How Do Cryptocurrencies Price Economic News?*

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Abstract

We use novel intraday data to study the price discovery process in cryptocurrency markets around U.S. monetary policy, inflation, and labor market announcements. Our analysis reveals the following: (1) volatility, trading volume, and bid–ask spreads rise sharply at announcement times and remain elevated for up to 30 minutes relative to comparable non-announcement intervals, indicating that cryptocurrency investors pay attention to these announcements and that information is quickly incorporated; (2) announcement surprises associated with higher yields or "risk-off" conditions cause substantial cryptocurrency price declines—pointing to a potential strengthening of U.S. monetary policy transmission to the real economy in recent years; (3) the time-varying magnitude and direction of price reactions more closely resemble those of U.S. equities than those of fiat currencies or commodities, suggesting that cryptocurrencies behave primarily as risk-sensitive assets; (4) price impact estimates of order flow around announcements are consistent with rising institutional participation in cryptocurrency markets and their crucial role for price discovery.

JEL Codes: E44, E52, F31, G12, G14

Keywords: Cryptocurrency, Macroeconomic News Announcements, Monetary Policy, Bitcoin, Ethereum, Price Discovery, High-frequency Identification

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1 Introduction

The cryptocurrency market has grown tremendously over the last 16 years since the first cryptocurrency, Bitcoin, was created in 2009. The left panel of Figure 1 displays the exceptional growth in average trading volume on cryptocurrency markets since 2016. With more than $130 billion in daily trading volume in 2025, global cryptocurrency trading has surpassed that of major markets such as European equity markets and U.S. corporate and municipal bond markets. Moreover, excluding the U.S. dollar stablecoin Tether, the two dominant cryptocurrencies—Bitcoin (BTC) and Ethereum (ETH)—individually recorded trading volumes comparable to those of mid-sized major fiat currencies, including the Korean won and the Brazilian real, as shown in the right panel of Figure 1. Despite its size, the cryptocurrency market remains less well understood than more traditional financial markets, reflecting both its relative novelty and distinct characteristics.[1]

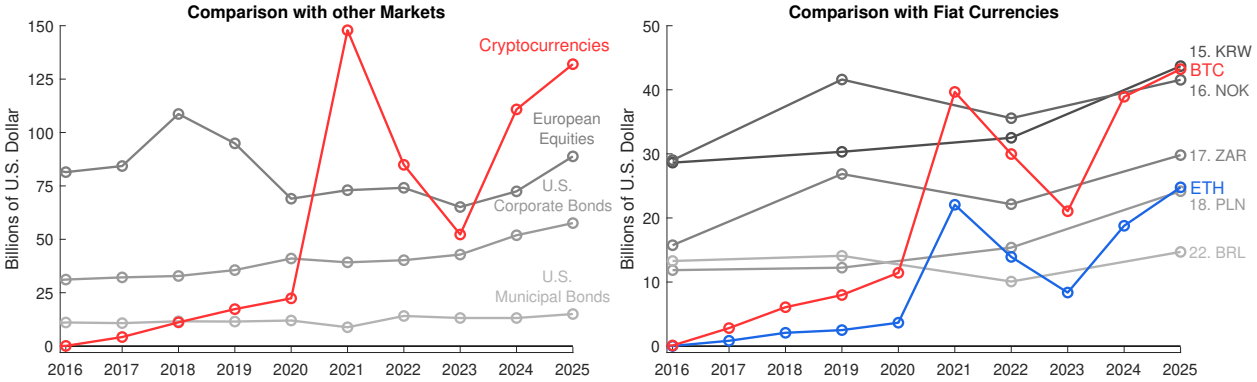
In this paper, we use a novel dataset covering more than 90 percent of global trading activity in cryptocurrencies over the past decade to study how major U.S. macroeconomic news information is incorporated (if at all) into cryptocurrency prices. Our data comes from *CoinDesk* and contains minute-by-minute transaction and quote information from 158 cryptocurrency exchanges and 18,403 currency pairs over the sample from 2015 to 2025. For our analysis, we focus on Bitcoin and Ethereum trading (vis-a-vis the U.S. dollar) on the three largest exchanges: Binance, OKX, and Coinbase. We use a high-frequency event study methodology to identify the effects of three major U.S. macroeconomic announcements on these cryptocurrencies: Federal Open Market Committee (FOMC) monetary policy decisions, Consumer Price Index (CPI), and nonfarm payroll employment (NFP) releases.[2]

Our high-frequency approach—focusing on narrow windows around announcement times—mitigates concerns about reverse causality and omitted variable bias (Bauer and Swanson, 2023) and has been widely used to advance our understanding of price discovery in traditional financial markets, including equities (McQueen and Roley, 1993), bonds (Fleming and Remolona, 1999), and exchange rates (Andersen et al., 2003). Our analysis reveals the following four findings regarding cryptocurrency markets and their response to monetary policy decisions as well as the state of the economy.

[1] In contrast to other financial assets, cryptocurrencies have multiple uses and regulatory treatments. For example, Bitcoin is treated as an asset for tax purposes by the Internal Revenue Service (IRS) and as a commodity by the Commodity Futures Trading Commission (CFTC). Survey evidence shows that investors use cryptocurrency as an investment, a means of payment, and a means to transfer money (Federal Reserve Board, 2025).

[2] We focus on these announcements because prior work shows that announcement timing and intrinsic information content determine which announcements have an effect on asset prices (Gilbert et al., 2017). FOMC, CPI, and NFP releases are both timely and central within their respective categories—interest rates, inflation, and economic activity.

Figure 1: Average Daily Trading Volume of Cryptocurrencies



Notes: This figure reports average daily trading volumes for a given year since 2016. The left panel shows global cryptocurrency volume (red) alongside volumes in the U.S. corporate and municipal bond markets. The right panel compares the trading volumes of Bitcoin (red) and Ethereum (blue) with those of fiat currencies ranked by their trading volume in 2025 from 15th place (Korean Won) to 22nd place (Brazilian Real). All figures refer exclusively to spot trading volumes. Cryptocurrency volumes are based on data from CoinDesk, which covers more than 90% of global cryptocurrency trading activity; Section 2 provides additional details. Statistics on European equities are from the Federation of European Securities Exchanges (FESE), and statistics on U.S. corporate and municipal bond trading are from the Securities Industry and Financial Markets Association (SIFMA). Data on fiat currencies are from the Bank for International Settlements (BIS) Triennial Survey and refer to average daily trading volume in April of the respective year. Abbreviations: BTC—Bitcoin; ETH—Ethereum; KRW—Korean Won; NOK—Norwegian Krone; ZAR—South African Rand; PLN—Polish Zloty; BRL—Brazilian Real.

First, cryptocurrency markets respond sharply and nearly instantaneously to macroeconomic announcements. Relative to non-announcement days, volatility and trading volume spike and bid–ask spreads widen at release times. The difference between announcement and non-announcement days is not only highly statistically significant but also economically large, reaching up to three standard deviations. In a world where investors are flooded with information, but have only limited time and resources to properly digest it, we interpret an increase in price volatility and trading volume at the time of the news releases as cryptocurrency investors paying attention to this particular type of news (e.g., DellaVigna, 2009; Andrei and Hasler, 2014) and incorporating information into prices. Elevated price volatility, in turn, causes bid-ask spreads to widen because liquidity providers demand compensation for bearing inventory costs (Ho and Stoll, 1981) and adverse selection costs (Glosten and Milgrom, 1985; Kyle, 1985).

Price volatility, trading volume, and bid-ask spreads revert to normal levels within 15–30 minutes, consistent with rapid price discovery comparable to that observed in U.S. Treasury markets (Fleming and Remolona, 1999). FOMC and CPI announcements generate stronger effects than NFP releases, and the FOMC press conference itself triggers a significant re-

sponse, consistent with recent evidence for U.S. Treasury and equity markets (Swanson, 2023). Across exchanges, Coinbase, the exchange with the highest trading fees, exhibits larger increases in trading costs and slower reversals.

Second, we find that contractionary monetary policy shocks identified using Nakamura and Steinsson (2018) produce significant declines in Bitcoin and Ethereum prices. Non-yield monetary policy shocks (Boehm and Kroner, 2024) associated with "risk-off" conditions similarly generate pronounced price declines. CPI and NFP surprises that raise yields—higher-than-expected inflation or stronger employment—also lead to immediate and significant price drops. Both the conventional headline surprise (Andersen et al., 2003) and the non-headline surprise (Gürkaynak, Kısacıkoğlu, and Wright, 2020) matter, with the latter often exerting stronger effects. Across specifications, Bitcoin and Ethereum respond qualitatively similarly, although Ethereum's reactions are typically larger in magnitude.

As we document quantitatively stronger reactions of Bitcoin and Ethereum compared to other asset prices such as equities, our evidence suggests that cryptocurrency markets may have amplified the transmission of U.S. monetary policy to the broader economy through wealth effects associated with cryptocurrency holdings and the resulting changes in consumption behavior. Aiello et al. (2023), using micro-level data on U.S. households, document that variation in household cryptocurrency wealth has an effect on their consumption behavior and thus the real economy. In particular, they find that the propensity to consume out of cryptocurrency wealth is twice that of equity wealth.[3] Additionally, there is evidence that a fraction of cryptocurrency investors are first-time investors and do not own any other investment products.[4] Taken together, even though we do not have a counterfactual to compare to, the evidence suggests that cryptocurrency wealth effects may have strengthened U.S. monetary policy transmission in recent years and could grow in importance going forward.

Third, our analysis also sheds light on cryptocurrency price behavior by comparing its response to macroeconomic news announcements to the response of other asset classes. On average, prices of U.S. equities, fiat currencies (the euro and Japanese yen), and commodities (gold and oil) generally decline in response to positive surprises associated with increases in interest rates, and hence respond qualitatively similarly to each other and to Bitcoin

[3]For context, 7 percent of U.S. households invested in cryptocurrencies as of 2024 compared to 58 percent in equities (Federal Reserve Board, 2025).

[4]JPMorgan Chase (2025) document—using data on 10 million active Chase checking account users—that over time 5–25 percent of cryptocurrency investors are first-time investors, with the highest share of first-time investors reached in 2021. More direct evidence of retail cryptocurrency investors not owning other investment products comes from Ontario Securities Commission's (2023) Crypto Asset survey of 2,360 Canadians conducted in 2023. The survey suggests that up to 20 percent of Canadian cryptocurrency investors are first-time investors that do not own any other investment products.

and Ethereum, making a clear distinction difficult at first glance. However, we investigate the possibility of a time-varying response to news and find a striking difference across asset classes. When the response of cryptocurrencies to news intensifies, we also observe increased sensitivity of U.S. equities to news. In contrast, fiat currencies and commodities become less responsive during these periods. Moreover, for NFP news we observe a sign flip in cryptocurrency reactions around the same time as for U.S. equities, the latter being a well-documented result in the literature (Boyd, Hu, and Jagannathan, 2005).[5] Overall, the findings indicate that, in terms of how economic information is incorporated into prices, Bitcoin and Ethereum prices are most similar to equity prices, suggesting that cryptocurrencies behave primarily as a risk-sensitive asset class.

Fourth, our results indicate that the market sensitivity of Bitcoin and Ethereum to economic news substantially increased post-2021, both in absolute terms and relative to other asset classes, coinciding with the increased participation of institutional investors in cryptocurrency markets (Huang, Lin, and Wang, 2022; DeVault, Turtle, and Wang, 2025). We investigate this link further by estimating the price impact of order flow—a measure of aggressive net demand for the asset—across the three cryptocurrency exchanges. Prior work that studies the price impact of order flow in the U.S. Treasury market argues that certain institutional investors possess superior capacity to process macroeconomic information ("informed traders"), leading to information asymmetries and increased price impact of order flow around economic news announcements (Green, 2004; Pasquariello and Vega, 2007; Czech et al., 2021). Thus, if the increased market sensitivity of cryptocurrencies to news is indeed associated with the rise in institutional trading activity, we also expect to find an increased price impact of order flow around announcements compared to non-announcement periods.

For the Binance and OKX exchanges, we generally find positive and significant contemporaneous and long-term price impact of order flow. Consistent with the notion that institutional traders—who specialize in processing economic news—have increasingly en-

[5] Boyd, Hu, and Jagannathan (2005) argue that good news for employment during good times (economic expansionary periods) may be bad news for the stock market because the negative discount rate (higher interest rate and risk premium) effect dominates the positive cash flow (higher earnings) effect. Good employment news may increase firm's earnings in the near future, causing equity prices to rise, but the discount rate (interest rate and risk premium) may also increase because the Fed is more likely to tighten monetary policy after good employment news, causing equity prices to go down. During bad times, good news is unambiguously good news for the stock market because it implies higher firm's earnings without a higher probability of the Fed tightening monetary policy (Gilbert et al., 2017). For cryptocurrencies, there are no earnings, but there are two opposing effects. Good employment news means people are more likely to purchase cryptocurrency, raising prices, but good employment news during good times means the cryptocurrency discount rate (interest rates and risk premia) is likely to go up as the Fed is more likely to tighten monetary policy, causing prices to go down.

tered cryptocurrency markets in recent years, we find a higher price impact of trades on announcement days relative to non-announcement days starting in 2021. Further, we document a larger price impact after announcements than before, consistent with increased information asymmetry arising from certain investors' superior ability to process economic information. For Coinbase, in contrast, we generally find no evidence of informed trading activity: price impacts are often significantly negative prior to 2021 and mostly insignificant thereafter, potentially suggesting a more dominant role for contrarian retail trading activity. Overall, our findings suggest a structural break around 2021, affecting both the response of cryptocurrency prices to economic news and the price impact of order flow.

Related literature Our paper contributes to several strands of the literature. First and foremost, we contribute to work studying the pricing of cryptocurrencies.[6] Prior work mostly documents a disconnect between macroeconomic conditions and cryptocurrency prices. For example, Liu and Tsyvinski (2021) and Liu, Tsyvinski, and Wu (2022) show that cryptocurrency returns are captured by pricing factors specific to cryptocurrency markets, rather than by factors common across markets or related to broader economic conditions. In a similar spirit to our analysis, Corbet et al. (2020), Pyo and Lee (2020), and Benigno and Rosa (2023) study the effects of U.S. economic news announcements on Bitcoin prices, documenting limited effects at best. For example, Benigno and Rosa (2023) find that Bitcoin generally does not respond to U.S. monetary and macroeconomic news surprises, with the exception of CPI surprises.

We contribute to this existing line of work by using novel high-quality data that allows us to document how economic news leads to statistically and economically significant reactions in Bitcoin and Ethereum markets. Specifically, our analysis differs from prior work in that we use granular intraday data on cryptocurrency markets (rather than relying solely on aggregated price indices), exploit a longer sample period, and employ recent advances in measuring economic news (Gürkaynak, Kısacıkoğlu, and Wright, 2020; Boehm and Kroner, 2024). Additionally, we show that market reactions of cryptocurrencies to economic announcements have increased in recent years. This finding echoes Karau (2023), who shows that Bitcoin begins to respond to U.S. monetary policy news after 2020, and helps explain why earlier papers find it harder to detect systematic reactions.

Our findings also relate to a large literature on the transmission channels of U.S. monetary policy to U.S. and foreign economies, and more generally how U.S. macroeconomic news

[6] By now, this is a voluminous literature. Key references include Abadi and Brunnermeier (2018), Schilling and Uhlig (2019), Makarov and Schoar (2019, 2020), and Sockin and Xiong (2023), among many others.

affects foreign economies. Prior work has documented the importance of both U.S. monetary policy and macroeconomic news for global financial markets (Miranda-Agrippino and Rey, 2020; Boehm and Kroner, 2026). Since Bitcoin and Ethereum investors are global, U.S. macroeconomic news can affect foreign economies through a cryptocurrency wealth effect. Specifically, our results in combination with the findings by Aiello et al. (2023) suggest an amplified transmission of U.S. monetary policy to the U.S. and foreign real economies through changes in households' wealth and consumption behavior. Our findings also contribute to the voluminous body of work analyzing the response of asset prices to monetary policy announcements to understand different monetary policy transmission channels to the real economy (e.g., Bernanke and Kuttner, 2005; Nakamura and Steinsson, 2018).

