify monetary policy surprises, I use a high-frequency approach that merges intraday data on interest rates with the dates and times of central bank announcements.

The paper's first contribution is to show that monetary policy surprises follow the global interest rate cycle. When central banks are tightening (easing) their policy stance, monetary policy surprises are positive (negative). Nearly all the large deviations in average developed country monetary policy surprises above and below zero take place during global tightenings and easings, respectively. The size of these deviations is substantial. During the dot-com bust and the Great Recession, each central bank in the sample generated monetary policy surprises equivalent, on average, to a cut of approximately one-quarter point, while during the post–COVID-19 tightening, monetary policy surprises were equivalent to an increase of about one-quarter point.

As its second contribution, this paper identifies and describes the factors that most strongly predict monetary policy surprises. Consistent with monetary policy surprises co-moving with the global interest rate cycle, I find that recent change in global interest rates strongly predicts monetary policy surprises. That is, a 1 percentage point rise in the six-month interest rate in developed countries/zones in the 15 days before a central bank announcement is associated with a 12.1 basis point increase in the monetary policy surprise resulting from that announcement. This association is significant at the 0.1 percent level. I find similar effects when measuring the dependent and independent variables in different windows and when considering alternative measures of interest rates.

Though other variables have been shown to predict monetary policy surprises—notably asset price changes (Schmeling, Schrimpf, and Steffensen, 2022) and economic news surprises (Bauer and Swanson, 2023a) before central bank announcements—I find that changes in global interest rates are the strongest predictor. I show this by comparing the strength of the individual explanations in a horse-race regression and in leave-one-out regressions. I also show that global interest rates have strong predictive power for individual countries/zones, including the United States.

The paper's third contribution is to examine why global interest rates predict monetary policy surprises. Sastry (2022) argues that there are two reasons why monetary policy surprises may be predictable. First, central banks may react differently to news than markets expect. Second, markets may misperceive the precision of economic signals. Using the approach in Sastry (2022), I show that markets underreact to signals related to the global interest rate cycle (the second case), yielding predictability. Notably, I do not find evidence that markets underreact to changes in the non-global component of domestic interest rates. Therefore, it seems that markets have greater difficulty interpreting global signals. Since economists have only recently begun to understand the importance and wide implications of global cycles (Rey, 2016; Miranda-Agrippino and Rey, 2020, 2022), it is not surprising that financial markets may also have underestimated their significance. This helps explain why markets appear to have persistently missed the opportunity to profit from predictable interest rate movements around central bank announcements.

This paper relates to three areas of the literature. First, it contributes to the literature examining how errors in interest rate expectations are predictable. Cieslak (2018) first documented this phenomenon, demonstrating that the largest errors occur during contractions when markets overestimate future short rates, leading to excess bond returns. Schmeling, Schrimpf, and Steffensen (2022) demonstrate that similar patterns also hold in money market derivatives and show that stock price declines predict excess returns from going long in money market futures. Bauer and Swanson (2023a) and Sastry (2022) show that public information available before a central bank announcement predicts the monetary policy surprise associated with that announcement. My contribution is to show that recent change in global interest rates is the strongest predictor of monetary policy surprises.

Second, the paper contributes to the literature examining why public information available before central bank announcements predicts the monetary policy surprises around those announcements. The traditional view of monetary policy surprises is that they represent "shocks" to monetary policy, that is, deviations from the standard monetary policy reaction function. Romer and Romer (2000) proposed an alternative view—that surprises may result from private central bank signals being conveyed to markets during central bank announcements.[1] However, neither of these views can explain empirically why public signals before a central bank announcement predict the monetary policy surprise associated with that announcement.[2] Bauer and Swanson (2023b) argue that this predictability results from central banks responding differently to news than markets expect. In particular, they argue that central banks have responded with growing strength to economic shocks, meaning that markets have consistently under-predicted the response.[3] Sastry (2022) proposes a different explanation, suggesting instead that markets may place too little faith in public signals about shocks to the economy. The author proposes a test to distinguish between the two potential explanations and finds that this second explanation fits the data better. I show that markets notably underreact to the signals coming from global interest rates. I do not find evidence for the same under-reaction for the non-global component of domestic interest rates. Therefore, my results suggest that monetary policy surprises are predictable because markets have more difficulty processing global signals.

Third, this paper contributes to the literature studying the global financial cycle. Rey (2016) argues that there is a global financial cycle in capital flows, asset prices, and credit growth. Later papers aim to identify more precisely the drivers of this cycle. One common explanation is that changes in monetary policy, typically at the Federal Reserve, lead to capital inflows to the United States, a decline in risk-taking behavior, and a contraction in global credit (Kalemli-Özcan, 2020; Miranda-Agrippino and Rey, 2020, 2022). Other papers investigate which types of news move markets and the degree to which they do so (Kerssenfischer and Schmeling, 2024; Boehm and Kroner, 2025). This paper is the first to demonstrate that monetary policy surprises also co-move with and are predicted by these global cycles, especially the global interest rate cycle. In other words, while other studies document that monetary policy surprises impact global cycles, this paper shows that the reverse also holds.

The paper proceeds as follows. The empirical approach and data are outlined in Section 2. Section 3 describes how monetary policy surprises co-move with each other and with the global interest rate cycle. Section 4 examines the predictability of monetary policy surprises. Section 5 investigates why the global interest rate cycle predicts monetary policy surprises. Section 6 concludes.

## 2 Data

I use a high-frequency approach to identify the impact of monetary policy surprises from nine central banks in developed countries/zones on economic forecasts. I focus on the central banks of developed

[1] In another paper (Cotton, 2022), I analyze how economic forecasts respond to monetary policy surprises in a large panel of countries/zones. That paper studies in more detail implications for information effects. I previously considered the results in that paper and this one together but, based on the advice of reviewers, have separated the two sets of findings.

[2] Monetary policy shocks are exogenous to public information. Assuming that markets have appropriately responded to public signals, private central bank signals should move markets only to the extent that they are orthogonal to information already held by markets.

[3] Cieslak (2018) and Schmeling, Schrimpf, and Steffensen (2022) also present evidence that supports this argument.

countries/zones because it seems more likely that they have detailed private information that could cause information effects and because it is easier to obtain data for these countries/zones. To construct monetary policy surprises, I require two types of data for each of the nine countries/zones: (1) high-frequency data on interest rates and (2) dates and times of central bank announcements.

The interest rate data are primarily from Refinitiv, which offers intraday tick data from 1996 onward. I download data on benchmark bonds (for example, the closest one-, two-, three-, five-, or ten-year bond for which the underlying bond changes over time), non-benchmark bonds (for example, a specific bond expiring on a specific day), and interest rate swaps for each country/zone.[4] Refinitiv has an additional paywall for some US interest rate data, so I complement the Refinitiv data with CME interest rate swap data for the United States. I complement euro-zone interest rate data with German data.

I compile dates and times of the announcements immediately following the conclusion of central bank monetary policy committee meetings, which are commonly referred to as statements. I focus on these announcements because they span the full data set.[5] I use Bloomberg as my primary source. When dates and times were not available on Bloomberg, I used data gathered directly from national central bank websites. I also verify the releases using two additional websites that provide dates and times of central bank announcements (`www.investing.com` and `www.centralbanknews.info`). I reconcile the results from the different sources and adjust appropriately for time zone differences. By default, I exclude announcements that took place in 2020 from the regression analysis due to the large forecast revisions in the first year of the COVID-19 pandemic. A robustness check demonstrates that including these announcements does not qualitatively affect the results.

I use a high-frequency approach to identify surprises associated with central bank announcements. I use an extended version of Gürkaynak, Sack, and Swanson (2005)'s window to measure the surprises. I measure the interest rate before the announcement using the earliest available interest rate in a window from 10 minutes before to immediately beforehand. If this information is not available, I use the latest available interest rate in a window from 1 hour before to 10 minutes before the announcement. I measure the interest rate after the announcement using the latest available interest rate in a window from 10 minutes to 20 minutes after the announcement. If this information is not available, I use the earliest available interest rate in a window from 20 minutes to 1 hour after the announcement. I use this extended window as my primary measure because data are not always available in the narrow 30-minute window, especially for the smaller central banks in the sample. However, I show that the results are similar when I consider the 30-minute window as well as other longer windows.

I measure monetary policy surprises through the change in short-term interest rates, using bonds and

[4]Using a range of instruments helps ensure good coverage across my sample. I verify in Appendix A.5 that measures from different sources yield similar results.

[5]Some central banks host press conferences and issue minutes, but not all central banks do this and some central banks only began to do this in recent years. However, I do find similar results with longer windows that would cover press conferences that take place following the release of the statement.

swaps with a maturity of one year or less. I also construct the monetary policy surprise using a second approach whereby I fit a Nelson–Siegel yield curve using the interest rate data before and after the announcement and measure the monetary policy surprise as the change in the six-month interest rate for those fitted yield curves. I take several steps to clean the interest rate data. Crucially, I consider only bonds and swaps for which I have data both before and after the announcement so that I do not compare distinct bonds that could have different rates for other reasons. The Refinitiv interest rate data are based on indicative quotes submitted by banks. I drop any quote that is the same as a previously submitted quote to avoid the possibility that quotes have not been updated. Note that interest rates are measured precisely and that interest rate quotes are constantly changing, so it is highly unlikely that they would remain exactly the same even if a central bank announcement were unsurprising. I also remove a limited number of other outlier quotes that appear to be mismeasured. I provide more details on the construction of the monetary policy surprises in Appendix A.

I compare the monetary policy surprises I construct with established measures. My measure for the United States shows a correlation of 0.81 with the monetary policy surprise measure from Nakamura and Steinsson (2018) (and updated in Acosta (2023)). My measure for the United Kingdom shows a correlation of 0.86 with the monetary policy surprises from Cesa-Bianchi, Thwaites, and Vicondoa (2020). My measure for the euro zone shows a correlation of 0.95 with the six-month OIS measure from the Euro Area Monetary Policy Event-Study Database (EA-MPD), developed by Altavilla et al. (2019). I consider additional robustness checks. I verify that different sources and the different types of interest rate data I use yield similar monetary policy surprises. I demonstrate that the monetary policy surprises I construct under the two different approaches are highly correlated. I also show that including or excluding outliers has only a small impact on the surprises. These robustness checks are shown in Table A.1.

Table 1 summarizes the data. I consider the period from 1996, when the Refinitiv high-frequency data begin, to 2024. I know the time of the central bank announcements associated with 1,977 monetary policy committee meetings. I have the data to construct monetary policy surprises for 1,835 of these announcements. The number of monetary policy surprises varies depending on the frequency with which a central bank holds meetings and the availability of data for that central bank.

I obtain data for other measures of global conditions, including changes in benchmark interest rates, stock prices, exchange rates, and commodity prices. These are constructed using daily Bloomberg and Refinitiv data.[6] I also obtain data on the policy rates on a given day in each country/zone from the Bank for International Settlements.

I control for recent news by compiling the surprises from economic releases. These data come primarily from Bloomberg, but I extend series where possible with data from Informa. For most

[6]I use the following stock indexes: ASX200 (AUS), TSX Composite (CAN), SMI (CHE), Euro Stoxx 50 (ECB), FTSE100 (GBR), TOPIX (JPN), OBX (NOR), NZX50 (NZL), and OMX Stockholm 30 (SWE). I measure exchange rates relative to the United States except for the United States, which I measure relative to Canada. I measure oil prices using West Texas Intermediate prices.

Table 1: Data Summary by Country/Zone

| Country | Start Year | Number of Meetings | Number of MPS |
|---|---|---|---|
| Australia | 1998 | 295 | 244 |
| Canada | 2001 | 191 | 184 |
| Eurozone | 1999 | 301 | 301 |
| New Zealand | 1999 | 191 | 167 |
| Norway | 1999 | 208 | 183 |
| Sweden | 1999 | 167 | 158 |
| Switzerland | 2004 | 87 | 87 |
| United Kingdom | 1997 | 298 | 273 |
| United States | 1996 | 239 | 238 |
| Total | | 1977 | 1835 |

Notes: The second column represents the first year for which I have the time the announcement took place. The third column represents the number of announcements for which I have the time of the announcement. The fourth column represents the number of announcements for which I have both the time and interest rate data such that I can construct the default monetary policy surprise measure. Sources: Bloomberg, CME, Consensus Economics, and Refinitiv.

series, I measure the surprise as the release minus the forecast.[7] Bloomberg provides a measure of the relevance of each economic release, which is calculated from the share of Bloomberg Terminals that have requested updates for that economic release. I exclude central bank policy rate announcements and variables with fewer than 20 surprises available. I compile surprises for the top 10 most relevant surprises plus the most relevant surprises for CPI inflation, GDP, and unemployment. The most relevant surprises correspond to the series I would expect would be the most closely followed, with inflation, GDP, and unemployment measures all showing high relevance. There are some differences across countries. For example, housing starts are more relevant in economies such as Australia, Canada, and New Zealand, due perhaps to their faster-growing populations. I summarize the economic releases in Table A.2.

To test why global interest rates predict monetary policy surprises, I obtain economic forecasts for the countries/zones in the panel from Consensus Economics, which compiles forecasts at the start of each month for key economic indicators for the current and subsequent year. The forecast for the current year is likely to respond more to monetary policy surprises that occur earlier in the year than to those that occur later in the year because the earlier surprises have more of the year remaining to have an effect. Therefore, I focus on the forecast for the closest year that has at least six months remaining; for January through June, I look at the change in the forecast for the current year, and

[7]For example, if the forecast of month-over-month CPI inflation was 0.2 percent, but the number in the release was 0.3 percent, the surprise would be 0.1 percentage point. For a handful of series measured in levels, such as the number of people employed, I divide the surprise by the forecast level (and multiply it by 100) so that the surprise is stationary. For a handful of series that are measured as changes in levels, such as the change in the number of people employed, I divide the surprise by an appropriate variable in levels (such as the number of people employed) so that the surprise is stationary. The most relevant GDP series are annualized for some countries but not for others. To ensure that these series are comparable, I divide the surprises for annualized countries/zones by four. I show which level variables I divide by and any scalar adjustments in Table A.2. I set the primary CPI measure for Sweden to be the month-over-month change, which is available for many more surprises than the CPI level, even though the CPI level has a slightly higher relevance number.

for July through December, I look at the change in the forecast for the subsequent year. I focus on the GDP growth, CPI inflation, and unemployment forecasts. I consider the mean of all forecasts available for a given variable in a given month.[8]

## 3 Monetary Policy Surprises and the Global Interest Rate Cycle

In this section, I present the monetary policy surprises that I consider in this paper and discuss the novel findings that these co-move with each other and with the global interest rate cycle.

I start by considering the average movement in monetary policy surprises over time. In Figure 1, I plot in dark blue the sum of monetary policy surprises around central bank announcements in a five-month moving window, averaged across the central banks in my sample.[9] Average monetary policy surprises appear to correlate with each other over time. This is surprising because central bank announcements are not made at the same time, so if there has been a positive monetary policy surprise, markets might be expected to update their expectations for future central bank announcements accordingly. In that case, future monetary policy surprises should not correlate with earlier surprises.[10]

Moreover, monetary policy surprises co-move with the global interest rate cycle. I plot in light blue the change in the policy rate in a five-month moving window averaged across the countries/zones in the sample. The scale is shown on the right-hand side and is ten times greater than the scale for the monetary policy surprises. Average monetary policy surprises and average changes in policy rates move together.[11]

To further elucidate this relationship, I plot tightening and easing periods with shaded bars. I plot tightening periods (that is, when policy rates are rising across developed countries/zones) in green and easing periods (that is, when policy rates are falling across developed countries/zones) in red. I define a tightening (easing) period to be when policy rates in the countries/zones in the sample rose, on average, by more (less) than 50 basis points (two quarter points) in a five-month moving window.[12] During the five easing periods, when global interest rates were falling, monetary policy

[8]There is a large jump in the forecast for unemployment in the United Kingdom for the current year from 3.2 percent in September 2014 to 6.3 percent in October 2014. Outside of the COVID-19 period, this is by far the largest change in unemployment in the sample. While the Scottish Independence Referendum took place around that period, I do not see why it would lead to such a change, so I exclude it.

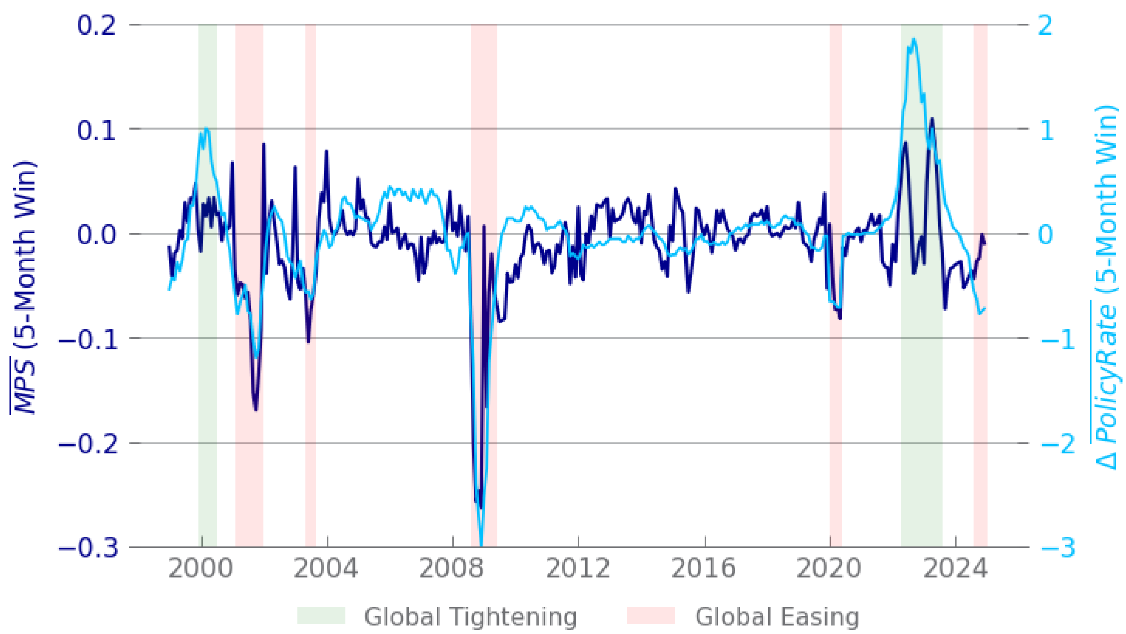
[9]I compute the sum of monetary policy surprises for each country/zone during a five-month moving window. I then take the average across the countries/zones in my sample. If a country/zone has no monetary policy surprises during a window, then I ignore it.

