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How High Does High Frequency Need to Be? A Comparison of Daily and Intradaily Monetary Policy Surprises

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How High Does High Frequency Need to Be? A Comparison of Daily and Intradaily Monetary Policy Surprises.

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Abstract

This paper investigates the utility of daily data in measuring high-frequency monetary policy surprises, comparing various announcement-day asset price changes with their intradaily (30-minute) counterparts. We find that both frequencies are similarly distributed and often highly correlated, particularly for longer-horizon measures. Testing daily surprises for systematic contamination from non-monetary policy news, we find no evidence to suggest that contemporaneous news releases bias their measurement. Empirical applications, including high-frequency passthrough to Treasury yields and proxy SVAR models, suggest that daily surprises produce results comparable to those obtained with intradaily data. Our findings suggest that while intradaily data remains invaluable for certain applications, daily data offers a practical and robust alternative for assessing monetary policy surprises, particularly when the event, or the reaction to it, extends beyond a narrow window, or when intradaily data is unavailable.

Keywords: Monetary policy surprises, high frequency identification, event study.

JEL Codes: E43, E44, E52, E58, G14.

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The views expressed are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Kansas City or the Federal Reserve System.

1 Introduction

Recent economic developments, including the global financial crisis (GFC), the Covid-19 pandemic, and subsequent inflationary episodes, have highlighted the complexities of measuring the effects and transmission mechanisms of monetary policy. Despite theoretical agreement about the qualitative impact of monetary policy on key variables, measuring these relationships empirically remains an open challenge.

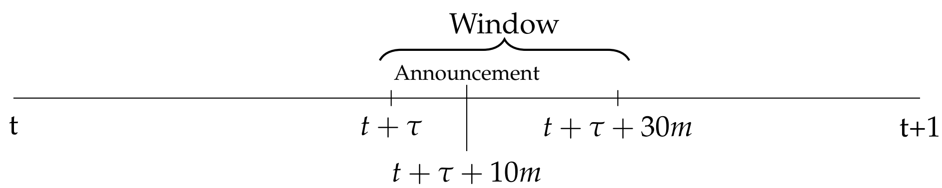
Because monetary policy decisions reflect policy makers' reactions to the state of the economy, any subsequent developments stem from both the policy decision *and* the conditions that preceded it. Moreover, standard theory predicts that rational actors observe the state of the economy and, with some knowledge of the central bank's priorities and mandate, anticipate future rate changes and adjust their output and consumption decisions accordingly. Thus, only monetary policy actions that differ from market expectations are likely to have a detectable and identifiable impact on real and financial variables.

The challenge, then, is to disentangle the effect of contemporaneous economic developments from that of the monetary policy response. Although the practice and particular details will vary, the economic literature on monetary policy has explored three general strategies for achieving this separation. The first applies a series of assumptions based in theory to characterize exogenous monetary policy changes. Among common assumptions are functional form of the Fed's "reaction function" (which characterizes the Fed's reaction to economic conditions), variables the Fed considers and has at its disposal when setting its policy, the long-run impacts of policy, as well as assumptions over the tools the central bank uses to achieve its policy ends (Christiano (1999); Faust and Leeper (1997); Pagan and Robertson (1995)). The obvious challenge of these approaches lay in developing and defending such assumptions. A second strategy identifies monetary policy surprises using a narrative approach emanating from Romer and Romer (1989); this method has given rise, in turn, to growing literature using machine learning to characterize monetary policy surprises.

The third strategy, which is the focus of our paper, extracts monetary policy unrelated to extant conditions by measuring the high frequency reaction of financial variables immediately following a monetary policy announcement. The usefulness of high frequency identification (HFI) arises from the assumption of rationality in asset markets: if all prices fully reflect available information, then the effects of an unexpected event will be reflected immediately in prices. Underlying the validity of the event study approach are the following assumptions. First, policy makers determine the announcement prior to observing asset price movements within the announcement window—this rules out the simultaneous determination of policy and asset prices. Second, all changes in expectations about policy occur during the event windows and these changes in expectations are fully priced during the event windows. The key identifying assumption is that news released about the economy on the day the Federal Open Market Committee (FOMC) meets does not affect the policy choice—only information available before the opening of the measurement window is relevant.

The effort to fulfill these assumptions about the arrival impact of non-monetary policy information has led to the adoption of increasingly narrow windows around monetary policy announcements. While early work in this vein often (although not exclusively) used daily changes in asset prices to extract monetary policy surprises, recent papers feature 90-, 60-, and especially 30-minute windows, with the open price measured ten minutes before the announcement, and the close price measured 20 minutes after the announcement has concluded. Figure 1 depicts the timeline of a typical intradaily (30-minute) monetary policy surprise. t indexes the opening of trading on the day of an announcement (which reflects the price on the close of the previous day), $t + \tau$ denotes the start of the window, $t + \tau + 30m$ marks the end of the intradaily window, and $t + 1$ indexes the close of trading on the day.

Figure 1: Announcement Window Timeline



While short windows offer a better chance at separating reactions to monetary policy from other news that might be revealed during the day, they can also cut certain (arguably important) events short. The most prominent example of this is the press conference following FOMC announcements—while the FOMC's decision is generally announced at 2:00pm EST, the Chair's press conference begins at 2:30pm and averages around 54 minutes duration (De Pooter (2021)). At every other FOMC meeting, the press conference includes the Summary of Economic Projections (SEP), which plays a crucial role in forward guidance. Short windows around announcements may also miss slow-moving reactions to news, which are particularly acute in some relevant asset markets. The issue of "dead quotes" will be particularly acute among less liquid assets, like those we might like to use to measure monetary policy surprises in smaller or less well developed financial markets.

Moreover, the construction of intraday surprises can prove both arduous and costly, posing a potential barrier to research. Recently, researchers at the European Central Bank (ECB), the Federal Reserve Bank of San Francisco (FRBSF), and the Bank of England (BoE) have started publishing the announcement-window asset price changes needed to construct an array of monetary policy surprises for their respective markets (Altavilla et al. (2019), Bauer and Swanson (2023b), Braun et al. (2025)). While these online releases represent a substantial service to research and policy analysis, they are not a panacea—which announcements constitute monetary policy news is subjective (including the decision to extend the window to cover press conferences), the assets included in the releases vary between one another (limiting comparability between central banks), and the coverage is limited to those three largest central banks.

The objective of this work is to ask: is the intraday standard always necessary? Can daily data lead to similar conclusions in some applications?

In an effort to provide a satisfactory answer, we compare intraday monetary policy surprises to their matched daily versions in a number of settings, starting with a comparison of their announcement-day statistical properties. We find that daily and intraday surprises are similarly distributed and often highly correlated with one another. Moreover, similarities between the surprises increase with the maturity of the underlying asset. This distinction is made more meaningful by the necessity for longer-horizon assets to measure a surprise change in monetary policy at the effective lower bound (ELB).

Testing the degree to which the surprises filter contaminating news both on the day of the announcement and leading up to the meeting, we find that daily surprises do not evince systematic contamination from news released on the day of FOMC announcements. This suggests that the use of daily surprises instead of intraday is unlikely to introduce systematic bias in the estimate of monetary policy transmission. In a similar vein, we also find that surprises measured at daily frequency are no more predictable by intra-meeting economic developments than are their intraday counterparts.

To explore the practical implications of frequency selection, we compare the respective estimates they produce in both a high frequency and a low frequency setting. For our high frequency setting, we compare the pass-through of the two surprise frequencies to Treasury yields across the yield curve at various points in time using both full sample and rolling regressions. We show that passthrough measured using daily surprises does not differ appreciably from those measured using intraday data, particularly when using a monetary policy surprise designed to capture variation both at and away from the effective lower bound. To show that aggregating to lower frequencies does not aggravate the small differences we do observe between daily and intradaily-measured changes, we replicate the structural vector autoregression exercises features in Gertler and Karadi (2015) and Bauer and Swanson (2023b). Although the results obtained with daily data are attenuated relative to their intradaily counterparts, the differences are seldom statistically significant. In both applications, we are able to replicate the patterns traced out using intradaily data, suggesting that daily data can indeed be useful in the absence of tick data.

In all, we find that while intraday measurement is very useful, not all variables of interest are accessible or usable intraday, what is available is costly, and in some circumstances daily windows are likely to be adequate. In particular, applications at (or even just including) the ELB may not necessitate the use of intraday data. Thus, in contexts where intraday data is unavailable, daily measures may still provide useful insights into monetary policy dynamics at the ELB.

This paper joins an extensive empirical literature exploring high frequency, market-based approaches to the monetary policy surprise identification (HFI), which exploits financial asset price adjustments in short windows around an event Kuttner (2001), (Bernanke and Kuttner (2005), Gürkaynak, Sack, and Swanson (2005) Nakamura and Steinsson (2018), and Bauer and

Swanson (2023b). As aforementioned, applications of HFI in monetary policy identification increasingly rely on short (e.g., 30 minute) windows (Gürkaynak et al. (2005)). We contribute to the HFI literature by explicitly and thoroughly comparing the statistical and informational characteristics of surprises measured at intradaily and daily frequency, and testing the degree to which the results obtained with them differ in meaningful ways. Our findings suggest that daily monetary policy surprises are not systematically biased by news outside of the 30-minute window, and that daily series yield similar empirical results at high and low frequencies.

This paper also contributes to a more varied literature which compares and contrasts different econometric specifications and data choice in identifying monetary policy surprises. A few papers attempt to identify and reconcile divergences in the estimated impact of monetary policy obtained using alternative identification approaches. Coibion (2012), for example, compares the macroeconomic effects of monetary policy surprises obtained using a VAR with those from narrative approaches. He find that identifying and controlling for three contributing factors - different contractionary impetus, time coverage, and lag length selection - , brings the estimated impact closer together in magnitude. The nearest neighbor to this paper, (Brennan et al., 2024), explores the degree to which different high-frequency monetary policy surprise series yield diverging estimates. They find that correlations across various types of monetary policy surprises can be as low as 0.3, with signs agreeing around only half of the time. Critically, they find that both the underlying data and alternative methods produce differences that are especially stark at the effective lower bound. In particular, surprise series based on long-term rates better capture monetary policy effects during ELB due to their responsiveness to forward guidance and LSAPs, whereas surprise series using only short-term futures tend to flatten out at the ELB and understate the policy stimulus. We find similar results as their ELB analysis and conclude that adding longer maturities in the surprise series would help prevent understatement of the policy stimulus during the ELB.

Early empirical work in the identification of monetary policy's effects suggested, counter to what standard macroeconomic theory predicts, a positive relationship between the federal funds rate and inflation. This counterintuitive empirical pattern became known as the "price puzzle" (Bernanke and Blinder (1992); Christiano (1999) and Sims (1992)). In a bid to align empirical HFI findings with standard macroeconomic models, two contrasting explanations have emerged. Literature on the central bank information effect resolves the price puzzle by assuming that the Fed possesses an informational advantage over private market participant. In this framework, market participants react not only to the Fed's interest rate decisions but also to the release of private information related to the state of the economy at the time of policy announcements. Empirically, accounting for a central bank information effect reverses counter-intuitive empirical results by accounting for the Fed's private information (Romer and Romer (2004), Campbell, Evans, Fisher, and Justiniano (2012), Nakamura and Steinsson (2018), and Miranda-Agrippino and Ricco (2021).

In contrast, Bauer and Swanson (2023a) and Bauer and Swanson (2023b) question the no-tion that the Federal Reserve and similar central banks possess private information, proposing instead that market participants may misjudge the Fed's monetary policy rule and miscalculate its sensitivity to incoming data. They argue that surveys of private forecasters show that agents rarely change their economic forecasts based on the FOMC announcements. Instead, both the Fed and the private sectors revise their forecasts in response to the incoming macroeconomic news. Bauer and Swanson (2023b) finds that a cleansed monetary policy surprise series orthogonalized to various publicly available macro variables produces stronger macro effects of monetary policy and avoids price puzzles. We make a modest contribution to this corner of the literature in showing that daily surprises follow the same pattern: a proxy SVAR model using our daily surprises as an external instrument does not produce puzzles, and estimates stronger macroeconomic effects when cleansed of their predictable component.

The paper proceeds as follows. Section 2 reviews the construction of our chosen monetary policy surprises, comparing their statistical and informational characteristics. Section 3 compares the results obtained using intradaily and daily surprises in a high frequency application measuring monetary policy passthrough to the Treasury yield curve. Section 4 provides a low frequency application by replicating impulse responses from Gertler and Karadi (2015) and Bauer and Swanson (2023b) using daily surprises. Section 5 concludes.

2 Data and methods

High frequency identification leans on the extraction of information regarding how market participants have altered their view of the monetary policy stance in reaction to the content of an announcement. From the announcement of decisions, to the issuance of forward guidance and the publication of the Summary of Economic Projections (SEP), to the adoption of large scale asset purchases, the conduct of monetary policy has substantially evolved over time, extending (and retracting) what we might think of as the potential maturity structure of the reaction. As a result, the assets needed to capture all dimensions of the monetary policy decision have also changed. To gain well-rounded understanding of the conditions under which daily and intradaily asset price changes can be substitutes, we compare surprises of various types.

Early work exploiting high frequency identification extracted the unexpected element from futures contracts based on the policy rate. Expectations of Fed policy actions are not directly observable, but futures prices are a natural, market-based proxy for those expectations. The abundance of short-term interest rates that potentially measure federal funds rate expectations has led to a proliferation of asset price– based monetary policy expectation measures. For example, Kuttner (2001) and Faust, Swanson, and Wright (2004) use the current-month federal funds futures contract, Cochrane and Piazzesi (2002) the one-month eurodollar deposit rate, and Rigobon and Sack (2004) the three-month-ahead eurodollar futures rate (ED1).