Our analysis is also able to speak to the similarities of cryptocurrencies to other asset classes, in particular with respect to their hedging properties. Advocates of cryptocurrencies often argue that they act as safe-haven assets (i.e., a hedge against global downturns) or inflation hedges, similar to gold or the U.S. dollar.[7] While prior work has found some evidence in support of such claims (Dyhrberg, 2016; Blau, Griffith, and Whitby, 2021), there is also evidence against them (Smales, 2019; Baur and Hoang, 2021). As we document that the price discovery of cryptocurrencies in response to economic news resembles that of equities rather than that of fiat currencies or commodities, our findings suggest that Bitcoin and Ethereum behave more like risk-sensitive assets than inflation hedges or safe-haven assets.

Lastly, we contribute to the literature that studies information asymmetry and how information is incorporated into asset prices. Green (2004) and Pasquariello and Vega (2007) document that U.S. Treasury order flow becomes more informative for asset prices following major macroeconomic announcements, consistent with information asymmetries increasing as certain investors possess superior capacity to process economic information (Kim and Verrecchia, 1994, 1997). Czech et al. (2021) and Kondor and Pintér (2022)—using regulatory data on the U.K. government bond market—more directly show that sophisticated institutional investors such as hedge funds and mutual funds possess these superior processing capacities. We find that the price discovery process surrounding economic news fundamentally changed with the entry of institutional investors into cryptocurrency markets, consistent with their superior information-processing abilities increasing information asymmetry. By illustrating the similarities in the informational role of trading between traditional and cryptocurrency markets, our findings also echo the results of Easley et al.

[7] For example, Paul Tudor Jones—CEO of Tudor Investment—argued in 2020 that Bitcoin is a hedge against inflation (https://www.bloomberg.com/news/articles/2020-05-07/paul-tudor-jones-buys-bitcoin-says-he-s-reminded-of-gold-in-70s?sref=b88bZRaf, accessed March 16, 2026).

(2024), who document that major cryptocurrencies on the Binance exchange for 2021–2023 exhibit market dynamics broadly comparable to those of traditional financial markets.

Roadmap The paper proceeds as follows. Section 2 introduces the data used in this study. In Section 3, we investigate the general dynamics of cryptocurrency markets around economic news announcements, before estimating the sensitivity of cryptocurrency prices to economic news in Section 4. In Section 5, we study the role of institutional trading for the price discovery to economic news. Lastly, we conclude in Section 6.

2 Data

In this section, we describe the data used in our empirical analyses. We first discuss the intraday data on cryptocurrency markets, then outline the construction of our macroeconomic news variables, and finally describe the intraday data on other asset prices.

2.1 Cryptocurrencies

A number of characteristics make the cryptocurrency market a unique laboratory for studying price formation. There are over 18,000 cryptocurrencies that trade in non-integrated and independently owned exchanges around the world. On an individual basis the majority of these exchanges function like traditional exchange rate markets where investors submit buy and sell orders, and the exchange clears trades based on a centralized order book.

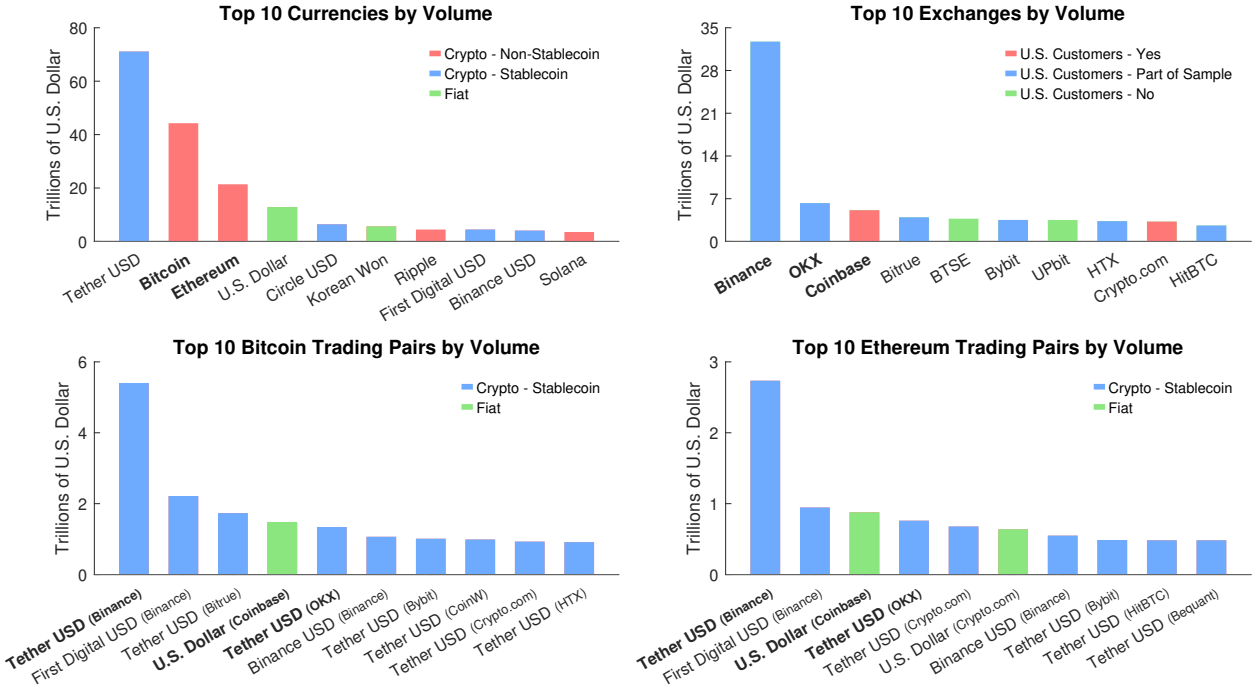
Our data on global cryptocurrency trading comes from *CoinDesk* and unifies data on a wide range of centralized cryptocurrency exchanges, covering over 90 percent of the global cryptocurrency trading activity.[8] For a given currency pair on a given exchange, the dataset provides a variety of summary statistics on trading and order book prices and quantities at the minute-by-minute frequency. Online Appendix A.1 provides an overview of the provided variables and their definitions. For our analysis, we exclusively focus on spot trading on a given exchange. The sample period runs from the start of 2015 until the end of 2025. However, the dataset is highly unbalanced as most exchanges did not exist in 2015 and order book information is only available starting in 2021.

The data allows us to identify which cryptocurrencies and exchanges are the most liquid and important ones, based on monthly trading volume in U.S. dollars.[9] One concern with cryptocurrency trading is that unregulated exchanges inflate the reported trading volumes

[8]The data was originally called *CryptoCompare Enterprise PRO API and Custom Measures Data*, before CoinDesk acquired data provider CryptoCompare in 2024.

[9]The dataset provides trading volume in the quote currency over a given interval. When the quote currency is not in U.S. Dollars or Tether, we convert it with end of day exchange rates to U.S. Dollars.

Figure 2: Overview of Global Cryptocurrency Trading



Notes: This figure displays the top entities in the global cryptocurrency trading by trading volume across four categories. In particular, it shows total trading volume in U.S. Dollars for the sample period 2015–2025. Bold fonts indicate the currency, exchange, and trading pairs chosen for our analysis.

(Cong et al., 2023). To mitigate this concern, we exclude months with highly irregular trading volume for a given currency pair on a given exchange, as detailed in Online Appendix A. Considering that the large majority of exchanges in the dataset are unregulated and our outlier procedure is conservative, the aggregate statistics on trading volumes should still be seen as an upper bound. Our dataset contains information on 158 cryptocurrency exchanges and 18,403 currency pairs. Figure 2 provides an overview of the most important currencies, exchanges, as well as Bitcoin and Ethereum trading pairs ranked by total trading volume over the sample period. We use total rather than yearly or monthly average trading volume to place greater weight on the time-series dimension of the selected series.

The top-left panel of Figure 2 shows total trading volume in U.S. dollars over the sample period 2015–2025 for the 10 most traded currencies.[10] The most traded currency is the stablecoin Tether, which is pegged to the U.S. dollar.[11] It is the most popular quote currency in

[10]For a given currency, we add both the trading volume when the currency functions as the base as well as the quote currency. Hence, the total trading volume by currency will be the twice the trading volume in the sample.

[11]The issuer, Tether, maintains its peg to the U.S. dollar by holding reserves of assets. According to Spira and

cryptocurrency exchanges and the least expensive way to move funds across cryptocurrencies and exchanges.[12] Bitcoin and Ethereum are the second and third most traded currencies in our sample period, by far the most traded non-stablecoin cryptocurrencies, and the focus of our study.

The top-right panel of Figure 2 shows the biggest exchanges by trading volume. Binance is the largest cryptocurrency exchange in our sample period, with total trading volume of approximately 33 trillion U.S. dollars. Binance was founded in China in 2017 and reportedly moved its headquarters to the United Arab Emirates in 2021.[13] The second largest exchange is OKX (formerly known as OKEx and OKcoin) with a total volume of 6 trillion U.S. dollars. OKX was originally launched in Hong Kong in 2017 and in 2025 moved its headquarters to the U.S. Third, we have Coinbase, a publicly traded U.S. company founded in 2012 with a total volume of 5 trillion U.S. dollars.

Based on the top panels of Figure 2, we focus our study on the two largest cryptocurrencies (Bitcoin and Ethereum) traded on the three largest exchanges (Binance, OKX, and Coinbase). In total, we have six cryptocurrency-exchange pairs. On Binance and OKX, Bitcoin (BTC) and Ethereum (ETH) are quoted against Tether (USDT), while on Coinbase, Bitcoin and Ethereum are quoted against the U.S. Dollar (USD). The bottom panels of Figure 2 confirm this selection as the three Bitcoin and the three Ethereum pairs are ranked among the top 5 trading pairs for Bitcoin and Ethereum, respectively. Table 1 provides summary statistics for the minute-by-minute return, volatility (absolute value of the return), trading volume, and bid-ask spread for the six cryptocurrency-exchange pairs.

There are a few takeaways from Table 1. First, the sample periods differ, as both Binance and OKX were founded in 2017, while Coinbase was founded in 2015, and Ethereum only began trading on exchanges in 2016 and 2017.[14] Second, despite the differences in sample periods, the returns and their volatility are very similar indicating that the price differences across the three exchanges are relatively small over the overlapping sample, which is con-

Wessel (2025)'s calculations, 81 percent of Tether's reserves are held in cash or cash equivalents (U.S. Treasury bills), while the rest are held in secured loans, Bitcoin, precious metals, and other investments.

[12] Cryptocurrency exchanges prefer stablecoins to fiat currencies as they allow for more efficient transactions to non-stablecoin cryptocurrencies, for example, in terms of settlement speed (Lyons and Viswanath-Natraj, 2023), and also reduce the need for exchanges "to establish a legitimate fiat banking relationship" (Griffin and Shams, 2020, p. 1914). Stablecoins such as Tether and Circle also enable investors to move funds easily between cryptocurrency exchanges and profit from arbitrage opportunities by avoiding capital controls (Makarov and Schoar, 2020).

[13] Binance has traditionally kept the location of its headquarters opaque, arguably to avoid regulatory oversight (`https://finance.yahoo.com/news/did-binance-just-abu-dhabi-180000427.html`, accessed on February 2, 2026).

[14] The data covers minutes of market activity for a given cryptocurrency-exchange pair. Since cryptocurrency exchanges are essentially open 24 hours a day, seven days a week, minutes in which one market observes activity while others do not can further contribute to differences in the number of observations.

Table 1: Summary Statistics of Main Cryptocurrency-Exchange Pairs

Minute-by-minute	Bitcoin			Ethereum		
Frequency	Binance (USDT)	Coinbase (USD)	OKX (USDT)	Binance (USDT)	Coinbase (USD)	OKX (USDT)
Return (bp)						
Mean	0.01	0.01	0.01	0.01	0.01	0.01
SD	9.48	8.42	8.32	11.71	11.93	10.49
Obs.	4,404,719	5,785,920	4,013,532	4,404,719	5,061,574	4,237,490
Sample	2017–2025	2015–2025	2017–2025	2017–2025	2016–2025	2017–2025
Absolute Return (bp)						
Mean	5.79	4.90	5.29	7.33	7.05	6.81
SD	7.51	6.85	6.43	9.13	9.63	7.98
Obs.	4,404,719	5,785,920	4,013,532	4,404,719	5,061,574	4,237,490
Sample	2017–2025	2015–2025	2017–2025	2017–2025	2016–2025	2017–2025
Volume ($ Millions)						
Mean	1.16	0.23	0.30	0.58	0.16	0.16
SD	1.78	0.45	0.50	0.98	0.30	0.29
Obs.	4,404,720	5,785,920	4,013,533	4,404,720	5,061,575	4,237,491
Sample	2017–2025	2015–2025	2017–2025	2017–2025	2016–2025	2017–2025
Bid-Ask Spread (bp)						
Mean	0.07	0.37	0.03	0.06	0.56	0.06
SD	0.18	0.55	0.01	0.11	0.77	0.09
Obs.	2,350,023	2,627,153	2,290,501	2,353,607	2,629,277	2,295,196
Sample	2021–2025	2021–2025	2021–2025	2021–2025	2021–2025	2021–2025

Notes: This table provides the summary statistics of the six cryptocurrency-exchange pairs used for our analysis. Mean, standard deviation (SD), number of observations (Obs.), and sample period are provided at minute-by-minute frequency for four variables: return, absolute return, trading volume, and bid-ask spread. Bitcoin and Ethereum are quoted against the U.S. Dollar (USD) on the Coinbase exchange or against Tether (USDT) on the Binance and OKX exchanges. Returns are winsorized at the top and bottom 0.5 percent, while trading volume and bid-ask spreads are winsorized at the top 1 percent.

firmed in Online Appendix Table A1. Third, Binance has by far the largest trading volume for both Bitcoin and Ethereum, confirming Figure 2. Lastly, the bid–ask spread is substantially larger on Coinbase than on Binance and OKX. This difference is likely driven in part by differences in trading fees, reflecting both the U.S. Securities and Exchange Commission (SEC) regulatory compliance costs faced by Coinbase as well as the fact that Binance and OKX compete aggressively for customers through lower trading fees.[15]

2.2 Monetary Policy and Macroeconomic News

2.2.1 FOMC Announcements

We follow a large prior literature and focus on FOMC announcements to study the impact of monetary policy news (e.g., Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018). We obtain timestamps of the FOMC statement releases and the

[15]For example, Binance eliminated fees for certain Bitcoin trading pairs in 2022 (https://research.kaiko.com/insights/the-impact-of-binances-zero-fee-volume, accessed on February 2, 2026), while OKX is usually seen as having one of the lowest fee structures among exchanges (https://www.forbes.com/sites/javierpaz/2025/01/28/the-worlds-most-trustworthy-crypto-exchanges/, accessed on February 2, 2026).

subsequent press conferences from *Bloomberg* and cross-check them with information on the Federal Reserve website. Over our sample period from 2015–2025, we have 87 scheduled FOMC announcements, 71 of them including a press conference.[16]

To measure traditional monetary policy news, we follow Nakamura and Steinsson (2018) and construct updated versions of their policy news shock, which aims to capture the common variation in unexpected yield changes. As will become clearer shortly, we refer to their shock as the yield shock for the rest of the paper. In particular, *yield shock* s_t^y is estimated as the first principal component from the following specification:

$$\Delta y_t = \zeta s_t^y + \varepsilon_t, \tag{1}$$

where t refers to the FOMC meeting date. Δy_t is the vector of changes in interest rates, where we use the standard $MP1$, $MP2$, $ED2$, $ED3$, and $ED4$ variables as in Nakamura and Steinsson (2018). These variables are measured as changes over a window from 10 minutes before the statement release to 60 minutes after the start of the press conference, as constructed by Acosta et al. (2025).[17] We allow the window to include the press conference as recent papers document its importance for the transmission of monetary policy news to financial markets (e.g., Swanson, 2023).