[10]The fact that this does not happen suggests there is predictability, which is discussed further in Section 4.

[11]Figure B.1, Figure B.2, and Figure B.3 show that the results are similar without applying a moving average, when the monetary policy surprises are measured using a strict 30-minute window, and when the monetary policy surprises are measured using the Nelson–Siegel approach, respectively.

[12]By this definition, there were two easing periods in 2001 (February to May and July to December), but both were associated with the dot-com bust, so I combine them. The last easing was still ongoing as of the end of 2024, when my data set ends.

Figure 1: Monetary Policy Surprises and the Global Interest Rate Cycle




Notes: The lines represent the sum of monetary policy surprises in a five-month moving window averaged across the countries/zones in the sample (left axis) and the change in the policy rate in a five-month moving window averaged across the countries/zones in the sample (right axis). The green (red) bars indicate that the average change in the policy rate across all countries/zones in the sample in a five-month moving window was more than 50 (less than –50) basis points. Sources: Bloomberg, CME, and Refinitiv.

Table 2: Monetary Policy Surprises during Tightening and Easing Cycles

| Description | Start Month | End Month | $\Delta \overline{PolicyRate}$ | $\overline{MPS}$ (Default) | $\overline{MPS}$ (2-Day) |
|---|---|---|---|---|---|
| Dot-Com Bubble | 1999.12 | 2000.06 | 1.17 | 0.05 | 0.11 |
| Dot-Com Bust | 2001.02 | 2001.12 | -1.86 | -0.24 | -0.29 |
| Mid-2003 Easing | 2003.05 | 2003.08 | -0.56 | -0.09 | -0.08 |
| Great Recession | 2008.08 | 2009.05 | -3.64 | -0.28 | -0.65 |
| COVID-19 Easing | 2020.01 | 2020.05 | -0.68 | -0.06 | -0.31 |
| Post-COVID Tightening | 2022.04 | 2023.07 | 3.94 | 0.17 | 0.45 |
| Post-Pandemic Easing | 2024.08 | 2024.12 | -0.78 | -0.03 | -0.07 |

Notes: The fourth column is the average change in the policy rate for the countries/zones in the sample from one month before the start month to the end month. To construct the fifth column, I take the sum of the monetary policy surprises that occured from the start month to the end month for all events and all countries/zones in the sample and divide this number by the number of countries/zones for which I observe monetary policy surprises during that period. I construct the sixth column similarly to how I construct the fifth column, except that I measure monetary policy surprises in a two-day window. Sources: Bloomberg, CME, Refinitiv.

surprises were negative. During the two tightening periods, when global interest rates were rising, monetary policy surprises were positive. Other periods generally show smaller monetary policy surprises.

Most of the easings and tightenings are familiar. Central banks tightened policy during the dot-com bubble and eased it during the dot-com bust. Central banks eased policy during the Great Recession and the onset of the COVID-19 pandemic. Central banks tightened policy during the burst of inflation following the reopening after the pandemic and then eased it at the end of 2024. The other period of easing occurred in 2003, when several central banks cut interest rates in anticipation of a recession that did not arise. I summarize the easing and tightening cycles in Table 2. The second and third columns show the start and end dates associated with these cycles. The fourth column shows the average change in the policy rate of developed countries/zones from the beginning to the end of the cycle. In the fifth column, I compute the sum of the baseline monetary policy surprises during that cycle averaged across each country/zone. I do the same in the sixth column, except I compute this with monetary policy surprises measured in a two-day window.

The degree to which monetary policy surprises vary with the global interest rate cycle is sizable. Across the easing cycles associated with the dot-com bust and the Great Recession, I find that the sum of the monetary policy surprises at each of the central banks in the sample was, on average, –0.24 and –0.28 percentage points, respectively. In other words, during those cycles, the central bank of each developed country/zone generated monetary policy surprises that, on average, equated approximately to a surprise one-quarter-point cut. Similarly, during the post–COVID-19 tightening cycle, each developed country's/zone's central bank generated monetary policy surprises that, on average, equated approximately to a surprise one-quarter-point rise. If the monetary policy surprises are measured using a wider two-day window, the effects are even stronger. The tightenings and easings associated with the dot-com bust, the COVID-19 easing, and the post–COVID-19 tightening were equivalent to more than a quarter-point change at each central bank. The easing associated with

Table 3: Correlation between Monthly Monetary Policy Surprises and Global Cycle Measures

| | $\overline{MPS}_m$ | $\Delta\overline{PolicyRate}_m$ | $\Delta\overline{\log(Stock_m)}$ | $\Delta \log(Oil_m)$ | $\Delta \log(Gold_m)$ |
|---|---|---|---|---|---|
| $\overline{MPS}_m$ | 1.0 | | | | |
| $\Delta\overline{PolicyRate}_m$ | 0.46 | 1.0 | | | |
| $\Delta\overline{\log(Stock_m)}$ | 0.07 | 0.18 | 1.0 | | |
| $\Delta \log(Oil_m)$ | 0.21 | 0.25 | 0.36 | 1.0 | |
| $\Delta \log(Gold_m)$ | -0.01 | 0.01 | 0.01 | 0.11 | 1.0 |

Notes: For monetary policy surprises, I measure the mean monetary policy surprises across all central bank announcements in that month. For other variables, I measure the change from the end of the preceding month to the end of the current month. For stock prices, I compute the change in the log price of the benchmark stock index for each country/zone in my sample and then take the mean. Sources: Bloomberg, CME, Haver, and Refinitiv.

the Great Recession was equivalent to more than two quarter-point cuts.[13]

Other measures of global cycles demonstrate less co-movement. I show the monthly correlation between average monetary policy surprises, the average change in policy rates, and the average change in the log price of stocks, oil, and gold in Table 3.[14] The first column shows the correlation between average monetary policy surprises and measures of the global cycle. Monetary policy surprises show some correlation with changes in the prices of global stocks and oil, but they have the strongest correlation with the global interest rate cycle.

# 4 Predicting Monetary Policy Surprises

In Section 3, I demonstrate that there is significant correlation between the change in global interest rates and monetary policy surprises. This section moves beyond correlations to investigate which variables best predict monetary policy surprises.

Unlike in the previous section, where I average by month, for the rest of the paper, each point in the data covers a central bank announcement in country/zone $z$ on day $t$.[15] I consider predictive regressions of the form given in Equation (1). I predict a monetary policy surprise in country/zone $z$ on day $t$, $MPS_{z,t}$ using public signals that took place before day $t$ and that are denoted by $Z_{z,t-\delta}$, where $\delta > 0$.[16] I mostly consider pooled regressions in which I regress the monetary policy surprise for every country/zone in my sample on the change in economic conditions before the announce-

[13]One explanation for the larger effects in the two-day window is that it takes time for markets to process central bank announcements. Another explanation is that other events take place within the two-day window that correlate with the tightening/easing cycle. I take the conservative approach and use a narrower time frame by default in later sections.

[14]I measure the average change in the log price of stocks by first computing the log change in the benchmark stock index for each country/zone in my sample. I then compute the mean across countries/zones.

[15]The data set is therefore indexed by country/zone $z$ and day $t$. A point is only included in the data set if a monetary policy announcement took place in that country/zone on that day.

[16]I consider both domestic public signals, where the $z$ subscript for $Z_{z,t}$ is needed, and global public signals, where it is not.

ment associated with that surprise. However, I also show analysis breaking out the impact by country/zone:

$$MPS_{z,t} = \alpha + \beta Z_{z,t-\delta} + u_{z,t}. \tag{1}$$

### 4.1 Establishing a Predictive Relationship

I start by examining the relationship between the change in global interest rates before a central bank announcement and the monetary policy surprise resulting from that announcement. I denote the change in the short-term interest rate for country $z$ from $x$ days before the central bank announcement to $y$ days before the announcement by $\Delta_{t-x,t-y}I_{st,z}$.[17] I denote the change in the global short-term interest rate from $x$ days to $y$ days before the announcement by $\Delta_{t-x,t-y}\bar{I}_{st}$. I compute this by taking the average of $\Delta_{t-x,t-y}I_{st,z}$ across all the countries/zones in my sample.

I begin by investigating the predictability of global interest rates measured in different windows before monetary policy surprises in Table 4. In regressions (1) through (4), I regress the surprise resulting from a central bank announcement on the change in the global interest rate beforehand. I consider the change in the global interest rate from seven days to one day before, 15 days to one day before, 30 days to one day before, and 90 days to one day before, respectively. The results are all significant at the 0.1 percent level. The highest $R^2$ is for the second regression, that is, the 15-days-to-one-day measure. This regression suggests that a 1 percentage point increase in the global interest rate from 15 days to one day before the central bank announcement is associated with a 12.1 basis point increase in the monetary policy surprise resulting from that announcement .

In regression (5), I decompose the change from 90 days to one day before the central bank announcement into four separate windows, from 90 days to 30 days, 30 days to 15 days, 15 days to seven days, and seven days to one day before the announcement. I find that the two later windows covering 15 days to one day before the announcement are significant at least at the 5 percent level, with relatively large coefficients. On the other hand, I find that the two earlier windows are significant at most at the 10 percent level, with smaller coefficients. Therefore, I focus on the predictive power of the change in global interest rates from 15 days to one day before a central bank announcement.

The convention in the monetary policy surprise literature has been to consider narrow windows, following Gürkaynak, Sack, and Swanson (2005). Other, more recent papers suggest wider windows to allow more time for markets to process the information around central bank announcements and to capture press conferences (Altavilla et al., 2019; Acosta et al., 2025). In Table 5, I consider how changing the window of the monetary policy surprise (that is, the dependent variable) affects the results. In regressions (1), (3), (4), (5), and (6), I consider 30-minute, two-hour, four-hour, one-day, and two-day windows, respectively.[18] In regression (2), I consider the default measure, which is

[17] I measure the change in the short-term interest rate as the average change in interest rates up to a maturity of one year.

[18] The 30-minute window compares the earliest trades from 10 minutes to just before a central bank announcement

Table 4: Investigating Predictability: Window for the Measurement of the Global Interest Rate

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Intercept | -0.003* | -0.003* | -0.003* | -0.003* | -0.003* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\Delta_{t-7d,t-1d}\bar{I}_{st}$ | 0.173*** | | | | 0.109** |
| | (0.040) | | | | (0.035) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | | 0.121*** | | | |
| | | (0.026) | | | |
| $\Delta_{t-30d,t-1d}\bar{I}_{st}$ | | | 0.061*** | | |
| | | | (0.013) | | |
| $\Delta_{t-90d,t-1d}\bar{I}_{st}$ | | | | 0.026*** | |
| | | | | (0.007) | |
| $\Delta_{t-15d,t-7d}\bar{I}_{st}$ | | | | | 0.104* |
| | | | | | (0.050) |
| $\Delta_{t-30d,t-15d}\bar{I}_{st}$ | | | | | -0.006 |
| | | | | | (0.018) |
| $\Delta_{t-90d,t-30d}\bar{I}_{st}$ | | | | | $0.018^{+}$ |
| | | | | | (0.011) |
| N | 1764 | 1764 | 1764 | 1764 | 1764 |
| $R^2$ | 0.020 | 0.031 | 0.025 | 0.027 | 0.037 |
| $R^2_{adj}$ | 0.020 | 0.031 | 0.025 | 0.027 | 0.035 |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

Table 5: Investigating Predictability: Monetary Policy Surprise Window

| $MPS_{z,t}$ | 30-min | 2-hour narrow | 2-hour | 4-hour | 1-day | 2-day |
|---|---|---|---|---|---|---|
| Intercept | -0.004** | -0.003* | -0.003* | -0.003* | -0.005** | -0.005** |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.114*** | 0.121*** | 0.124*** | 0.126*** | 0.140*** | 0.230*** |
| | (0.028) | (0.026) | (0.029) | (0.035) | (0.026) | (0.041) |
| N | 1403 | 1764 | 1763 | 1806 | 1773 | 1749 |
| $R^2$ | 0.027 | 0.031 | 0.028 | 0.026 | 0.037 | 0.056 |
| $R^2_{adj}$ | 0.027 | 0.031 | 0.028 | 0.026 | 0.036 | 0.055 |

Notes: $^+$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

a narrow two-hour measure whereby I effectively consider points in the 30-minute window when they are available and points in the two-hour window otherwise. Each regression suggests a positive relationship that is significant at the 0.1 percent level. Up to a one-day window, the results suggest that a 1 percentage point increase in the global interest rate from 15 days to one day before the central bank announcement is associated with an increase of 11 to 14 basis points in the monetary policy surprise resulting from that announcement. The results for a two-day window are stronger, suggesting a 23 basis point rise. The results grow slightly with the window, which suggests that the degree of predictability may be higher for longer windows, as markets have more time to process the monetary policy announcement. However, measuring the monetary policy surprise in a longer window is likely to induce more noise in the measurement of monetary policy surprises because it gives more time for unrelated events that also affect interest rates to occur. This can be observed in the two-day regression, which has the highest standard error. I focus on the two-hour narrow window to reduce potential noise. However, in Sections 4.2 and 4.3, I also report my primary results for two-day windows, which are similar.

In Table 6, I investigate the predictability of different interest rate measures. In regression (1), I report the baseline measure, which is the same as regression (2) in Table 4. In regression (2), I include the recent change in medium-term interest rates as well as the recent change in short-term interest rates.[19] The recent change in the short-term global interest rate becomes more positive, while the medium-term global interest rate is significantly negative. This result suggests that if medium-term interest rates have also moved in the same direction as short-term rates in the preceding 15 days,

with the latest trades from 10 minutes to 20 minutes after the announcement. The two-hour window compares the trades from one hour to just before an announcement with the latest trades from 10 minutes to one hour after the announcement. The four-hour window compares the trades from two hours to just before an announcement with the latest trades from 10 minutes to two hours after the announcement. The one-day window compares the trades at the close of business the business day before a central bank announcement with the trades at the close of business the day of the announcement (or the next business day in the unusual case that an announcement does not take place on a business day). The two-day window compares the trades at the close of business the business day before an announcement with the trades at the close of business the day after an announcement.

[19] I measure the change in the medium-term interest rate as the average change in interest rates for instruments with a maturity of one to three years.

Table 6: Investigating Predictability: Interest Rate Measures

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -0.003* | -0.003* | -0.003* | -0.003* | -0.003* | -0.003* | -0.004* | -0.003* | -0.003** |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.121*** | 0.224*** | | 0.231*** | | | | | 0.220*** |
| | (0.026) | (0.035) | | (0.035) | | | | | (0.041) |
| $\Delta_{t-15d,t-1d}\bar{I}_{mt}$ | | -0.089*** | | -0.097*** | 0.040 | | | | -0.078** |
| | | (0.025) | | (0.026) | (0.025) | | | | (0.024) |
| $\Delta_{t-15d,t-1d}(I_{st,z} - \bar{I}_{st})$ | | | 0.059* | 0.065* | | | | | 0.070** |
| | | | (0.026) | (0.026) | | | | | (0.026) |
| $\Delta_{t-15d,t-1d}(I_{mt,z} - \bar{I}_{mt})$ | | | 0.020 | 0.009 | 0.050* | | | | 0.014 |
| | | | (0.023) | (0.023) | (0.021) | | | | (0.025) |
| $\Delta_{t-15d,t-1d}I_{st,USA}$ | | | | | | 0.036 | | | -0.031 |
| | | | | | | (0.024) | | | (0.022) |
| $\overline{MPS}^{Prior15Days}$ | | | | | | | 0.136** | | 0.021 |
| | | | | | | | (0.053) | | (0.068) |
| $\Delta_{t-15d,t-1d}\overline{PolicyRate}$ | | | | | | | | 0.113** | 0.046 |
| | | | | | | | | (0.041) | (0.043) |
| N | 1764 | 1764 | 1662 | 1662 | 1755 | 1759 | 1581 | 1764 | 1486 |
| $R^2$ | 0.031 | 0.042 | 0.015 | 0.055 | 0.014 | 0.007 | 0.008 | 0.024 | 0.070 |
| $R^2_{adj}$ | 0.031 | 0.040 | 0.013 | 0.053 | 0.013 | 0.006 | 0.008 | 0.023 | 0.066 |

Notes: $^+$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

then the predictability of short-term rates is weaker. One explanation for this finding is that interest rates of different maturities tend to move together due to the portfolio rebalancing channel (Vayanos and Vila, 2021). Short-term rate movements that result from news related to longer-term rates are likely to convey less information and provide less predictability for monetary policy surprises than movements from news related to short-term rates. The adjusted $R^2$ rises to 4.0 percent.