Sometimes, however, market reactions are spurred by what the FOMC says rather than what it does. Gürkaynak et al. (2005) propose alternative surprise measures that capture changes in market expectations of policy over slightly longer horizons, a distinction made increasingly important by the formal adoption of forward guidance. To capture changes in expectations about future meetings, many authors use the fourth fed funds contract (FF4), or the 2nd, 3rd, or 4th Eurodollar contract (ED2 - ED4) instead of, or in addition to, FF1 or ED1. Alternatively, some papers measure the surprise to the target and expected path of policy using the factor structure of various contract horizons (see e.g., Bauer and Swanson (2023b); Nakamura and Steinsson (2018)). Due to data constraints in the fed funds futures contracts, we use Eurodollar contracts ED1 and ED4, along with the first principal component of ED1 - ED4 to compare the characteristics of intradaily versus daily surprises of shorter maturity. For short, we will refer to this measure as the ”short compound surprise” henceforth (label MPS).

The adoption of tools intended to ease monetary conditions at the ELB has altered the informativeness of these short-rate-based futures. Surprises designed to capture changes in the policy rate (contemporaneously or several months in the future) may be ill-suited to measuring the impact of Large Scale Asset Purchase (LSAP) announcements, and similarly, changes in Treasuries bond futures likely provide a distorted view of revisions to expectations about the policy rate. As a result, the HFI literature following the first round of quantitative easing in the GFC introduced the identification of monetary policy surprises with assets capable of reflecting a long impact horizon or the explicit use of long duration assets in the conduct of policy. One way of going about this is to orthogonalize various tenors to one another as in Swanson (2023) or Rogers, Scotti, and Wright (2018) to generate target, forward guidance, and LSAP-type factors.

Another popular route uses the first (or first and second) principal component of futures-implied yield changes across the yield curve, capturing surprises related to LSAPs by including bond futures along with fed funds and/or Eurodollar futures as in Rogers, Scotti, and Wright (2014) and Dilts Stedman (2019). Monetary policy surprises derived from the cross-section of yields have the advantage of subsuming policies aimed at different maturities in the yield curve. Such compound measures summarize surprises to the overall stance of monetary policy both at and away from the effective lower bound. To assess the differences in daily versus intradaily surprises measured with intent to include stimulus at the ELB, we’ll compare the behavior of ten year Treasuries futures, two year Treasury futures, and of a compound measure comprising the first principal component of ED1 - ED4 with the implied yields on 2-, 5-, and 10-year Treasuries futures. We refer to this measure as the ”long compound surprise” (label MPS long).

2.1 Data Description and Properties

Our data sample covers the period from 1994 to the end of 2023.[1] Using data from Bloomberg, we match the intraday variables published by The Center for Monetary Research with their daily counterparts. Table 1 displays summary statistics for the variables we use to generate monetary policy surprises. Notably, the average price change does not vary appreciably between tenors and frequencies. Unsurprisingly, daily monetary policy surprises feature larger standard deviations, although the difference is small in context, ranging 1.2 - 2.5 basis points. In contrast, the differences among minimum and maximum price changes can be substantial, with daily data featuring larger ranges.

Table 1: Summary Statistics: Underlying Assets

	Daily Mean	SD	Min	5th	95th	Max	Intradaily Mean	SD	Min	5th	95th	Max
ED1	-0.6	8.0	-32.0	-13.0	7.5	71.0	-1.0	6.2	-46.8	-10.0	5.5	18.3
ED2	-0.9	8.5	-31.0	-14.0	10.8	62.0	-1.0	6.1	-31.0	-10.8	7.8	15.0
ED3	-0.9	7.8	-31.0	-14.5	12.5	38.0	-0.8	6.4	-29.0	-12.3	9.3	17.8
ED4	-1.0	7.9	-31.5	-14.5	11.5	27.5	-0.9	6.7	-27.5	-12.5	10.0	24.3
2-year futures	-0.8	6.9	-26.3	-12.9	10.2	19.9	-0.7	5.6	-29.6	-10.0	7.3	20.5
5-year futures	-0.9	7.8	-44.4	-13.9	12.1	20.7	-0.5	5.3	-20.1	-10.6	7.4	23.5
10-year futures	-0.7	6.6	-45.7	-11.2	9.0	24.7	-0.3	4.2	-29.6	-6.7	5.5	16.4

Table 1 compares summary statistics of the daily and intraday monetary policy surprises around FOMC announcements from 1994 to 2023. Intraday monetary policy surprises are measured over an interval of 10 minutes pre- to 20 minutes post-announcement.

We visually compare these differences using overlaid kernel density plots in Figure 2, along with plots for the two compound monetary policy measures.[2] As the summary statistics suggest, the surprises cluster around zero regardless of frequency, and the mass in the tails of the distribution varies little. The main distinction, as Table 1 highlights, is that the daily surprises tend to feature longer tails. This is particularly the case for the first Eurodollar contract and ten year bond futures. Kernel density plots of the two compound measures show that they inherit a combination of features from the underlying data.

To empirically assess whether the surprises differ significantly from one another, we include in each density plot the p-value from a Kolmogorov-Smirnov test for equality of distributions. Statistically insignificant p-values ($p > 0.1$) indicate that, in five out of six measures, we cannot reject the null hypothesis that the two samples are from the same distribu-

[1]We exclude pre-1994 periods for two reasons. First, monetary policy decisions have become more transparent since 1994, when the Federal Open Market Committee started announcing their policy decisions more regularly. Second, economic report releases—especially the employment report—that routinely coincide with monetary policy announcements before 1994 may endogenously move the futures prices throughout the day, systematically biasing estimation.

[2]We omit summary statistics for the compound monetary policy surprises because their units are arbitrary without scaling.

tion. The only exception is 10-year Treasury futures, where daily data features fatter, longer tails, along with a contractionary skew. However, the ten year futures-implied yield is seldom used on its own to measure monetary policy surprises, and these differences do not extend to the long compound monetary policy surprise. Taken together, we conclude that the unconditional properties of most monetary policy surprises do not differ appreciably between daily and intradaily frequencies, particularly in their compound form.

Figure 2: Kernel Density Distributions for Daily and Intradaily surprises

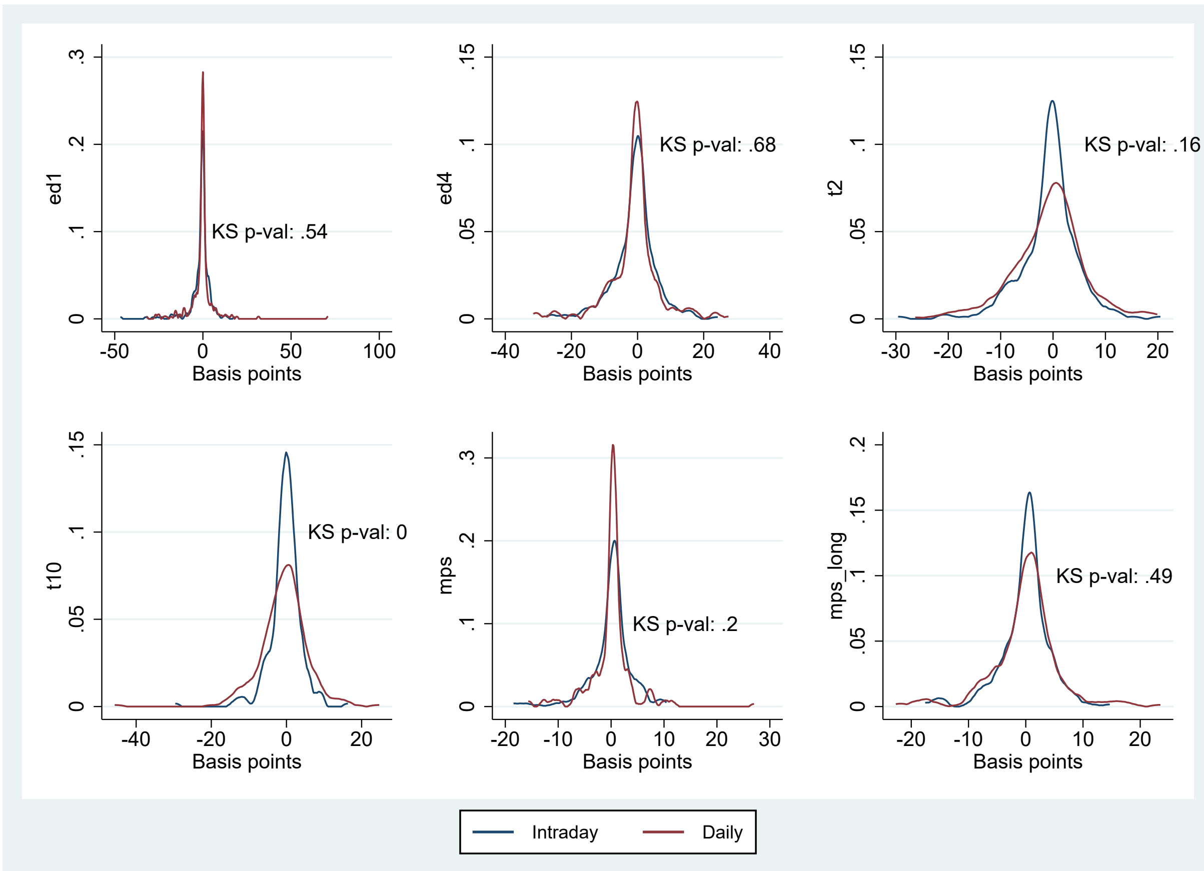


Figure 2 displays kernel density plots for each monetary policy surprise measure at intradaily and daily frequency. P-values correspond to a Kolmogorov-Smirnov Test for equality of distributions, where the null hypothesis is that the two samples are from the same distribution.

Time varying liquidity

We have already discussed briefly the degree to which shorter-horizon assets may miss some salient aspects of monetary policy at the ELB, but a related issue arises from limited trading when the policy rate is pinned near zero. In particular, when the policy rate is at the effective lower bound, policy surprises tend not to induce trading at shorter horizons. This is not only because the policy rate cannot sink (much) below zero, but also because the predicted (and telegraphed) horizon of liftoff from the ELB has generally been quite long. Throughout the period from 2008 to 2015, estimates from yields and futures prices suggested that policy rates were not expected to liftoff from zero for more than a year in the future at any given time. Limited expectation of near-term policy rate changes resulted in limited trading of short-horizon futures around FOMC meetings. Limited trading, in turn, renders estimates of monetary policy's effects at the ELB near to noise. We illustrate this point in two ways.

First, Table 2 compares the variance of the monetary policy surprises at and away from the ELB. The first noteworthy pattern applies to shorter duration assets, which we hypothesize to have a more tenuous relationship to monetary policy expectations when the policy rate is pinned near zero. Indeed, the variance of the shorter duration surprise measures falls substantially at the ELB, at both daily and intradaily frequency. The second pattern applies to surprises measured using ten year Treasuries futures, which should gain salience with the use of heavy forward guidance and unconventional monetary policy tools like LSAPs. These surprises see their variance increase at the ELB. The only underlying asset with statistically constant variance across regimes is the five year Treasury futures contract, which is more likely to reflect forward guidance relative to 10-year yields, and more likely to reflect expectations of LSAPs relative to short futures.

Although these patterns appear largely invariant to the sampling frequency, they suggest that these underlying assets' trading activity may be lower on announcement days when they are not central to the monetary policy tool kit. This exercise supports the inclusion of longer maturities in monetary policy surprises because doing so helps to preserve meaningful variation during "low-for-long" periods. As we showed in kernel density plots, and as we will see further in section 3, compound monetary policy surprises that integrate Treasuries futures differ less when switching between frequencies.

Table 2: Standard Deviations at and away from the ELB

	Intra			**Daily**		
	Non-ELB SD	ELB SD	p-value	Non-ELB SD	ELB SD	p-value
ED1	6.75	3.47	0.00	9.41	2.38	0.00
ED2	6.77	3.86	0.00	9.86	3.89	0.00
ED3	6.99	4.38	0.00	8.95	4.36	0.00
ED4	7.23	4.90	0.00	8.96	4.89	0.00
US2Y	6.10	3.65	0.00	7.57	5.06	0.00
US5Y	5.29	5.06	0.69	7.49	8.54	0.16
US10Y	3.76	4.90	0.00	5.88	8.05	0.00

Table 2 shows the standard deviation of intradaily and daily changes in Eurodollar futures (3-, 6-, 9-, 12 month) and 2-, 5-, and 10-year Treasuries futures implied yields at and away from the ELB. P-values correspond to a test for equality of variances.

As a second check, we use data on volumes traded obtained from Refinitiv, covering 203

FOMC announcement dates from 2000 to March 2023. Collecting minute-by-minute trading volumes for 3-month ahead Eurodollar futures, 24-month ahead Eurodollar futures, and 10-year Treasury futures on FOMC announcement dates, we examine the degree to which the trading volumes of these futures contracts differ during and away from the ELB.