To study the effects of monetary policy news not captured by the yield curve, we also employ the Fed *non-yield shock* by Boehm and Kroner (2024). The authors document that conventional high-frequency shocks (such as the Nakamura and Steinsson's (2018) shock)—constructed solely from interest rate movements—fail to capture the full extent of monetary policy news. In particular, risky asset prices respond to FOMC news beyond the effects reflected in the yield curve. Conceptually, Boehm and Kroner (2024) estimate the non-yield shock s_t^{ny} from an equation of the following form:

$$\Delta p_t = \beta \Delta yc_t + \gamma s_t^{ny} + \varepsilon_t, \tag{2}$$

where Δp_t is a vector of returns in U.S. stocks and U.S. Dollar exchange rates, and Δyc_t is the change in the yield curve around FOMC announcements, which includes a broader set than Δy_t above. We take Boehm and Kroner's (2024) estimated shock series off-the-shelf

[16] Fed Chair Bernanke held the first press conference in April 27, 2011. From 2011 to 2018, Fed Chair press conferences were held four times a year coinciding with the release of the Summary of Economic Projections (SEP). On January 2019, Fed Chair Powell expanded press conferences to every FOMC meeting, eight times a year.

[17] For meetings with no press conference, Acosta et al. (2025) use the typical 30-minute window around the statement release.

for our analysis and renormalize it so that it corresponds to a one standard deviation over our sample period (2015–2025).[18] The top panel of Online Appendix Figure A1 displays the time series of the yield and non-yield shocks over the sample period.

2.2.2 CPI and NFP Announcements

To study the effects of macroeconomic news, we focus on the CPI release and the release of NFP as part of the employment situation report. We obtain data on CPI and NFP announcements from Bloomberg's U.S. Economic Calendar, which provides—among other things—the release date and time, the real-time realized values of the announcement's headline variables (as opposed to the revised figures), as well as the corresponding Bloomberg survey expectation prior to the release. We focus on these announcements because prior work shows that announcement timing and intrinsic information content determine which announcements have an effect on asset prices (Gilbert et al., 2017). CPI and NFP releases are both timely and central within their respective categories— inflation and labor markets. Consistent with this view, the NFP release is widely considered the most market-moving macroeconomic data release (e.g., Andersen et al., 2007; Boehm and Kroner, 2026). In addition, the CPI release has emerged as the most impactful data release during the 2021–2023 inflation surge (Kroner, 2025). Over our sample period from 2015–2025, we have 131 CPI announcements and 128 NFP announcements.[19]

For both CPI and NFP releases, we follow the prior literature (e.g., Andersen et al., 2003), and construct a *headline surprise* series $s_t^{h(k)}$, by subtracting from the realized announced value its survey forecast, that is,

$$s_t^{h(k)} = \frac{A_t^{(k)} - E_t^{(k)}}{\sigma_i^{(k)}}, \quad \text{for} \quad k \in \{\text{CPI, NFP}\}\,, \tag{3}$$

where $A_t^{(k)}$ denotes the realized value of announcement k at time t, $E_t^{(k)}$ refers to the Bloomberg survey expectation of indicator k prior to the release, and σ_k is the sample standard deviation of the surprise component, $A_t^{(k)} - E_t^{(k)}$. As Bloomberg allows forecasters to update their predictions until the release time, these forecasts should incorporate all publicly available information by the time of the announcement. Since σ_k is a constant for

[18] Boehm and Kroner's (2024) non-yield shock is available through July 2025. Hence, the last three FOMC meetings in 2025 are missing, leaving us with 84 observations for analyses that use it.

[19] As done by prior work, we exclude the NFP releases at the onset of the pandemic for which headline surprises (as defined in (3)) exceeded 9 standard deviations. In particular, we drop the releases in May, June, and July 2020. Further, note that both the CPI and employment situation report for October 2025 were not published due to a government shutdown.

each indicator k, the standardization does not affect the significance of the estimated response coefficients, nor the fit of the regression compared to the results based on the surprise component, $A_t^{(k)} - E_t^{(k)}$.[20]

To measure news not captured by the headline surprises, we construct *non-headline surprise* series for each announcement following Gürkaynak, Kısacıkoğlu, and Wright (2020). The authors show that markets react to the information of macroeconomic data releases beyond the headline surprises for which survey estimates exist. These "non-headline news" can be backed out from the excess volatility of the yield curve movements in a narrow window around the releases compared to non-release days. In particular, the non-headline surprise $s_t^{nh(k)}$ can be estimated from the following specification (with a slight abuse of notation):

$$\Delta y_t^{(k)} = \beta^{(k)} s_t^{h(k)} + \gamma^{(k)} s_t^{nh(k)} + \varepsilon_t^{(k)}, \quad \text{for} \quad k \in \{\text{CPI, NFP}\}\,. \tag{4}$$

$\Delta y_t^{(k)}$ denotes the vector of 6 yield changes in a 20-minute window around the announcement k at time t, where we use $ED1$, $ED4$, TU, FV, TY, and US as in Gürkaynak, Kısacıkoğlu, and Wright (2020). $s_t^{h(k)}$ is the headline surprise as defined in equation (3) and $\varepsilon_t^{(k)}$ is a vector of white noise with diagonal covariance matrix. We estimate equation (4) over the period from 1996–2025 to increase the precision of the estimates. We then renormalize the series so that they correspond to a one standard deviation over our 2015–2025 sample.[21] The middle and bottom panels of Online Appendix Figure A1 display the time series of the headline and non-headline surprises for CPI and NFP, respectively.

2.3 Other Financial Market Data

To investigate the intraday effects of economic news on other asset prices, we employ intraday asset price data from *London Stock Exchange Group (LSEG) Tick History* (formerly known as Thomson Reuters or Refinitiv Tick History), a standard dataset widely used for high-frequency analysis. Online Appendix Table A2 provides an overview of all intraday financial instruments employed in the main text.

[20] For the CPI, we use year-over-year rather than month-over-month inflation surprises, which allows us to include the November 2025 release since the October 2025 data was not collected and could not be recovered retroactively. For NFP releases, the October 2025 data was jointly published with the November release. Consequently, we calculate a cumulative surprise for that release.

[21] Despite differences in the sample period, our non-headline CPI and NFP surprises have correlations of 82 and 83 percent, respectively, with the original estimates of Gürkaynak, Kısacıkoğlu, and Wright (2020) for the overlapping sample.

3 Market Dynamics Around Economic Announcements

3.1 Price Volatility, Trading Volume, and Bid-Ask Spread

In this section, we analyze the effect that U.S. economic announcements (regardless of the size and sign of the surprise) have on cryptocurrency price volatility, trading volume, and trading costs. Since the effect economic news has on asset prices can change over time and over the business cycle (McQueen and Roley, 1993; Boyd, Hu, and Jagannathan, 2005), the simplest way to show that news is incorporated into cryptocurrency prices is to show that news raises price volatility (Jones, Lamonth, and Lumsdaine, 1998; Andersen et al., 2003) and trading volume (Chaboud et al., 2004). In a world where investors are flooded with information but have only limited time and resources to properly digest it, an increase in price volatility and trading volume at the time of news releases can be interpreted as information being incorporated into asset prices. It also reflects investors paying attention to this particular news, increasing the speed with which information is incorporated (e.g., DellaVigna, 2009; Andrei and Hasler, 2014). Increased volatility, in turn, causes bid-ask spreads to widen because liquidity providers demand compensation for bearing inventory costs (Ho and Stoll, 1981) and adverse selection costs (Glosten and Milgrom, 1985; Kyle, 1985).

Our methodology is similar to that of Fleming and Remolona (1999). We estimate the difference in means of minute-by-minute price volatility (measured as the absolute value of log returns), trading volume, and bid-ask spreads on announcement and non-announcement days. Each panel in Figure 3 shows this difference or the reaction of volatility (red), trading volume (blue), and bid-ask spreads (green) to an announcement (FOMC, CPI, and NFP), for a given cryptocurrency (Bitcoin and Ethereum) and exchange (Binance, Coinbase, and OKX). Each column displays results for an announcement. The top three rows show the results for Bitcoin across the three exchanges, while the bottom three rows show the results for Ethereum. For ease of interpretation, each series is normalized by its standard deviation for a given cryptocurrency–exchange pair. Solid dots indicate that the difference in means is statistically significant at the 5-percent level.

Across announcements and exchanges, we observe a sharp and nearly instantaneous price change at the time of the announcements (marked by dashed vertical lines), a surge in trading volume, and a widening of bid-ask spreads. Volatility, trading volume, and trading costs (bid-ask spreads) decline slowly after the initial reaction but stay elevated for at least 15 minutes across all releases. Based on prior work, a natural interpretation of the elevated price

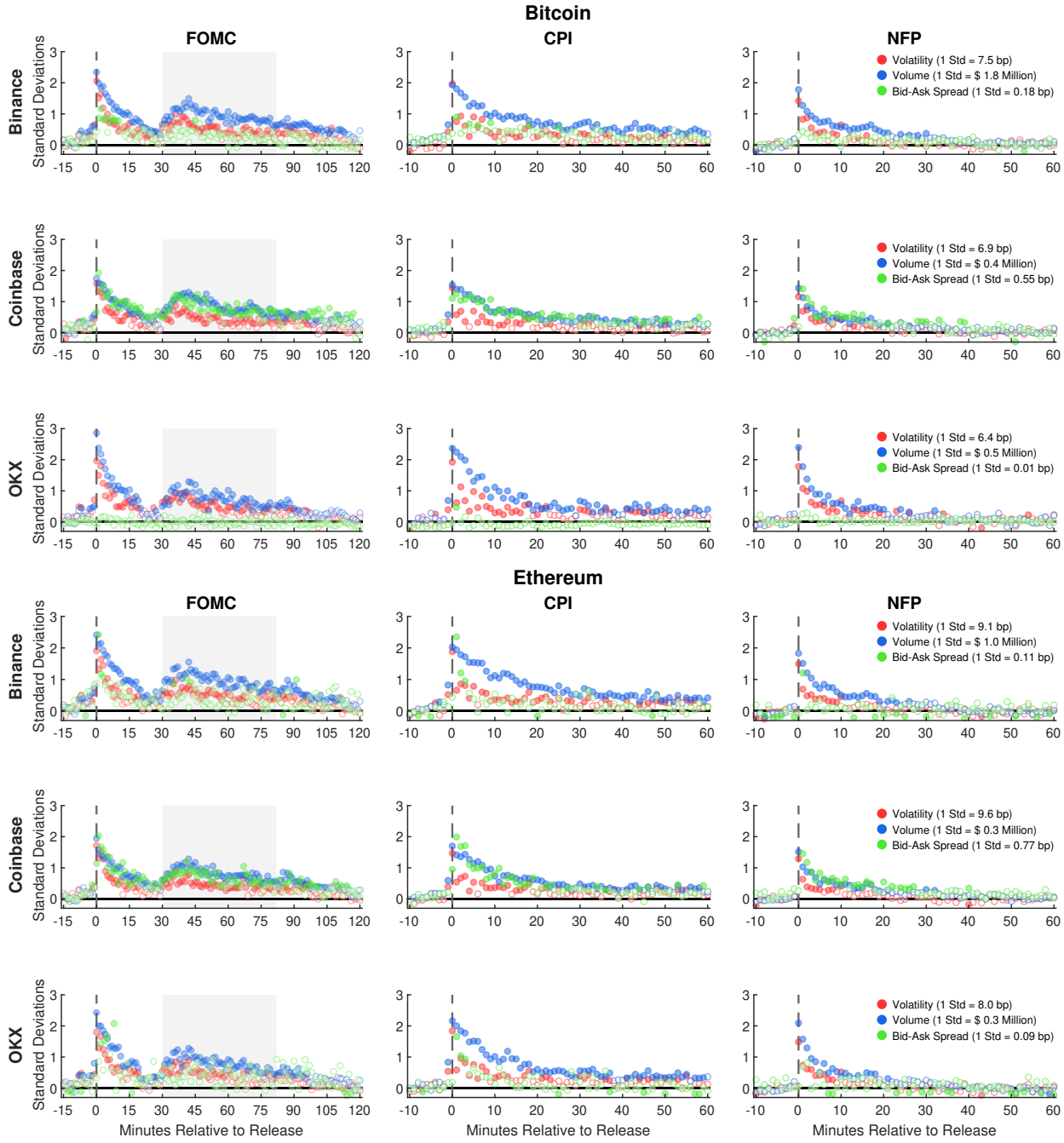
volatility and trading volume is that investors are paying attention to these announcements (e.g., DellaVigna, 2009; Andrei and Hasler, 2014) and information is incorporated into prices. Since investors are likely to have different views as to what an announcement means for prices depending on their analyses as well as their customer order flows, it takes time and trading volume for these differing views to be incorporated into prices (Fleming and Remolona, 1999). During these times of heightened uncertainty, price volatility, and trading volume, liquidity providers widen bid-ask spreads to be compensated for bearing inventory risk and adverse selection costs.

The reaction of cryptocurrencies to FOMC, CPI, and NFP announcements is similar in speed to the reaction of Treasury securities to these announcements (Fleming and Remolona, 1999; Fleming and Piazzesi, 2005). For interest rates, the effects of U.S. monetary policy decisions and macroeconomic news are well understood (e.g., Balduzzi, Elton, and Green, 2001, among many others), and it is therefore not surprising that information is rapidly incorporated into Treasury prices. For cryptocurrencies, however, such a rapid response is less expected given prior work. In particular, Benigno and Rosa (2023) document that there is a "disconnect" between the macroeconomy and cryptocurrency prices, with the exception of inflation news. In addition, Bhambhwani, Delikouras, and Korniotis (2023) argue that the fundamental drivers of cryptocurrency prices are network size and computing power. Similarly, Liu and Tsyvinski (2021) document that cryptocurrency prices are driven by factors that are specific to cryptocurrency markets. Moreover, cryptocurrency markets are often characterized as inefficient (Makarov and Schoar, 2020). In contrast, our results suggest that macroeconomic information is quickly incorporated into cryptocurrency prices.

Despite the broadly similar impact, there are important differences across the three announcements. For FOMC announcements, Figure 3 shows that volatility, trading volume, and trading costs surge again and remain elevated during the Fed Chair's press conference (shaded in gray), highlighting its importance for markets. That said, the peak magnitude of the surge during the press conference is smaller than that following the statement release, presumably because information is revealed more continuously during the press conference.[22] The impact of CPI announcements is similar in magnitude to that of FOMC statements, as indicated by the size of the immediate jump and the duration for which volatility, trading volume, and bid–ask spreads remain significantly elevated—approximately 30 minutes. In

[22]The Fed Chair started to have post-FOMC meeting press conferences in 2011, after every other meeting. Only in 2019, the Chair began to hold a press conference after every FOMC meeting. Therefore, in the first four years of our sample period we have 8 days out of the 16 FOMC meeting days without a press conference, which depresses average volatility, bid-ask spreads, and trading volume during the shaded press-conference period in our sample period.

Figure 3: Effects of Announcements on Price Volatility, Trading Volume, and Bid-Ask Spread



Notes: This figure displays the difference in means of minute-by-minute price volatility (measured as the absolute log-return), trading volume, and the bid–ask spread on announcement days relative to non-announcement days. For a given cryptocurrency and market, each series is normalized by its standard deviation; the legend in each row reports the mapping from standard deviations to the original units. Filled dots indicate that the difference in means between announcement and non-announcement days is statistically significant at the 5 percent level (based on a t-test assuming unequal variances). For FOMC releases, the grey shaded area indicates the average timing of the FOMC press conference over the sample period. The sample period is from 2015 to 2025.

contrast, NFP announcements trigger a more muted and short-lived reaction, with market indicators remaining significantly elevated for about 10 minutes.

There are also differences across the three exchanges. Reactions on Binance and OKX are slightly stronger than on Coinbase. For volatility and trading volume, the Coinbase sample is about two years longer, which could explain part of the difference.[23] While all three exchanges exhibit similar initial spikes in bid–ask spreads, trading costs on Coinbase remain elevated for much longer than on Binance and OKX. In particular, OKX shows a very rapid decline in trading costs after the announcement. This may reflect differences in market structure across exchanges, which are also evident in the average trading costs discussed in Section 2.

Somewhat surprisingly, there are almost no visible differences between Bitcoin and Ethereum in Figure 3, suggesting that price discovery operates similarly for both cryptocurrencies. Given the many technological differences between them—for example, differences in blockchain mechanisms (proof-of-work versus proof-of-stake)—this indicates that such technological distinctions are not of first-order importance for price formation in response to economic news. Finally, Online Appendix Figures B2–B4 show the average 10-hour long intraday paths for announcement and non-announcement days, confirming the results in Figure 3.