Recent changes in domestic interest rates also offer some predictability. In regression (3), I consider the change in domestic interest rates from 15 days to one day before the central bank announcement. I measure these relative to the change in the global interest rate so that I consider domestic rate changes not captured by global rate changes.[20] A 1 percentage point rise in short-term domestic interest rates relative to global rates predicts a 5.9 basis point higher monetary policy surprise and is significant at the 5 percent level. Therefore, domestic rates offer some additional predictive power beyond global rates. In regression (4), I consider the global and domestic rates together. The coefficients remain similar, while the adjusted $R^2$ rises to 5.3 percent.

[20]If the monetary policy surprise is regressed on $\Delta_{t-15d,t-1d}\bar{I}_{st}$ and $\Delta_{t-15d,t-1d}I_{st,z}$, then the global interest rate would show the 1 percentage point rise in the developed country's/zone's rates, holding constant the domestic interest rate. This is not ideal because a movement in the global interest rate cycle would also be expected to affect the domestic interest rate. Instead, the monetary policy surprise is regressed on $\Delta_{t-15d,t-1d}\bar{I}_{st,Dev}$ and $\Delta_{t-15d,t-1d}I_{st,z} - \Delta_{t-15d,t-1d}\bar{I}_{st}$. In this case, $\Delta_{t-15d,t-1d}\bar{I}_{st}$ captures the impact of a recent rise in global interest rates that also raises domestic interest rates, while $\Delta_{t-15d,t-1d}I_{st,z} - \Delta_{t-15d,t-1d}\bar{I}_{st}$ captures the impact of a recent rise in domestic interest rates relative to global interest rates.

I consider other potential interest rate measures. In regression (5), I consider only the change in medium-term interest rates, which yields an adjusted $R^2$ of 1.3 percent. The lower $R^2$ is not surprising, since changes in short-term rates seem more likely to predict monetary policy surprises. It has been shown that the United States drives global cycles (Rey, 2016; Kalemli-Özcan, 2020; Miranda-Agrippino and Rey, 2020). Therefore, one reasonable conclusion is that changes in US domestic interest rates may predict monetary policy surprises and stand in for the change in global rates. In regression (6), I consider the change in US six-month interest rates from 15 days to one day before the central bank announcement. This variable is positive but not significant. One potential explanation is that the signals provided by changes in US interest rates about monetary policy at central banks in developed countries/zones may be better understood than signals provided by changes in global interest rates.

In regression (7), I consider how well the monetary policy surprise resulting from a central bank announcement is predicted by earlier monetary policy surprises.[21] I find that a 1 percentage point increase in the mean monetary policy surprise over the prior 15 days predicts that a monetary policy surprise will be 13.6 basis points higher. This is significant at the 1 percent level, with an adjusted $R^2$ of 0.8 percent. In regression (8), I consider the predictive power of the change in policy rates across developed countries/zones. I find that a 1 percentage point rise in the change in policy rates is associated with a 11.3 basis point increase in the monetary policy surprise. This is significant at the 1 percent level, and the regression has an adjusted $R^2$ of 2.3 percent. One concern is that there may be only a few monetary policy events in the preceding 15 days, which could indicate that the mean recent monetary policy surprise and mean policy rate change in regressions (7) and (8) are quite noisy. In Table C.1, I obtain similar results for regressions (7), (8), and (9) when I instead consider the 30-day change in these variables.

In regression (9), I consider all interest rate measures together. The coefficients for the short-term global and domestic interest rates remain very similar to those from regressions (2) and (4). By contrast, the coefficients for the sum of monetary policy surprises and the recent change in policy rates become insignificant. This suggests that short-term global and domestic interest rates are stronger predictors than the sum of monetary policy surprises and the change in policy rates. A couple of factors may explain this finding. First, short-term interest rates, which I measure as the average interest rate for maturities up to one year, reflect the latest information about expected rates in upcoming months, whereas policy rates may evolve more slowly. For example, a central bank may signal a rate cut in advance, in which case short-term rates will change while policy rates will change only when the rate cut is made. Second, policy rates change in discrete intervals (typically quarters of a percentage point), which make them a noisier measure. Therefore, I focus on the change in short-term global and domestic interest rates moving forward.

[21] To compute this, I find the sum of any monetary policy surprises for each central bank in the sample over the 15 days before the central bank announcement. I then take the mean across the countries/zones in my sample. I ignore any countries/zones for which I have no monetary policy surprises during that period.

### 4.2 What Are the Best Predictors of Monetary Policy Surprises?

I find that the change in interest rates before a central bank announcement predicts monetary policy surprises. However, other explanations have been proposed. Schmeling, Schrimpf, and Steffensen (2022) suggest that a decline in stock prices predicts a monetary policy surprise easing in line with the concept of a "Fed put" (Cieslak and Vissing-Jorgensen, 2021). In other words, central banks ease policy by more than markets expect in response to falling stock prices. Bauer and Swanson (2023a) argue that economic news in the days before a central bank announcement predicts surprises around that announcement, suggesting that markets underestimate the degree to which central banks respond to economic news.[22] In this section, I explore which of these sets of variables—interest rate changes, declines in stock prices, or economic news—best predicts monetary policy surprises.

Table 7 compares the predictability of the different sets of variables. In this regression, I standardize the regressors and the monetary policy surprise by subtracting the mean and dividing by the standard deviation. This allows for easier comparison of the strength of the different explanations. I show the results in non-standardized format in Table C.2. In regression (1) and (2), I consider the predictive impact of the change in global interest rates and the change in domestic rates relative to global rates, corresponding to regressions (2) and (3) in Table 6. I find that a 1 standard deviation increase in global rates over the 15 days before a central bank announcement is associated with a 0.33 standard deviation increase in the surprise resulting from that announcement, and this is significant at the 0.1 percent level. Domestic (relative to global) rates also have a significant impact but to a lesser degree. I find that global interest rates have an adjusted $R^2$ of 4.0 percent, while domestic interest rates have an adjusted $R^2$ of 1.3 percent.

In regression (3), I control for asset price measures. In line with Schmeling, Schrimpf, and Steffensen (2022), I consider the change in these prices over the 30 days before the central bank announcement. I control for the change in global stock prices, domestic (relative to global) stock prices, exchange rates, gold prices, and oil prices. As global/domestic stock prices and the domestic exchange rate worsen, monetary policy surprises are more likely to be negative, which aligns with central banks cutting more than markets expect. A rise in gold prices is associated with negative surprises, which aligns with gold's safe-haven properties. Only the change in exchange rates is significant (at the 1 percent level), and the adjusted $R^2$ is 0.4 percent.[23]

In regression (4), I consider the explanatory power of US economic news surprises. On release days, the news surprise is measured as the actual release minus the forecast (see Section 2 for more details). When there is no release, the surprise for that day is set to zero. Following Bauer and Swanson

[22] Schmeling, Schrimpf, and Steffensen (2022) and Bauer and Swanson (2023a) consider other factors but focus on these explanations.

[23] In Table 7, I do not find that either global or domestic stock prices offer predictive power. Schmeling, Schrimpf, and Steffensen (2022) find that domestic stock prices have predictive power. However, they consider month-long excess returns in interest rates rather than the narrow window around central bank announcements, and I also control for other asset price changes. When I consider the change in asset prices over the preceding 90 days, following Bauer and Swanson (2023a), I do find that global stock prices are significant at the 5 percent level. In that case, the adjusted $R^2$ rises a little to 1.1 percent, which is still lower than the predictive power of global or domestic interest rates.

Table 7: Comparing the Predictability of Different Sets of Variables

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.000 | -0.001 | 0.001 | -0.001 | -0.002 | -0.002 | -0.000 | -0.002 | -0.001 | -0.003 |
| | (0.023) | (0.028) | (0.026) | (0.026) | (0.026) | (0.025) | (0.027) | (0.023) | (0.025) | (0.025) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.328*** | | | | | 0.318*** | | 0.292*** | 0.317*** | 0.344*** |
| | (0.052) | | | | | (0.052) | | (0.046) | (0.049) | (0.055) |
| $\Delta_{t-15d,t-1d}\bar{I}_{mt}$ | -0.182*** | | | | | -0.155** | | -0.131* | -0.176** | -0.180*** |
| | (0.051) | | | | | (0.056) | | (0.054) | (0.055) | (0.055) |
| $\Delta_{t-15d,t-1d}(I_{st,z} - \bar{I}_{st})$ | | 0.097* | | | | 0.127** | 0.115* | | 0.124** | 0.106* |
| | | (0.044) | | | | (0.047) | (0.047) | | (0.047) | (0.043) |
| $\Delta_{t-15d,t-1d}(I_{mt,z} - \bar{I}_{mt})$ | | 0.033 | | | | 0.017 | 0.025 | | 0.028 | 0.008 |
| | | (0.039) | | | | (0.043) | (0.045) | | (0.043) | (0.038) |
| $\Delta_{t-30d,t-1d}\overline{\log(Stock)}$ | | | 0.015 | | | -0.037 | 0.006 | -0.025 | | -0.040 |
| | | | (0.038) | | | (0.033) | (0.037) | (0.030) | | (0.032) |
| $\Delta_{t-30d,t-1d}(\log(Stock_z) - \overline{\log(Stock)})$ | | | 0.003 | | | 0.014 | 0.010 | 0.019 | | 0.005 |
| | | | (0.029) | | | (0.030) | (0.028) | (0.030) | | (0.028) |
| $\Delta_{t-30d,t-1d}\log(ExchangeRate_z)$ | | | 0.077** | | | 0.052 | 0.068* | 0.082** | | 0.040 |
| | | | (0.027) | | | (0.032) | (0.032) | (0.029) | | (0.029) |
| $\Delta_{t-30d,t-1d}\log(GoldPrice)$ | | | -0.047 | | | 0.009 | -0.020 | -0.014 | | 0.006 |
| | | | (0.033) | | | (0.032) | (0.030) | (0.030) | | (0.031) |
| $\Delta_{t-30d,t-1d}\log(OilPrice)$ | | | -0.004 | | | -0.039 | -0.020 | -0.043 | | -0.027 |
| | | | (0.038) | | | (0.030) | (0.035) | (0.028) | | (0.028) |
| $\sum_{k=1}^{30} UnemploymentRateNewsSurprise_{USA,t-k}$ | | | | -0.016 | | | | | | |
| | | | | (0.028) | | | | | | |
| $\sum_{k=1}^{30} PPIFinalDemandMoMNewsSurprise_{USA,t-k}$ | | | | 0.012 | | | | | | |
| | | | | (0.029) | | | | | | |
| $\sum_{k=1}^{30} Conf.BoardConsumerConfidenceNewsSurprise_{USA,t-k}$ | | | | 0.037 | | | | | | |
| | | | | (0.037) | | | | | | |
| $\sum_{k=1}^{30} RetailSalesAdvanceMoMNewsSurprise_{USA,t-k}$ | | | | 0.004 | | | | | | |
| | | | | (0.024) | | | | | | |
| $\sum_{k=1}^{30} U.of Mich.SentimentNewsSurprise_{USA,t-k}$ | | | | -0.025 | | | | | | |
| | | | | (0.032) | | | | | | |
| $\sum_{k=1}^{30} ISMManufacturingNewsSurprise_{USA,t-k}$ | | | | 0.067* | | | | | | |
| | | | | (0.029) | | | | | | |
| $\sum_{k=1}^{30} CPIYoYNewsSurprise_{USA,t-k}$ | | | | 0.070 | | | | | | |
| | | | | (0.046) | | | | | | |
| $\sum_{k=1}^{30} GDPAnnualizedQoQNewsSurprise_{USA,t-k}$ | | | | -0.018 | | | | | | |
| | | | | (0.023) | | | | | | |
| $\sum_{k=1}^{30} CPIMoMNewsSurprise_{USA,t-k}$ | | | | -0.055 | | | | | | |
| | | | | (0.043) | | | | | | |
| $\sum_{k=1}^{30} InitialJoblessClaimsNewsSurprise_{USA,t-k}$ | | | | -0.023 | | | | | | |
| | | | | (0.025) | | | | | | |
| $\sum_{k=1}^{30} ChangeinNonfarmPayrollsNewsSurprise_{USA,t-k}$ | | | | 0.036 | | | | | | |
| | | | | (0.027) | | | | | | |
| N | 1764 | 1662 | 1763 | 1764 | 1764 | 1661 | 1661 | 1763 | 1662 | 1661 |
| $R^2$ | 0.042 | 0.015 | 0.007 | 0.012 | 0.104 | 0.156 | 0.126 | 0.140 | 0.152 | 0.058 |
| $R^2_{adj}$ | 0.040 | 0.013 | 0.004 | 0.006 | 0.004 | 0.049 | 0.017 | 0.039 | 0.048 | 0.052 |
| All Local News by Zone | | | | | * | * | * | * | * | |
| All USA News by Zone | | | | | * | * | * | * | * | |
| Number of Regressors | 2 | 2 | 5 | 11 | 178 | 187 | 185 | 185 | 182 | 9 |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. The dependent and independent variables are standardized by subtracting the mean and dividing by the standard deviation by variable. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

(2023a), I look at the sum of each news surprise from 30 days to one day before the monetary policy surprise. For monthly variables, there is typically one release during the preceding 30 days, but occasionally, depending on the dates of news releases, there are two or zero. For weekly variables, such as US nonfarm payrolls, there are multiple releases. I first consider news surprises for the United States on the basis that US news has been shown to be an important driver of the Global Financial Cycle (Boehm and Kroner, 2025). I include the 10 most relevant US macroeconomic news surprises (as defined by Bloomberg; see Section 2) plus the unemployment news surprise.[24] The Institute for Supply Management manufacturing index is significant at the 1 percent level, but other variables are not significant. I find an adjusted $R^2$ of 0.6 percent, suggesting that economic news has limited predictive power.

I find similar results when I allow for the differential effects of both domestic and US news. In regression (5), I regress monetary policy surprises on the 10 most relevant domestic macroeconomic news surprises plus the 11 US news surprises from regression (4) while allowing for each US news surprise to have a differential effect by country/zone.[25] In this case, I find an adjusted $R^2$ of 0.4 percent, suggesting that news surprises have less predictive power than global interest rates. I consider many other permutations of news surprises in Appendix C.2, including considering only news surprises for CPI, GDP, and unemployment, and considering domestic/US news surprises separately. I continue to find that news surprises have low adjusted $R^2$ and have at best limited predictive power for monetary policy surprises.

In regression (6), I combine all the possible explanations: global interest rates (regression (1)), domestic relative to global rates (regression (2)), asset prices (regression (3)), and local/US news by country/zone (regression (5)). The coefficients for domestic and global interest rates remain quite similar after the introduction of the additional controls, as does their statistical significance. On the other hand, asset prices cease to show significant effects. Regression (6) also indicates that when the explanations are considered together, a one standard deviation increase in short-term global interest rates has by far the largest impact on monetary policy surprises, raising the monetary policy surprise by 0.31 standard deviation. In regressions (7) through (10), I leave out one explanation relative to regression (6).[26] Leaving out global rates in regression (7) leads to the largest decline in adjusted $R^2$.[27]

[24]Unemployment is the 13th most relevant variable for the United States. Therefore, there are 11 regressors in regression (4).

[25]For Switzerland, I include nine news surprises because I exclude retail sales, since that variable is available for fewer than 20 events. Therefore, I have 10 surprises for each country/zone except for Switzerland, for which I have nine, and the United States, for which I have 11 (due to the inclusion of unemployment), yielding a total of 90 domestic regressors. Then, for the eight non-US countries/zones, I consider the impact of the 11 US news surprises, allowing for a differential effect from each, and adding 88 additional regressors. Note that a non-US news surprise, such as the UK CPI news surprise, is included with an interaction term so that it is regressed only on that country's/zone's central bank announcements, for example, $\mathbb{1}_{UK} \sum_{k=1}^{30} CPINewsSurprise_{UK,t-k}$. On the other hand, a US news surprise, such as the US CPI news surprise, is included with interaction terms for every country/zone separately so that it can have a differential effect for each country/zone: $\sum_z \mathbb{1}_z \sum_{k=1}^{30} CPINewsSurprise_{US,t-k}$.

[26]Regressions (7) through (10) leave out global interest rates, domestic rates, asset prices, and economic news surprises, respectively.

[27]These results align with those in Kerssenfischer and Schmeling (2024), who explore the impact of news on stock prices

Overall, the change in global interest rates has the strongest adjusted $R^2$ when the explanations are considered separately, has the strongest impact when the explanations are considered together, and leads to the largest reduction in adjusted $R^2$ when it is excluded. Therefore, I conclude that global interest rates are the strongest predictor of monetary policy surprises among the proposed explanations. I find very similar results for two-day monetary policy surprises in Table C.4.