Table 3 shows median and total trading volume of these contracts at and away from the ELB. Along with the median and total volume traded in the 30 minute window, a third column includes standard errors from a t-test of differences in mean. Standing in for short-horizon contracts, the three-month-ahead Eurodollar contract shows statistically significantly higher median trading volume away from the ELB, consistent with the centrality of short maturities to conventional monetary policy. Although its total trading volume is not statistically significantly different across periods, the intuition is the same (i.e., more trading volume away from the ELB). In contrast, 24-month futures, which reflect forward guidance more than the immediate policy rate, trade more often when the policy rate is at the ELB. Similarly, because LSAPs were not part of the monetary policy toolkit before 2008 and were considered a remote possibility from 2015 until March of 2020, the FOMC-window trading volume of 10 year Treasury futures was statistically significantly lower away during periods of conventional monetary policy.

These patterns in announcement-time liquidity, combined with the mechanics of monetary policy at and away from the ELB, underscore the utility of monetary policy measures that incorporate information across the yield curve. We'll see the importance of these characteristics assert themselves more clearly in our empirical applications.

News contamination

One very reasonable concern about the use of daily data for the identification of monetary policy surprises stems from the potential for other news about the economy to contaminate the estimate. While major data releases from the federal government seldom coincide with the date of an FOMC announcement, some private data releases do overlap, and meeting dates also sometimes coincide with non-announcement developments. In particular, if the additional activity observed in daily futures prices (outside of the 30-minute announcement window) systematically reflects expectations about variables affected by monetary policy, then the results obtained using daily data will be biased.

Whether news on the date of an announcement confounds identification relative to the narrow window hinges critically on when the information is released relative to time of the monetary policy news. Decomposing the information flow on announcement day into information released before, during, and after the 30 minute window, we can express the reaction of any asset price on the day as the sum of changes across the three intervals:

Table 3: Trading volume at and away from the ELB

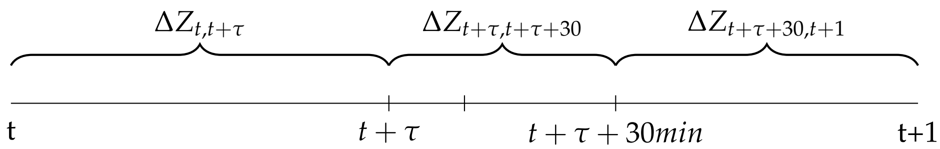
(a) Across the announcement day

	Median			**Total**		
	Non-ELB	ELB	se	Non-ELB	ELB	se
3-month ahead Eurodollar	101.9	56.7	7.8***	231878.3	192720.7	24701.8
24-month ahead Eurodollar	51.9	59.0	4.5	89524.2	166503.4	18907.5***
10-year Treasury futures	311.1	367.5	27.5**	865337.2	1312196.8	81594.1***
N	121	82	203	121	82	203

(b) In a 30 minute window

	Median			**Total**		
	Non-ELB	ELB	se	Non-ELB	ELB	se
3-month ahead Eurodollar	174.4	90.6	20.9***	7664.7	7605.0	1318.6
24-month ahead Eurodollar	89.2	115.9	14.4*	3416.6	6748.1	918.8***
10-year Treasury futures	1316.6	1681.4	152.1**	36483.3	59885.1	5316.1***
N	98	82	180	120	82	202

Table 3a shows the median and total trading volumes on the day of an FOMC announcement among 3-month ahead and 24-month ahead Eurodollar futures, along with 10 year Treasury bond futures, at and away from the ELB (defined as periods when the policy rate was set to 0 - 25BPs). Columns 3 and 6 contain standard errors from a t-test of means, where ***, **, and * denote significance at the 1%, 5% and 10% level, respectively. Table 3b repeats the exercise within a 30 minute window of the FOMC announcement.



$$\Delta Z_{t,t+1} = \Delta Z_{t,t+\tau} + \Delta Z_{t+\tau,t+\tau+30} + \Delta Z_{t+\tau+30,t+1}$$

Information released during the window, reflected in asset price changes $\Delta Z_{t+\tau,t+\tau+30}$, are common to intradaily and daily surprises. Information released between the end of the window and the end of the day are reflected in $\Delta Z_{t+\tau+30,t+1}$. Whether these post-announcement developments reflect monetary policy news (as in the case of a press conference or of slow-moving market reactions) or could be plausibly unrelated (like an intentionally late-scheduled earnings announcement) is unconcerning from an endogeneity standpoint for two reasons. First, information revealed after the meeting from a non-policy source obviously cannot affect the actions of policy makers. Second, because U.S. data releases are vanishingly rare in the afternoon, post-FOMC news is likely to be idiosyncratic and thus unlikely to systematically bias estimates of the impact of monetary policy. Moreover, in the case of monetary policy news that continues to develop or process after the narrow window has ended, those reactions arguably should be included in the measured monetary policy surprise.

Data releases, along with other pre-window news, *can* create a real endogeneity concern in the first term, $\Delta Z_{t,t+\tau}$. Any news relevant to the decision of policy makers occurring between the close of the previous day and the start of the announcement window has the potential to drive both policy and the variables of interest that react to it. The potential severity of this concern is heightened by the overwhelming tendency of data releases to print in the morning. In order to assess the degree of news contamination present in the daily monetary policy surprises, we run the following pair of regressions. First, we regress each of the daily surprises on their intradaily counterparts to separate information processed within the 30-minute window to reactions outside of it.

$$MP_t^D = \alpha_0 + \beta MPS_t^{ID} + \epsilon_t \tag{1}$$

Where MP_t^D is the daily monetary policy surprise, MPS_t^{ID} is its intraday counterpart and t indexes central bank announcements. The residual of this regression reflects reactions to additional news during the day, in addition to any slow moving reactions to the monetary policy announcement. To test whether price movements outside the tight announcement window are systematically biased by other data releases, we regress the collected residuals on news surprises from the *Bloomberg ECO US Surprise Index* (N_t).

$$\hat{\epsilon}_t = \alpha_1 + \gamma N_t + e_t \tag{2}$$

These news surprises measure the degree to which news releases in a number of categories differ from the Bloomberg Consensus forecast. Categories include inflation, growth, labor markets, cyclical indicators, housing, retail, and industrial production. The index compares each economic data release to the consensus estimate, and the difference is standardized. A positive reading indicates better than expected incoming data, while a negative reading indicates that data have printed worse than expected.

Table 4a shows the results of the first stage, regressing daily on intradaily surprises, while Table 4b shows the second stage. Parameter values in the first stage are all statistically significant at the 1% level. Moreover, the relationships between each pair of surprises become tighter as maturities lengthen: the coefficient values tend toward one with longer maturities, reaching one-for-one change for 5- and 10-year Treasury futures. The increasing R^2 values also show more co-movement for longer maturities, peaking at 43%. Inheriting these characteristics, the variation explained by the intradaily compound monetary policy surprises averages 40%. These parameter values are comforting given that even different series of same-frequency (i.e., intradaily) monetary policy surprises do not agree with one another, with a correlation coefficient as low as 0.3 and the same sign in only one half of observations (Brennan et al. (2024)).

The results shown in Table 4b suggests that non-monetary policy data releases do not seem to systematically affect daily monetary policy surprises of any maturity. Table 4c takes a closer look at the news categories included in the index which we might expect to be most systematically related to the pre-window residual and the policy decision—labor market developments, inflation news, and growth news. Most estimates are not found to be statistically different from zero, and instances of statistically significant parameter values correspond to precise zeroes. Moreover, the fit of these regressions is poor, with R^2 statistics under 0.05. These results imply that data released on the same day as FOMC announcements is unlikely to systematically bias estimates obtained with daily surprises compared to intradaily surprises.

However, it is important to keep in mind that rates throughout the day (particularly before the FOMC meeting) contain additional information that may be obscured by daily surprises (open to close). That is, although news contamination pictured here is insignificant, we cannot necessarily conclude that there is no information throughout the day that could not be captured by *additional* tick data. For example, if one were to consider the change in monetary policy measures by the half-hour, hour, etc, and submit them to a similar contamination regression, changes before the FOMC meeting would likely yield significant results since data release also exclusively occur before the FOMC meeting, which is conceivably when the market is still incorporating information. Likewise, changes after the meeting could also be significant since asset prices can sometimes take additional time to incorporate relevant information or unwind mispricing. Our analysis thus leaves open the possibility that an optimal window size exists, and may even be time and/or asset specific.

Table 4: Daily to Intradaily News Contamination Test

(a) Relationship between daily and intradaily monetary policy surprises

	dED1	dED2	dED3	dED4	d2Y	d5Y	d10Y	dShort	dLong
ED1	0.45***								
	(2.87)								
ED2		0.73***							
		(6.28)							
ED3			0.73***						
			(6.95)						
ED4				0.70***					
				(7.09)					
2-Year Furures					0.76***				
					(5.38)				
5-Year Futures						0.99***			
						(8.66)			
10-Year Futures							1.09***		
							(8.55)		
Short MPS								0.58***	
								(7.26)	
Long MPS									0.60***
									(7.74)
N	254	254	254	254	255	255	255	254	254
R^2	0.11	0.27	0.34	0.34	0.36	0.43	0.46	0.33	0.40

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(b) Explanatory power of other data releases in daily driving monetary policy surprises

	dED1_r	dED2_r	dED3_r	dED4_r	d2Y_r	d5Y_r	d10Y_r	dShort_r	dLong_r
fed_news	-3.16	8.83	10.90	13.77	2.47	9.43	10.95	1.61	2.47
	(-0.34)	(0.81)	(0.85)	(1.17)	(0.15)	(0.58)	(0.78)	(0.64)	(0.60)
N	204	204	204	204	205	205	205	204	204
R^2	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4a displays the results from regressing the daily monetary policy surprise measures on their intradaily counterparts. Table 4b displays the results from regressing the resulting residuals onto aggregated news surprises (ECSURPUS Index) from Bloomberg.

Table 4c: Daily to Intradaily News Contamination Test (Cont.)

	dED1_r	dED2_r	dED3_r	dED4_r	d2Y_r	d5Y_r	d10Y_r	dShort_r	dLong_r
Labor News	0.00	0.00	0.00	0.00	0.00**	0.00*	0.00*	0.01	0.01
	(1.24)	(0.99)	(1.26)	(1.63)	(2.19)	(1.91)	(1.70)	(1.32)	(1.64)
Inflation News	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
	(0.00)	(1.03)	(1.02)	(1.07)	(1.03)	(0.48)	(1.40)	(1.02)	(1.04)
Growth News	-0.00	-0.00	-0.00	0.00	0.00	0.00*	0.00**	-0.00	0.01
	(-0.25)	(-0.35)	(-0.23)	(0.08)	(1.61)	(1.85)	(1.98)	(-0.26)	(0.82)
N	204	204	204	204	205	205	205	204	204
R^2	0.00	0.01	0.02	0.03	0.04	0.03	0.04	0.02	0.03

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4c displays the results from regressing the resulting residuals onto selected subcomponents of US news surprises from Bloomberg. Covered data releases can be found in Table 1.

Central Bank Information Effect vs. Fed Response to News

A related issue arises from central bank information effects, wherein central banks affect asset prices via agents' beliefs not only about policy, but about the path of the economy (Leombroni et al. (2021); Nakamura and Steinsson (2018); Melosi (2017); Jarociński and Karadi (2020)). While central banks aim to produce "Odyssean" forward guidance in the form of information about the path of policy, the central bank may also generate "Delphic" information, wherein the announcement reveals news about the state of the economy. If, for example, the central bank enacts a more aggressive rate cut than expected or communicates a longer cycle than expected, market participants may infer that the central bank possesses better information on downside growth risks and update their beliefs accordingly.[3] The presence of a central bank information effect would complicate the identification of monetary policy transmission, because the state of the economy and the policy are revealed simultaneously from the informational standpoint of financial market participants. In particular, the presence of an information effect would bias estimates toward zero.

Bauer and Swanson [(2023a), (2023b)] offer an alternative view of the central bank information effect, providing evidence that the patterns attributed to it reflect instead financial markets lacking full information about the Fed's monetary policy rule and miscalculating its sensitivity to incoming data. Bauer and Swanson show that commonly used monetary surprise can be predicted by pre-meeting developments and are therefore not entirely exogenous. In order to test whether daily data aggravates this form of surprise contamination, we repeat the exercise in Bauer and Swanson (2023b) testing whether monetary policy surprises can be

[3]See Leombroni et al. (2021) for a very nice discussion of the mechanism.

predicted by relevant data in the recent past:

$$MPS_t^j = \alpha_2 + \sum_{i=1}^{6} \beta_{2,i}^j S_{i,t} + \nu_t \quad (3)$$

where j indicates daily or intraday versions of the six types of monetary policy surprises. $S_{1,t} \ldots S_{6,t}$ comprise 1.) the surprise component of the most recent nonfarm payrolls release, 2.) employment growth over the last year, 3.) the log change in the S&P500 from 3 months before to the day before the FOMC announcement, 4.) the change in the yield curve slope over the same period, 5.) the log change in a commodity price index over the same period, and 6.) the option-implied skewness of the 10-year Treasury yield from Bauer and Chernov (2024).

The results displayed in Table 5 suggest that daily monetary policy surprises are no more predictable than surprises measured in a narrow window. Intraday surprises are especially predictable with respect to the most recent nonfarm payrolls release, year-on-year employment growth, and the option-implied skewness of the 10-year Treasury yield. In contrast, our daily measures do not move in response to these variables in a statistically significant way except for the 10-year Treasury skewness measure and, to a very limited extent, employment growth over the last year.