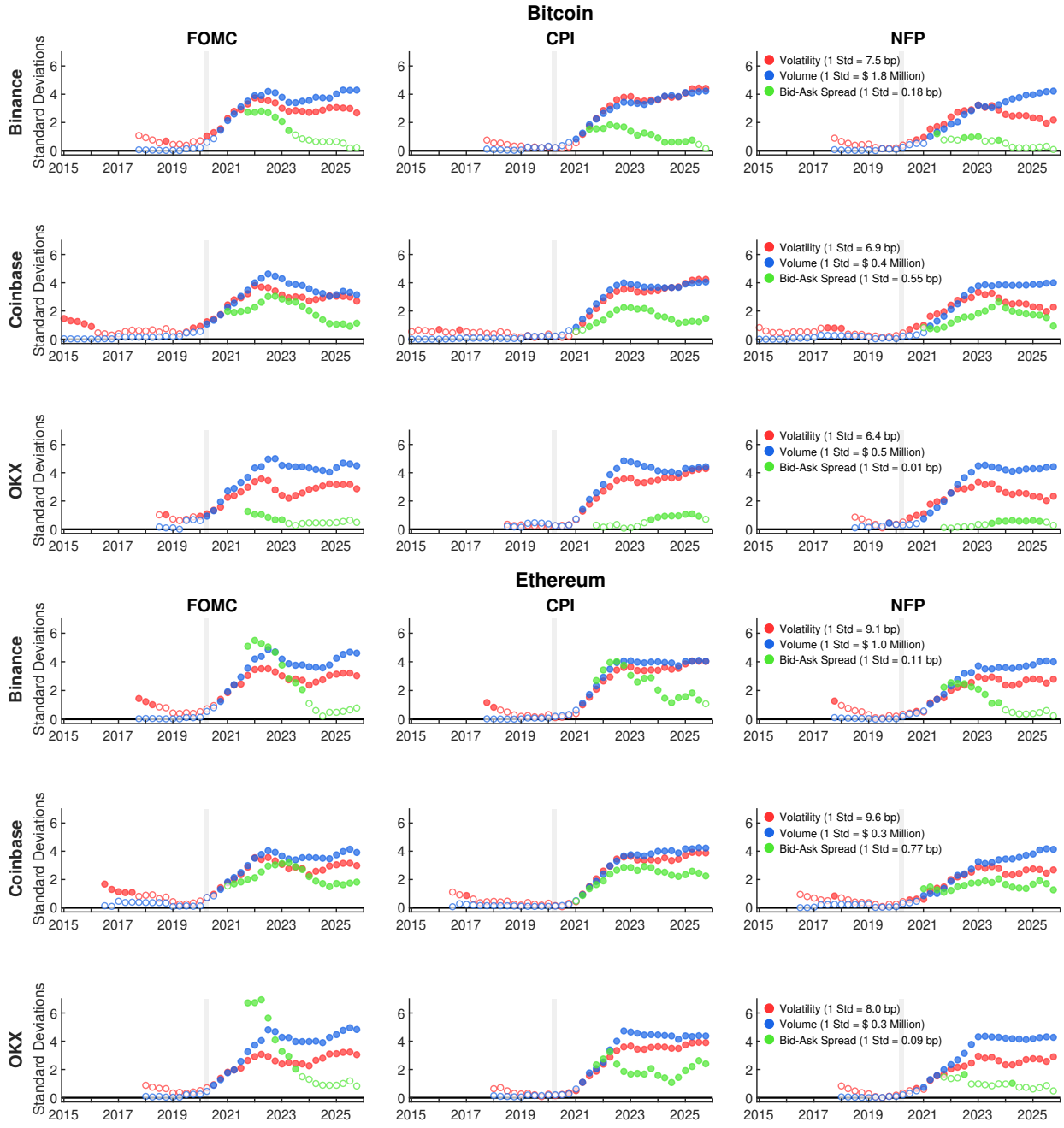
3.2 Time-Variation in Announcement Effects

As indicated in Figure 1 in the Introduction, cryptocurrency markets have undergone an extraordinary transformation over the last 10 years. For this reason, we now investigate how the trading behavior around FOMC, CPI, and NFP releases—illustrated in Figure 3—changes over the sample period. To do so, we estimate the difference in means of minute-by-minute price volatility (measured as the absolute value of log returns), trading volume, and bid–ask spreads on announcement compared to non-announcement days using a rolling window. In particular, for each month, we consider a 2-year rolling window centered around the first trading day of that month and compute the maximum difference in means—within a window from 5 minutes before to 30 minutes after the release—on announcement days relative to non-announcement days. Figure 4 displays the estimates.

Figure 4 yields several key takeaways. First, prior to 2020, cryptocurrency markets generally exhibit limited systematic reactions to announcements, as volatility and trading volume

[23] Additionally, on Coinbase, Bitcoin and Ethereum are quoted in U.S. dollars, whereas on Binance and OKX they are quoted against the stablecoin Tether. Although Tether is pegged to the U.S. dollar, small price differences between the two may arise, which could contribute to differences in measured price reactions across exchanges. We investigate this further in Online Appendix Figure B1.

Figure 4: Time-Variation in Announcement Effects over the Sample Period



Notes: This figure displays the maximum difference in means of minute-by-minute price volatility (measured as the absolute log return), trading volume, and the bid–ask spread on announcement days relative to non-announcement days, computed on a rolling basis over the sample period. Each dot indicates the maximum difference in means around a given announcement, computed within a window from 5 minutes before to 30 minutes after the release, using a 2-year rolling window centered around the first trading day of each quarter. For a given cryptocurrency and market, each series is normalized by its standard deviation; the legend in each row reports the mapping from standard deviations to the original units. Filled dots indicate that the difference in means between announcement and non-announcement days is statistically significant at the 10 percent level (based on a t-test assuming unequal variances). Grey bars indicate NBER recession periods.

do not increase significantly around releases in most cases. Across announcements, FOMC ones show the strongest evidence of market reactions based on excess volatility. Second, from 2020 to 2023, both Bitcoin and Ethereum begin to react systematically to announcements, with pronounced spikes in volatility and trading volume. The magnitudes of excess volatility and trading volume rise sharply until 2022 and grow more gradually thereafter. Finally, we find that spikes in bid-ask spreads around announcements have generally diminished since 2023, indicating increased market liquidity and more efficient price discovery.

These findings echo the results of Karau (2023), who documents that prior to 2020 the price of Bitcoin did not respond to FOMC monetary policy surprises; however, thereafter significant effects emerge. The muted market reactions in the earlier part of our sample may also explain why prior work such as Corbet et al. (2020), Pyo and Lee (2020), and Benigno and Rosa (2023) does not find significant effects of announcement surprises on aggregated Bitcoin prices for their sample period ending in 2022. Lastly, the increase in market reactions around 2020–2021 aligns with the cryptocurrency adoption of institutional investors (e.g., Huang, Lin, and Wang, 2022), who are typically regarded as the key investor group that incorporates macroeconomic information into asset prices. We investigate this link further in Section 5.

4 Market Sensitivity to Economic News

4.1 Effects of Economic News on Cryptocurrency and Other Asset Prices

After documenting that both Bitcoin and Ethereum markets react sharply to economic news, we now investigate how their prices incorporate such information. In particular, we address two questions: Does economic news lead to a systematic reaction in cryptocurrency prices? If so, how does this reaction compare with that of traditional asset prices and what can we learn from it regarding the fundamental information driving cryptocurrency prices?

To investigate these questions, we estimate the following specification for an announcement released at time t:

$$r_t^w = \alpha + \beta s_t + \varepsilon_t. \tag{5}$$

For FOMC announcements, s_t encompasses the yield and non-yield shocks as defined in (1) and (2), i.e., $s_t = [\, s_t^y \; s_t^{ny} \,]$, whereas for CPI and NFP announcements, it encompasses the headline and non-headline surprises as defined in (3) and (4), i.e., $s_t = [\, s_t^{h(k)} \; s_t^{nh(k)} \,]$ for $k \in \{\text{CPI, NFP}\}$. The dependent variable, r_t^w, is the return or log-return of the asset price of interest in window w around announcement release time t.

Besides the six cryptocurrency series, we also look at the reaction of bond yields, the stock market, exchange rates (Euro/Dollar and Yen/Dollar), as well as commodities (gold and oil). The rationale is that we seek to understand which of these assets most closely resemble cryptocurrencies in their reaction to economic news. As mentioned in the introduction, advocates of cryptocurrencies often argue that they act as safe-haven assets or inflation hedges, similar to gold or the U.S. dollar. However, there is also evidence that cryptocurrencies might have commonalities with equities (Iyer, 2022). Based on the evidence above (see Figure 3), we construct returns using a 2-hour window (10 minutes before to 2 hours after) around FOMC announcements and a 30-minute window (10 minutes before to 20 minutes after) for CPI and NFP announcements.

We begin our analysis by examining the effects of our news measures on the yield curve. We do so to confirm the interpretation of the measures based on prior work over our sample period and to get a sense of the relative magnitudes of the surprise measures, which are all normalized to correspond to a one standard deviation increase over the sample period. Prior work has shown that interest rates provide the clearest asset price reaction to macroeconomic news (Andersen et al., 2007). Table 2 reports the effects of our news measures on bond yields, estimated using specification (5).

For FOMC news, a one-standard-deviation positive yield shock of Nakamura and Steinsson (2018) has a significant positive effect across the entire yield curve, whereas the non-yield shock of Boehm and Kroner (2024)—signed to decrease stock prices and appreciate the U.S. Dollar—leaves the yield curve essentially unchanged. Both the CPI headline surprise (higher-than-expected CPI inflation) and NFP headline surprise (stronger-than-expected employment growth) significantly raise yields. The corresponding non-headline surprises by Gürkaynak, Kısacıkoğlu, and Wright (2020) also raise yields, allowing us to interpret them similarly to headline surprises under a standard Taylor-rule interpretation of the yield curve. Overall, the results in Table 2 confirm the results of prior work and validate the interpretation of the news surprises over our sample period.

Having documented their effects on the yield curve, we now turn to the effects macroeconomic news have on cryptocurrencies and other asset classes, estimated using equation (5) and reported in Table 3. Starting with *Bitcoin and Ethereum* prices, we find that both cryptocurrencies respond significantly to macroeconomic news. News that raises yields—or mimics a risk-off shock in the case of the non-yield shock—leads to significant Bitcoin and Ethereum price declines, with the estimates for FOMC news being somewhat noisier (likely due to the smaller sample size). Furthermore, Ethereum displays a quantitatively stronger

Table 2: The Effects of Economic News on Yields

	ED1	ED4	2-Year	5-Year	10-Year	30-Year
FOMC						
Yield Shock	2.75***	7.65***	6.20***	6.21***	4.34***	2.20***
	(0.46)	(0.56)	(0.42)	(0.57)	(0.50)	(0.48)
Non-Yield Shock	0.13	-0.04	0.10	0.74	0.80*	0.63
	(0.22)	(0.33)	(0.27)	(0.47)	(0.44)	(0.40)
R^2	0.60	0.86	0.86	0.71	0.60	0.32
Observations	84	84	84	84	84	84
CPI						
Headline Surprise	0.49***	1.37***	1.20***	1.66***	1.29***	0.73***
	(0.15)	(0.18)	(0.16)	(0.21)	(0.13)	(0.17)
Non-Headline Surprise	2.54***	6.49***	5.34***	6.11***	4.71***	3.57***
	(0.23)	(0.14)	(0.11)	(0.17)	(0.16)	(0.16)
R^2	0.75	0.94	0.95	0.95	0.94	0.83
Observations	131	131	131	131	131	131
NFP						
Headline Surprise	2.03***	4.45***	3.75***	4.75***	3.82***	2.95***
	(0.25)	(0.23)	(0.17)	(0.17)	(0.19)	(0.24)
Non-Headline Surprise	3.09***	6.51***	5.43***	6.37***	4.99***	3.76***
	(0.37)	(0.25)	(0.16)	(0.20)	(0.20)	(0.24)
R^2	0.47	0.91	0.93	0.95	0.93	0.80
Observations	128	128	128	128	128	128

Notes: This table reports the effects of FOMC, CPI, and NFP news on asset prices around announcement times, based on equation (5). The units are basis points per one standard deviation shock. The top panel presents results for FOMC news using 2-hour windows, while the bottom two panels report results for CPI and NFP news using 30-minute windows. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

price reaction relative to Bitcoin. The coefficients are generally very similar across exchanges when the sample sizes are comparable.

As all news variables are in units of standard deviations, the coefficient estimates are indicative of their relative importance for cryptocurrency prices. The estimates suggest that all news types lead to substantial price reactions. For CPI and NFP, non-headline surprises are more important than the headline ones, in line with their stronger effects on the yield curve. For FOMC news, the relative magnitudes are somewhat more mixed, with the yield shock generally having a stronger effect on Ethereum. That being said, our results confirm those of Boehm and Kroner (2024): the non-yield shock—despite having no effect on the yield curve—leads to substantial effects on other asset prices.

We now turn to the estimates for the *non-cryptocurrency prices* in Table 3. We start with the S&P 500: consistent with prior evidence, both the yield and the non-yield shock lead to significantly negative effects on U.S. equities. The same holds for CPI news. For NFP news,

Table 3: The Effects of Economic News on Cryptocurrencies and Other Asset Prices

	Bitcoin			Ethereum			S&P 500	Fiat Currencies		Commodities	
	Binance	Coinbase	OKX	Binance	Coinbase	OKX		Euro	Yen	Gold	Oil
FOMC											
Yield Shock	-52.19*	-44.50*	-48.68*	-88.67**	-92.07***	-84.12**	-35.22***	-28.04***	-29.03***	-46.89***	-25.37**
	(27.57)	(24.68)	(27.76)	(34.39)	(33.63)	(35.43)	(11.49)	(4.04)	(4.37)	(7.19)	(12.70)
Non-Yield Shock	-61.97**	-33.63	-58.66**	-75.20**	-50.63*	-66.92**	-37.91***	-25.02***	-12.80***	-27.66***	-26.29***
	(26.71)	(20.90)	(28.26)	(29.32)	(29.02)	(28.45)	(8.30)	(3.38)	(3.34)	(7.02)	(8.88)
R^2	0.22	0.14	0.20	0.35	0.29	0.31	0.42	0.69	0.61	0.59	0.20
Observations	63	84	61	63	73	61	84	84	84	84	84
CPI											
Headline Surprise	-29.36***	-30.10***	-24.05**	-46.21***	-43.45***	-31.64**	-19.13***	-8.26***	-9.70***	-2.75	-3.99
	(9.21)	(8.67)	(9.45)	(13.32)	(13.10)	(12.46)	(3.40)	(1.68)	(1.62)	(3.16)	(3.77)
Non-Headline Surprise	-70.69***	-67.26***	-48.43***	-98.32***	-95.92***	-56.64***	-47.19***	-26.77***	-29.66***	-34.48***	-30.99***
	(11.83)	(11.06)	(14.28)	(16.28)	(16.07)	(17.19)	(5.89)	(2.52)	(4.18)	(4.07)	(5.36)
R^2	0.45	0.41	0.31	0.51	0.46	0.28	0.71	0.74	0.69	0.61	0.33
Observations	99	131	96	99	114	96	131	131	131	131	131
NFP											
Headline Surprise	-32.86***	-25.56**	-37.42***	-35.78***	-31.24***	-37.61***	-5.82	-26.01***	-30.81***	-41.42***	-8.53
	(10.11)	(9.89)	(7.65)	(9.70)	(9.74)	(7.73)	(4.66)	(2.26)	(1.97)	(4.42)	(10.95)
Non-Headline Surprise	-40.22***	-30.04***	-37.03***	-44.65***	-38.79***	-38.08***	-12.15*	-31.78***	-37.47***	-44.62***	-4.51
	(9.70)	(7.85)	(9.05)	(9.67)	(9.30)	(9.36)	(6.65)	(2.92)	(2.09)	(4.94)	(6.88)
R^2	0.22	0.14	0.26	0.23	0.17	0.21	0.07	0.72	0.81	0.62	0.02
Observations	96	128	93	96	111	93	128	128	128	128	128

Notes: This table reports the effects of FOMC, CPI, and NFP news on asset prices around announcement times, based on equation (5). The units are basis points per one standard deviation shock. The top panel presents results for FOMC news using 2-hour windows, while the bottom two panels report results for CPI and NFP news using 30-minute windows. Exchange rates are in U.S. dollars per unit of foreign currency so that a decrease reflects a depreciation against the dollar. Green cells indicate positive coefficients, and red cells indicate negative coefficients. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

while the effects are also negative, they are much more muted, potentially reflecting the sign-switching nature of equity responses to employment news over time, as documented in prior work (Boyd, Hu, and Jagannathan, 2005). Both the euro and the Japanese yen generally depreciate against the U.S. dollar in response to positive surprises. For gold and oil prices, we also generally observe declines, but only some are statistically significant. Table 3 also illustrates that cryptocurrency prices are more sensitive to news compared to other asset prices.