### 4.3 Results by Country/Zone

Next, I examine how well global interest rates predict the monetary policy surprises of individual countries/zones in my sample. To do this, I interact the primary independent variable with indicator variables for the country/zone in which each central bank announcement occurs. Table 8 reports the results. In regression (1), I consider only the interest rate interactions plus zone dummies. The 0.098 coefficient for $\Delta_{t-15d,t-1d}I_{6m,Dev} * \mathbb{1}_{USA}$ indicates that a 1 percentage point rise in global interest rates in the 15 days before a central bank announcement in the United States is associated with a 9.8 basis point increase in the resulting monetary policy surprise. Note that for regression (1), this approach yields the same coefficient for each country/zone as I would obtain by running a regression of the monetary policy surprises only for that country/zone on the change in global rates in the preceding 15 days. Absent other controls, four of the nine coefficients indicate a significant relationship, and none is negative.

In regressions (2) through (4), I control for the other variables considered in Table 7. I add other interest rate controls, asset price controls, and all local/US news by country/zone one at a time, respectively, into the regressions. After adding these controls, I find a high degree of significance across all regressions. In regressions (2) and (3), eight of the nine coefficients are significant at the 10 percent level or higher. In regression (4), all the coefficients are significant, and in regressions (2) through (4), four of the coefficients are significant at the 0.1 percent level or higher. Again, I find that every coefficient is positive. Therefore, I conclude that recent changes in global interest rates appear to offer broad predictive power for the monetary policy surprises across the developed countries/zones in my sample.

I find very similar results for two-day monetary policy surprises in Table C.5. Other papers in the literature typically focus on predicting US monetary policy surprises. I show additional results with only US monetary policy surprises in Appendix C.3.

### 4.4 Robustness Checks

In this section, I consider other robustness checks. I summarize several robustness checks in Table 9. In the table, I regress monetary policy surprises on my baseline measure of the change in global inter-

and bond yields. In an application, they find that news releases from other global central banks predict changes in US and euro-zone two-year yields around central bank announcements in those countries/zones more, while domestic and foreign macroeconomic news releases have less predictive power.

Table 8: Impact of Global Interest Rates by Country/Zone

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{AUS}$ | 0.248 | 0.339 | 0.339 | 0.340$^{+}$ |
| | (0.216) | (0.210) | (0.207) | (0.191) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{CAN}$ | 0.173*** | 0.266*** | 0.272*** | 0.222*** |
| | (0.052) | (0.063) | (0.068) | (0.065) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{CHE}$ | 0.136 | 0.272** | 0.278** | 0.279*** |
| | (0.095) | (0.096) | (0.098) | (0.076) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{ECB}$ | 0.049 | 0.115* | 0.122* | 0.106$^{+}$ |
| | (0.048) | (0.054) | (0.056) | (0.062) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{GBR}$ | 0.039 | 0.164$^{+}$ | 0.167$^{+}$ | 0.145$^{+}$ |
| | (0.080) | (0.088) | (0.086) | (0.077) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{NOR}$ | 0.160 | 0.261** | 0.262** | 0.313*** |
| | (0.112) | (0.085) | (0.090) | (0.093) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{NZL}$ | 0.249** | 0.353*** | 0.353*** | 0.323** |
| | (0.091) | (0.094) | (0.094) | (0.110) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{SWE}$ | 0.109* | 0.211*** | 0.215*** | 0.186** |
| | (0.052) | (0.052) | (0.058) | (0.069) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{USA}$ | 0.098* | 0.204*** | 0.210*** | 0.189*** |
| | (0.043) | (0.051) | (0.053) | (0.056) |
| N | 1764 | 1662 | 1661 | 1661 |
| $R^2$ | 0.045 | 0.068 | 0.070 | 0.171 |
| $R^2_{adj}$ | 0.036 | 0.057 | 0.056 | 0.056 |
| Zone Dummies | * | * | * | * |
| Other Interest Controls | | * | * | * |
| Asset Price Controls | | | * | * |
| All Local News by Zone | | | | * |
| All USA News by Zone | | | | * |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Zone dummies are dummy variables for each zone. Other interest rate controls correspond to the three interest rate controls added in regression (4) relative to regression (1) in Table 6. Asset price controls and all local/US news by zone refer to the controls added in regressions (3) and (5) in Table 7, respectively. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

Table 9: Robustness Checks

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| A. Baseline | 0.121*** | 0.231*** | 0.234*** | 0.217*** |
| B. Including COVID-19 Pandemic | 0.124*** | 0.225*** | 0.236*** | 0.224*** |
| C. Removing Outliers | 0.105** | 0.220*** | 0.222*** | 0.213*** |
| D. MPS with Nelson-Siegel | 0.121*** | 0.206*** | 0.218*** | 0.206*** |
| Intercept | * | * | * | * |
| Other Interest Rate Controls | | * | * | * |
| Asset Price Controls | | | * | * |
| All Local News by Zone | | | | * |
| All USA News by Zone | | | | * |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Other interest rate controls correspond to the three additional interest rate controls added in regression (4) relative to regression (1) in Table 6. Asset price controls and all local/US news by zone refer to the controls added in regressions (3) and (5) in Table 7, respectively. Monetary policy surprises in 2020 are excluded by default. Sources: Bloomberg, CME, and Refinitiv.

est rates over the preceding 15 days. In regression (1), I control only for an intercept. In regressions (2) through (4), I add other controls. Row A gives the baseline results. By default, I do not include central bank announcements that took place in 2020 in my sample due to the risk that distortions from the COVID-19 pandemic would introduce large outliers. I introduce these announcements in Row B. In Row C, I exclude large outliers, which I measure as changes in global interest rates in the 15 days before a central bank announcement that exceed 50 basis points. By default, I construct monetary policy surprises by considering the average change in the interest rate for instruments with a maturity of up to one year. In Row D, I consider an alternative approach to measuring the monetary policy surprises. I fit a Nelson–Siegel yield curve before and after the central bank announcement and compute the monetary policy surprise as the change in the fitted yield curves at a six-month maturity. Each of these robustness checks yields results that are very similar to the baseline. A full regression table for each robustness check is provided in Appendix C.4.

I consider how the relationship between global interest rates and monetary policy surprises evolves in narrow five-year windows in Table C.6. Regression (1) shows the baseline result for all years, while regressions (2) through (7) show the results for 1996 through 1999, 2000 through 2004, 2005 through 2009, 2010 through 2014, 2015 through 2019, and 2020 through 2024. All the coefficients are reasonably positive. Four of the six windows are significant. The two windows that are not significant are 1996 through 1999, for which I have fewer data points available, and 2020 through 2024, which contains the COVID-19 pandemic period. I present the baseline regression, corresponding to regression (2) in Table 4, as a scatter plot in Figure C.1.

## 5 Why Do Global Interest Rates Predict Monetary Policy Surprises?

The preceding section demonstrated that changes in global interest rates before a central bank announcement predict the monetary policy surprise resulting from that announcement. This is surprising. Interest rate derivatives are an important derivative market, and short-term interest rates are a key pillar of asset pricing. Moreover, central bank interest rate announcements are key moments in the financial calendar that are closely followed by markets. The predictability of monetary policy surprises presents the possibility for agents to make significant excess returns around central bank announcements. In this section, I investigate how this predictability can occur despite the excess return it presents.

To do so, I draw upon the results in Sastry (2022), who proposes two reasons for why monetary policy surprises may be predictable. First, markets may underestimate the degree to which the central bank responds to a public signal about economic fundamentals. This is the argument made by Bauer and Swanson (2023a). I call this Case 1. Second, markets may place too little faith in the precision of the public signal, an argument originated by Sastry (2022). I call this Case 2.

To show this formally, Sastry (2022) introduces a model that I summarize here.[28] There are four periods, $T = 0, 1, 2, 3$. At $T = 0$, the central bank and markets both receive a public signal, $Z$, about an exogenous fundamental, $\theta$, that together with the real interest rate, $r$, determines economic performance, $Y = a\theta - r$ where $a \geq 1$. The signal has the distribution $Z \sim N\left(\theta, \frac{1}{\tau_z}\right)$, where $\tau_z$ is the precision of the signal. The central bank also receives a private signal for $\theta$, which is denoted by $F$. At $T = 1$, the central bank sets interest rates according to its expectations of $\theta$ from the two signals it received at $T = 0$. It sets the real interest rate to be a linear function of the central bank's two signals: $r = \mathbb{E}_{F,0}[\theta] = aF + bZ$, where $a, b$ depend on the central bank's beliefs about the precision of the signals. At $T = 2$, another public signal about the exogenous fundamental, $\theta$, is released. At $T = 3$, $Y$ is realized.

Case 1 is modeled by assuming that the market underestimates the degree to which the central bank responds to the first public signal when setting interest rates. Formulaically, markets believe that the central bank sets $r = aF + (b - w)Z$ rather than $r = aF + bZ$, where $w > 0$. Case 2 is modeled by assuming that the market underreacts to the first public signal. Formulaically, markets believe the precision of the public signal is $\tilde{\tau}_z$, where $\tilde{\tau}_z < \tau_z$. In both cases, the public signal will correlate positively with monetary policy surprises at $T = 1$.[29] Therefore, either case could explain the results in Section 4.

Sastry (2022) introduces a test to select between the two cases based on how the forecasts of economic performance evolve after the central bank decision. The author demonstrates that if case 1 holds but case 2 does not, then $Cov(\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z) \leq 0$. Intuitively, under case 1, if there is a

[28]See Sastry (2022) for the full model and derivations.

[29]In this model, the monetary policy surprise is given by $\Delta = r - \mathbb{E}_{M,0}[r]$. In both cases, $Cov(\Delta, Z) \geq 0$.

Table 10: Applying Sastry (2022) to Examine Reasons for Predictability

| $\Delta_{s(t),s(t)+1m} VarForecast_z$ | CPI | GDP | Unemp. | CPI | GDP | Unemp | CPI | GDP | Unemp |
|---|---|---|---|---|---|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.774*** | 0.623*** | -0.422*** | 0.765*** | 0.608*** | -0.412*** | 0.841*** | 0.434** | -0.392*** |
| | (0.095) | (0.162) | (0.066) | (0.093) | (0.162) | (0.067) | (0.156) | (0.137) | (0.096) |
| $\Delta_{t-15d,t-1d}(I_{st,z} - \bar{I}_{st})$ | | | | 0.035 | 0.054 | -0.022 | -0.030 | -0.012 | 0.072 |
| | | | | (0.056) | (0.059) | (0.044) | (0.081) | (0.069) | (0.058) |
| N | 1842 | 1842 | 1387 | 1812 | 1812 | 1358 | 1785 | 1785 | 1344 |
| $R^2$ | 0.113 | 0.061 | 0.088 | 0.110 | 0.059 | 0.086 | 0.331 | 0.298 | 0.251 |
| $R^2_{adj}$ | 0.112 | 0.060 | 0.087 | 0.109 | 0.058 | 0.085 | 0.252 | 0.216 | 0.175 |
| Intercept | * | * | * | * | * | * | * | * | * |
| Other Interest Rate Controls | | | | | | | * | * | * |
| Asset Price Controls | | | | | | | * | * | * |
| All Local News by Zone | | | | | | | * | * | * |
| All USA News by Zone | | | | | | | * | * | * |

Notes: $^+$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Other interest rate controls correspond to the interest rate controls in regression (5) in Table 6. Asset price controls and all local/US news by zone refer to the controls added in regressions (3) and (5) in Table 7, respectively. Sources: Bloomberg, CME, Consensus Economics, Informa Global Markets, and Refinitiv.

positive public signal, central banks raise interest rates by more than markets expect.[30] Markets believe this is because central banks received a positive private signal. Therefore, they form more positive beliefs about economic outcomes than are justified by the first public signal alone. As more public information is released (at $T = 2$), they revise their beliefs downward. Therefore, there is a negative correlation between the public signal and the revision of forecasts taking place after the central bank announcement.

On the other hand, if case 2 holds but case 1 does not, Sastry (2022) shows that $Cov(\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z) \geq 0$. Intuitively, under case 2, if there is a positive public signal, markets do not place enough faith in that signal. Therefore, they form overly low expectations about economic outcomes, which are revised upward as more public information is released. Thus, there is a positive correlation between the public signal and the revision of forecasts taking place after the central bank announcement.

Table 10 shows the implementation of this test. The forecast that takes place after a central bank announcement is denoted by $s(t)$. The change in economic forecasts from the survey after an announcement, $s(t)$, to the second survey after an announcement, $s(t) + 1m$, is regressed on the change in global interest rates before that announcement. It is important to note that the change in global interest rates is measured entirely before the announcement, while the change in forecasts takes place entirely after it.

The first three columns in Table 10 suggest that the change in global interest rates before central bank announcements is associated with improvements in economic forecasts after the announcement.[31] These coefficients are highly significant, with each having a significance of less than 0.1 percent. This

[30]Central banks raise rates by $r = aF + bZ$ rather than $r = aF + (b - w)Z$, as markets expect.

[31]The unemployment coefficient is negative, which is akin to an improving economic forecast.

suggests that global interest rates predict monetary policy surprises because markets place too little confidence in the signals conveyed by changes in global rates before central bank announcements (case 2).

By contrast, the results for the change in domestic interest rates before central bank announcements are ambiguous. The second set of three columns in Table 10 also includes the change in domestic interest rates. This was also shown to predict monetary policy surprises in Table 6. However, this variable has an insignificant impact on the future change in all the forecasts considered, suggesting that markets do not place too little confidence in domestic interest rate signals. Note that in Table 10, I control for the change in domestic interest rates relative to the change in global rates, $\Delta(I_{6m,z} - I_{6m,Dev})$, similarly to Section 4, but I obtain the same result if I control for the nonrelative change in domestic interest rates, $\Delta I_{6m,z}$, as I show in Table D.1.

Finally, in regressions (7) through (9), I introduce other interest rate controls, asset price controls, and local/US news surprises so that I have the same controls as those in regression (6) in Table 7. This yields very similar results for both global and domestic interest rates.

Again, these results suggest that the reason the change in global interest rates predicts monetary policy surprises is because markets have too little confidence in the signals conveyed by global interest rates. In other words, financial markets underestimate the degree to which global monetary policies move together and provide signals about each other. It is not surprising that markets have struggled to understand the signals from these cycles, since economists only recently have begun to understand the dynamics of the Global Financial Cycle (Miranda-Agrippino and Rey, 2020, 2022). This explains why markets have had greater difficulty parsing the signals from global interest rates than from domestic rates. Ultimately, it also explains why markets appear to have persistently missed the opportunity to profit from predictable interest rate movements around central bank announcements.

Another explanation that may come to mind for the results in this paper is that central banks change policy rates in discrete amounts (typically quarter points) and financial markets may price in most but not all of each discrete amount. This would imply that a rise in interest rates before a central bank announcement in anticipation of an increase in interest rates would be associated with a positive monetary policy surprise resulting from that announcement.[32] Though possible, this would manifest primarily through changes in domestic interest rates, rather than global rates, predicting monetary policy surprises.

[32] For example, if a central bank was expected to raise its policy rate by 25 basis points, short-term interest rates may rise by 20 basis points in anticipation of this. In this case, if the central bank then does raise its policy rate by 25 basis points, the monetary policy surprise would be positive (5 basis points).

## 6 Conclusion

This paper is the first to show that monetary policy surprises follow the global interest rate cycle. When global central banks are tightening (easing) policy, monetary policy surprises are positive (negative). These changes are sizable and have often been equivalent to a quarter point cut (increase) across an easing (tightening) cycle.

In line with this, I find that recent change in global interest rates strongly predicts monetary policy surprises. This holds for a range of different interest rate measures, for different windows of the monetary policy surprises, and across individual countries/zones. Therefore, while other papers show that cycles in global assets are affected by monetary policy surprises, I show the reverse, that is, the global interest rate cycle predicts monetary policy surprises. I consider other explanations for why monetary policy surprises may be predictable and find that, among these, recent change in global interest rates most strongly predicts monetary policy surprises.

Finally, I argue that recent change in global interest rates predicts monetary policy surprises because markets underreact to the signals from global rates. This appears to be because the signals from global interest rates are more difficult to parse, which makes sense since economists have only recently begun to understand global cycles in financial assets. Indeed, markets do not seem to underreact to the signals coming from domestic interest rates. This can help explain why, even though markets have strong profit incentives to correctly estimate movements in interest rates around central bank announcements, monetary policy surprises are predictable.

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# Appendices

## A Section 2 Appendix (Data)

### A.1 Processing Central Bank Date/Time Data

I primarily obtain information on central bank data from the following sources:

- Bloomberg: I use data from the Bloomberg calendar, which gives dates and times beginning in 1997 for prominent developed countries and later for other countries. The calendar provides the dates and times of statement releases. For some countries, the calendar also provides the dates (and times) of minutes releases (more detailed summaries of monetary policy events after the initial release of the statement). For some releases, the date but not the time is available. The calendar sometimes also provides a measure of the policy rate before and after the event. These data are "Used with permission of Bloomberg Finance L.P."
- Direct collection from central bank websites: I compile the dates and, where possible, the times of monetary policy statement releases for a range of global central banks. I focus on doing this when dates/times of statement releases are not available on Bloomberg.

Other data sources that I reference to check dates but that are not included in the IMPS data set are:

- `centralbanknews.info`: a website summarizing monetary policy events. This provides daily data and is used to verify the dates.
- `investing.com`: a website providing a wide array of financial data. This is used to verify the dates.
- BIS policy rate changes data set: a dataset summarizing daily changes in policy rates of different countries. I use this to check that the dates appear correct (by verifying whether the dates align with changes in policy rates).