Table 5: Monetary Policy Surprise Predictability

	Daily				**Intra**			
	ED1	ED4	Short MPS	Long MPS	ED1	ED4	Short MPS	Long MPS
NFP_SURP	0.00	0.00	0.00	0.00	0.00**	0.00***	0.00***	0.00***
	(0.97)	(1.61)	(1.47)	(0.89)	(2.32)	(2.88)	(2.84)	(2.68)
NFP_12M	-0.00	0.00*	0.01	0.02	0.00**	0.01***	0.04***	0.04***
	(-0.10)	(1.73)	(1.17)	(1.33)	(2.16)	(3.03)	(3.04)	(2.99)
SP500_3M	-0.03	0.04	0.08	0.16	0.17**	0.10	1.04**	1.03*
	(-0.36)	(0.48)	(0.20)	(0.25)	(2.39)	(1.47)	(2.13)	(1.95)
SLOPE_3M	-0.03	-0.01	-0.12	-0.07	-0.01	-0.01	-0.11*	-0.09
	(-1.45)	(-1.15)	(-1.47)	(-0.74)	(-1.52)	(-1.35)	(-1.71)	(-1.26)
BCOM_3M	-0.01	0.10	0.31	0.60	0.02	0.12*	0.61	0.79
	(-0.18)	(1.13)	(0.69)	(0.86)	(0.26)	(1.94)	(1.29)	(1.61)
TR_SKEW	0.03*	0.03*	0.16**	0.26**	0.03**	0.04***	0.28***	0.29***
	(1.74)	(1.85)	(1.98)	(2.27)	(2.01)	(2.92)	(2.88)	(2.95)
N	254	254	254	254	256	256	256	256

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 shows results regressing daily and intradaily monetary policy surprises on 1.) the most recent nonfarm payrolls surprise, 2.) employment growth over the last year, 3.) log change in the S&P500 from 3 months before to the day before the FOMC announcement, 4.) change in the yield curve slope over the same period, 5.) log change in a commodity price index over the same period, and 6.) option-implied skewness of 10-year Treasuries.

Although the relationships are seldom statistically significant, we note that the estimated parameters carry the same (economically intuitive) signs as their intradaily counterparts. Given the amount of variation in the daily surprises explained by intradaily data, we should not be surprised. Given these relationships, it is important to note that unadjusted monetary policy shocks will likely produce estimates that are, like their intradaily counterparts, biased toward zero. Our intention here is only to show that daily surprises are no *more* predictable than intradaily ones.

In sum, comparing the base characteristics of daily and intradaily surprises seems to suggest that the differences between them are not particularly large. However, even small differences, distributed systemically, can make a big difference in estimated parameters. To more thoroughly explore the practical consequences of a narrow (or broad) window, we pursue three applications switching between daily and intradaily measures.

3 High frequency application: interest rate passthrough

One basic and straightforward application of monetary policy surprises at high frequency tests the passthrough of the measured surprise to various maturities along the yield curve. Ideally, the passthrough regression shows the degree to which monetary policy affects borrowing costs at various maturities. Given time variation in the central bank tool kit (emanating chiefly from bouts at the effective lower bound), examining time varying passthrough lends us a glimpse into the potentially heterogeneous effects of monetary policy, along with information regarding the time-varying suitability of a particular measure. To do so, we implement the following rolling regression in overlapping windows comprising 25 announcements advancing in steps of one event.

$$\Delta Y_t^n = \alpha + \beta_j MPS_t^j + \epsilon_t \tag{4}$$

Where Y_t^n is the announcement-day change in 1-, 5- and 10-year Treasuries, MPS_t^j is one of the six monetary policy surprises described above measured at daily or intraday frequency (frequency indexed by j), and t indexes central bank announcement dates. For ease of interpretation, compound monetary policy surprises are normalized such that a unit surprise raises two year yields by ten basis points. Figures 3 - 4 display the parameter estimates from rolling regressions, along with 90% robust confidence intervals.

Starting in Figure 3, we see the passthrough of surprises to daily changes in the 1-year Treasury yield show similar patterns for both daily and intradaily surprises: low-level of pass-through during the ELB and increasingly larger pass-through outside of ELB. The effects of the measures are similar for longer maturities, and shows the most consistent pattern in the long compound monetary policy surprise. In terms of substitutability among frequencies, it seems that where daily surprises diverge, they produce larger passthrough estimates compared to intradaily surprises. This is particularly evident in 1-year ahead Eurodollar futures (center top), which passes through to the short compound measure forcefully. In Treasuries futures, the divergence between daily and intradaily estimates is limited to the pre-GFC period, when longer-duration bond futures would be a less relevant metric of surprises to the monetary policy stance. Among the compound monetary policy surprises, the daily short duration compound surprise produces larger point estimates from 2015 to 2020, when the Fed was normalizing monetary policy by slowly tightening policy rates and tapering balance sheet purchases. Here, the short measure is inheriting patterns from the 4th Eurodollar contract. That divergence gets smoothed when we add bond futures to generate the long compound measure (bottom right).

Figure 3: Impact of monetary policy surprises on 1-year US Treasury yields

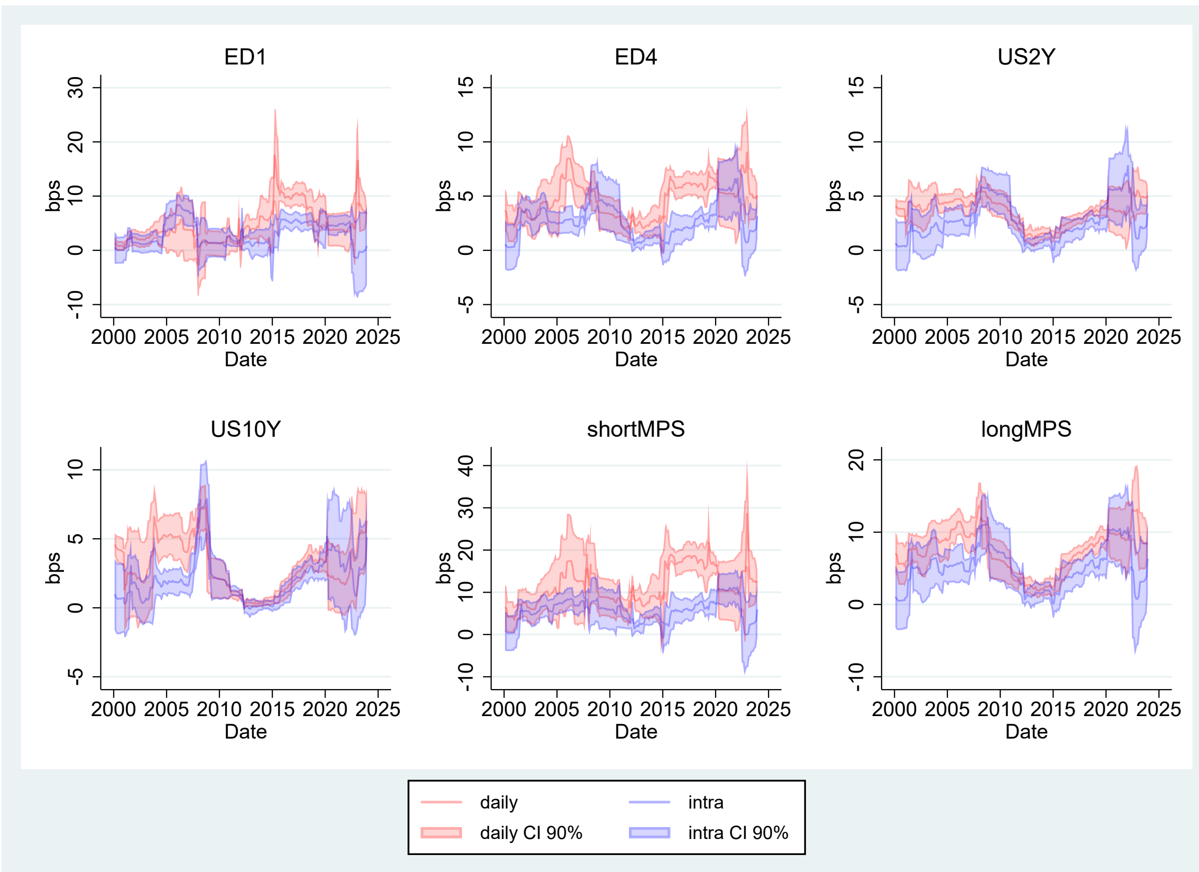


Figure 3 compares the time-varying effects of selected monetary policy surprises - ED1, ED4, 2- and 10-year Treasury futures, short MPS and long MPS - on daily changes in 1-year Treasury yields from 2000 to 2023. Regressions cover 25 FOMC announcement dates ($\backsim$ 3 years) and sequentially advance by one announcement at a time.

Figure 4 shows the time varying passthrough of the surprises to the ten year Treasury bond, which bears some similarities to one year yield passthrough but is nonetheless distinct. All measures of monetary policy surprises suggest that passthrough to the ten year yield rises at the ELB, reflecting the role of LSAPs in monetary policy when short rates are pinned near zero. Comparing the estimates obtained with daily with intradaily measures, the top left and center panels show that the estimates from the first and fourth Eurodollar contract rarely differ at standard levels of statistical significance. The top right and bottom left panels show that the estimates obtained using Treasury futures differ most before the GFC, when once again they would be less relevant for measuring surprises to monetary policy. In the bottom center and bottom right panels, daily compound monetary policy surprises produce larger estimates of passthrough compared to intradaily surprises, particularly for the long compound measure. This is due not only to larger parameter values but also due to increased precision in the estimates obtained using Treasury futures. This finding echoes Nakamura and Steinsson (2018)'s finding that changes in long term interest rates can be confounded by background noise at daily frequency. Even so, the difference is only sometimes statistically significant, and only at the 10% level. Moreover, it is possible to allay these concerns using a Rigobon and Sack (2003) heteroskedasticity-based estimator to avoid overstating statistical precision as in Bu, Rogers, and Wu (2021). For brevity, we reserve passthrough to the to the five year Treasury bond yield for the appendix (Figure 1), because the patterns we observe there very closely reflect ten year bond yields.

Taken all together, it appears that daily surprises most consistently overshoot intradaily surprises using measures of a single horizon, particularly when the maturity of the underlying asset is not fully reflective of the monetary policy toolkit. Specifically, estimates of passthrough using treasury futures at 2- and 10-year horizons are larger in general before onset of the effective lower bound, while estimates of passthrough to one-year yields obtained using the fourth Eurodollar contract are larger using daily data from 2015 - 2020 (i.e., after after liftoff). These differences in time-varying passthrough in single-asset surprise measures are smoothed away to a significant extent using compound monetary policy surprises.

Examining time varying passthrough provides a granular look at the representativeness of the surprise over time, but it is sensitive both to the underlying relationship and the time varying characteristics of the surprises. In particular, as shown in Table 2, the variance of the surprises on announcement days varies significantly with the monetary policy regime. Therefore, Table 6 and Figure 5 show the full sample passthrough results for each of the surprises, paired for comparison. The table shows point estimates normalized to a 10 basis point tightening, with robust standard errors in parantheses. Estimates of passthrough to one- and ten-year yields from daily and intradaily versions of the surprise are all within each other's 90% confidence intervals in the full sample, varying by at most three basis points. For ease of visual inspection, Figure 5 shows the results for the one- and ten-year yield, normalizing the coefficients to reflect the proportion passed through, with daily and intradaily results organized pairwise. In this representation, we see not only that the confidence intervals overlap, but that in most cases the parameter estimate obtained using daily data lies within the confidence interval of the intradaily estimate, and vice versa.

In sum, we do not observe statistically or economically significant differences in the high frequency patterns estimated using daily versus intradaily surprises. Still, small differences at high frequency may add up to large differences in low frequency (i.e., aggregated) settings. To

Figure 4: Impact of monetary policy surprises on 10-year US Treasury yields

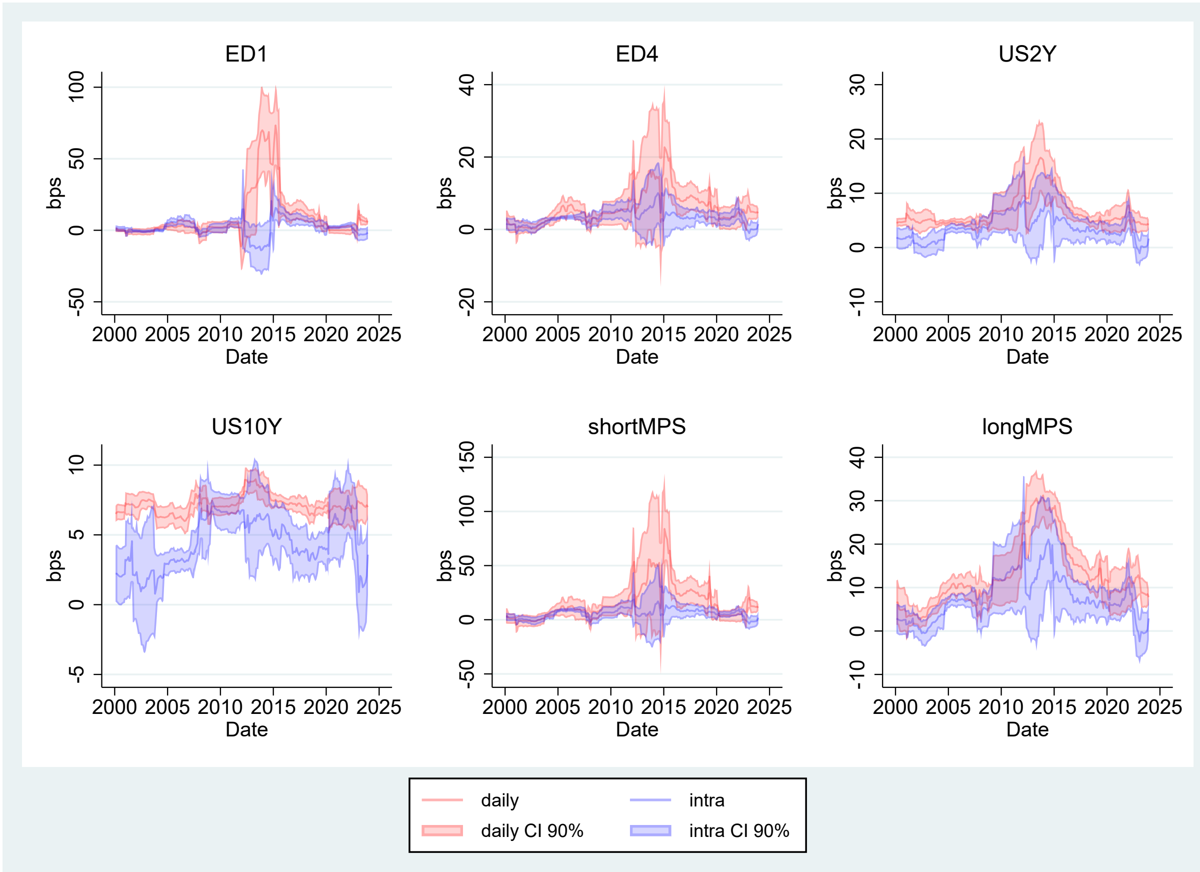


Figure 4 compares the time-varying effects of selected monetary policy surprises - ED1, ED4, 2- and 10-year Treasury futures, short MPS and long MPS - on daily changes in 10-year Treasury yields from 2000 to 2023. Regressions cover 25 FOMC announcement dates (∽ 3 years) and sequentially advancing one announcement at a time.

provide a sense of the degree to which these differences influence applications using aggregation, we next apply our surprises to a well-known low frequency setting.