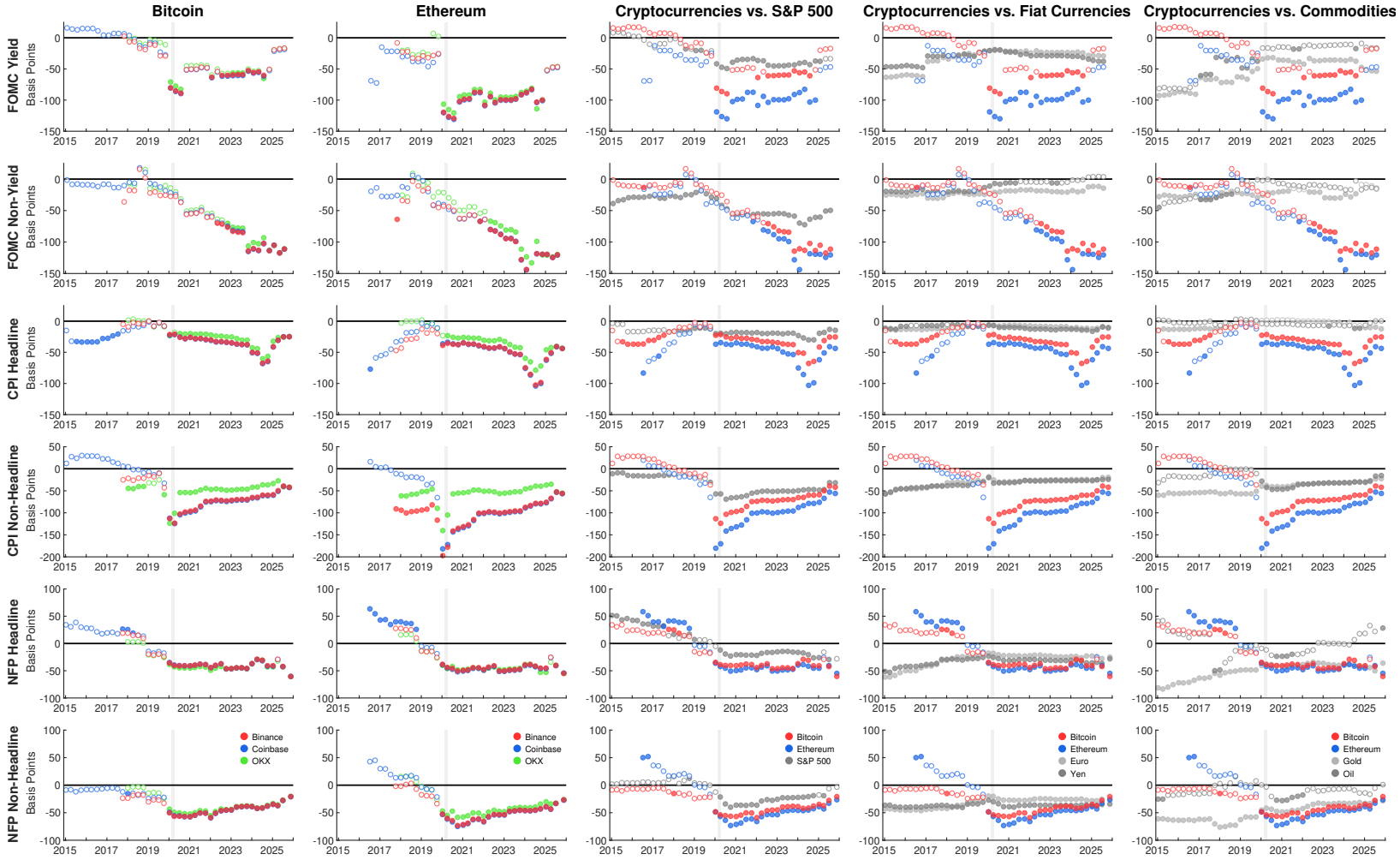
As all asset prices fall on average in response to our news series, Table 3 provides only limited information to differentiate their reactions and determine which assets cryptocurrencies resemble most. The time-varying nature of news transmission, however, might be helpful to identify periods that more clearly distinguish the responses across asset classes. Consequently, we investigate this next.

4.2 Effects of Economic News over Time

To study the time-varying effects of our news surprises, we estimate specification (5) for each quarter using a 5-year rolling window centered around that quarter to ensure a sufficient number of announcements. At each end of the sample, we require at least two-and-a-half years of data, which corresponds to at least 20 FOMC announcements and 30 CPI and NFP announcements in a given estimation window. Figure 5 displays the results. Each dot represents the estimate for a given window, with filled ones indicating a significant effect at the 10 percent level.

We start with the first two columns of Figure 5, showing the results for *Bitcoin and Ethereum*. The reactions to the FOMC yield shock (first row) were muted prior to 2020, then intensified and became significantly negative, before becoming somewhat more muted in the most recent period. In contrast, the sensitivities to the non-yield shock (second row) gradually intensified over the sample period, with the strongest effects in 2025. For CPI headline surprises (third row), we already observe significant negative effects prior to 2019, which then became more muted, peaking again toward the end of the 2021–2023 inflation surge. In contrast, the effects of CPI non-headline surprises (fourth row) peaked around 2020 and have become somewhat more muted since then. For NFP headline surprises (fifth row), we observe a sign flip in the reactions, from positive prior to 2020 to negative thereafter. For NFP non-headline surprises (sixth row), the reactions are broadly similar to the headline ones, although the positive effects are much more muted.

Figure 5: Time-Varying Effects of Economic News on Cryptocurrencies and Other Asset Prices



Notes: This figure reports the effects of FOMC, CPI, and NFP news on asset prices, based on equation (5) computed on a rolling basis over the sample period. The units are basis points per one standard deviation shock. The top two rows present results for FOMC news using 2-hour windows, while the bottom four rows display results for CPI and NFP news using 30-minute windows. Each dot shows the coefficient estimate for announcements in a 5-year window centered around a given quarter. Filled dots indicate statistical significance at the 10 percent level, using heteroskedasticity-robust standard errors. *Bitcoin* and *Ethereum* refer to estimates using volume-weighted average prices based on Binance, Coinbase, and OKX. Grey bars indicate NBER recession periods.

In summary, Bitcoin and Ethereum exhibit the same time-varying patterns across news surprises, but Ethereum consistently shows quantitatively stronger reactions. Price differences across exchanges are minor, except for the CPI non-headline surprise, for which price reactions on OKX are somewhat more muted. We next turn to the comparison with other asset prices, shown in columns three to five of Figure 5. As the price reactions across the three cryptocurrency exchanges are very similar, and to facilitate exposition, we construct volume-weighted average prices for Bitcoin (red) and Ethereum (blue) based on the series from Binance, Coinbase, and OKX.

Starting with the comparison to the S&P 500 (column three), the estimates for equities (gray) are generally smaller than those for cryptocurrencies. More importantly, however, we see that the responses evolve qualitatively similarly over time: when the sensitivity of equities increases, the same is true for Bitcoin and Ethereum. In addition, we observe a similar sign flip in reactions to NFP news around 2020 (fifth row). In contrast, the comparison with fiat currencies (column four) shows that the sensitivities of the Euro and Yen (gray) are consistently negative and generally move in the opposite direction to those of cryptocurrencies. A very similar pattern emerges for commodities (column five). Overall, the results in Figure 5 indicate that Bitcoin and Ethereum respond to economic news most closely in line with the S&P 500.

To make the similarity between cryptocurrency reactions and those of the S&P 500 more concrete, Table 4 displays the time-series correlations of Bitcoin and Ethereum price sensitivities with those of other asset prices for each news measure as well as the average across all six measures. The table confirms the visual evidence in Figure 5: correlations with the S&P 500 sensitivity are highly positive across all news types for both Bitcoin and Ethereum. In contrast, for fiat currencies and oil, the correlations are strongly negative, implying that Bitcoin and Ethereum are more sensitive in times when the U.S. dollar and gold prices are less sensitive. Lastly, oil prices are on average weakly correlated with considerable heterogeneity across news surprises. Overall, the findings suggest that cryptocurrencies behave like risk-sensitive assets, such as equities, rather than as safe-haven assets or inflation hedges (such as gold or the U.S. dollar).

5 Role of Institutional Trading

Sections 3 and 4 document that around 2021 cryptocurrency markets underwent a marked shift in how they incorporate economic announcements. The fact that market sensitivity of Bitcoin and Ethereum to economic announcements increased post-2021 (both in abso-

Table 4: Comovements of Cryptocurrency and Other Asset Price Sensitivities

	S&P 500	Fiat Currencies		Commodities		Obs.
		Euro	Yen	Gold	Oil	
Bitcoin	0.89	-0.63	-0.46	-0.61	0.08	
FOMC Yield Shock	0.94	-0.80	-0.70	-0.94	-0.86	43
FOMC Non-Yield Shock	0.89	-0.77	-0.92	-0.37	-0.44	43
CPI Headline Surprise	0.67	0.26	0.62	0.01	0.70	44
CPI Non-Headline Surprise	0.96	-0.78	-0.80	-0.76	0.72	44
NFP Headline Surprise	0.95	-0.80	-0.62	-0.91	0.18	44
NFP Non-Headline Surprise	0.94	-0.86	-0.32	-0.70	0.18	44
Ethereum	0.88	-0.49	-0.34	-0.51	0.14	
FOMC Yield Shock	0.83	-0.41	-0.24	-0.75	-0.63	37
FOMC Non-Yield Shock	0.89	-0.68	-0.89	-0.22	-0.30	37
CPI Headline Surprise	0.77	0.48	0.48	0.24	0.65	38
CPI Non-Headline Surprise	0.94	-0.68	-0.73	-0.63	0.80	38
NFP Headline Surprise	0.95	-0.75	-0.38	-0.92	-0.10	38
NFP Non-Headline Surprise	0.92	-0.88	-0.27	-0.77	0.40	38

Notes: This table reports the correlations between the time-varying sensitivity of Bitcoin/Ethereum to news and that of other asset prices. For both panels, each row shows the correlation for a given news series, while the top row displays the average correlations across all six news series. *Bitcoin* and *Ethereum* refer to estimates using volume-weighted average prices based on Binance, Coinbase, and OKX. Abbreviations: Obs.—Number of Observations.

lute terms and relative to other asset classes) further points to an explanation specific to cryptocurrency markets rather than a broader one. In this section, we provide evidence that this shift in market dynamics around economic announcements is driven in part by the increased adoption of cryptocurrencies by institutional investors. We first discuss why institutional cryptocurrency adoption likely drove this shift, drawing on prior work and narrative evidence, before providing supporting evidence from the price impact of trading.

5.1 The Case for Institutional Trading Behind the 2021 Shift

Prior work on traditional financial markets provides a variety of evidence indicating that institutional investors are crucial for the price discovery process around economic announcements. Using data from the U.S. Treasury market, Green (2004) and Pasquariello and Vega (2007) document that order flow becomes more informative following major macroeconomic announcements, consistent with certain investors possessing superior capacity to process macroeconomic information (Kim and Verrecchia, 1994, 1997). More directly, Czech et al. (2021) and Kondor and Pintér (2022) provide evidence—using regulatory data on the U.K.

government bond market—that sophisticated institutional investors such as hedge funds and mutual funds have superior ability to gather, process, and interpret macroeconomic information (i.e., acquire private information) and thus are essential to price discovery around economic announcements.

Together, this evidence from well-developed markets suggests that the entry of sophisticated institutional investors into a market will represent a crucial shift in its price discovery around economic announcements. As we discuss next, such an entry of institutional traders appears to have occurred in cryptocurrency markets around 2021, as evidenced by both narrative accounts and empirical evidence provided by prior work.

Reports suggest that several hedge funds—specialized in global or macro trading strategies—started to invest in cryptocurrencies around 2021. For example, Paul Tudor Jones, founder and CEO of hedge fund Tudor Investment Corporation, announced in May 2020 that his fund started to invest a sizeable share of its portfolio in Bitcoin.[24] In August 2021, hedge fund Point72 announced its first investment in the cryptocurrency space,[25] and in September 2021, hedge fund Brevan Howard launched its cryptocurrency division, BH Digital.[26] The reasons for these entries vary—e.g., cryptocurrencies might serve as inflation hedges—but in general, institutional investors viewed cryptocurrency markets as sufficiently developed to warrant investing (Auer et al., 2022).

Consistent with these reports, prior work has also documented an increase in institutional adoption of cryptocurrencies around 2021. Huang, Lin, and Wang (2022) and DeVault, Turtle, and Wang (2025) document this rise using a proxy based on institutional investors' holdings data, while Auer et al. (2022) employ quarterly reports filed by Coinbase. In general, cryptocurrency holdings by institutional investors can only be gauged very indirectly. One reason for this is that Bitcoin and Ethereum holdings do not need to be reported by institutional investors operating in the U.S., as they are classified as commodities (rather than securities) under U.S. regulations. Following DeVault, Turtle, and Wang (2025), in Online Appendix Figure B5 we plot a proxy of institutional cryptocurrency adoption, which confirms the prior evidence of a clear increase around 2021.

[24] https://www.bloomberg.com/news/articles/2020-05-07/paul-tudor-jones-buys-bitcoin-says-he-s-reminded-of-gold-in-70s?sref=b88bZRaf (accessed on March 10, 2026).

[25] https://markets.businessinsider.com/news/currencies/point72-messari-series-funding-steve-cohen-21-million-cryptocurrency-2021-8 (accessed on March 10, 2026).

[26] https://www.bloomberg.com/news/articles/2022-01-28/brevan-howard-bolsters-crypto-arm-as-assets-grow-to-250-million?sref=b88bZRaf (accessed on March 10, 2026).

5.2 Evidence from the Price Impact of Trading

While our data does not directly allow us to connect price movements to institutional trading, we can indirectly test the hypothesis that institutional trading has indeed changed the price discovery process in general and specifically around economic announcements by studying the price impact of order flows in cryptocurrency markets. Following the seminal theoretical contributions of Kyle (1985) and Glosten and Milgrom (1985)—which demonstrate how the degree of information asymmetry among market participants affects the sensitivity of prices to order flow—a large literature has examined the price impact of order flow in traditional financial markets to better understand the presence of "informed" traders in the market.

For our purposes, we focus on two questions regarding the price impact of order flow. First, do we observe a change in price impact of order flow around 2021? A large price impact of order flows is indicative of low market liquidity (e.g., Hasbrouck, 1991; Brandt and Kavajecz, 2004). If cryptocurrency markets have become more liquid in recent years, we expect to observe a lower price impact of trading after 2021 compared before. Second, do we find evidence of increased institutional trading activity following macroeconomic news announcements? As mentioned above, prior work provides substantial evidence indicating that institutional investors are crucial for the price discovery process around economic announcements. Consistent with that evidence, increased trading activity around these releases by institutional investors—who have superior ability to process economic news—should be associated with a higher price impact around announcements compared to non-announcement times.