Key steps for processing all sources:

- Convert all the available times into coordinated universal time (UTC), also known as Greenwich Mean Time (GMT).
- For daily data, I ensure that the local day was the date that the event took place in local time. This was mainly an issue in Australia and New Zealand, where the day in UTC can be one day later than the day in local time, since UTC and local time are quite different in those countries/zones.

Steps for processing Bloomberg dates:

- Go through any event containing the word "minutes" (or its derivatives). Set relevant events as event type "minutes," that is, the release of central bank minutes.
- Drop any other events that are not "minutes" or tickers, which are codes that seem to be assigned when Bloomberg can track a series associated with that event. Since policy rates are series that can be tracked over time, statement releases in which policy rates may change seem to generally have tickers.
- Go through the tickers. Set relevant tickers to be "meeting" events, that is, events where the central bank meets and typically changes the policy rate. I ignore tickers that are unrelated to monetary policy statements such as bond auctions.

Merging the events:

- To remove duplicates with the same time: I keep only one event by zone/minute/event type. When there is more than one event, I keep Bloomberg over my directly compiled dates. When there are multiple Bloomberg events with different tickers available, I keep the most relevant ticker.
- To remove duplicates with the same day and no time: For events with no time, I also keep one event by zone/day/event type (using an approach similar to the one in the previous step).
- There are sometimes duplicates that take place on the same day but in which one event has a time and one does not. Therefore, when there are events for the same zone/event type that take place on the same day, I drop an event that has no time if there is an event that has a time.
- Additional checks: I flag any events that are the same zone and event type but different times that take place on the same day. I also flag any events from data that were directly collected from central bank websites that take place within seven days of another event of the same type in that zone (in case the date is wrong).
- Resolve any flags manually by looking online at central bank records. This includes removing duplicates caused by times being recorded incorrectly but keeping any events that occurred quickly after each other.

Specific event changes:

- Switzerland, 01/15/15: The Swiss National Bank announced that it was dropping its peg to the euro from that day onward. Asset markets responded very strongly, with the Swiss Franc immediately rising 20 percent in response (a large outlier compared with other events). I do not consider this in the sample, since the dynamics of asset prices and forecasts may be quite different following a peg change compared with a standard monetary policy change.

## A.2 Processing Refinitiv Intraday Data

Before I describe the high-frequency data, I need to make a clear distinction between the two types of bond data I use:

- Benchmark bonds: This is a measure of a specific maturity in which the underlying bond varies. For example, this might measure the 10-year interest rate. In this case, the data provider would aim to select the underlying bond such that it has a maturity close to 10 years. After a while, the underlying bond's maturity will be too short, so the underlying bond will switch.
- Non-benchmark bonds: This is a measure whereby I follow a specific bond from its issuance to its maturity (or until its latest maturity if the bond has not yet matured). The maturity of the bond will vary from long to short throughout this period. Note that it is possible that some non-benchmark bonds will sometimes be used as the underlying bonds for benchmark bonds. I take steps to ensure that I am not introducing duplicates in this case.

I download intraday data from DataSource, which provides intraday data dating back to the beginning of 1996 (although not all instruments are available this far back). I download data in five-minute increments on the following measures:

- Interest rates on benchmark bonds: I generally select all available benchmark bonds for all the countries/zones for which I compile high-frequency interest rate data. These data often begin in 1996, though they can begin later for some countries. There are access restrictions for the default, more comprehensive interest rate measures for US nominal bonds and for Japanese nominal bonds. I use non-default measures for US and Japan. I also use alternative sources for the United States, which are detailed below.
- Interest rates on non-benchmark bonds: This downloads data for a single bond and tracks all interest rates for that bond over time. For example, it might cover a 20-year bond that was issued on 1/15/1997 and expires on 1/15/2017. I add these bonds for countries/zones for which the benchmark bonds offer sparse coverage. Note that there is a possibility these bonds could sometimes also be covered by the benchmark bonds, but I adjust for this later.
- Interest rate swaps/overnight index swaps: I download the 10-year interest rate swaps and one-month/six-month/one-year overnight index swaps for my main countries/zones when they are available. I focus on short-term swaps because bond data are sometimes sparse at that frequency.
- Exchange rate data: I download the exchange rate for a range of countries/zones. For all countries/zones except the United States, I obtain the exchange rate relative to the dollar. Most exchange rates are given in the form (USD/zone), but some countries are given in the form (zone/USD). I adjust for this to obtain exchange rates that are all in the form (zone/USD). For the United States, I obtain the exchange rate relative to the Canadian dollar (USD/CAD).

- Stock indexes data: I download stock indexes (such as the SP500 and FTSE100) for a range of countries/zones. I select stock indexes based on the ones listed highest for that country/zone on Refinitiv Eikon. Stock index data for the United States is partly restricted, so I use the Refinitiv stock index measure for the United States.

I always take the following steps to clean the high-frequency data:

- I convert intraday data to be measured at five-minute intervals, and I correct for time zones to ensure that the data are measured in UTC. I measure the open and close of each five-minute interval.
- The high-frequency data often show the same value repeated many times (particularly overnight, when markets are closed). The values are quite precise. For example, intraday bond data are often given to 0.1 or even 0.01 basis points. Therefore, it is unlikely that the value actually remained the same from one period to the next (unless the relevant market was closed, in which case this is also not a good measure of high-frequency changes). Thus, whenever an index is the same in one 5-minute interval as the preceding five-minute interval (or is the same as a preceding day for daily data), I set that value to be missing. Note that the assumption that the values will not remain the same is especially likely to be true around monetary policy announcements.
- When relevant, I also drop any values that are exactly zero, which appear to be stand-ins for missing data.

For the euro zone:

- Exchange rate: I use the euro.
- Stock exchange: I use the STOXX Euro measures.
- Bond data: I use German bond data and euro-zone-level overnight interest swap/interest rate swap data. I verify that these behave similarly.

### A.3 Processing CME Intraday Data

I use CME data to obtain additional intraday data for the United States. In particular, I get Eurodollar futures data (beginning in December 1981), two-year Treasury note futures data (beginning in January 1991), five-year Treasury note futures data (beginning in July 1988), 10-year Treasury note futures data (beginning in January 1983), and 30-year Treasury bond futures data (beginning in October 1982).

I take the following preliminary steps before getting interest rates/maturities:

- I begin by converting the data into the open/close bids for five-minute intervals.
- I adjust the data to be in UTC.

**CME Bond Futures** For each of the Treasury bond types, there are bond futures offered every three months. Consider a five-year Treasury note future that expires on December 31, 2019. Someone who buys this note will receive the value of a five-year bond on December 31. Someone who sells this future has to deliver this value on December 31.[33] The futures begin trading about one year in advance (the future expiring on December 31, 2019, begins trading at the start of 2019), so at any time, there are typically four futures contracts trading (although they are traded more heavily closer to their expiry).

The seller may deliver any bond between a set of maturities. For the two-year bond future, the bond delivered must be of maturity one year and nine months to two years. For the five-year bond future, the bond must be of maturity four years and two months to five years and three months. For the 10-year bond future, the bond must be of maturity 6.5 years to 10 years. For the 30-year bond future, the bond must be of maturity 15 to 25 years.

Since different bonds can be delivered with different coupons/maturities, the bond prices are converted into the price they would receive if the coupon were 6 percent (8 percent for expiry dates pre-2000). This rate is called the "pricing coupon." This means that if the interest rate on a bond is more/less than or equal to the pricing coupon, then it would make sense to deliver the longest/shortest/any maturity bond. For example, consider a bond that actually has a coupon payment equal to the pricing coupon (for simplicity). If interest rates for that maturity bond are 6 percent, then the bond should be worth exactly the principal one gets back. If interest rates are less than 6 percent, then the bond should be worth more than 100, and the longer the maturity of the bond, the more it is worth, so sellers will want to give buyers shorter-maturity bonds.

In practice, since 1991, interest rates have nearly always been lower than the pricing coupon. Therefore, I set the maturity of the bond that is effectively being traded on as the shortest maturity possible at the expiry date (that is, one year and nine months for two-year bond futures, etc.) plus however many days remain until the expiry of the future. For example, if the five-year bond future expiring on December 31 was traded on June 30, then I would set the maturity of that bond to be four years and eight months.

I then back out interest rates from the underlying bond being traded using the pricing coupon and the maturity at expiry.

**CME Eurodollar Futures** Eurodollar futures contracts expire at the quarter-end months (that is, March, June, September, and December) and extend 10 years[34]. The last trading day/expiration date

[33] In practice, the buyer only has to pay some fraction of the amount, and the seller only gives some relative amount.

[34] There are also contracts for other months extending one year, but I do not use these.

of the contract is the second London business day before the third Wednesday of the delivery month. Price quotes for Eurodollars futures contracts are set using the International Monetary Market (IMM) Index. $IMM = 100 - R$, where, in this case, $R$ is the three-month annualized USD LIBOR on the third Wednesday of the delivery month. For example, if a Eurodollar futures contract is trading at $97, then at that time, the implied three-month annualized USD LIBOR on the third Wednesday of the delivery month is 3 percent.[35] I set the expiration date to be the third Wednesday of the maturity month.

Eurodollar futures are not immediately comparable to bond interest rates because they only capture the expected interest rate at a period of time rather than capturing the expected interest rates throughout the duration of a bond. To make the Eurodollar futures comparable to the other bond data I use, I therefore set:

- three-month interest rate: the one-quarter-ahead Eurodollar future.
- six-month interest rate: the mean of the one-quarter-ahead and two-quarter-ahead Eurodollar future.
- nine-month interest rate: the mean of the one-quarter-ahead, the two-quarter-ahead, and the three-quarter-ahead Eurodollar future.
- x-year interest rate: the mean of all Eurodollar futures between now and x years from now.

I interpolate gaps but do not fill gaps outside the earliest and latest available quarters, except that if the first quarter does not have a value, I set it to be the value for the second quarter.

### A.4 Processing Interest Rate Data

For interest rate data, I take additional steps to process the raw shocks (that is, the raw measures of interest rates before/after monetary policy events) for a few reasons:

- I obtain many measures for the change in interest rates around monetary policy events. I need to select an appropriate interest rate from the measures.
- By combining the different measures, I can fill in gaps in individual measures (intraday interest rate data are quite spotty).
- While benchmark bonds may be listed as having a specific maturity, the underlying bonds will vary around this maturity. I try to more precisely measure the maturity.

[35]Each Eurodollar futures contract represents a $1 million interest-yielding bank deposit (at a bank outside the United States) with a three-month maturity. Eurodollars are cash-settled, which means that at expiration/settlement of the contract, the seller must pay the buyer an amount that is equivalent to the value (including interest) of a three-month deposit made at the time of settlement.

- The interest rate data sometimes show outliers, and I want to produce a measure from which outliers are removed.

There are two steps I go through to process the raw shocks:

1. Initial processing: For each event/time frame:
   - I keep only interest rates for which I have data both before/after the event.
   - I exclude benchmark bonds when the measured window around an event overlaps with a day on which the underlying bond changed (which could lead to a large change in the measured interest rate for other reasons).
   - I produce measures including/excluding outliers. To exclude outliers, I take the following steps for each event/time frame:
     (a) For each instrument, I construct a comparison window. This is 0–2 years for bonds with a maturity of less than 1.25 years. It is half of the maturity of the bond to two times the maturity of the bond for maturities of more than 1.25 years. I compute the median comparison level as the median interest rate of other bonds in the comparison window before the event. I compute the median comparison change as the median change in the interest rate of other bonds in the comparison window around the event. Note that I consider all sources when doing this.
     (b) If there are no other instruments in the comparison window, I set the instrument to be an outlier if its change in the window was more than 20 basis points.
     (c) If there are other instruments in the comparison window, I set the instrument to be an outlier if:
       – The rate of the instrument before the event differs from the comparison level by more than 5 percentage points.[36]
       – The change in the instrument around the event is more than 20 basis points and has the opposite sign to the comparison change.
       – The change in the instrument around the event is more than 20 basis points and is three times larger than the comparison change in absolute terms.
     (d) I repeat this process until no further instruments are marked as outliers.
2. Constructing yield curve measures: For each yield curve measure I want to create, I go through each event one at a time and construct the yield curve measure.
   - Sometimes a bond can appear twice for the same event because it can appear as a non-benchmark bond and as a benchmark bond (see details in Appendix A.2). I can typically observe this by determining if a specific ID appears more than once for an event. I drop duplicate occurrences of the same ID.

[36]More precisely, I set this condition to be $|1/(1+comparison/100) - 1/(1+instrument/100)| > 0.05$ to avoid making it more likely that the outlier condition will be met when interest rates are large.

I use different measures for the yield curve to allow for different scenarios:

- With the window approach, I compute the average change in the interest between a lower-maturity bound and an upper-maturity bound. This is a non-parametric approach (relative to the Nelson-Siegel parametric approach).
- The Nelson-Siegel approach allows me to use all points available to construct the yield curve before/after and then compute the difference between the two at specific maturities.

Notes for the Nelson-Siegel approach:

- I only construct Nelson-Siegel estimates when an event has at least four instruments that have data both before and after the monetary policy event.
- Occasionally, the Nelson-Siegel estimation fails to run either before or after the event. In that case, I restrict the value of $\tau$ to be one and rerun the estimation both before and after the event. $\tau = 1$ is a standard value in Nelson-Siegel estimation.
- I only compute the interest rate for a specific maturity from a Nelson-Siegel estimated yield curve if that maturity is within the maturities of instruments that were used to estimate the Nelson-Siegel yield curves before/after the event.

In practice, these approaches tend to yield quite similar results as I demonstrate in Appendix A.5.

I obtain the maturities for benchmark bonds from Refinitiv Eikon. For benchmark bonds, I set the maturity to be the maturity of the underlying bond. If the data are not available, I set the maturity to be the benchmark maturity. Note that a 10-year benchmark bond will only very rarely have a maturity of exactly 10 years. Instead, the appropriate maturity will be whatever the underlying bond is.

### A.5 Data Checks

The first panel compares the shocks I construct (measured in a 30-minute window using the window approach) with other measures of monetary policy shocks. Note that these other measures were only constructed for single countries/zones, so I only compare the shocks I have available for the relevant country/zone with the other measure. A1 compares the US monetary policy shocks constructed in Nakamura and Steinsson (2018) (and updated in Acosta (2023)) with the US shocks in my data set. Nakamura and Steinsson (2018) use futures with a maturity of up to one year. Therefore, I compare their measure to a monetary policy shock for all instruments with a maturity between zero and one years. The correlation of 0.81 is strong. I also compare to UK monetary policy shocks from Cesa-Bianchi, Thwaites, and Vicondoa (2020) (A2), which yields a correlation of 0.86. Finally, I find very strong correlation of 0.95 between my euro-zone shocks and the surprises in the Euro Area Monetary Policy Event-Study Database (EA-MPD), which relates to Altavilla et al. (2019) (A3).

Table A.1: Robustness Checks for Monetary Policy Shocks

| Comparison | Correlation | Num. Obs. |
|---|---|---|
| *A: Comparison with Other Monetary Policy Shock Measures* | | |
| A1: USA NS (2018) Shock v Window y00-y01 | 0.81 | 210 |
| A2: GBR CTV Target Shock v Window y00-y01 | 0.86 | 146 |
| A3: EA-MPD OIS 6m v Window y00-y01 | 0.95 | 288 |
| *B: Comparison of Alternative Sources* | | |
| B1: Refinitiv OIS y00-y01 v Refinitiv bond y00-y01 | 0.68 | 489 |
| B2: ECB OIS y00-y01 v DEU bond y00-y01 | 0.73 | 240 |
| B3: CME y00-y01 v Refinitiv bond y00-y01 | 0.63 | 152 |
| B4: CME y01-y03 v Refinitiv bond y01-y03 | 0.92 | 278 |
| *C: Comparison of Window v NS Approach* | | |
| C1: NS m06 v Window y00-y01 | 0.98 | 1506 |
| C2: NS y02 v Window y01-y03 | 0.98 | 2264 |
| *D: Comparison when Outliers are Included* | | |
| D1: Window y00-y01: with v without outliers | 0.86 | 2030 |
| D2: Window y01-y03: with v without outliers | 0.97 | 2392 |
| D3: NS m06: with v without outliers | 0.84 | 1506 |
| D4: NS y02: with v without outliers | 0.97 | 2298 |

Sources: Bloomberg, CME, and Refinitiv.

Most of the underlying data used to construct my shocks come from Refinitiv data on the change in interest rates for bonds (both benchmark and non-benchmark) from that country. However, I also use swap data from Refinitiv because bond data do not always offer proficient coverage, particularly for shorter maturities. For the United States, where I face restrictions on Refinitiv intraday bond data, I also include data from CME to improve the coverage of my shocks. In Panel B, I verify that these alternative sources have a strong correlation with the Refinitiv intraday bond data. In B1, I compare the correlation of shocks constructed using only Refinitiv overnight interest rate swaps (OIS) with shocks constructed using only Refinitiv bond data. I do not use interest rate data for bonds for the European Central Bank (ECB). I instead proxy for this using bond data from Germany. On the other hand, I do have intraday swap data for the ECB. In B2, I compare the correlation of ECB OIS data with German bond data. I find strong correlation. In B3 and B4, I compare the correlation of US shocks constructed using CME swap data relative to shocks constructed using Refinitiv data. Note that I use CME data for the United States because Refinitiv bond data are not available in earlier periods. I find a strong correlation between the two data sources.

In Panel C, I compare the correlation of shocks constructed using the Nelson-Siegel approach and shocks constructed using the window approach. The correlation is very high.