Table 6: Full sample passthrough

	1-Year		5-Year		10-Year	
	Intra	Daily	Intra	Daily	Intra	Daily
ED1	2.3*** (0.78)	2.2** (1.01)	1.9** (0.96)	2.2** (0.97)	1.0 (0.71)	1.4* (0.71)
ED4	3.2*** (0.48)	4.0*** (0.43)	4.3*** (0.52)	5.1*** (0.59)	2.7*** (0.45)	3.7*** (0.58)
Short MPS	6.3*** (1.10)	8.3*** (1.93)	7.1*** (1.31)	10.0*** (2.17)	4.3*** (1.11)	7.0*** (1.75)
Short MPS Orth	6.3*** (1.12)	8.2*** (1.86)	7.1*** (1.34)	10.2*** (2.17)	4.3*** (1.12)	7.3*** (1.78)
Long MPS	5.9*** (0.97)	7.1*** (0.82)	8.5*** (1.31)	11.3*** (1.07)	5.9*** (1.20)	8.8*** (1.11)
Long MPS Orth	5.9*** (0.94)	7.1*** (0.84)	8.6*** (1.27)	11.4*** (1.05)	6.0*** (1.16)	8.9*** (1.11)

standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6 shows the passthrough of daily and intradaily monetary policy surprises (ED1, ED4, short compound and long compound) to 1-, 5-, and 10-year bond yields. Short compound surprises comprise the first principal component of announcement-day changes in the yields implied by first through fourth Eurodollar futures contracts (ED1 - ED4), while the long measure comprises the first principal component of announcement-day changes in ED1 - ED4, along with the implied yields from 2-, 5-, and 10-year Treasuries futures contracts.

Figure 5: Proportional passthrough of surprises, full sample

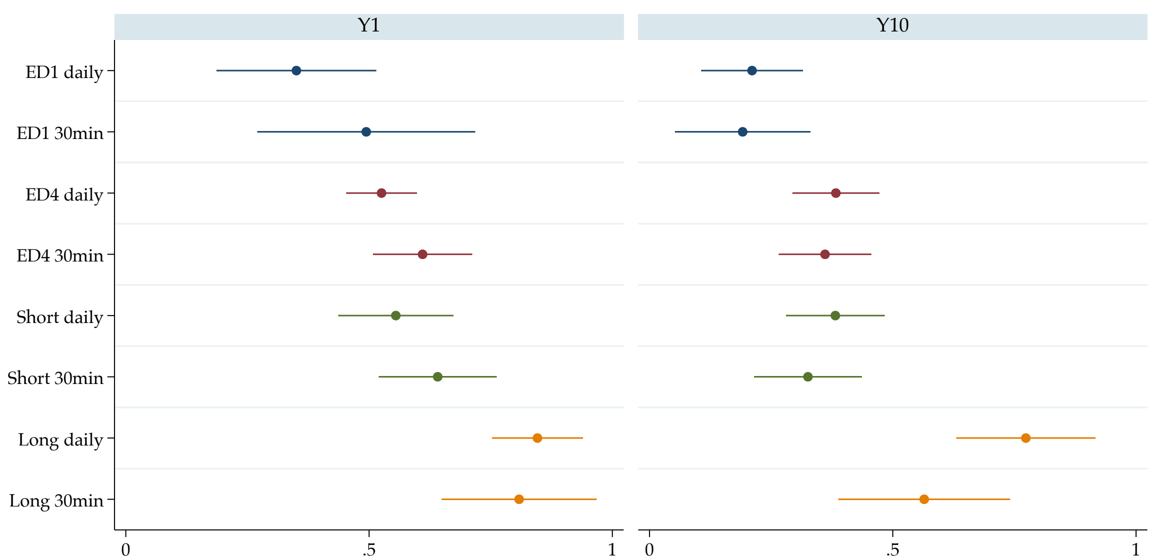


Figure 5 shows the proportional passthrough of daily and intradaily monetary policy surprises (ED1, ED4, short compound and long compound) to 1- and 10-year bond yields. Short compound surprises comprise the first principal component of announcement-day changes in the yields implied by first through fourth Eurodollar futures contracts(ED1 - ED4), while the long measure comprises the first principal component of announcement-day changes in ED1 - ED4, along with the implied yields from 2-, 5-, and 10-year Treasuries futures contracts. Lines reflect 90% robust confidence intervals.

4 Low frequency applications: Proxy SVAR

For our low frequency empirical application, we replicate the proxy structural vector autoregression (proxy SVAR) from Gertler and Karadi (2015) (heretofore GK) with both intradaily and daily monetary policy surprises as instruments. Because GK is considered a benchmark application in the use of high frequency monetary policy surprises to estimate the effects of policy on macroeconomic variables in a VAR, we regard a replication of their results as proof of concept.[4] We begin by estimating a reduced form VAR with four monthly macroeconomic variables: log industrial production (IP), log prices (CPI), the excess bond premium of Gilchrist and Zakrajšek (2012) (EBP), and the 1-year Treasury yield. Stacking these variables into a vector Y_t, the reduced form VAR can be expressed as:

$$Y_t = \alpha + B(L)Y_{t-1} + v_t \tag{5}$$

Where $B(L)$ is the lag operator and v_t is a vector of serially uncorrelated residuals. Following Gertler and Karadi (2015), we run our specifications with 12 lags using data covering the period from July 1979 to June 2012.[5] In standard fashion, we assume that the reduced form shocks are a linear function of the underlying structural shocks:

$$v_t = S\epsilon_t \tag{6}$$

Ordering monetary policy first in the vector of structural surprises, the first column of S describes the impact of the structural monetary policy surprise ϵ_t^{mp} on v_t and Y_t. To identify the impact of the structural monetary policy shock, Gertler and Karadi (2015) use high frequency identification under the assumptions that high frequency monetary policy surprises are 1.) relevant in driving the monetary policy instrument and 2.) exogenous with respect to the other structural surprises in S. For full explanation of the inner workings of proxy SVARs see for example Mertens and Ravn (2013), Gertler and Karadi (2015), Kilian and Lütkepohl (2017), or Stock and Watson (2018). Following the baseline in the paper, we use the fourth fed funds futures contract as the external instrument. Following Bauer and Swanson (2023b), we aggregate the surprises to monthly frequency by summing the announcement changes up within a month. In months with no event, the surprises is equal to zero.[6]

Figure 6 depicts the impulse response functions (IRFs) from the replication exercise, where

[4]Early examples of this identification strategy are Cochrane and Piazzesi (2002), Faust et al. (2004), and Stock and Watson (2012). Other notable applications include Ramey (2016) and Stock and Watson (2018).

[5]Macro and financial variables start in July 1979 because of the differences in monetary policy regime pre- and post-Volcker era. However, due to data availability, their policy instrument starts in January 1990 through end of sample. Thus, the full sample is used to estimate lag coefficients and reduced form residuals. These values are, in turn, used to estimate the impact of contemporaneous impact of monetary policy surprises.

[6]In their 2015 paper, G&K cumulate the surprises on any FOMC days during the previous 31 days (e.g. on February 15, we cumulate all the FOMC day surprises since January 15), and average the resultant monthly surprises across each day of the month. We choose to sum the surprises within the month because G&K's method of aggregation introduces autocorrelation.

results obtained with daily and intradaily surprises are depicted together in red and blue, respectively. Note that both sets of IRFs closely track one another, to such an extend that even with generous confidence intervals (90%), the point estimates obtained with intradaily data falls within the bands from daily estimates and vice versa. The only exception is the excess bond premium, where the impact of daily-measured surprises is sufficiently attenuated as to differ not only from Gertler and Karadi's point estimates, but also does not appear to differ from zero statistically. As highlighted by Bauer and Swanson (2023b) and affirmed in the next exercise, the estimate is likely to be attenuated by omitted variable bias linked to predictability. In a similar vein, the impact of daily surprises on log CPI attenuates the estimate out of statistical significance; however, we will see that Bauer and Swanson's approach to orthogonalizing the monetary policy surprise measure aids identification in this case as well. Finally, as in the original intradaily setup, we see a modest production puzzle in log IP; however, confidence intervals suggest that the estimate is not statistically different from zero.

Figure 6: Impulse Responses for FF4 Intra vs Daily as in G&K baseline

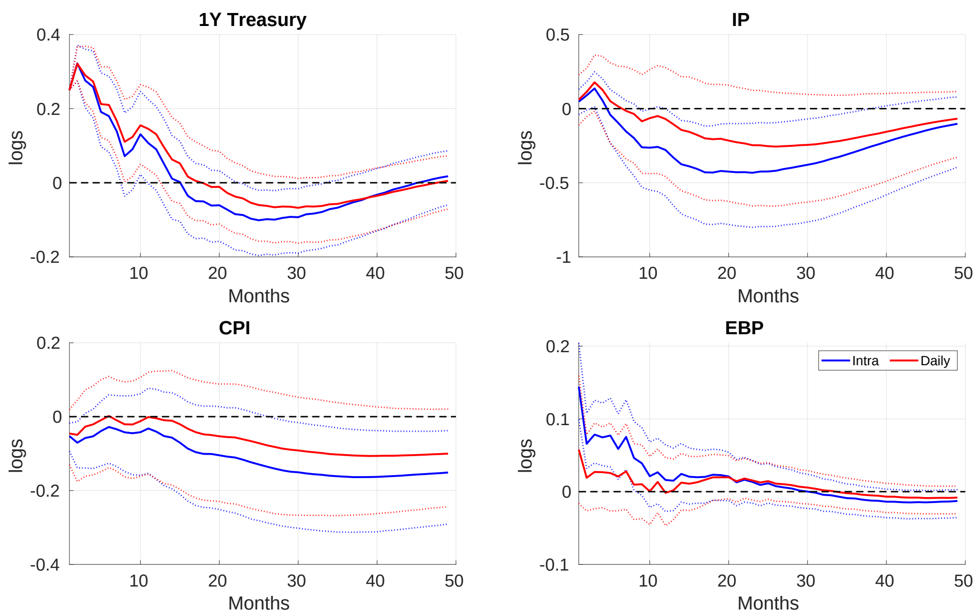


Figure 6 depicts the impulse responses of the effects of 1-year Treasury on log industrial production and log CPI, using changes in 3-month ahead federal funds futures (FF4) as instruments for both intradaily and daily frequencies. IRF results are scaled to reflect the 25BP rise in 1-year Treasury yield changes. Blue lines trace out effects of intradaily surprises and red lines trade out effects of daily surprises over a 48-month horizon. Error bands reflect 90% confidence intervals.

Comparing the IRFs, we observe similar dynamics between the two frequencies. The impact on log IP peaks after about 18 months for intradaily counterparts and after 25 months for daily surprises, before gradually converging. At the peak, intradaily surprise impact reduces log IP a only slightly more than daily surprises. The impact on log CPI peaks about 40 months out for both intradaily and daily surprises, and the gaps is persistent. At the peak, intradaily surprise impact reduces log CPI slightly more than daily surprises.

Bauer and Swanson (2023b) (heretofore referred to as B&S) replicate Gertler and Karadi's baseline using a monetary policy surprise that is purged of its predicted elements. In particular, the ex post predictability that B&S document violates the assumption that the (unadjusted) external proxy is plausibly exogenous with respect to the other structural surprises in S. For example, as shown in table 5, expansionary news about non-farm payrolls is associated with more contractionary monetary policy, biasing the estimated impact of monetary policy on output and inflation toward zero. Although our daily series do not bear a statistically significant relationship with many of the macroeconomic and financial variables included in B&S, some of the variables are statistically predictive, and all of the estimated parameters carry the same sign as the loadings on intradaily surprises.