Following prior work on the Treasury market (e.g., Benamar, Foucault, and Vega, 2021), we estimate the effect of net order flows (purchases minus sales) on cryptocurrency prices around the economic news announcements. With slight abuse of notation, let t denote timestamps of the announcement (e.g., 8:30 am ET for NFP) and the corresponding times on non-announcement days in our sample period, and let δ denote the time difference from announcement time t in minutes. We can then estimate the effects of order flow on cryptocurrency prices using the following minute-by-minute specification:

$$r_{\delta,t} = \alpha + (1_{NA}\lambda_0 + 1_{A,\delta<0}\lambda_1 + 1_{A,\delta\geq 0}\lambda_2)\,\mathrm{of}_{\delta,t} + 1_{A,\delta=0}\,\beta\,s_t + \varepsilon_{\delta,t}. \tag{6}$$

For FOMC announcements, we use a four-hour window (two hours before and after), i.e., $\delta \in [-120, 119]$ and for CPI and NFP announcements, we use a narrower one-hour window (30 minutes before and after), i.e., $\delta \in [-30, 29]$, for $k \in \{\mathrm{CPI}, \mathrm{NFP}\}$, following

Green (2004) and our earlier evidence. $r_{\delta t}$ is the one-minute log-return, and $\text{of}_{\delta t}$ is the net order flow (purchases minus sales) for the given minute. The indicator 1_{NA} equals one on non-announcement days and zero otherwise; $1_{A,\delta<0}$ equals one during the two hours before an announcement; and $1_{A,\delta\geq 0}$ equals one during the two hours after an announcement. Thus, λ_0 measures price impact on non-announcement days, while λ_1 and λ_2 measure price impact on announcement days before and after announcements, respectively. As is standard, we also control for both yield and non-yield shocks. We estimate specification (6) separately for the period up to the end of 2020 (pre-2021) and for the period starting in 2021 (post-2021). For FOMC announcements, $s_t = [\, s_t^y \; s_t^{ny} \,]$, whereas for CPI and NFP announcements, it encompasses the headline and non-headline surprises as defined in (3) and (4), i.e., $s_t = [\, s_t^{h(k)} \; s_t^{nh(k)} \,]$ for $k \in \{\text{CPI, NFP}\}$.

Table 5 reports the price impact estimates, i.e., the estimates of λ_0, λ_1, and λ_2, along with the differences across them. The table reveals a clear discrepancy across exchanges: Binance and OKX generally exhibit a positive and highly significant price impact of net order flow, consistent with standard theory and extensive evidence from traditional markets. For example, 100 net purchases are associated with a 2.94 basis point increase in the Bitcoin price on the Binance exchange pre-2021. In contrast, estimates based on Coinbase often show significant negative price effects in the pre-2021 period and mixed effects post-2021. Given this distinction, we first discuss the results for Binance and OKX before turning to the estimates for Coinbase.

With respect to *Binance and OKX*, there are three main takeaways. First, across both periods, estimates suggest that Binance is a more liquid market than OKX (i.e., lower price impacts), consistent with the statistics on trading volumes, alleviating concerns that trading volume may not be an informative summary statistic for cryptocurrency markets. While it is usually not easy to directly compare price impact estimates across papers due to differences in construction, our results are broadly consistent with Easley et al. (2024), who argue that general market dynamics in Bitcoin and Ethereum on Binance are comparable to traditional markets. Second, comparing the price impact coefficients between the pre- and post-2021 periods (i.e., the first three rows in each of the three panels), we observe a substantial decline in the price impact of trading in Bitcoin and Ethereum in the post-2021 period across both announcement and non-announcement days, consistent with a generally more liquid market. The R^2 values rise substantially, ranging between 23 and 30 percent.

Table 5: Price Impact of Order Flow around Announcements

	Pre-2021						Post-2021					
	Binance		Coinbase		OKX		Binance		Coinbase		OKX	
FOMC	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum
λ_0: Non-Ann. Days	2.94***	7.85***	-15.74***	-24.67***	6.62***	10.54***	0.61***	1.02***	0.36***	0.44***	2.32***	3.67***
λ_1: Ann. Days—Before	2.67***	5.68***	-15.23***	-24.11***	5.87***	8.78***	0.66***	1.16***	-0.17	-0.25	2.70***	4.34***
λ_2: Ann. Days—After	2.68***	6.79***	-16.59***	-28.53***	6.48***	9.36***	0.85***	1.48***	-0.45**	-0.43	2.71***	4.42***
$\lambda_1 - \lambda_0$	-0.27	-2.17***	0.51	0.56	-0.75*	-1.76**	0.05***	0.14***	-0.53***	-0.70**	0.38***	0.67***
$\lambda_2 - \lambda_0$	-0.25	-1.07	-0.85**	-3.86***	-0.14	-1.18	0.23***	0.45***	-0.81***	-0.87***	0.38***	0.75***
$\lambda_2 - \lambda_1$	0.02	1.10	-1.36**	-4.42***	0.61	0.58	0.19***	0.31***	-0.28	-0.18	0.01	0.08
R^2	0.10	0.09	0.35	0.30	0.14	0.11	0.29	0.24	0.00	0.00	0.29	0.28
Observations	204,000	204,000	362,640	279,600	163,546	186,060	300,960	300,960	300,960	300,960	298,633	298,692
CPI												
λ_0: Non-Ann. Days	2.50***	6.75***	-17.03***	-25.22***	5.83***	8.09***	0.60***	1.00***	-0.10*	-0.16**	2.45***	3.84***
λ_1: Ann. Days—Before	2.70***	8.81***	-17.48***	-21.29***	5.84***	8.51***	0.65***	1.08***	0.07	0.84*	2.16***	3.02***
λ_2: Ann. Days—After	2.28***	7.87***	-15.18***	-25.76***	6.09***	6.13***	0.81***	1.38***	-0.59	-0.46	2.84***	4.30***
$\lambda_1 - \lambda_0$	0.20	2.06**	-0.45	3.94***	0.01	0.43	0.05	0.07	0.17	1.00**	-0.28*	-0.82***
$\lambda_2 - \lambda_0$	-0.22	1.12	1.85**	-0.53	0.26	-1.96*	0.21***	0.38***	-0.48	-0.30	0.39***	0.46***
$\lambda_2 - \lambda_1$	-0.42	-0.94	2.30	-4.47**	0.24	-2.38	0.16***	0.30***	-0.65	-1.30*	0.68***	1.28***
R^2	0.09	0.09	0.34	0.27	0.14	0.09	0.27	0.23	0.01	0.01	0.30	0.30
Observations	51,060	51,060	90,780	70,020	40,158	46,500	75,300	75,300	75,300	75,300	74,520	74,400
NFP												
λ_0: Non-Ann. Days	2.47***	6.89***	-16.96***	-25.29***	5.82***	8.03***	0.61***	1.02***	-0.15**	-0.17**	2.46***	3.84***
λ_1: Ann. Days—Before	3.03***	3.44*	-16.54***	-23.48***	5.96***	8.51***	0.66***	1.08***	0.25	-0.09	2.63***	3.90***
λ_2: Ann. Days—After	3.33***	3.77**	-18.54***	-21.54***	6.86***	9.64***	0.74***	1.14***	0.03	-0.13	2.59***	4.10***
$\lambda_1 - \lambda_0$	0.56	-3.45*	0.42	1.81	0.14	0.48	0.04	0.06	0.40	0.08	0.17	0.05
$\lambda_2 - \lambda_0$	0.86***	-3.13*	-1.58**	3.75**	1.04**	1.61	0.13***	0.11*	0.17	0.03	0.13	0.26
$\lambda_2 - \lambda_1$	0.30	0.33	-2.00**	1.94	0.90	1.13	0.08*	0.06	-0.22	-0.05	-0.04	0.21
R^2	0.10	0.09	0.34	0.27	0.14	0.09	0.27	0.23	0.00	0.00	0.30	0.30
Observations	51,000	51,000	90,720	69,900	40,098	46,440	75,420	75,420	75,420	75,420	74,640	74,520

Notes: This table reports the impact of net order flow (purchases minus sales) on cryptocurrency prices around FOMC, CPI, and NFP announcements, based on specification (6). All estimates are expressed in basis points per 100 net trades. *Pre-2021* refers to specifications estimated for the years prior to 2021, while *Post-2021* refers to specifications estimated for 2021 and subsequent years. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used throughout.

Third, we do find evidence for Binance and OKX that the informational role of trading around economic announcements has increased since 2021. Focusing on the coefficient differences for each cryptocurrency-exchange-announcement triplet (rows four to six in each panel), there is little evidence in the pre-2021 period of an increase in the informational role of trading on announcement versus non-announcement days—and in many cases we find a decrease. This is consistent with a limited presence of institutional investors with specialized expertise in trading on macroeconomic information. In contrast, in the post-2021 period, we find strong evidence that trading is more informative on announcement days, as reflected in the differences $\lambda_1 - \lambda_0$ and $\lambda_2 - \lambda_0$. This effect is particularly pronounced after announcements relative to before, as captured by $\lambda_2 - \lambda_1$. These results suggest that information asymmetry increases after public releases due to heterogeneity in investors' capacity to process and act on public information. Consistent with Green's (2004) analysis for U.S. Treasuries, we also find that the increased informativeness of trades is more pronounced for releases associated with larger price impacts—in our case, FOMC and CPI announcements versus NFP announcements.

For the *Coinbase* exchange, the price impact estimates in Table 5 are difficult to interpret in light of standard theory. We generally find a large and significantly negative price impact of trading in the pre-2021 period, meaning that, on average, net purchases are associated with price decreases. These results are at odds with standard predictions and suggest that liquidity providers do not adjust prices upward in response to observed order flow. Instead, these findings are consistent with evidence of contrarian trading by retail investors, as documented in equity markets (e.g., Kaniel et al., 2012). In the post-2021 period, the price impact estimates fluctuate around zero and order flow has essentially no explanatory power (as reflected in the R^2 values), consistent with a less influential role for retail investors and offsetting trades by institutional investors. Further, the differences in coefficient estimates (rows four to six in each panel) show no clear pattern in the informativeness of trading.

Overall, the evidence shows that since 2021, market liquidity rose substantially and trading behavior around announcements changed across all exchanges. Further, on Binance and OKX—considered more attractive to institutional investors—order flow has played a crucial role in price discovery around announcements since 2021, consistent with a shift in market dynamics driven by the increased adoption of cryptocurrencies by institutional investors. In contrast, on Coinbase—likely characterized by a larger share of retail investor trading—liquidity providers appear to adjust prices independently of the observed order flow, potentially following movements on other exchanges.

We also conduct two robustness checks, both designed to ensure that our estimated price impacts are not polluted by order processing or inventory holding costs which have temporary effects on the price impact of order flow. First, we reestimate (6) using the 10-minute return (1 minute before to 9 minutes after) on the left-hand side.[27] Online Appendix Table B1 shows that the results are very close to the baseline ones. Second, we reestimate (6) using the unanticipated net order flow, which, following Pasquariello and Vega (2007), we construct by first regressing the order flow on its lags and the lagged returns and taking the residual.[28] Online Appendix Table B2 shows that the results are again very close to the baseline ones.

6 Conclusion

We use novel intraday data on cryptocurrencies to study their price discovery process around U.S. monetary policy, inflation, and labor market announcements. Our analysis reveals the following key findings. Volatility, trading volume, and bid–ask spreads rise sharply at announcement times and remain elevated for up to 30 minutes relative to comparable non-announcement intervals, indicating that cryptocurrency investors pay attention to these announcements and quickly incorporate this information into prices. Announcement surprises associated with higher yields or "risk-off" conditions cause substantial cryptocurrency price declines—pointing to a potential strengthening of U.S. monetary policy transmission to the real economy in recent years. The time-varying magnitude and direction of price reactions more closely resemble those of U.S. equities than those of fiat currencies or commodities, suggesting that cryptocurrencies behave primarily as risk-sensitive assets. Finally, price impact estimates of order flow around announcements are consistent with rising institutional participation in cryptocurrency markets and their crucial role for price discovery.

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[27] In essence, we are running a Jordà (2005) local projection, which estimates the same cumulative effect as a VAR (Plagborg-Møller and Wolf, 2021). While the VAR is traditionally the more commonly used method in the literature, for our specification it is more practical to run a local projection. Recent evidence shows that impulse responses of local projection are less prone to misspecification than that of VARs (Montiel Olea et al., 2024).

[28] In particular, we use 30 minutes of lags, which is conservative. Equation (A2) shows the precise equation.

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Online Appendix

for

How Do Cryptocurrencies Price Economic News?*

March 20, 2026

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*The views expressed are those of the authors and do not necessarily reflect those of the Federal Reserve Board or the Federal Reserve System.

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A Data Appendix

A.1 Cryptocurrencies

CoinDesk provides comprehensive data on spot trading on global cryptocurrency exchanges, both at the daily and 1-minute frequency. The data at the daily frequency is used for the overview of the cryptocurrency exchanges in Section 2 and to identify the most important cryptocurrency-exchange pairs, while the data at the 1-minute frequency is employed for all of our analyses in the paper based on the selected pairs.

A.1.1 Monthly Summary Statistics from Daily Data

CoinDesk provides data at daily frequency. The convention for a day in the dataset is that a timestamp such as March 14, 2025 refers to the interval [March 14, 2025 0:00:00 am UTC, March 15, 2025 0:00:00 am UTC), where March 15, 2025 0:00:00 am UTC is excluded. We construct the summary dataset of trading volume for a given currency pair on a given exchange (hereafter currency-exchange pair) as follows:

1. Trading volume is in units of the quote currency. When the quote currency is not in U.S. Dollars or Tether, we convert it to U.S. Dollars using end-of-day (5 pm ET) exchange rates obtained from Bloomberg.
2. We sum daily volumes to the monthly level.
3. We drop any currency-exchange pair with fewer than 12 observations over our sample period.
4. We identify outliers based on the median absolute deviation (Rousseeuw and Hubert, 2011). For a given currency-exchange pair, we drop observations in the top 5 percent of median absolute deviation values in the dataset, corresponding to values larger than 18, which is conservative.

A.1.2 1-Minute Intraday Data

CoinDesk provides data at 1-minute frequency, offering a variety of variables for a given minute τ based on trading and order book information. The convention for minute τ is that a timestamp such as 8:02:00 am UTC refers to the interval [8:02:00 am, 8:03:00 am), where 8:03:00 am is excluded. In the following, minute τ refers to a minute of market activity. For a given cryptocurrency-exchange pair, we use the following variables:

- p_τ: price of the last trade in quote currency (i.e., U.S. Dollar or Tether).
- vol_τ: trading volume in millions of quote currency (i.e., U.S. Dollar or Tether), winsorized at the top 1 percent.
- pur_τ: number of purchases.
- sal_τ: number of sales.

- r_τ: 1-minute log-return, constructed as

$$r_\tau = \log(p_\tau) - \log(p_{\tau-1}),$$

multiplied by 100^2 to convert to basis points, and winsorized at the top and bottom 0.5 percent.

- r^a_τ: absolute return, defined as

$$r^a_\tau = |r_\tau|.$$

- d^a_τ: absolute deviation from parity, defined as

$$d^a_\tau = |p_\tau - 1|. \tag{A1}$$

- of_τ: net order flow, constructed as

$$\text{of}_\tau = pur_\tau - sal_\tau,$$

and winsorized at the top and bottom 0.5 percent.

- of^u_τ: unanticipated net order flow, constructed as the residual from the following regression:

$$\text{of}_\tau = \alpha + \sum_{i=1}^{30} b_i \,\text{of}_{\tau-i} + \sum_{i=1}^{30} c_i \, r_{\tau-i} + \text{of}^u_\tau. \tag{A2}$$

- bid_τ: best bid price.

- ask_τ: best ask price.

- $spread_\tau = \frac{ask_\tau - bid_\tau}{(ask_\tau + bid_\tau)/2}$: quoted bid-ask spread, multiplied by 100^2 to convert to basis points and winsorized at the top 1 percent.