I exclude outliers by default in the shocks. In Panel D, I consider how including outliers affects the shocks. The shocks are highly correlated, which suggests outliers are generally not a major problem.

## A.6 Economic Releases

Table A.2: Summary of Economic Releases

| Zone | Event | Rank | CPI | GDP | Unemp | Divide by Var | Divide by Scalar |
|---|---|---|---|---|---|---|---|
| AUS | Unemployment Rate | 1 | | | y | | |
| AUS | Employment Change | 2 | | | | Australia: Employment (SA, Thous) | |
| AUS | GDP SA QoQ | 3 | | y | | | |
| AUS | CPI YoY | 4 | y | | | | |
| AUS | CPI QoQ | 5 | | | | | |
| AUS | Retail Sales MoM | 6 | | | | | |
| AUS | Building Approvals MoM | 7 | | | | | |
| AUS | GDP YoY | 8 | | | | | |
| AUS | Trade Balance | 9 | | | | Australia: Gross Domestic Product (SA, Mil.A$) | |
| AUS | Participation Rate | 10 | | | | | |
| CAN | CPI YoY | 1 | y | | | | |
| CAN | Unemployment Rate | 2 | | | y | | |
| CAN | CPI NSA MoM | 3 | | | | | |
| CAN | Quarterly GDP Annualized | 4 | | y | | | 4 |
| CAN | Net Change in Employment | 5 | | | | Canada: Employment (SA, Thous) | |
| CAN | GDP MoM | 6 | | | | | |
| CAN | Housing Starts | 7 | | | | | |
| CAN | Retail Sales MoM | 8 | | | | | |
| CAN | GDP YoY | 9 | | | | | |
| CAN | Building Permits MoM | 10 | | | | | |
| CHE | CPI YoY | 1 | y | | | | |
| CHE | CPI MoM | 2 | | | | | |
| CHE | PMI Manufacturing | 3 | | | | | |
| CHE | Unemployment Rate | 4 | | | y | | |
| CHE | GDP QoQ | 5 | | y | | | |
| CHE | GDP YoY | 6 | | | | | |
| CHE | Unemployment Rate SA | 7 | | | | | |
| CHE | Retail Sales Real YoY | 8 | | | | | |
| CHE | Producer & Import Prices MoM | 9 | | | | | |
| CHE | Producer & Import Prices YoY | 10 | | | | | |
| ECB | CPI YoY | 1 | | | | | |
| ECB | GDP SA QoQ | 2 | | y | | | |
| ECB | GDP SA YoY | 3 | | | | | |
| ECB | CPI MoM | 4 | | | | | |
| ECB | CPI Estimate YoY | 5 | y | | | | |
| ECB | CPI Core YoY | 6 | | | | | |
| ECB | Unemployment Rate | 7 | | | y | | |
| ECB | Consumer Confidence | 8 | | | | | |
| ECB | ZEW Survey Expectations | 9 | | | | | |
| ECB | Industrial Production SA MoM | 10 | | | | | |
| GBR | CPI YoY | 1 | y | | | | |
| GBR | CPI MoM | 2 | | | | | |
| GBR | GDP QoQ | 3 | | y | | | |
| GBR | GDP YoY | 4 | | | | | |
| GBR | CPI Core YoY | 5 | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| GBR | Jobless Claims Change | 6 | | | | U.K.: LFS: Employment: Aged 16 and Over [3-Mo Moving Avg] (SA, Thous) | |
| GBR | Industrial Production MoM | 7 | | | | | |
| GBR | ILO Unemployment Rate 3Mths | 8 | | | y | | |
| GBR | Manufacturing Production MoM | 9 | | | | | |
| GBR | Nationwide House PX MoM | 10 | | | | | |
| NOR | DNB/NIMA PMI Manufacturing | 1 | | | | | |
| NOR | CPI YoY | 2 | y | | | | |
| NOR | CPI MoM | 3 | | | | | |
| NOR | Industrial Production MoM | 4 | | | | | |
| NOR | Unemployment Rate | 5 | | | y | | |
| NOR | CPI Underlying YoY | 6 | | | | | |
| NOR | Unemployment Rate AKU | 7 | | | | | |
| NOR | GDP QoQ | 8 | | | | | |
| NOR | CPI Underlying MoM | 9 | | | | | |
| NOR | GDP Mainland QoQ | 10 | | y | | | |
| NZL | CPI QoQ | 1 | y | | | | |
| NZL | GDP SA QoQ | 2 | | y | | | |
| NZL | Unemployment Rate | 3 | | | y | | |
| NZL | Trade Balance NZD | 4 | | | | New Zealand: Gross Domestic Product (SA, Mil.NZ$) | |
| NZL | Food Prices MoM | 5 | | | | | |
| NZL | Building Permits MoM | 6 | | | | | |
| NZL | CPI YoY | 7 | | | | | |
| NZL | Employment Change QoQ | 8 | | | | | |
| NZL | GDP YoY | 9 | | | | | |
| NZL | Retail Sales Ex Inflation QoQ | 10 | | | | | |
| SWE | CPI Level | 1 | | | | | |
| SWE | Swedbank/Silf PMI Manufacturing | 2 | | | | | |
| SWE | CPI YoY | 3 | y | | | | |
| SWE | Unemployment Rate | 4 | | | y | | |
| SWE | CPI MoM | 5 | | | | | |
| SWE | GDP QoQ | 6 | | y | | | |
| SWE | Retail Sales MoM | 7 | | | | | |
| SWE | Economic Tendency Survey | 8 | | | | | |
| SWE | CPIF YoY | 9 | | | | | |
| SWE | PPI MoM | 10 | | | | | |
| USA | Change in Nonfarm Payrolls | 1 | | | | U.S.: Total Employees on Nonfarm Payrolls (SA, Thous) | |
| USA | Initial Jobless Claims | 2 | | | | | |
| USA | CPI MoM | 3 | y | | | | |
| USA | GDP Annualized QoQ | 4 | | y | | | 4 |
| USA | CPI YoY | 5 | | | | | |
| USA | ISM Manufacturing | 6 | | | | | |
| USA | U. of Mich. Sentiment | 7 | | | | | |
| USA | Retail Sales Advance MoM | 8 | | | | | |
| USA | Conf. Board Consumer Confidence | 9 | | | | | |
| USA | PPI Final Demand MoM | 10 | | | | | |
| USA | Unemployment Rate | 13 | | | y | | |

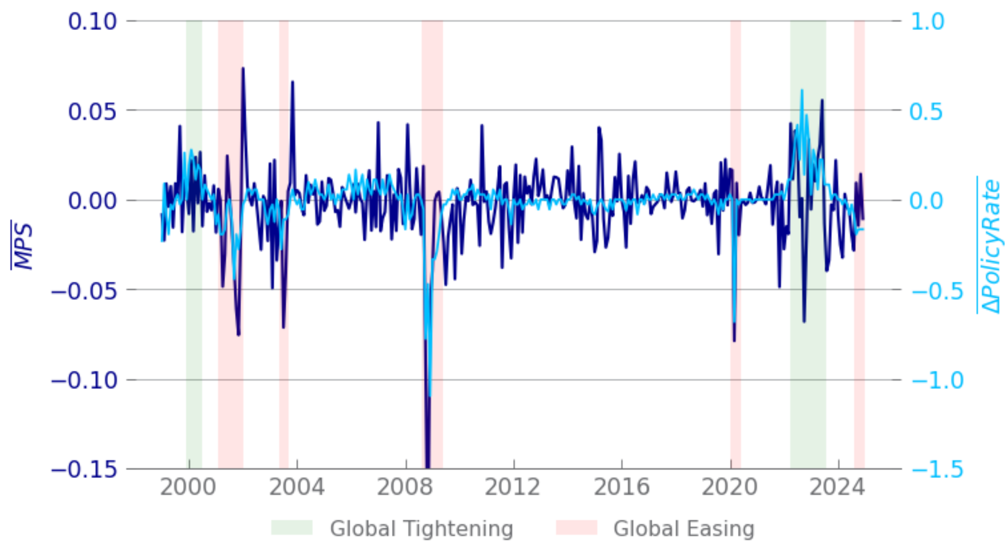
Notes: The first column shows the country/zone of the economic release. The second column describes the economic variable. The third column shows the rank of the variable based on the relevance measure on the Bloomberg Terminal. The fourth, fifth, and sixth columns show the most relevant variable for CPI inflation, GDP, and unemployment, respectively. The seventh column shows the level variable I divide by in the case of variables that are changes in levels. The eighth column shows additional scalar adjustments I made to variables so that they are comparable across countries/zones.

Sources: Bloomberg and Informa Global Markets

# B Section 3 Appendix (MPS and Global Rate Cycle)

## B.1 Average Monetary Policy Surprise Time Series

Figure B.1: Average Monetary Policy Surprises over Time: No Moving Average

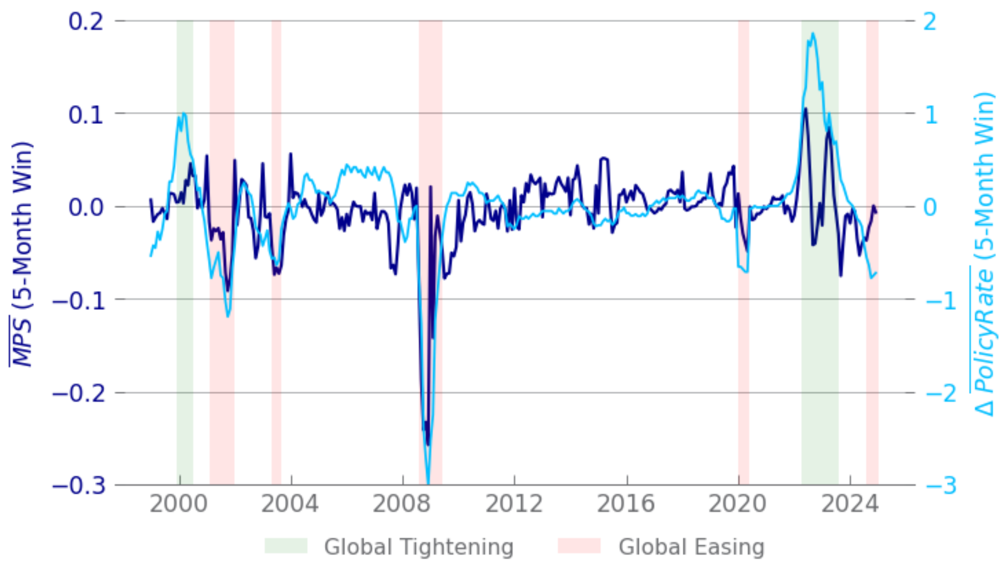



Notes: The lines represent the sum of monetary policy surprises averaged across the countries/zones in the sample (left axis) and the change in the policy rate averaged across the countries/zones in the sample (right axis). The green (red) bars indicate that the average change in the policy rate across all countries/zones in the sample in a five-month moving window was more than 50 (less than –50) basis points. Sources: Bloomberg, CME, and Refinitiv.

Figure B.2: Average Monetary Policy Surprises over Time: Two-Day Window


Notes: The lines represent the sum of monetary policy surprises measured in a two-day window in a five-month moving window averaged across the countries/zones in the sample (left axis) and the change in the policy rate in a five-month moving window averaged across the countries/zones in the sample (right axis). The green (red) bars indicate that the average change in the policy rate across all countries/zones in the sample in a five-month moving window was more than 50 (less than –50) basis points. Sources: Bloomberg, CME, and Refinitiv.

Figure B.3: Average Monetary Policy Surprises over Time: Nelson-Siegel




Notes: The lines represent the sum of monetary policy surprises measured using the Nelson-Siegel approach in a five-month moving window averaged across the countries/zones in the sample (left axis) and the change in the policy rate in a five-month moving window averaged across the countries/zones in the sample (right axis). The green (red) bars indicate that the average change in the policy rate across all countries/zones in the sample in a five-month moving window was more than 50 (less than –50) basis points. Sources: Bloomberg, CME, and Refinitiv.

# C Section 4 Appendix (Predicting MPS)

## C.1 Supplemental Figures/Tables

Table C.1: Investigating Predictability: Interest Rate Measures with a 30-Day Window

| $MPS_{z,t}$ | (1) | (2) | (3) |
|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | | | 0.211*** |
| | | | (0.043) |
| $\Delta_{t-15d,t-1d}\bar{I}_{mt}$ | | | -0.069** |
| | | | (0.026) |
| $\Delta_{t-15d,t-1d}(I_{st,z} - \bar{I}_{st})$ | | | 0.063* |
| | | | (0.025) |
| $\Delta_{t-15d,t-1d}(I_{mt,z} - \bar{I}_{mt})$ | | | 0.010 |
| | | | (0.023) |
| $\Delta_{t-15d,t-1d}I_{st,USA}$ | | | -0.032$^{+}$ |
| | | | (0.019) |
| $\overline{MPS}^{Prior30Days}$ | 0.166** | | -0.007 |
| | (0.062) | | (0.091) |
| $\Delta_{t-30d,t-1d}\overline{PolicyRate}$ | | 0.077** | 0.034 |
| | | (0.025) | (0.031) |
| N | 1745 | 1764 | 1642 |
| $R^2$ | 0.009 | 0.028 | 0.061 |
| $R^2_{adj}$ | 0.008 | 0.027 | 0.057 |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

Table C.2: Comparing the Predictability of Different Explanations: Without Standardization

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | -0.003* | -0.003* | -0.003$^{+}$ | -0.004* | -0.003 | -0.002 | -0.002 | -0.002 | -0.002 | -0.003* |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.002) | (0.001) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.224*** | | | | | 0.217*** | | 0.199*** | 0.216*** | 0.234*** |
| | (0.035) | | | | | (0.036) | | (0.031) | (0.033) | (0.037) |
| $\Delta_{t-15d,t-1d}\bar{I}_{mt}$ | -0.089*** | | | | | -0.076** | | -0.064* | -0.086** | -0.088*** |
| | (0.025) | | | | | (0.028) | | (0.026) | (0.027) | (0.027) |
| $\Delta_{t-15d,t-1d}(I_{st,z} - \bar{I}_{st})$ | | 0.059* | | | | 0.077** | 0.070* | | 0.075** | 0.065* |
| | | (0.026) | | | | (0.028) | (0.028) | | (0.028) | (0.026) |
| $\Delta_{t-15d,t-1d}(I_{mt,z} - \bar{I}_{mt})$ | | 0.020 | | | | 0.010 | 0.015 | | 0.017 | 0.005 |
| | | (0.023) | | | | (0.026) | (0.027) | | (0.026) | (0.023) |
| $\Delta_{t-30d,t-1d}\overline{\log(Stock)}$ | | | 0.000 | | | -0.000 | 0.000 | -0.000 | | -0.001 |
| | | | (0.000) | | | (0.000) | (0.000) | (0.000) | | (0.000) |
| $\Delta_{t-30d,t-1d}(\log(Stock_z) - \overline{\log(Stock)})$ | | | 0.000 | | | 0.000 | 0.000 | 0.000 | | 0.000 |
| | | | (0.001) | | | (0.001) | (0.001) | (0.001) | | (0.001) |
| $\Delta_{t-30d,t-1d}\log(ExchangeRate_z)$ | | | 0.002** | | | 0.001 | 0.001* | 0.002** | | 0.001 |
| | | | (0.001) | | | (0.001) | (0.001) | (0.001) | | (0.001) |
| $\Delta_{t-30d,t-1d}\log(GoldPrice)$ | | | -0.001 | | | 0.000 | -0.000 | -0.000 | | 0.000 |
| | | | (0.000) | | | (0.000) | (0.000) | (0.000) | | (0.000) |
| $\Delta_{t-30d,t-1d}\log(OilPrice)$ | | | -0.000 | | | -0.000 | -0.000 | -0.000 | | -0.000 |
| | | | (0.000) | | | (0.000) | (0.000) | (0.000) | | (0.000) |
| $\sum_{k=1}^{30} UnemploymentRateNewsSurprise_{USA,t-k}$ | | | | -0.007 | | | | | | |
| | | | | (0.011) | | | | | | |
| $\sum_{k=1}^{30} PPIFinalDemandMoMNewsSurprise_{USA,t-k}$ | | | | 0.002 | | | | | | |
| | | | | (0.004) | | | | | | |
| $\sum_{k=1}^{30} Conf.BoardConsumerConfidenceNewsSurprise_{USA,t-k}$ | | | | 0.000 | | | | | | |
| | | | | (0.000) | | | | | | |
| $\sum_{k=1}^{30} RetailSalesAdvanceMoMNewsSurprise_{USA,t-k}$ | | | | 0.000 | | | | | | |
| | | | | (0.002) | | | | | | |
| $\sum_{k=1}^{30} U.of Mich.SentimentNewsSurprise_{USA,t-k}$ | | | | -0.000 | | | | | | |
| | | | | (0.001) | | | | | | |
| $\sum_{k=1}^{30} ISMManufacturingNewsSurprise_{USA,t-k}$ | | | | 0.002* | | | | | | |
| | | | | (0.001) | | | | | | |
| $\sum_{k=1}^{30} CPIYoYNewsSurprise_{USA,t-k}$ | | | | 0.030 | | | | | | |
| | | | | (0.020) | | | | | | |
| $\sum_{k=1}^{30} GDPAnnualizedQoQNewsSurprise_{USA,t-k}$ | | | | -0.010 | | | | | | |
| | | | | (0.013) | | | | | | |
| $\sum_{k=1}^{30} CPIMoMNewsSurprise_{USA,t-k}$ | | | | -0.025 | | | | | | |
| | | | | (0.019) | | | | | | |
| $\sum_{k=1}^{30} InitialJoblessClaimsNewsSurprise_{USA,t-k}$ | | | | -0.000 | | | | | | |
| | | | | (0.000) | | | | | | |
| $\sum_{k=1}^{30} ChangeinNonfarmPayrollsNewsSurprise_{USA,t-k}$ | | | | 0.030 | | | | | | |
| | | | | (0.022) | | | | | | |
| N | 1764 | 1662 | 1763 | 1764 | 1764 | 1661 | 1661 | 1763 | 1662 | 1661 |
| $R^2$ | 0.042 | 0.015 | 0.007 | 0.012 | 0.104 | 0.156 | 0.126 | 0.140 | 0.152 | 0.058 |
| $R^2_{adj}$ | 0.040 | 0.013 | 0.004 | 0.006 | 0.004 | 0.049 | 0.017 | 0.039 | 0.048 | 0.052 |
| All Local News by Zone | | | | | * | * | * | * | * | |
| All USA News by Zone | | | | | * | * | * | * | * | |
| Number of Regressors | 2 | 2 | 5 | 11 | 178 | 187 | 185 | 185 | 182 | 9 |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