Thus, we repeat the above replication following the procedure outlined in B&S, which uses the 2-year Treasury yield as the monetary policy instrument and uses the short compound monetary policy surprise (first principal component of ED1 - ED4) as the external proxy. As in their paper, our sample covers January 1973 to February 2020. Although the authors show that adding speeches and testimony to the data improves the strength of the instrument, we limit our analysis to FOMC announcements because it is this set of events that the authors make available online.

Figure 7 shows impulse response functions replicating the SVAR in the baseline, without augmenting the data using speeches. In response to a contractionary monetary policy surprise, the qualitative patterns obtained using intradaily and daily data match up—two year Treasury yields rise, industrial production falls, CPI falls, and the excess bond premium rises. In general, parameter values obtained using daily data are attenuated relative to those obtained with intradaily measures–industrial production and CPI fall by less, while the excess bond premium rises less. At peak impact, the intradaily estimates are 2 - 3 times larger than their daily counterparts. However, consulting the 90% confidence intervals suggests that the differences between the IRFs are seldom statistically significant. Our results not only affirm B&S's results—the severity of attenuation is mitigated, and the IP puzzle from Figure 6 is reversed—but also demonstrate that using a daily monetary policy surprise can benefit from their cleaning procedure and reproduce their results.

Recall that replicating B&S's prediction exercise (Table 5) suggested that daily-measured surprises show less (statistically significant) ex post predictability. This should not imply definitively that monetary policy surprises are not predictable—combined with the finding that intraday surprises *are* predictable and strongly related to daily surprises, we should perhaps be just as inclined to conclude that daily surprises are just noisier. Thus, as we might anticipate, we get a smaller boost using the orthogonalized surprises relative to the intradaily baseline.

Figure 8 visualizes this point, comparing the IRFs obtained using daily and intradaily monetary policy surprises with and without adjusting for predictive macroeconomic and financial variables. Like their intradaily counterparts in Figure 8a, the daily surprises pro-

Figure 7: Orthogonalized Short MPS Intradaily vs Daily (Baseline)

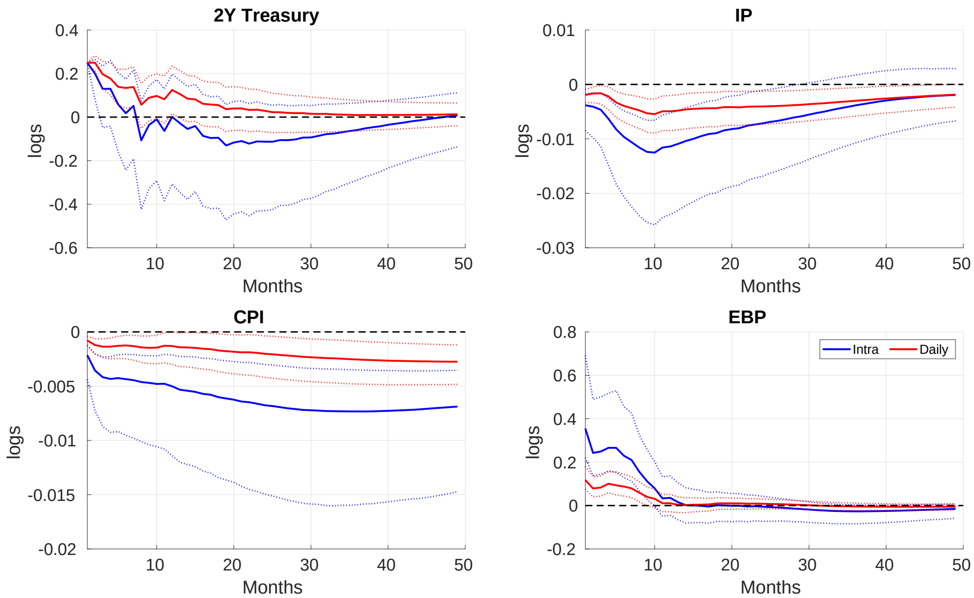


Figure 7 depicts the impulse responses of the effects of 2-year Treasury on log industrial production and log CPI, using first principal component of ED1-ED4 as instruments for both intradaily and daily frequencies. Monetary policy surprises are scaled so that 1-unit change in MPS raises intradaily ED4 by 1 percentage point. IRF results are scaled to reflect the 25BP rise in 2-year Treasury yield changes. Blue lines trace out effects of intradaily surprises and red lines trade out effects of daily surprises over a 48-month horizon. Error bands reflect 90% confidence intervals.

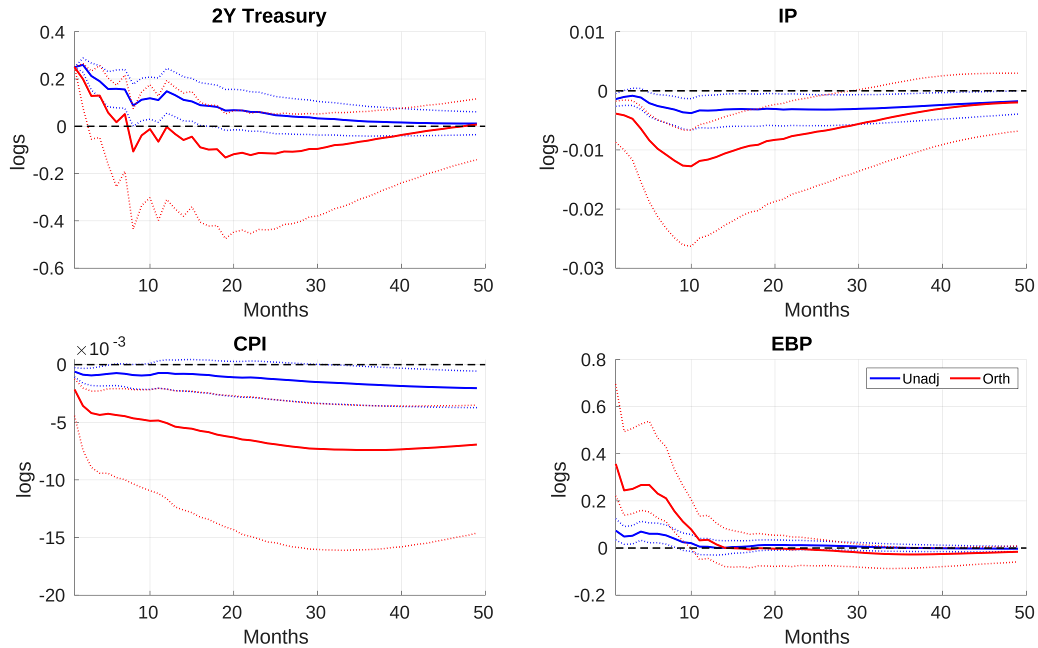
duce impulse responses that are more in line with standard macroeconomic theory when we orthogonalize them against macroeconomic predictors (Figure 8b), validating B&S's baseline conclusions.[7] While the estimated impact of the cleaned intradaily surprise is up 4 times larger relative to the unadjusted estimate, the daily version improves by a smaller but still considerable factor of 2-3 times. Thus, orthogonalizing the daily data to potentially predictive variables does allay some of the attenuation, and we leave open the possibility that a different or expanded set of predictors could narrow the gap.

Having found in our high frequency application that the long compound monetary policy surprise produces the most overlap between passthrough obtained at intradaily versus daily frequency, we repeat the SVAR exercise using the surprise comprising both Eurodollar futures and Treasuries futures in Figure 9. Here again, the broad conclusions match those suggested by the baseline. However, the IRFs obtained using daily data in this case more closely match their intradaily counterparts. This result, like the rolling passthrough exercise, suggests that using a monetary policy surprise that includes Treasuries futures can help bridge the gap between daily and intradaily data.

[7] Like B&S, our orthogonalized results produce substantially lower F-stats (around 2) vs the non-orthognalized F-stats (above 10 in general), particularly because we do not have an intradaily surprise series corresponding to

Figure 8: Impulse Responses using Orthogonalized and Unadjusted surprises

(a) **Intradaily**



(b) **Daily**

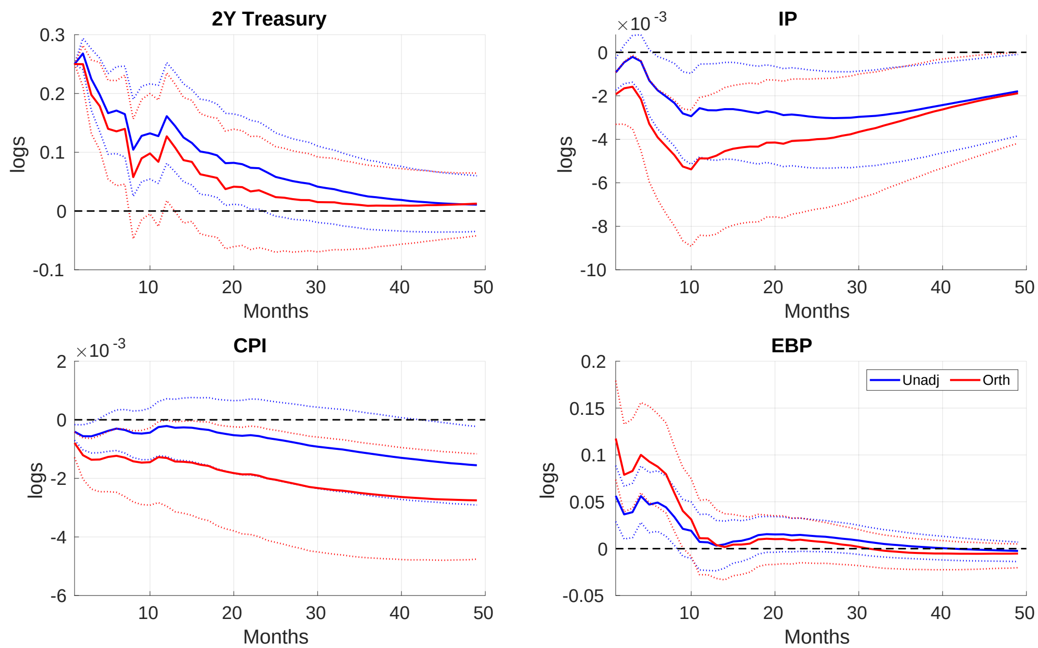


Figure 8 depicts the impulse responses of the effects of 2-year Treasury on log industrial production and log CPI, using first principal components of ED1-ED4 as instruments for both intradaily and daily frequencies. Monetary policy surprises are scaled so that 1-unit change in MPS raises intradaily ED4 by 1 percentage point. IRF results are scaled to reflect the 25BP rise in 2-year Treasury yield changes. Blue lines trace out effects of intradaily surprises and red lines trade out effects of daily surprises over a 48-month horizon. Error bands reflect 90% confidence intervals.

Figure 9: Impulse Responses for **Orthogonalized** Long MPS Intra vs Daily

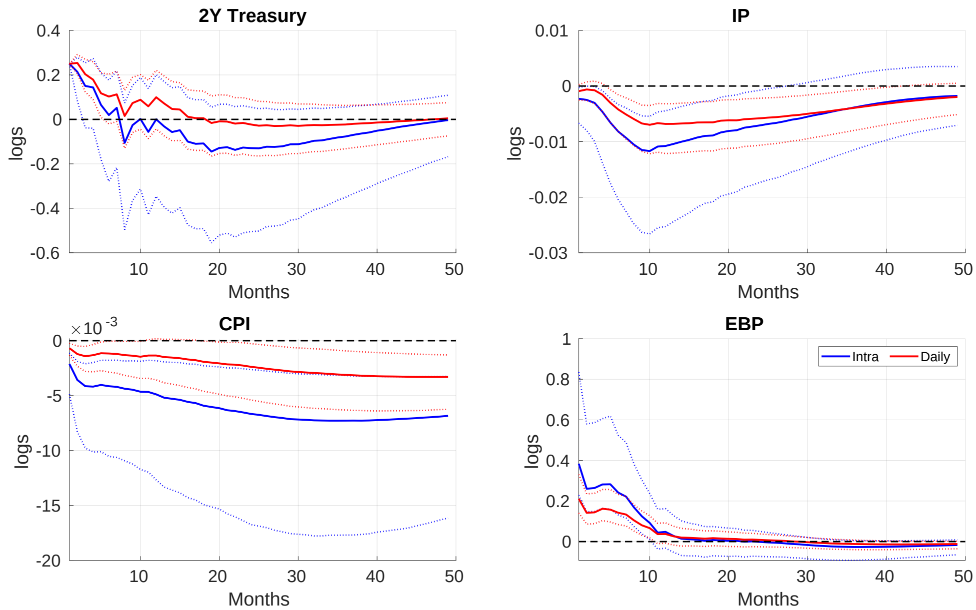


Figure 9 depicts the impulse responses of the effects of 2-year Treasury on log industrial production and log CPI, using first principal components of ED1-ED4, 2y-, 5y-, and 10-year Treasury futures as instruments for both intradaily and daily frequencies. Monetary policy surprises are scaled so that 1-unit change in MPS raises intradaily ED4 by 1 percentage point. IRF results are scaled to reflect the 25BP rise in 2-year Treasury yield changes. Blue lines trace out effects of intradaily surprises and red lines trade out effects of daily surprises over a 48-month horizon. Error bands reflect 90% confidence intervals.

5 Concluding remarks

In sum, our paper documents comparative analyses of daily and intradaily monetary policy surprises in an effort to explore the usefulness of daily data in identifying monetary policy surprises. Using daily counterparts to an array of high-frequency monetary policy surprises data from Bauer and Swanson (2023b), our analysis suggests that while intradaily surprises provide a more precise measure of immediate market reactions, daily surprises can still offer valuable insights, particularly when high-frequency data is not available or practical to use.