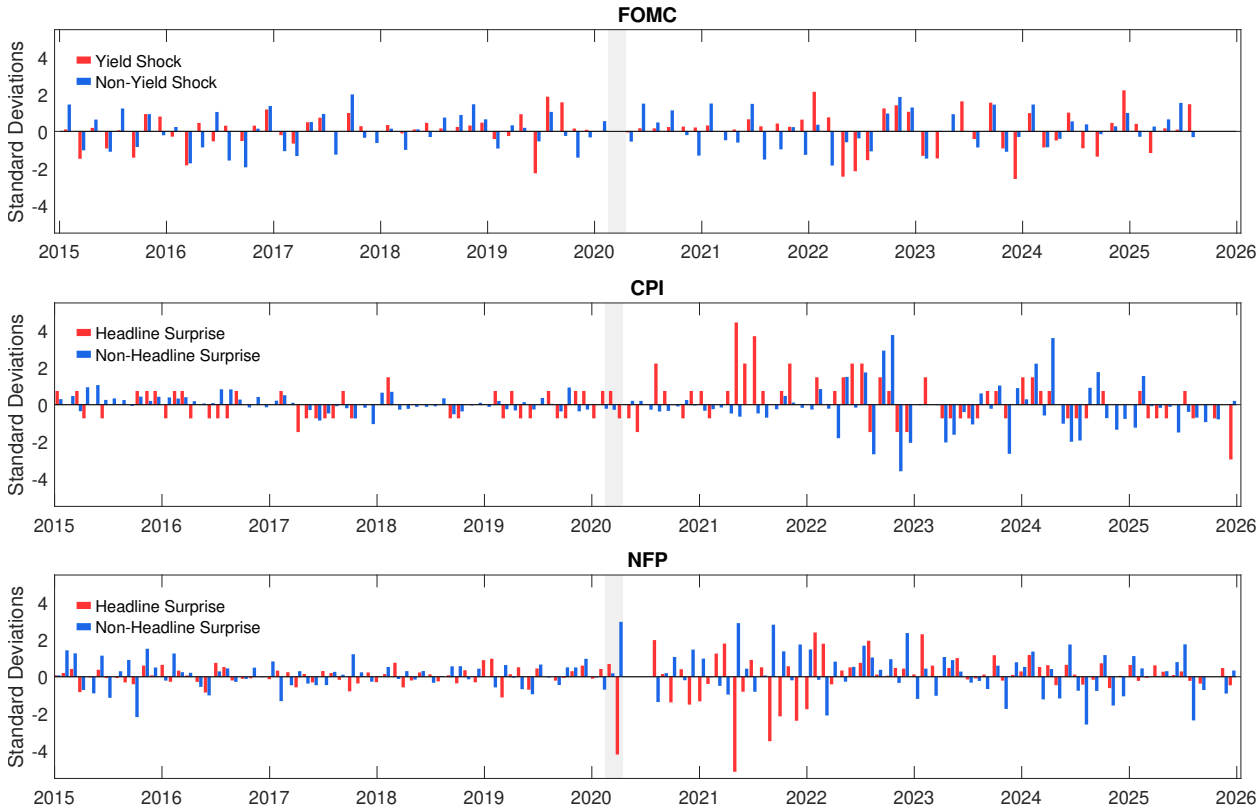
Table A1: Summary Statistics of Main Cryptocurrency-Exchange Pairs (balanced)

Minute-by-minute	Bitcoin			Ethereum		
Frequency	Binance (USDT)	Coinbase (USD)	OKX (USDT)	Binance (USDT)	Coinbase (USD)	OKX (USDT)
Return (bp)						
Mean	0.01	0.01	0.01	0.01	0.01	0.01
SD	8.96	8.46	8.32	11.14	10.99	10.49
Obs.	4,013,532	4,013,532	4,013,532	4,237,490	4,237,490	4,237,490
Sample	2017–2025	2017–2025	2017–2025	2017–2025	2017–2025	2017–2025
Absolute Return (bp)						
Mean	5.61	5.21	5.29	7.14	6.83	6.81
SD	6.99	6.66	6.43	8.55	8.61	7.98
Obs.	4,013,532	4,013,532	4,013,532	4,237,490	4,237,490	4,237,490
Sample	2017–2025	2017–2025	2017–2025	2017–2025	2017–2025	2017–2025
Volume ($ Millions)						
Mean	1.25	0.33	0.30	0.60	0.19	0.16
SD	1.80	0.50	0.50	0.99	0.32	0.29
Obs.	4,013,533	4,013,533	4,013,533	4,237,491	4,237,491	4,237,491
Sample	2017–2025	2017–2025	2017–2025	2017–2025	2017–2025	2017–2025
Bid-Ask Spread (bp)						
Mean	0.06	0.32	0.03	0.06	0.46	0.06
SD	0.17	0.47	0.01	0.11	0.57	0.09
Obs.	2,248,981	2,248,981	2,248,981	2,258,404	2,258,404	2,258,404
Sample	2021–2025	2021–2025	2021–2025	2021–2025	2021–2025	2021–2025

Notes: This table provides a balanced-sample version of Table 1, restricting the data to minutes for which observations are available across all three exchanges. Mean, standard deviation (SD), number of observations (Obs.), and sample period are provided at minute-by-minute frequency for four variables: return, absolute return, trading volume, and bid-ask spread. Bitcoin and Ethereum are quoted against the U.S. Dollar (USD) on the Coinbase exchange or against Tether (USDT) on the Binance and OKX exchanges. Returns are winsorized at the top and bottom 0.5 percent, while trading volume and bid-ask spreads are winsorized at the top 1 percent. As return construction and winsorization are performed on the full sample, minor differences in summary statistics may still arise even if the underlying variables are identical.

A.2 Economic Announcements

Figure A1: Time Series of Economic News Surprises



Notes: This figure displays the time series of the economic news surprises for each of the three announcements over the sample period. Their construction is detailed in Section 2. Grey bars indicate NBER recession periods.

A.3 Other Financial Market Data

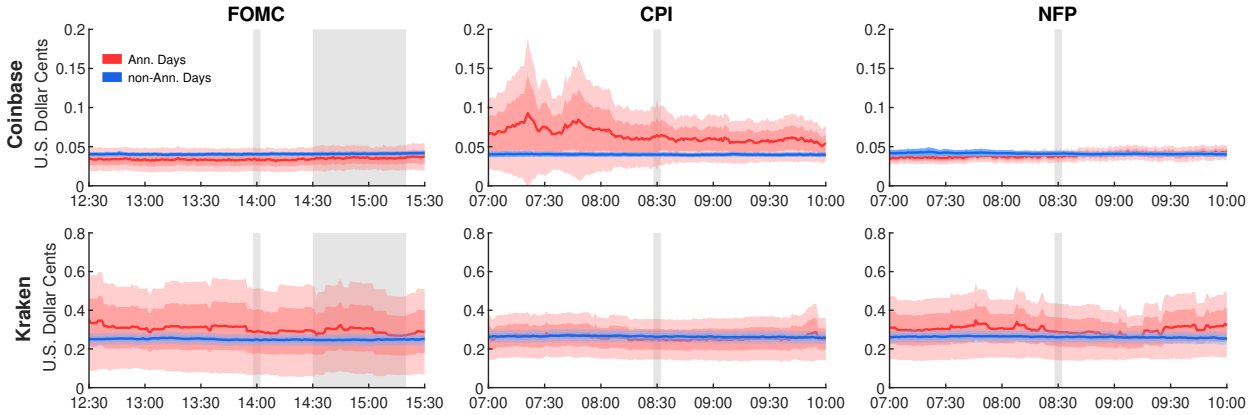
Table A2: Overview of Intraday Financial Data from LSEG Tick History

Name	Description	Ticker	Sample
Interest Rates			
ED1	1st Quarterly Eurodollar/SOFR Futures	EDcm1/SRAcm2	2015–2025
ED4	4th Quarterly Eurodollar/SOFR Futures	EDcm4/SRAcm5	2015–2025
2-Year	2-Year Treasury Futures	TUc1/TUc2	2015–2025
5-Year	5-Year Treasury Futures	FVc1/FVc2	2015–2025
10-Year	10-Year Treasury Futures	TYc1/TYc2	2015–2025
30-Year	30-Year Treasury Futures	USc1/USc2	2015–2025
Other			
S&P 500	front-month E-mini S&P 500 Futures	ESc1	2015–2025
Euro	Euro/U.S. Dollar Spot Rate	EUR=	2015–2025
Yen	U.S. Dollar/Yen Spot Rate	JPY=	2015–2025
Gold	Gold Spot Price	XAU=	2015–2025
Oil	front-month Crude Oil (WTI) Futures	CLc1	2015–2025

Notes: This table lists the asset prices from *LSEG Tick History* used throughout the main text. For all series, the sample period starts in January 2015 and ends in December 2025. *Ticker* refers to the Reuters Instrument Code (RIC). Abbreviations: SOFR—Secured Overnight Financing Rate; WTI—West Texas Intermediate.

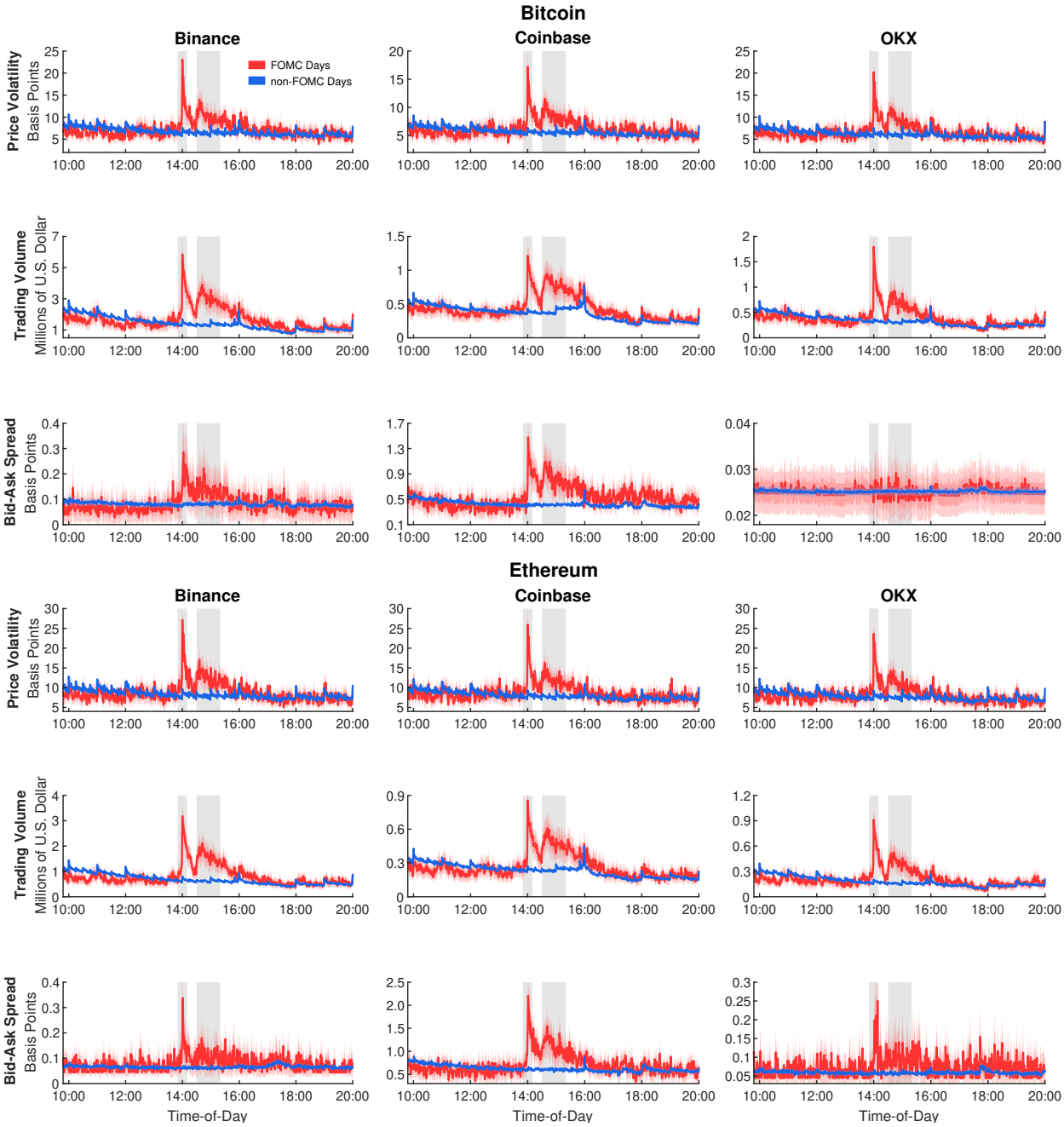
B Additional Results

Figure B1: Absolute Deviations of Tether from U.S. Dollar Parity around Announcements



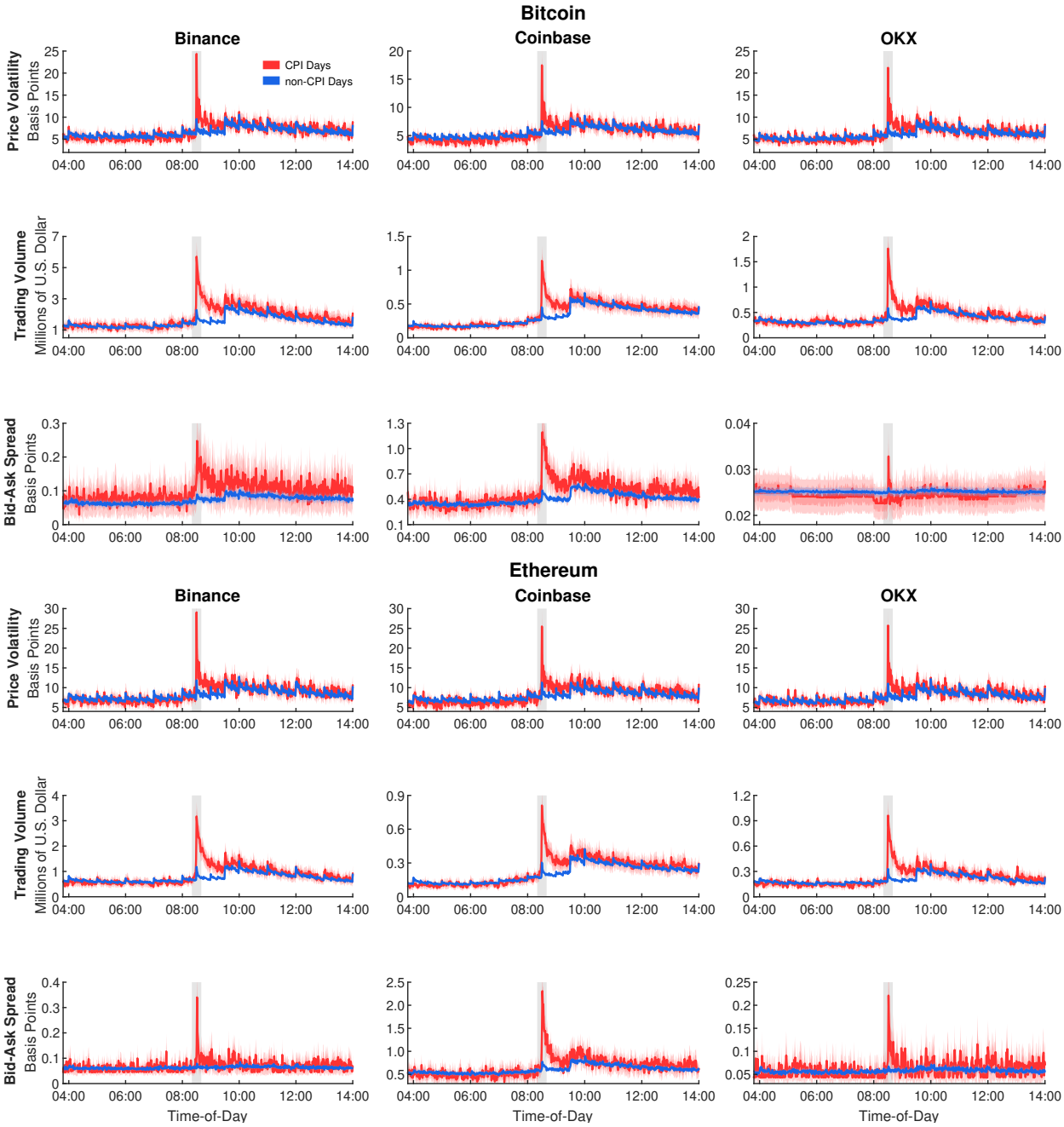
Notes: This figure plots the average minute-by-minute absolute deviation, as defined in equation (A1), of Tether from U.S. Dollar parity on the Coinbase and Kraken exchanges on announcement days (red) and non-announcement days (blue). 68 and 95 percent confidence intervals are shown in darker and lighter shaded bands around the point estimates, respectively. For the FOMC, the grey shaded areas indicate the timing of the FOMC announcement and the average timing of the FOMC press conference. For the CPI and NFP, the grey shaded areas indicate the timing of the respective release.