## Table C.3: Comparing the Predictability of Different Explanations: 90-Day Window Asset Prices

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.000 | -0.001 | 0.002 | -0.001 | -0.002 | -0.001 | 0.002 | 0.000 | -0.001 | -0.003 |
| | (0.023) | (0.028) | (0.025) | (0.026) | (0.026) | (0.024) | (0.026) | (0.022) | (0.025) | (0.024) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.328*** | | | | | 0.302*** | | 0.280*** | 0.317*** | 0.325*** |
| | (0.052) | | | | | (0.048) | | (0.043) | (0.049) | (0.047) |
| $\Delta_{t-15d,t-1d}\bar{I}_{mt}$ | -0.182*** | | | | | -0.174** | | -0.149** | -0.176** | -0.198*** |
| | (0.051) | | | | | (0.054) | | (0.051) | (0.055) | (0.052) |
| $\Delta_{t-15d,t-1d}(I_{st,z} - \bar{I}_{st})$ | | 0.097* | | | | 0.125** | 0.115* | | 0.124** | 0.108* |
| | | (0.044) | | | | (0.048) | (0.048) | | (0.047) | (0.044) |
| $\Delta_{t-15d,t-1d}(I_{mt,z} - \bar{I}_{mt})$ | | 0.033 | | | | 0.028 | 0.038 | | 0.028 | 0.016 |
| | | (0.039) | | | | (0.043) | (0.044) | | (0.043) | (0.038) |
| $\Delta_{t-90d,t-1d}\overline{\log(Stock)}$ | | | 0.088* | | | 0.040 | 0.086* | 0.043 | | 0.040 |
| | | | (0.038) | | | (0.039) | (0.037) | (0.036) | | (0.038) |
| $\Delta_{t-90d,t-1d}(\log(Stock_z) - \overline{\log(Stock)})$ | | | -0.018 | | | 0.001 | -0.001 | -0.007 | | -0.012 |
| | | | (0.038) | | | (0.034) | (0.034) | (0.033) | | (0.036) |
| $\Delta_{t-90d,t-1d}\log(ExchangeRate_z)$ | | | 0.007 | | | -0.021 | -0.016 | 0.006 | | -0.017 |
| | | | (0.037) | | | (0.041) | (0.043) | (0.036) | | (0.037) |
| $\Delta_{t-90d,t-1d}\log(GoldPrice)$ | | | 0.022 | | | 0.042 | 0.036 | 0.024 | | 0.044 |
| | | | (0.026) | | | (0.028) | (0.028) | (0.026) | | (0.027) |
| $\Delta_{t-90d,t-1d}\log(OilPrice)$ | | | 0.038 | | | 0.001 | 0.028 | -0.006 | | -0.000 |
| | | | (0.033) | | | (0.031) | (0.033) | (0.029) | | (0.029) |
| $\sum_{k=1}^{30} UnemploymentRateNewsSurprise_{USA,t-k}$ | | | | -0.016 | | | | | | |
| | | | | (0.028) | | | | | | |
| $\sum_{k=1}^{30} PPIFinalDemandMoMNewsSurprise_{USA,t-k}$ | | | | 0.012 | | | | | | |
| | | | | (0.029) | | | | | | |
| $\sum_{k=1}^{30} Conf.BoardConsumerConfidenceNewsSurprise_{USA,t-k}$ | | | | 0.037 | | | | | | |
| | | | | (0.037) | | | | | | |
| $\sum_{k=1}^{30} RetailSalesAdvanceMoMNewsSurprise_{USA,t-k}$ | | | | 0.004 | | | | | | |
| | | | | (0.024) | | | | | | |
| $\sum_{k=1}^{30} U.of Mich.SentimentNewsSurprise_{USA,t-k}$ | | | | -0.025 | | | | | | |
| | | | | (0.032) | | | | | | |
| $\sum_{k=1}^{30} ISMManufacturingNewsSurprise_{USA,t-k}$ | | | | 0.067* | | | | | | |
| | | | | (0.029) | | | | | | |
| $\sum_{k=1}^{30} CPIYoYNewsSurprise_{USA,t-k}$ | | | | 0.070 | | | | | | |
| | | | | (0.046) | | | | | | |
| $\sum_{k=1}^{30} GDPAnnualizedQoQNewsSurprise_{USA,t-k}$ | | | | -0.018 | | | | | | |
| | | | | (0.023) | | | | | | |
| $\sum_{k=1}^{30} CPIMoMNewsSurprise_{USA,t-k}$ | | | | -0.055 | | | | | | |
| | | | | (0.043) | | | | | | |
| $\sum_{k=1}^{30} InitialJoblessClaimsNewsSurprise_{USA,t-k}$ | | | | -0.023 | | | | | | |
| | | | | (0.025) | | | | | | |
| $\sum_{k=1}^{30} ChangeinNonfarmPayrollsNewsSurprise_{USA,t-k}$ | | | | 0.036 | | | | | | |
| | | | | (0.027) | | | | | | |
| N | 1764 | 1662 | 1762 | 1764 | 1764 | 1660 | 1660 | 1762 | 1662 | 1660 |
| $R^2$ | 0.042 | 0.015 | 0.014 | 0.012 | 0.104 | 0.154 | 0.131 | 0.136 | 0.152 | 0.058 |
| $R^2_{adj}$ | 0.040 | 0.013 | 0.011 | 0.006 | 0.004 | 0.047 | 0.022 | 0.034 | 0.048 | 0.053 |
| All Local News by Zone | | | | | * | * | * | * | * | |
| All USA News by Zone | | | | | * | * | * | * | * | |
| Number of Regressors | 2 | 2 | 5 | 11 | 178 | 187 | 185 | 185 | 182 | 9 |

Notes: $^+$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. The dependent and independent variables are standardized by subtracting the mean and dividing by the standard deviation by variable. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

Table C.4: Comparing the Predictability of Different Explanations: Two-Day MPS

| $MPS^{2d}_{z,t}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.006 | 0.012 | 0.006 | -0.001 | 0.004 | 0.004 | 0.008 | 0.001 | 0.010 | 0.005 |
| | (0.024) | (0.028) | (0.027) | (0.028) | (0.027) | (0.024) | (0.027) | (0.023) | (0.023) | (0.023) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.326*** | | | | | 0.301*** | | 0.298*** | 0.312*** | 0.316*** |
| | (0.087) | | | | | (0.060) | | (0.062) | (0.061) | (0.076) |
| $\Delta_{t-15d,t-1d}\bar{I}_{mt}$ | -0.121$^{+}$ | | | | | -0.115$^{+}$ | | -0.109$^{+}$ | -0.132* | -0.116$^{+}$ |
| | (0.070) | | | | | (0.060) | | (0.062) | (0.061) | (0.066) |
| $\Delta_{t-15d,t-1d}(I_{st,z} - \bar{I}_{st})$ | | 0.117* | | | | 0.112* | 0.099$^{+}$ | | 0.117* | 0.121* |
| | | (0.052) | | | | (0.051) | (0.052) | | (0.050) | (0.055) |
| $\Delta_{t-15d,t-1d}(I_{mt,z} - \bar{I}_{mt})$ | | 0.003 | | | | -0.006 | 0.004 | | 0.004 | -0.014 |
| | | (0.037) | | | | (0.039) | (0.041) | | (0.038) | (0.037) |
| $\Delta_{t-30d,t-1d}\overline{\log(Stock)}$ | | | 0.045 | | | -0.009 | 0.045 | -0.015 | | -0.010 |
| | | | (0.037) | | | (0.032) | (0.037) | (0.032) | | (0.030) |
| $\Delta_{t-30d,t-1d}(\log(Stock_z) - \overline{\log(Stock)})$ | | | -0.059$^{+}$ | | | -0.034 | -0.037 | -0.041 | | -0.045 |
| | | | (0.031) | | | (0.034) | (0.031) | (0.035) | | (0.032) |
| $\Delta_{t-30d,t-1d}\log(ExchangeRate_z)$ | | | 0.051* | | | 0.029 | 0.042 | 0.046$^{+}$ | | 0.020 |
| | | | (0.024) | | | (0.030) | (0.030) | (0.026) | | (0.029) |
| $\Delta_{t-30d,t-1d}\log(GoldPrice)$ | | | -0.039 | | | -0.003 | -0.031 | -0.011 | | 0.004 |
| | | | (0.036) | | | (0.037) | (0.032) | (0.035) | | (0.037) |
| $\Delta_{t-30d,t-1d}\log(OilPrice)$ | | | 0.026 | | | -0.022 | -0.004 | -0.017 | | -0.010 |
| | | | (0.039) | | | (0.025) | (0.029) | (0.025) | | (0.024) |
| $\sum_{k=1}^{30} UnemploymentRateNewsSurprise_{USA,t-k}$ | | | | -0.030 | | | | | | |
| | | | | (0.029) | | | | | | |
| $\sum_{k=1}^{30} PPIFinalDemandMoMNewsSurprise_{USA,t-k}$ | | | | 0.007 | | | | | | |
| | | | | (0.033) | | | | | | |
| $\sum_{k=1}^{30} Conf.BoardConsumerConfidenceNewsSurprise_{USA,t-k}$ | | | | 0.031 | | | | | | |
| | | | | (0.041) | | | | | | |
| $\sum_{k=1}^{30} RetailSalesAdvanceMoMNewsSurprise_{USA,t-k}$ | | | | 0.025 | | | | | | |
| | | | | (0.023) | | | | | | |
| $\sum_{k=1}^{30} U.ofMich.SentimentNewsSurprise_{USA,t-k}$ | | | | 0.015 | | | | | | |
| | | | | (0.033) | | | | | | |
| $\sum_{k=1}^{30} ISMManufacturingNewsSurprise_{USA,t-k}$ | | | | 0.053 | | | | | | |
| | | | | (0.032) | | | | | | |
| $\sum_{k=1}^{30} CPIYoYNewsSurprise_{USA,t-k}$ | | | | 0.044 | | | | | | |
| | | | | (0.048) | | | | | | |
| $\sum_{k=1}^{30} GDPAnnualizedQoQNewsSurprise_{USA,t-k}$ | | | | -0.025 | | | | | | |
| | | | | (0.028) | | | | | | |
| $\sum_{k=1}^{30} CPIMoMNewsSurprise_{USA,t-k}$ | | | | -0.000 | | | | | | |
| | | | | (0.045) | | | | | | |
| $\sum_{k=1}^{30} InitialJoblessClaimsNewsSurprise_{USA,t-k}$ | | | | -0.034 | | | | | | |
| | | | | (0.030) | | | | | | |
| $\sum_{k=1}^{30} ChangeinNonfarmPayrollsNewsSurprise_{USA,t-k}$ | | | | 0.025 | | | | | | |
| | | | | (0.028) | | | | | | |
| N | 1749 | 1744 | 1723 | 1810 | 1810 | 1718 | 1718 | 1723 | 1744 | 1718 |
| $R^2$ | 0.061 | 0.016 | 0.013 | 0.011 | 0.112 | 0.167 | 0.131 | 0.160 | 0.168 | 0.075 |
| $R^2_{adj}$ | 0.059 | 0.015 | 0.010 | 0.005 | 0.015 | 0.065 | 0.026 | 0.059 | 0.071 | 0.070 |
| All Local News by Zone | | | | | * | * | * | * | * | |
| All USA News by Zone | | | | | * | * | * | * | * | |
| Number of Regressors | 2 | 2 | 5 | 11 | 178 | 187 | 185 | 185 | 182 | 9 |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. This is similar to Table 7, except I consider a two-day window for the monetary policy surprises. The dependent and independent variables are standardized by subtracting the mean and dividing by the standard deviation by variable. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

Table C.5: Impact of Global Rates by Country/Zone: Two-Day MPS

| $MPS^{2d}_{z,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{AUS}$ | 0.657* | 0.715** | 0.708** | 0.728** |
| | (0.272) | (0.233) | (0.233) | (0.237) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{CAN}$ | 0.131 | 0.208 | 0.217 | 0.184 |
| | (0.107) | (0.143) | (0.145) | (0.136) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{CHE}$ | 0.373 | 0.518* | 0.468$^+$ | 0.475** |
| | (0.228) | (0.215) | (0.241) | (0.183) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{ECB}$ | 0.128* | 0.191* | 0.191* | 0.178* |
| | (0.052) | (0.082) | (0.083) | (0.086) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{GBR}$ | 0.079 | 0.202* | 0.196* | 0.214* |
| | (0.066) | (0.082) | (0.083) | (0.085) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{NOR}$ | 0.240 | 0.333* | 0.346* | 0.319* |
| | (0.182) | (0.165) | (0.168) | (0.144) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{NZL}$ | 0.151* | 0.269** | 0.257* | 0.236* |
| | (0.070) | (0.087) | (0.100) | (0.100) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{SWE}$ | 0.258** | 0.356*** | 0.355*** | 0.340** |
| | (0.081) | (0.098) | (0.098) | (0.112) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st} * \mathbb{1}_{USA}$ | 0.077 | 0.158$^+$ | 0.155$^+$ | 0.139$^+$ |
| | (0.064) | (0.082) | (0.083) | (0.083) |
| N | 1749 | 1744 | 1718 | 1718 |
| $R^2$ | 0.094 | 0.112 | 0.111 | 0.200 |
| $R^2_{adj}$ | 0.085 | 0.102 | 0.098 | 0.093 |
| Zone Dummies | * | * | * | * |
| Other Interest Controls | | * | * | * |
| Asset Price Controls | | | * | * |
| All Local News by Zone | | | | * |
| All USA News by Zone | | | | * |

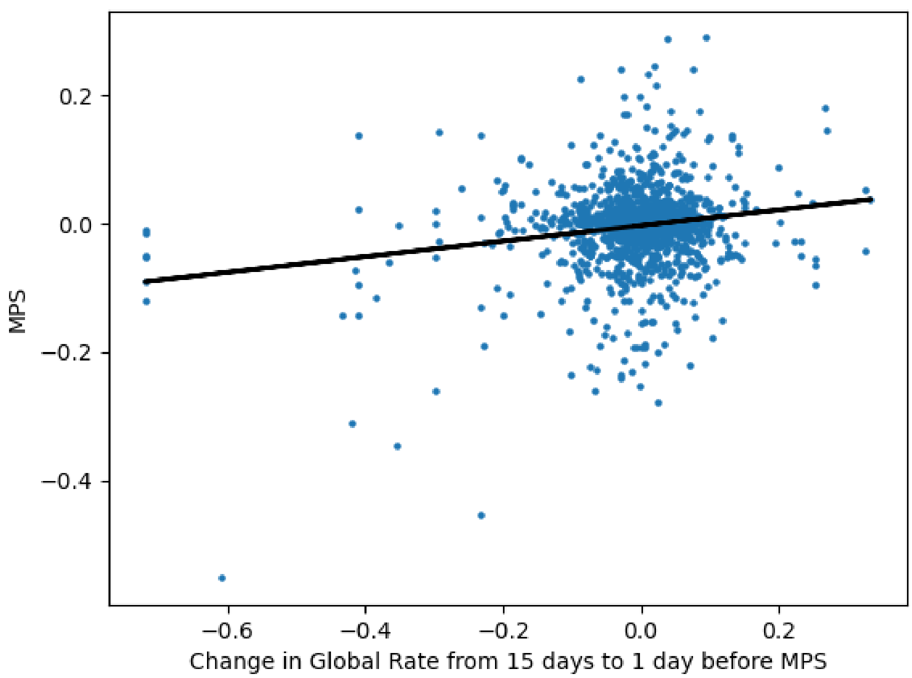
Notes: $^+$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. This is similar to Table 8, except that I consider a two-day window for the monetary policy surprises. Zone dummies are dummy variables for each zone. Other interest rate controls correspond to the three interest rate controls added in regression (4) relative to regression (1) in Table 6. Asset price controls and all local/US news by zone refer to the controls added in regressions (3) and (5) in Table 7, respectively. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

Table C.6: Investigating Predictability: Five-Year Subsets

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Intercept | -0.003* | -0.010$^{+}$ | -0.004 | -0.005$^{+}$ | -0.001 | 0.001 | -0.003 |
| | (0.001) | (0.005) | (0.003) | (0.003) | (0.002) | (0.002) | (0.003) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.124*** | 0.097 | 0.113** | 0.148*** | 0.084$^{+}$ | 0.132$^{+}$ | 0.078 |
| | (0.024) | (0.062) | (0.043) | (0.030) | (0.050) | (0.072) | (0.051) |
| N | 1835 | 95 | 335 | 376 | 375 | 323 | 331 |
| $R^2$ | 0.034 | 0.020 | 0.019 | 0.073 | 0.004 | 0.009 | 0.016 |
| $R^2_{adj}$ | 0.034 | 0.010 | 0.016 | 0.071 | 0.001 | 0.005 | 0.013 |
| Years | 1996-2024 | 1996-1999 | 2000-2004 | 2005-2009 | 2010-2014 | 2015-2019 | 2020-2024 |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Sources: Bloomberg, CME, and Refinitiv.