Comparing the unconditional characteristics of various high frequency asset price changes around FOMC announcements, we find that daily and intradaily surprises are similarly distributed and often highly correlated, especially for longer maturities. Using a series of tests over the difference in mean, variance, and distribution, we find that daily and intradaily shocks tend not to differ appreciably from each other, and that surprises combining movements at multiple horizons are the most similar across time. Our findings indicate that the necessity of intradaily surprises should be judged by the specific context and objectives of the analysis. For instance, in settings where the effective lower bound (ELB) is a significant considera-

speeches.

tion, incorporating longer maturities in the surprise measure can help bridge the gap between daily and intradaily data, making daily data a more usable option.

The principal doubt surrounding the use of daily data to identify monetary policy surprises lay in the possibility that such a wide time interval may fail to exclude other economically relevant news. We argue that potentially biasing contamination is limited to the hours before the policy announcement, as this pre-announcement interval has the potential to contain news that drives both the monetary policy decision and the variables it influences. This risk is aggravated by the fact that the overwhelming majority of official news releases occur in the morning. To explore contamination from non-monetary policy news on FOMC announcement days, we test the extent to which the divergence of daily monetary policy surprises from intradaily surprises can be explained by macroeconomic data release surprises. We find no evidence that the variation in daily surprises outside the narrow window on FOMC days is systematically explained by relevant non-policy news.

To offer proof of concept, we compare the results obtained using daily and intradaily surprises in both a high frequency and a low frequency setting. In high-frequency passthrough analysis on Treasury yields and two proxy SVAR replications, we provide evidence that daily surprises can produce results comparable to those obtained with intradaily data. This is especially true when using compound measures that integrate information across the yield curve, which helps bridge the gap between daily and intradaily frequencies. The patterns we document reflect the finding in Bauer and Swanson (2023b) that asset-based monetary policy surprises meet the bar for exogeneity in high frequency settings, but that identification in low frequency applications may require cleansing the surprises of predictive macroeconomic and financial predictors. Our results reaffirm the recommendation of Bauer and Swanson (2023b) to cleanse monetary policy shocks of relevant pre-meeting news.

Overall, intraday data remains invaluable for certain applications, and likely does perform better at filtering information that is not monetary policy news. However, we suggest that daily data provides a practical and robust alternative for assessing monetary policy surprises, particularly in settings where intraday data is not available or is prohibitively costly to obtain, or in situations when it is likely that reactions to the event take more time to process. We suggest that future research could further explore optimal window sizes and the ways in which different contexts and markets alter the optimal window size where monetary policy is concerned.

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A Appendix

Figure 1: Impact of monetary policy surprises on 5-year US Treasury yields

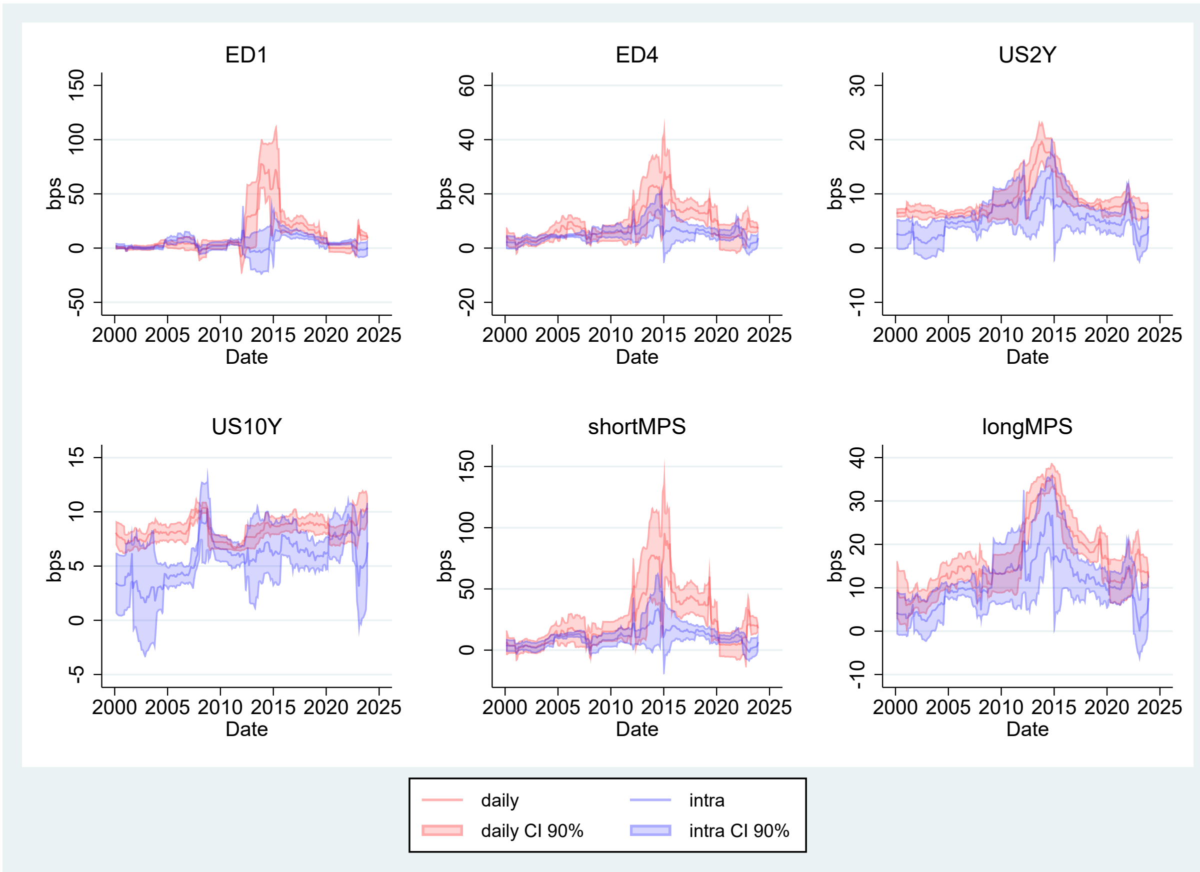
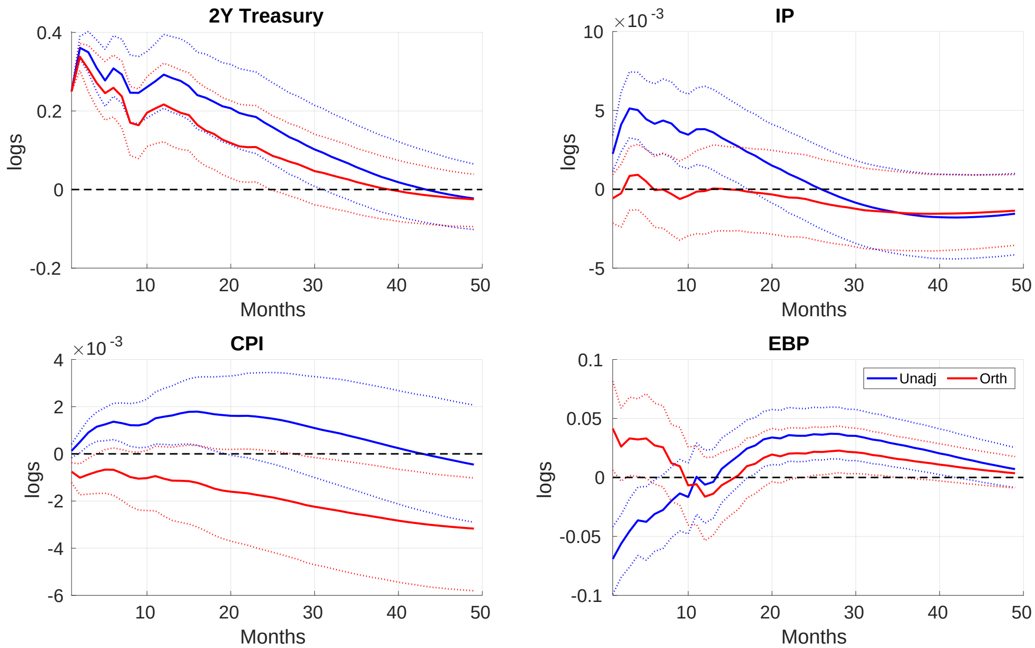


Figure 1 compares the time-varying effects of selected monetary policy surprises - ED1, ED4, 2- and 10-year Treasury futures, short MPS and long MPS - on daily changes in 5-year Treasury yields from 2000 to 2023. The regressions are run for 25 FOMC announcement dates (∽ 3 years) and sequentially advancing one announcement at a time.

A.1 Extending Bauer&Swanson Replication up to end of 2023

Figure 2: Impulse Responses using **Short** Orthogonalized and Unadjusted surprises

(a) **Intradaily**



(b) **Daily**

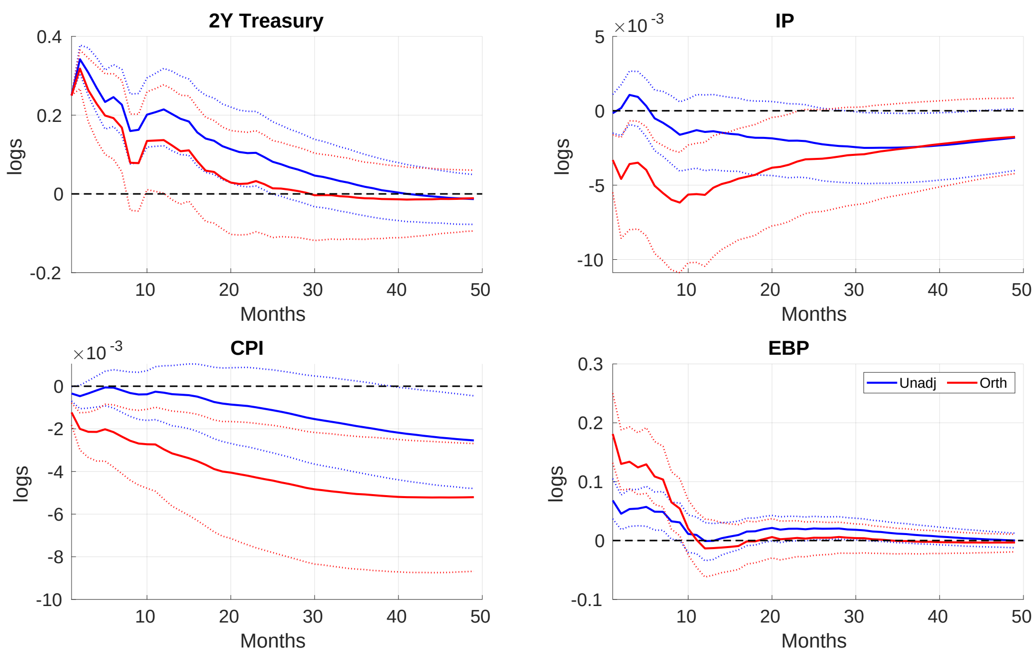
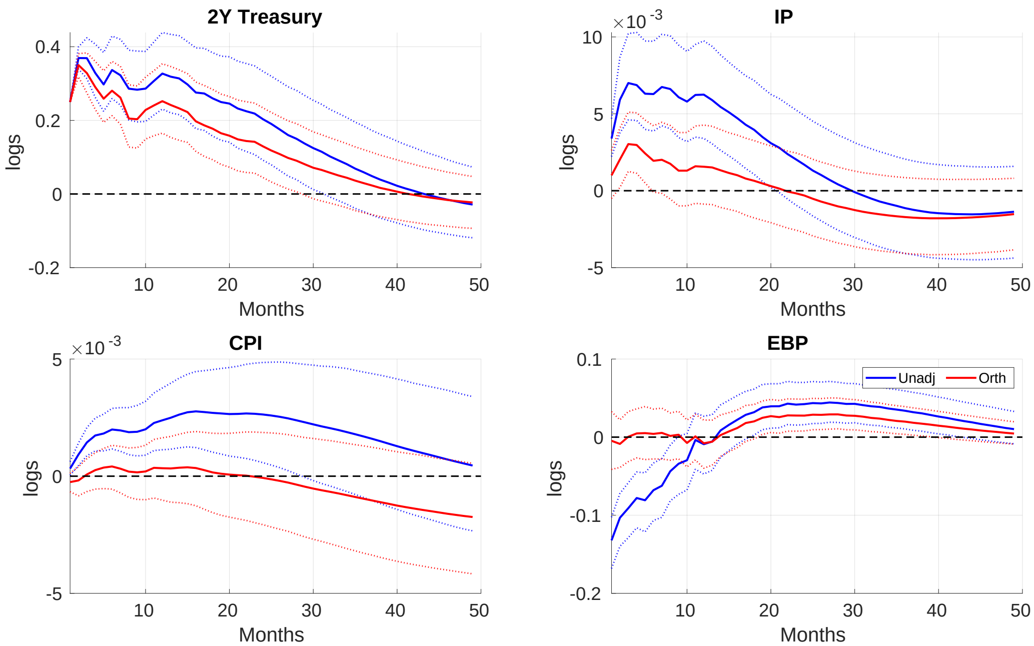


Figure 3: Impulse Responses using **Long** Orthogonalized and Unadjusted surprises