Figure B2: Cryptocurrency Markets on FOMC Days vs. Non-FOMC Days



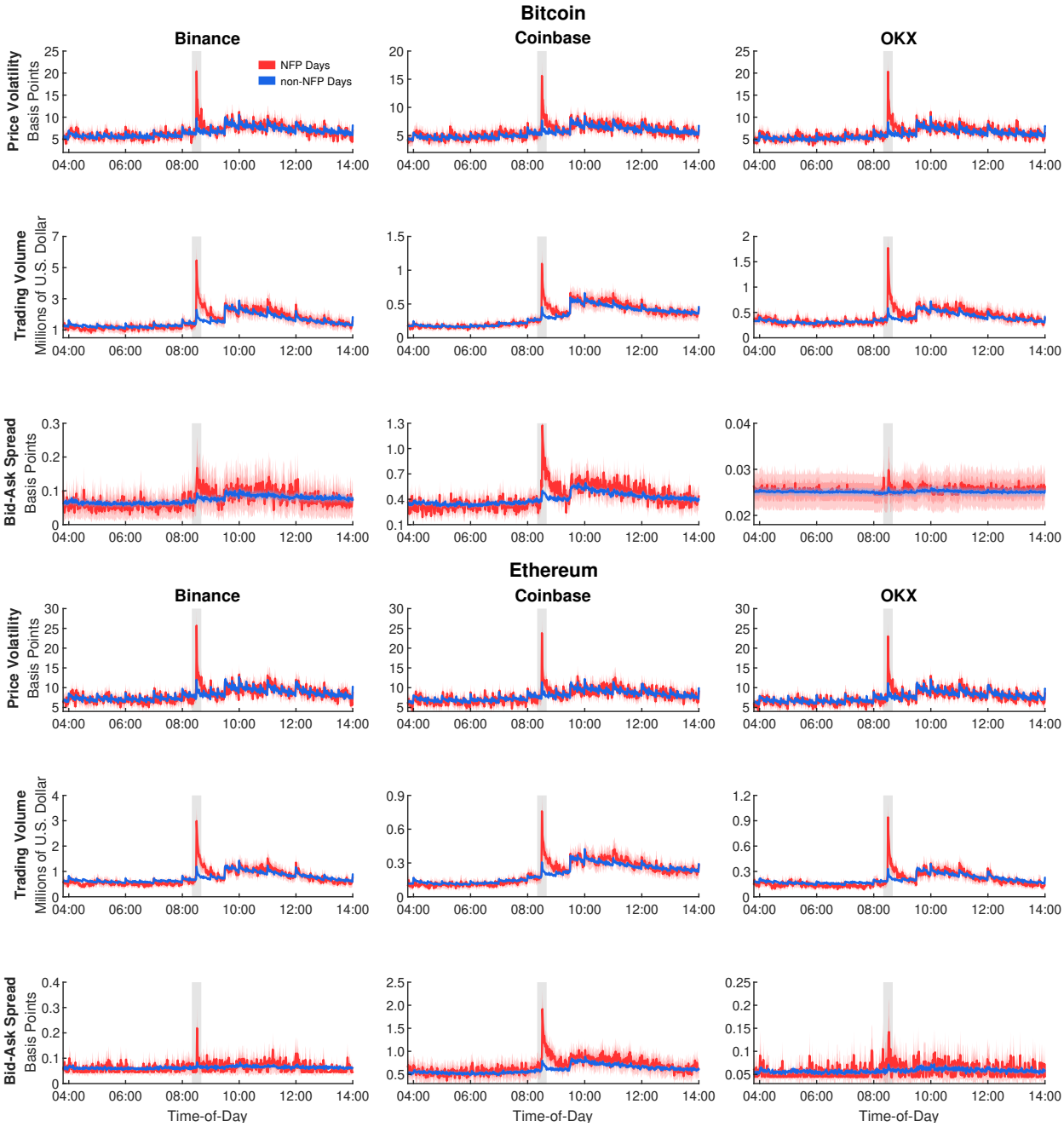
Notes: This figure displays the average minute-by-minute price volatility (measured as the absolute log-return), trading volume, and the bid–ask spread on FOMC days (red) and non-FOMC days (blue). 68 and 95 percent confidence intervals are shown in darker and lighter shaded bands around the point estimates, respectively. The grey shaded areas indicate the timing of the FOMC announcement and the average timing of the FOMC press conference.

Figure B3: Cryptocurrency Markets on CPI Days vs. Non-CPI Days



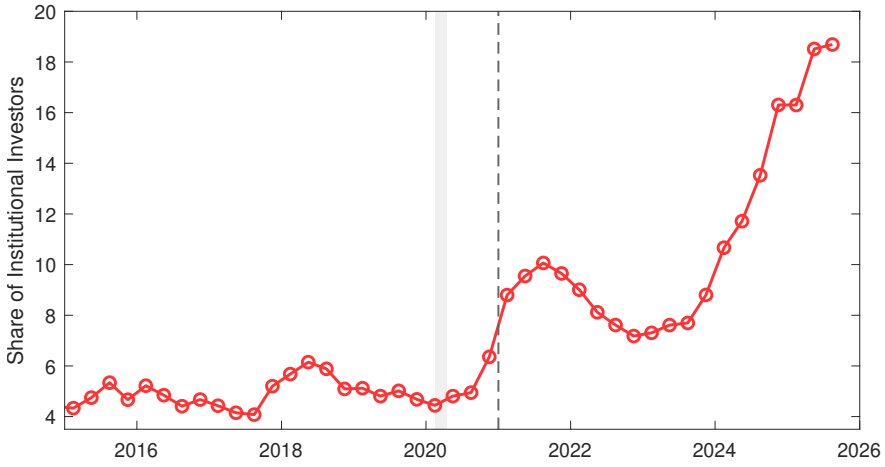
Notes: This figure displays the average minute-by-minute price volatility (measured as the absolute log-return), trading volume, and the bid–ask spread on CPI days (red) and non-CPI days (blue). 68 and 95 percent confidence intervals are shown in darker and lighter shaded bands around the point estimates, respectively. The grey shaded areas indicate the timing of the CPI release.

Figure B4: Cryptocurrency Markets on NFP Days vs. Non-NFP Days



Notes: This figure displays the average minute-by-minute price volatility (measured as the absolute log-return), trading volume, and the bid–ask spread on NFP days (red) and non-NFP days (blue). 68 and 95 percent confidence intervals are shown in darker and lighter shaded bands around the point estimates, respectively. The grey shaded areas indicate the timing of the NFP release.

Figure B5: Proxy of Institutional Cryptocurrency Adoption



Notes: This figure reports the share of 13F institutional investors that hold some cryptocurrency exposure based on the classification of DeVault, Turtle, and Wang (2025), which identifies cryptocurrency funds and individual stocks with high Bitcoin exposure as proxies for cryptocurrency holdings. Institutional investment managers operating in the U.S. that exercise investment discretion over $100 million or more in assets are required to submit a quarterly report of their holdings (the 13F form) to the U.S. Securities and Exchange Commission. The data comes from the LSEG Institutional 13F Holdings dataset obtained via the Wharton Research Data Services.

Table B1: Permanent Price Impact of Order Flow around Announcements

	Pre-2021						Post-2021					
	Binance		Coinbase		OKX		Binance		Coinbase		OKX	
FOMC	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum
λ_0: Non-Ann. Days	2.71***	7.26***	-15.10***	-26.48***	6.12***	10.45***	0.58***	1.03***	0.66***	0.86***	2.14***	3.41***
λ_1: Ann. Days—Before	2.60***	6.43***	-20.01***	-35.97***	6.08***	5.49**	0.57***	1.18***	-0.69	-0.16	2.04***	3.41***
λ_2: Ann. Days—After	2.05***	6.88***	-12.03***	-22.92***	5.12***	9.98***	0.80***	1.52***	-3.66***	-1.17	2.82***	4.26***
$\lambda_1 - \lambda_0$	-0.11	-0.83	-4.91**	-9.49**	-0.04	-4.96**	-0.01	0.15	-1.36**	-1.02	-0.10	-0.01
$\lambda_2 - \lambda_0$	-0.66	-0.38	3.07*	3.56	-1.00	-0.47	0.22***	0.48***	-4.32***	-2.03**	0.68***	0.85**
$\lambda_2 - \lambda_1$	-0.55	0.45	7.98***	13.05**	-0.95	4.49	0.23***	0.34**	-2.96***	-1.01	0.77**	0.85
R^2	0.01	0.01	0.03	0.04	0.01	0.01	0.03	0.03	0.00	0.00	0.03	0.02
Observations	204,000	204,000	362,640	279,600	162,720	186,060	300,960	300,960	300,960	300,960	298,305	298,455
CPI												
λ_0: Non-Ann. Days	2.37***	6.74***	-19.82***	-28.21***	5.25***	8.19***	0.52***	0.93***	-0.10	-0.07	2.02***	3.18***
λ_1: Ann. Days—Before	0.87	7.05***	-19.05***	-15.31***	5.28***	7.54***	0.47***	0.75***	4.83***	5.26***	0.36	1.80**
λ_2: Ann. Days—After	2.03**	14.38***	-26.20***	-47.27***	8.78***	10.38***	0.91***	1.41***	-0.74	-2.26	2.42***	4.79***
$\lambda_1 - \lambda_0$	-1.50	0.31	0.77	12.90***	0.03	-0.65	-0.05	-0.18	4.93***	5.32***	-1.65***	-1.38
$\lambda_2 - \lambda_0$	-0.34	7.65*	-6.38*	-19.07***	3.53*	2.19	0.39***	0.49**	-0.63	-2.19	0.40	1.61***
$\lambda_2 - \lambda_1$	1.16	7.34	-7.15	-31.96***	3.50	2.84	0.44**	0.67**	-5.57***	-7.52***	2.06***	3.00***
R^2	0.01	0.01	0.01	0.03	0.01	0.01	0.02	0.02	0.00	0.00	0.02	0.02
Observations	51,060	51,060	90,780	70,020	39,987	46,500	75,300	75,300	75,300	75,300	74,430	74,373
NFP												
λ_0: Non-Ann. Days	2.30***	6.85***	-19.91***	-28.59***	5.27***	8.25***	0.54***	0.95***	-0.04	-0.21	1.99***	3.29***
λ_1: Ann. Days—Before	2.40**	9.87	-16.83***	-20.92**	4.71***	7.87**	0.64***	0.90***	-0.71	-0.73	1.96***	3.04***
λ_2: Ann. Days—After	6.03***	2.51	-27.63***	-32.30***	9.68***	5.20*	0.66***	0.98***	0.78	2.75**	2.46***	3.30***
$\lambda_1 - \lambda_0$	0.10	3.02	3.08	7.67	-0.56	-0.39	0.11	-0.05	-0.67	-0.52	-0.04	-0.25
$\lambda_2 - \lambda_0$	3.74***	-4.34	-7.72*	-3.71	4.41***	-3.05	0.12	0.03	0.82	2.96**	0.47*	0.00
$\lambda_2 - \lambda_1$	3.63**	-7.36	-10.80*	-11.38	4.97**	-2.66	0.02	0.08	1.49	3.48*	0.50	0.25
R^2	0.01	0.01	0.01	0.03	0.01	0.01	0.02	0.02	0.00	0.00	0.02	0.02
Observations	51,000	51,000	90,720	69,900	39,927	46,440	75,420	75,420	75,420	75,420	74,550	74,493

Notes: This table reports the permanent impact of net order flow (purchases minus sales) on cryptocurrency prices around FOMC, CPI, and NFP announcements. The estimates are based on a version of specification (6), where the left-hand side is now the 10-minute log-return, i.e., $r^{10}_{\delta,t} = \log(p_{\delta+9,t}) - \log(p_{\delta-1,t})$. All estimates are expressed in basis points per 100 net trades. *Pre-2021* refers to specifications estimated for the years prior to 2021, while *Post-2021* refers to specifications estimated for 2021 and subsequent years. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used as recommended by Montiel Olea and Plagborg-Møller (2021).

Table B2: Price Impact of Unanticipated Order Flow around Announcements

	Pre-2021						Post-2021					
	Binance		Coinbase		OKX		Binance		Coinbase		OKX	
FOMC	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum
λ_0: Non-Ann. Days	3.27***	7.54***	-18.29***	-27.03***	7.14***	11.47***	0.66***	1.16***	0.67***	0.74***	2.61***	4.31***
λ_1: Ann. Days—Before	2.90***	5.66***	-17.60***	-25.39***	6.75***	8.64***	0.69***	1.25***	-0.35	-0.40	2.98***	4.91***
λ_2: Ann. Days—After	3.01***	6.35***	-19.01***	-29.98***	6.48***	9.33***	0.89***	1.59***	-0.21	-0.54	3.01***	4.88***
$\lambda_1 - \lambda_0$	-0.37	-1.88***	0.69	1.64*	-0.39	-2.83***	0.04**	0.09**	-1.02***	-1.14**	0.37***	0.60***
$\lambda_2 - \lambda_0$	-0.26	-1.19*	-0.72	-2.95***	-0.65	-2.14**	0.23***	0.44***	-0.88***	-1.28***	0.40***	0.57***
$\lambda_2 - \lambda_1$	0.12	0.69	-1.41**	-4.59***	-0.26	0.69	0.20***	0.34***	0.14	-0.14	0.03	-0.03
R^2	0.11	0.08	0.40	0.32	0.15	0.12	0.31	0.27	0.00	0.00	0.33	0.33
Observations	204,000	204,000	362,640	279,600	163,546	186,060	300,960	300,960	300,960	300,960	298,633	298,692
CPI												
λ_0: Non-Ann. Days	2.84***	6.71***	-19.62***	-28.75***	6.28***	9.04***	0.63***	1.13***	-0.21**	-0.27**	2.69***	4.39***
λ_1: Ann. Days—Before	2.99***	8.17***	-19.30***	-24.62***	5.93***	8.67***	0.69***	1.20***	-0.28	1.03	2.60***	4.13***
λ_2: Ann. Days—After	2.47***	7.22***	-17.61***	-25.90***	6.40***	6.59***	0.88***	1.55***	-0.80	-0.26	3.06***	4.85***
$\lambda_1 - \lambda_0$	0.14	1.46*	0.33	4.13**	-0.35	-0.36	0.05	0.07	-0.07	1.30*	-0.09	-0.26
$\lambda_2 - \lambda_0$	-0.37	0.51	2.01**	2.85**	0.12	-2.45**	0.25***	0.42***	-0.60	0.01	0.37***	0.46***
$\lambda_2 - \lambda_1$	-0.52	-0.95	1.69	-1.28	0.46	-2.09	0.19***	0.35***	-0.52	-1.29	0.46**	0.73**
R^2	0.11	0.09	0.38	0.30	0.15	0.11	0.29	0.26	0.01	0.01	0.33	0.34
Observations	51,060	51,060	90,780	70,020	40,158	46,500	75,300	75,300	75,300	75,300	74,520	74,400
NFP												
λ_0: Non-Ann. Days	2.82***	6.83***	-19.61***	-28.74***	6.27***	8.99***	0.64***	1.15***	-0.29***	-0.24*	2.72***	4.41***
λ_1: Ann. Days—Before	3.35***	3.77	-17.46***	-25.42***	5.83***	7.97***	0.68***	1.22***	0.57	-0.28	2.72***	4.49***
λ_2: Ann. Days—After	3.38***	4.05***	-21.11***	-25.22***	6.71***	9.90***	0.78***	1.40***	-0.03	-0.58	2.79***	4.60***
$\lambda_1 - \lambda_0$	0.53	-3.06	2.15***	3.32**	-0.44	-1.02	0.04	0.07	0.86*	-0.04	0.00	0.08
$\lambda_2 - \lambda_0$	0.56*	-2.78**	-1.50	3.52**	0.44	0.91	0.14***	0.25***	0.26	-0.34	0.07	0.19
$\lambda_2 - \lambda_1$	0.03	0.28	-3.65***	0.20	0.88	1.93	0.10**	0.17**	-0.60	-0.30	0.07	0.11
R^2	0.11	0.09	0.38	0.30	0.15	0.11	0.28	0.26	0.00	0.00	0.33	0.34
Observations	51,000	51,000	90,720	69,900	40,098	46,440	75,420	75,420	75,420	75,420	74,640	74,520

Notes: This table reports the impact of unanticipated net order flow (purchases minus sales) on cryptocurrency prices around FOMC, CPI, and NFP announcements. The estimates are based on a version of specification (6), where we use unanticipated net order flow (instead of net order flow). The unanticipated net order flow is constructed as detailed in equation (A2). All estimates are expressed in basis points per 100 net trades. *Pre-2021* refers to specifications estimated for the years prior to 2021, while *Post-2021* refers to specifications estimated for 2021 and subsequent years. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used throughout.

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