Figure C.1: Scatter Plot of Baseline Relationship




Notes: Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, and Refinitiv.

## C.2 News Surprises: Additional Predictability Regressions

In this section, I assess the predictive power of other news surprise regressions. I run regressions of the form in Equation (C.1). I regress the monetary policy surprise in zone $z$ at time $t$ on $J$ news surprises measured in the 30 days prior to the central bank announcement. A news surprise at time $t-k$ is set to zero if no release took place on day $t-k$. I allow for each news surprise to have a different impact, $\beta_j$, on the monetary policy surprise:

$$MPS_{z,t} = \alpha + \sum_{j \in J} \beta_j \left( \sum_{k=1}^{30} NewsSurprise^{j}_{z,t-k} \right) + u_{z,t}. \tag{C.1}$$

Table C.7: Predicting Monetary Policy Surprises: Additional Economic News Surprise Results

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | -0.003* | -0.004* | -0.004* | -0.003* | -0.002 | -0.004* |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) |
| $\sum_{k=1}^{30} CPINewsSurprise_{z,t-k}$ | 0.009 | | | | | |
| | (0.009) | | | | | |
| $\sum_{k=1}^{30} GDPNewsSurprise_{z,t-k}$ | 0.002 | | | | | |
| | (0.007) | | | | | |
| $\sum_{k=1}^{30} UnempNewsSurprise_{z,t-k}$ | 0.011 | | | | | |
| | (0.008) | | | | | |
| $\sum_{k=1}^{30} CPIMoMNewsSurprise_{USA,t-k}$ | | 0.005 | -0.025 | | | |
| | | (0.014) | (0.019) | | | |
| $\sum_{k=1}^{30} GDPAnnualizedQoQNewsSurprise_{USA,t-k}$ | | -0.010 | -0.010 | | | |
| | | (0.012) | (0.013) | | | |
| $\sum_{k=1}^{30} UnemploymentRateNewsSurprise_{USA,t-k}$ | | -0.005 | -0.007 | | | |
| | | (0.012) | (0.011) | | | |
| $\sum_{k=1}^{30} PPIFinalDemandMoMNewsSurprise_{USA,t-k}$ | | | 0.002 | | | |
| | | | (0.004) | | | |
| $\sum_{k=1}^{30} Conf.BoardConsumerConfidenceNewsSurprise_{USA,t-k}$ | | | 0.000 | | | |
| | | | (0.000) | | | |
| $\sum_{k=1}^{30} RetailSalesAdvanceMoMNewsSurprise_{USA,t-k}$ | | | 0.000 | | | |
| | | | (0.002) | | | |
| $\sum_{k=1}^{30} U.of Mich.SentimentNewsSurprise_{USA,t-k}$ | | | -0.000 | | | |
| | | | (0.001) | | | |
| $\sum_{k=1}^{30} ISMManufacturingNewsSurprise_{USA,t-k}$ | | | 0.002* | | | |
| | | | (0.001) | | | |
| $\sum_{k=1}^{30} CPIYoYNewsSurprise_{USA,t-k}$ | | | 0.030 | | | |
| | | | (0.020) | | | |
| $\sum_{k=1}^{30} InitialJoblessClaimsNewsSurprise_{USA,t-k}$ | | | -0.000 | | | |
| | | | (0.000) | | | |
| $\sum_{k=1}^{30} ChangeinNonfarmPayrollsNewsSurprise_{USA,t-k}$ | | | 0.030 | | | |
| | | | (0.022) | | | |
| N | 1764 | 1764 | 1764 | 1764 | 1764 | 1764 |
| $R^2$ | 0.002 | 0.001 | 0.012 | 0.015 | 0.039 | 0.068 |
| $R^2_{adj}$ | 0.000 | -0.001 | 0.006 | 0.000 | -0.013 | 0.012 |
| CPI/GDP/Unemp Local News by Zone | | | | * | | |
| All Local News by Zone | | | | | * | |
| All USA News by Zone | | | | | | * |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, Consensus Economics, Informa Global Markets, and Refinitiv.

Table C.7 presents the additional results for the degree to which news surprises predict monetary policy surprises. In the first regression, I compile the surprise from the CPI, GDP, and unemployment news releases that take place from 30 days before to one day before a central bank announcement in the country/zone of that announcement. Regressing six-month monetary policy surprises on these three variables, I find these variables are not significant at the 10 percent level and have an adjusted $R^2$ of zero, so they do not appear to explain monetary policy surprises. Note that in this case, I am assuming that the impact of a CPI/GDP/unemployment surprise is the same for each country/zone. It might be expected that smaller countries/zones would place more weight on US news than local news. Therefore, in regression (2), I repeat the exercise but with US CPI, GDP, and unemployment news. No variables are significant, and I find a negative adjusted $R^2$, which suggests that these variables do not explain monetary policy surprises. I also include the other 10 most relevant macroeconomic news releases for the United States plus unemployment in regression (3) (this repeats regression (4) in Table 7). The Institute for Supply Management manufacturing index is significant at the 1 percent level, but other variables are not significant. In this case, I find an adjusted $R^2$ of 0.6 percent, which suggests that broader US economic news has at best limited predictive power.

I find similar results when I allow for the differential effects of news. In the first three regressions, I assume that economic news has the same impact on monetary policy surprises for each country/zone in my sample. I relax this assumption in the next three regressions (the fourth to sixth regressions in Table C.7). In the fourth regression, I look again at the impact of CPI, GDP, and unemployment news surprises. Since this regression includes separate CPI, GDP, and unemployment news surprises for each country/zone, the number of regressors rises from three in regression (1) to 30 in regression (4), so I do not present the values for individual coefficients. The adjusted $R^2$ is zero, which suggests that these variables do not have predictive power. In regression (5), I regress monetary policy surprises on the 10 most relevant macroeconomic news surprises for each country/zone.[37] Again, I find a negative adjusted $R^2$, which suggests variables do not have predictive power. Finally, in regression (6), I regress monetary policy surprises on the most relevant US news surprises but, unlike in column (3), allow these to have differential effects by country/zone. I find a positive adjusted $R^2$ but only of 1.2 percent, which suggests these variables have limited predictive power.

## C.3 United States-only Predictability Regressions

Most papers in this literature consider results for the United States only. I repeat my analysis considering only US monetary policy surprises in Table C.8. Regression (1) considers only the primary measure of global interest rates. This suggests that a 1 percentage point increase in global rates in the 15 days prior to a Federal Reserve announcement is associated with an increase in the surprise of 9.8 basis points. This is the same as the coefficient in regression (1) in Table 8 where I consider the impact by country/zone. Regression (2) introduces the additional interest rate controls. The baseline global rate measure remains significant. Regression (3) considers asset price controls. However, these do not offer strong predictive power and have a negative adjusted $R^2$. Regression (4) considers US news surprises. This yields a negative adjusted $R^2$, which suggests that news releases overall do not predict US monetary policy surprises. The only news variable that is significant is nonfarm payrolls. This corresponds to Bauer and Swanson (2023a); Sastry (2022), who also find that nonfarm payrolls significantly predict monetary policy surprises. In regression (5), I consider all the controls together. I find that the change in short-term global interest rates is significant at the 1 percent level and has a very similar coefficient to regression (2). The significance for nonfarm payrolls declines, and other variables are not significant. Therefore, my results also hold for the United States.

[37] I exclude news surprises for which I have fewer than 20 (non-zero) observations. This only led to the exclusion of Swiss retail sales. Therefore, I have 10 surprises for each country/zone, except for Switzerland, for which I have nine, and the United States, for which I have 11 (due to the inclusion of unemployment), yielding a total of 90 regressors.

Table C.8: Predicting Monetary Policy Surprises: United States Only

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Intercept | -0.006* | -0.006* | -0.006* | -0.006* | -0.004 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.098** | 0.169** | | | 0.174** |
| | (0.030) | (0.057) | | | (0.063) |
| $\Delta_{t-15d,t-1d}\bar{I}_{mt}$ | | -0.058 | | | -0.061 |
| | | (0.040) | | | (0.044) |
| $\Delta_{t-15d,t-1d}(I_{st,z} - \bar{I}_{st})$ | | -0.000 | | | 0.009 |
| | | (0.041) | | | (0.044) |
| $\Delta_{t-15d,t-1d}(I_{mt,z} - \bar{I}_{mt})$ | | 0.011 | | | 0.004 |
| | | (0.047) | | | (0.050) |
| $\Delta_{t-30d,t-1d}\overline{\log(Stock)}$ | | | -0.001 | | -0.001 |
| | | | (0.001) | | (0.001) |
| $\Delta_{t-30d,t-1d}(\log(Stock_z) - \overline{\log(Stock)})$ | | | 0.000 | | 0.001 |
| | | | (0.001) | | (0.001) |
| $\Delta_{t-30d,t-1d} \log(ExchangeRate_z)$ | | | -0.001 | | -0.001 |
| | | | (0.002) | | (0.002) |
| $\Delta_{t-30d,t-1d} \log(GoldPrice)$ | | | -0.001 | | -0.000 |
| | | | (0.001) | | (0.001) |
| $\Delta_{t-30d,t-1d} \log(OilPrice)$ | | | 0.000 | | 0.000 |
| | | | (0.000) | | (0.000) |
| $\sum_{k=1}^{30} UnemploymentRateNewsSurprise_{USA,t-k}$ | | | | -0.019 | -0.011 |
| | | | | (0.020) | (0.021) |
| $\sum_{k=1}^{30} PPIFinalDemandMoMNewsSurprise_{USA,t-k}$ | | | | 0.004 | 0.002 |
| | | | | (0.008) | (0.008) |
| $\sum_{k=1}^{30} Conf.BoardConsumerConfidenceNewsSurprise_{USA,t-k}$ | | | | 0.000 | -0.000 |
| | | | | (0.001) | (0.001) |
| $\sum_{k=1}^{30} RetailSalesAdvanceMoMNewsSurprise_{USA,t-k}$ | | | | -0.002 | -0.001 |
| | | | | (0.005) | (0.005) |
| $\sum_{k=1}^{30} U.ofMich.SentimentNewsSurprise_{USA,t-k}$ | | | | 0.000 | 0.001 |
| | | | | (0.001) | (0.001) |
| $\sum_{k=1}^{30} ISMManufacturingNewsSurprise_{USA,t-k}$ | | | | 0.002 | 0.002 |
| | | | | (0.001) | (0.002) |
| $\sum_{k=1}^{30} CPIYoYNewsSurprise_{USA,t-k}$ | | | | 0.007 | -0.016 |
| | | | | (0.035) | (0.036) |
| $\sum_{k=1}^{30} GDPAnnualizedQoQNewsSurprise_{USA,t-k}$ | | | | -0.014 | -0.010 |
| | | | | (0.027) | (0.028) |
| $\sum_{k=1}^{30} CPIMoMNewsSurprise_{USA,t-k}$ | | | | -0.027 | -0.015 |
| | | | | (0.036) | (0.037) |
| $\sum_{k=1}^{30} InitialJoblessClaimsNewsSurprise_{USA,t-k}$ | | | | 0.000 | 0.000 |
| | | | | (0.000) | (0.000) |
| $\sum_{k=1}^{30} ChangeinNonfarmPayrollsNewsSurprise_{USA,t-k}$ | | | | 0.092* | 0.075$^{+}$ |
| | | | | (0.039) | (0.040) |
| N | 230 | 227 | 229 | 230 | 226 |
| $R^2$ | 0.044 | 0.055 | 0.013 | 0.042 | 0.096 |
| $R^2_{adj}$ | 0.039 | 0.038 | -0.009 | -0.006 | 0.007 |

Notes: $^{+}$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, Consensus Economics, Informa Global Markets, and Refinitiv.

## C.4 Robustness Checks Full Regression Tables

Table C.9: Robustness Check: Baseline (Row A in Table 9)

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.121*** | 0.231*** | 0.234*** | 0.217*** |
| | (0.026) | (0.035) | (0.037) | (0.036) |
| N | 1764 | 1662 | 1661 | 1661 |
| $R^2$ | 0.031 | 0.055 | 0.058 | 0.156 |
| $R^2_{adj}$ | 0.031 | 0.053 | 0.052 | 0.049 |
| Intercept | * | * | * | * |
| Other Interest Rate Controls | | * | * | * |
| Asset Price Controls | | | * | * |
| All Local News by Zone | | | | * |
| All USA News by Zone | | | | * |

$^+$, *, **, and *** represent a significance of less than 10%, 5%, 1%, and 0.1%, respectively. Standard errors clustered by survey month. Monetary policy surprises in 2020 are excluded by default. Monetary policy surprises in 2020 are excluded by default.

Table C.10: Robustness Check: Including COVID-19 Pandemic (Row B in Table 9)

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.124*** | 0.225*** | 0.236*** | 0.224*** |
| | (0.024) | (0.031) | (0.035) | (0.035) |
| N | 1835 | 1733 | 1732 | 1732 |
| $R^2$ | 0.034 | 0.060 | 0.063 | 0.153 |
| $R^2_{adj}$ | 0.034 | 0.058 | 0.058 | 0.050 |
| Intercept | * | * | * | * |
| Other Interest Rate Controls | | * | * | * |
| Asset Price Controls | | | * | * |
| All Local News by Zone | | | | * |
| All USA News by Zone | | | | * |

Similar to Table C.9 except that points in 2020 are included. Monetary policy surprises in 2020 are excluded by default.

Table C.11: Robustness Check: Removing Outliers (Row C in Table 9)

| $MPS_{z,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.105** | 0.220*** | 0.222*** | 0.213*** |
| | (0.035) | (0.049) | (0.051) | (0.045) |
| N | 1757 | 1655 | 1654 | 1654 |
| $R^2$ | 0.018 | 0.038 | 0.040 | 0.140 |
| $R^2_{adj}$ | 0.017 | 0.036 | 0.035 | 0.030 |
| Intercept | * | * | * | * |
| Other Interest Rate Controls | | * | * | * |
| Asset Price Controls | | | * | * |
| All Local News by Zone | | | | * |
| All USA News by Zone | | | | * |

Similar to Table C.9 except that outliers are excluded, that is, only changes in global rates that are less than 50 basis points are considered. Monetary policy surprises in 2020 are excluded by default.

Table C.12: Robustness Check: MPS with Nelson-Siegel (Row D in Table 9)

| $MPS^{NS}_{z,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.121*** | 0.206*** | 0.218*** | 0.206*** |
| | (0.029) | (0.036) | (0.040) | (0.041) |
| N | 1394 | 1300 | 1300 | 1300 |
| $R^2$ | 0.035 | 0.055 | 0.059 | 0.205 |
| $R^2_{adj}$ | 0.034 | 0.052 | 0.052 | 0.072 |
| Intercept | * | * | * | * |
| Other Interest Rate Controls | | * | * | * |
| Asset Price Controls | | | * | * |
| All Local News by Zone | | | | * |
| All USA News by Zone | | | | * |

Similar to Table C.9 except that the monetary policy surprises are measured using the Nelson-Siegel approach. Monetary policy surprises in 2020 are excluded by default.

# D Section 5 Appendix (Explaining Predictability)

## D.1 Supplemental Figures/Tables

Table D.1: Applying Sastry (2022): Nonrelative Domestic Rates

| $\Delta_{s(t),s(t)+1m} VarForecast_z$ | CPI | GDP | Unemp. | CPI | GDP | Unemp |
|---|---|---|---|---|---|---|
| $\Delta_{t-15d,t-1d}\bar{I}_{st}$ | 0.774*** | 0.623*** | -0.422*** | 0.730*** | 0.554** | -0.390*** |
| | (0.095) | (0.162) | (0.066) | (0.096) | (0.197) | (0.085) |
| $\Delta_{t-15d,t-1d}I_{st,z}$ | | | | 0.035 | 0.054 | -0.022 |
| | | | | (0.056) | (0.059) | (0.044) |
| N | 1842 | 1842 | 1387 | 1812 | 1812 | 1358 |
| $R^2$ | 0.113 | 0.061 | 0.088 | 0.110 | 0.059 | 0.086 |
| $R^2_{adj}$ | 0.112 | 0.060 | 0.087 | 0.109 | 0.058 | 0.085 |
| Intercept | * | * | * | * | * | * |

Notes: $^+$, *, **, and *** represent a significance of less than 10 percent, 5 percent, 1 percent, and 0.1 percent, respectively. Standard errors are clustered by month. Monetary policy surprises in 2020 are excluded. Sources: Bloomberg, CME, Consensus Economics, Informa Global Markets, and Refinitiv.