(a) **Intradaily**



(b) **Daily**

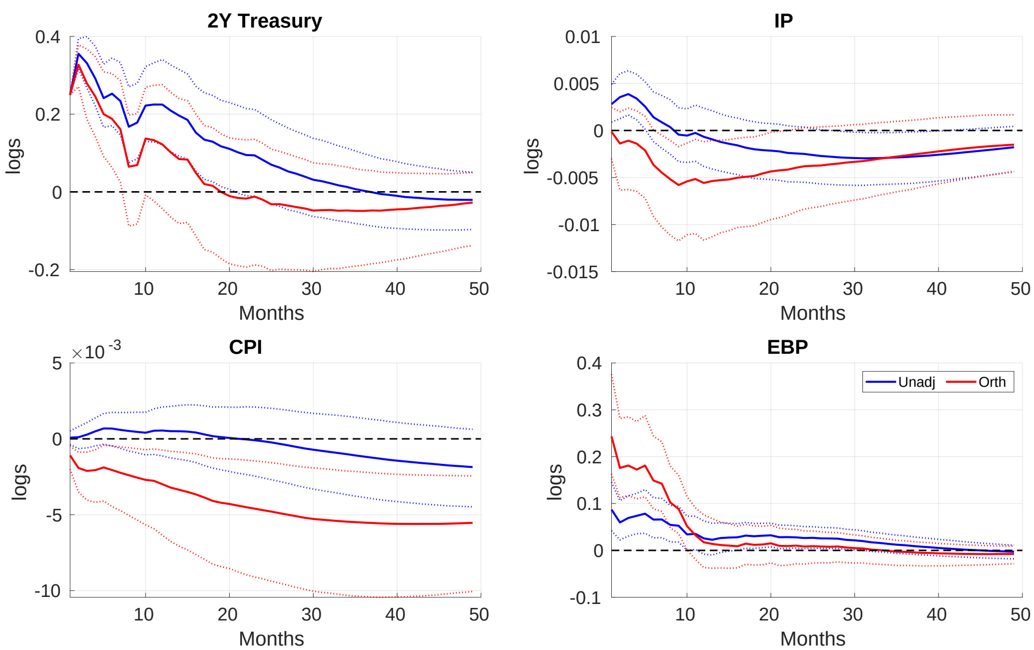
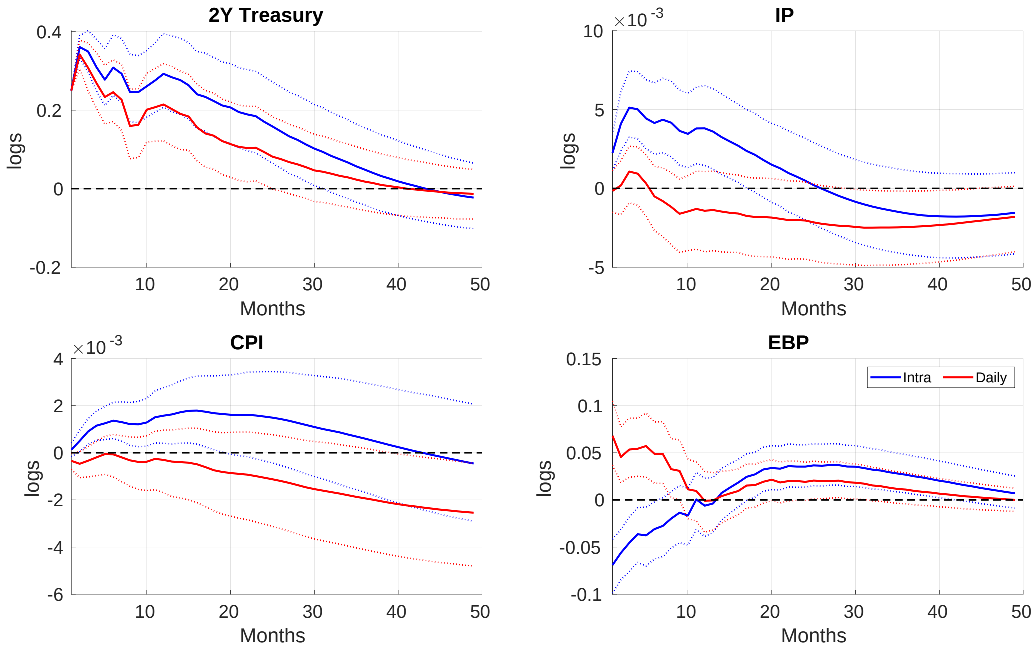


Figure 4: Impulse Responses using **Unadjusted** surprises

(a) **Short**



(b) **Long**

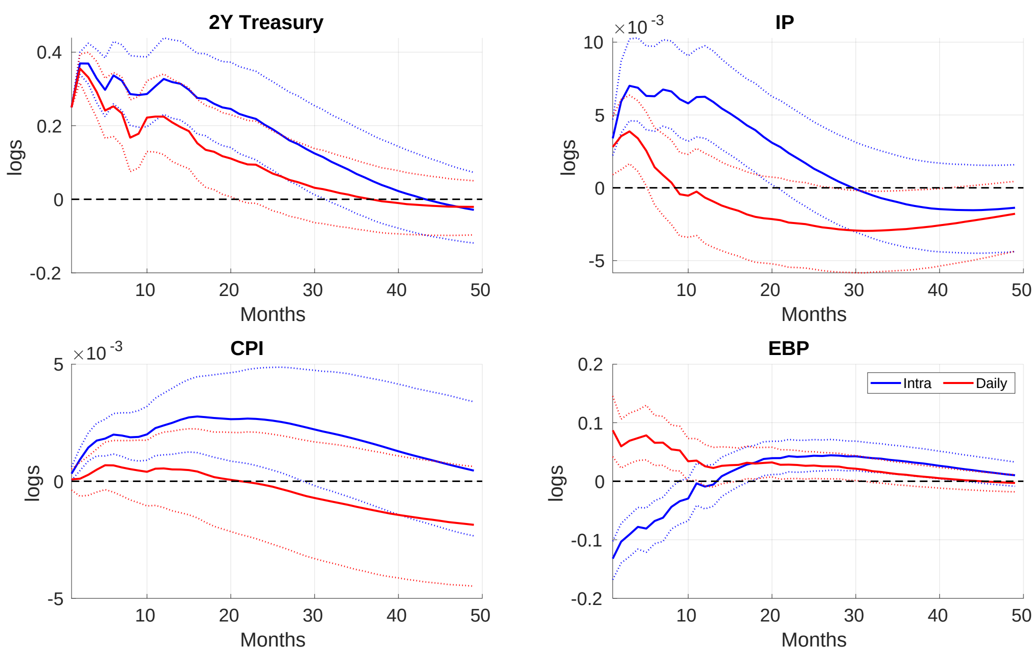
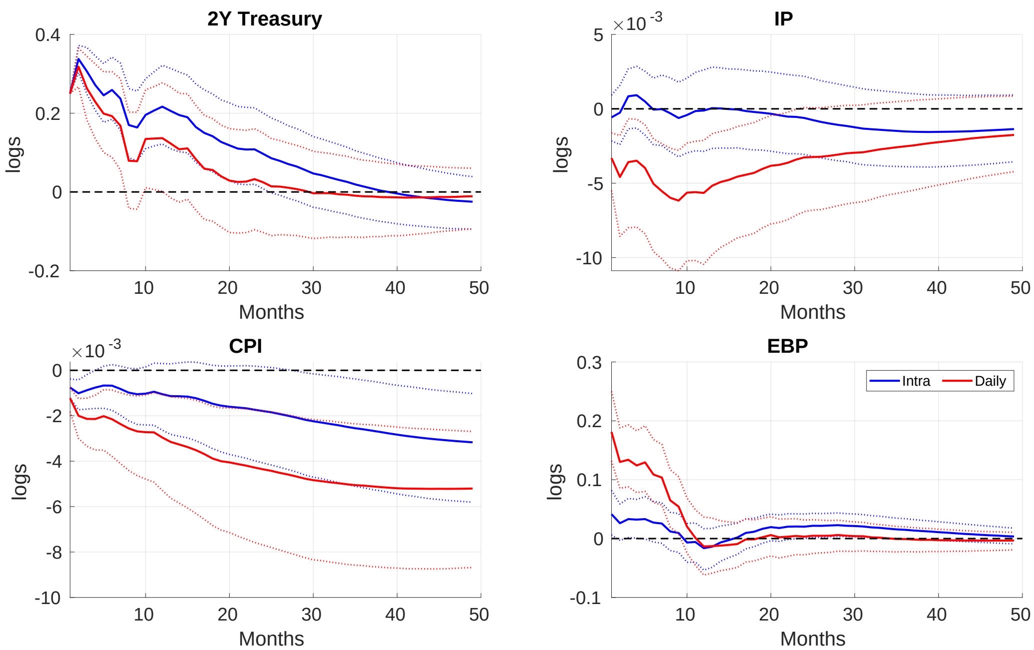
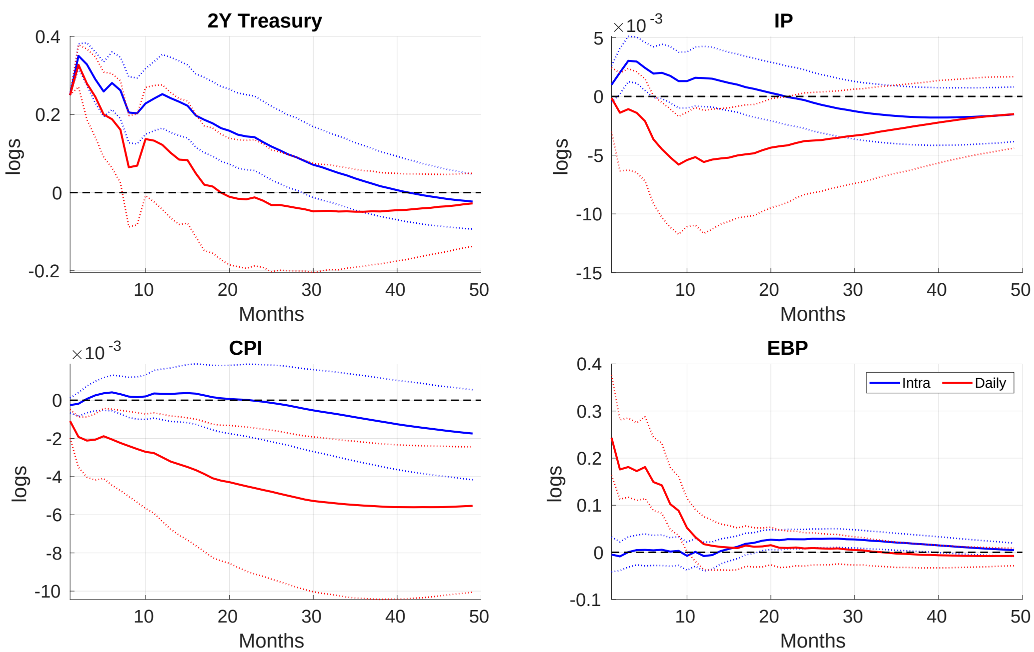


Figure 5: Impulse Responses using **Orthogonalized** surprises

(a) **Short**



(b) **Long**



A.2 Data

Table 1: Components of Bloomberg Economics Surprise Indices

Labor Market (ECSULBUS Index)	**Inflation Index (BCMPUSIF Index)**	**Growth Index (BCMPUSGR Index)**	**Growth Index (Cont.)**
ADP Employment Change	US GDP Price Index QoQ SAAR	Initial Jobless Claims	ISM Services PMI
Initial Jobless Claims	BLS Employment Cost	Continuing Claims	Construction Spending
Continuing Claims	PCE Core Price Index	GDP Chained 2012$	Philly Fed Business Outlook Survey
Change in Nonfarm Payrolls	Unit Labor Costs Nonfarm Bus.	PCE	US Pending Home Sales Index MoM
Change in Manufacturing Payrolls	CPI Urban Consumers	Labor Productivity Output	Durable Goods New Orders Total
Unemployment Rate	PPI Final Demand	U-Mich Survey of Consumers	Treasury Federal Budget Deficit
	PCE Prices	ISM Man. PMI	Services PMI Bus. Act.
	US Personal Income	Nonfarm Payrolls	Richmond Man. Survey
	CPI Urban Consumers Less Foods and Energy	Adjusted Retail & Food Service	Dallas Fed Man. Outlook
	US Import Price Index	Conf. Board Consumer Confidence	Chicago Fed National Activity Index
	ISM Man. Report on Businesses	Dur. Goods New Orders	US Treasury Int'l Capital
	FHFA House Price Purchase Price Index	New One Family Houses Sold	Capacity Utilization
	PPI Final Demand Less Foods and Energy	U-3 Unemp. Rate	Private Housing Authorized by Building Permits
	S&P CoreLogic Case-Shiller 20-city index	New Priv. Owned Housing	NFIB Small Business Optimism Index
	US Ave. Hourly Earnings	Ind. Production	Capital Goods New Orders Nondef.
		ADP National Emp. Report	Cap. Goods Shipments Ex Air.
		NAR Total Existing Homes Sales	Nat'l Assoc. of Home Builders Index
		Man. New Orders	US Auto Sales Total
		Trade Balance of Goods&Services	Fed Consumer Credit Report
		Empire State Man. Index	US Jobs Openings
		Conference Board US Leading Indicators	US Man.&Trade Inventories
		Market News Int'l Chicago Bus. Barometer	Private Housing Units Started
		Merchant Wholes. Inv.	US Ave. Weekly Hours All Employed
		Labor Force Participation Rate	KC Fed Man. Index
		Retail Sales Less Food Services	US Export Price by End Use All
		US Trade in Goods Balance Total	