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Informed Trading Through the COVID-19 Pandemic: Evidence from the Bitcoin Market

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Abstract

We investigate informed trading in the Bitcoin market throughout the COVID-19 pandemic. Compared to the pre-pandemic period, we find that informed trading is significantly higher in the affective first stage of the pandemic, before reverting to its pre-COVID-19 level during the later stage of the pandemic. Furthermore, information asymmetry tends to increase in daily COVID-19-related news: confirmed cases and deaths. Our findings are robust to alternative parameters and model specifications. The main implication for traders is that they should be extra cautious in timing their trading decisions during such events, as these tend to encourage informed trading.

Keywords: informed trading; information asymmetry; cryptocurrency; Bitcoin; COVID-19 pandemic

JEL Classification: D82; G14; H12; G01

1. Introduction

The ongoing novel COVID-19 pandemic is a global shock dragging down the national and global economies and affecting the life of all humanity. This unprecedented phenomenon has triggered the attention of researchers and engendered a fast-evolving literature on the financial effects of COVID-19 (Yarovaya et al., 2022). Those studies explore how the pandemic affects stock returns (Zhang et al., 2020), stock volatility (Zaremba et al., 2020), oil prices (Sharif et al., 2020), and firm performance (Miyakawa et al., 2021). A stream of this COVID-19 literature tests the hedging capabilities of cryptocurrencies during the pandemic (Conlon et al., 2020; Demir et al., 2020; J. W. Goodell & Goutte, 2021).

In this study, we examine the impact of COVID-19 on informed trading in the Bitcoin exchange. In market microstructure, informed trading refers to trades initiated by agents who possess (or can process) value-relevant information faster or more accurately than others, so their order flow is systematically correlated with subsequent price changes.¹ In canonical models, this creates adverse-selection risk for liquidity suppliers, who respond by widening spreads and/or reducing displayed depth as they try to protect themselves from trading at a loss against better-informed counterparties (Glosten & Milgrom, 1985). In this framework, liquidity (or “utility”) traders trade primarily for rebalancing, hedging, or



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cash-flow motives rather than informational advantage, and they effectively pay for immediacy when markets are more informationally asymmetric—because the cost of liquidity rises when order flow becomes more toxic (Kyle, 1985). This distinction is particularly relevant for Bitcoin, where trading is continuous (24/7), participation is heterogeneous (retail, professional, algorithmic market makers), and the information environment can shift abruptly (e.g., macro stress, policy/regulatory news, operational frictions), making transient information asymmetries plausible. For example, Urquhart (2016) shows Bitcoin's informational efficiency is not stable across subsamples, Dimpfl and Peter (2021) demonstrate that crypto markets exhibit substantial microstructure noise that can distort conventional microstructure metrics unless handled carefully, and Feng et al. (2018) find evidence of informed trading around major market-moving events—each consistent with abrupt shifts in the information environment for Bitcoin. VPIN is designed to operationalize this idea by measuring order-flow toxicity from volume-imbalanced trading, providing a high-frequency proxy for the intensity of adverse selection faced by liquidity providers and, by implication, the trading-cost burden borne by liquidity-motivated participants (Easley et al., 2012).

Volatility dynamics (Ardia et al., 2019; Katsiampa, 2019), hedging capabilities (Demir et al., 2018; Fang et al., 2019), price efficiency (Sensoy, 2019), herding behavior (Coskun et al., 2020), interaction with other financial assets (Maghyereh & Abdoh, 2020), and price determinants (Aysan et al., 2019; Kraaijeveld & De Smedt, 2020) of Bitcoin are widely explored in the literature.² In contrast, there is scarce number of studies examining the informed trading in Bitcoin markets. In one of the earliest studies, Feng et al. (2018) document evidence of informed trading in Bitcoin markets preceding impactful events. Recently, Wang et al. (2021) show that informed trading decreases the volatility in Bitcoin prices while its impact on returns depends on whether informed trading is dominated by the buy-side or sell-side. Kitvanitphasu et al. (2025) examine the relationship between order-flow toxicity that is measured by volume-synchronized probability of informed trading and jumps in Bitcoin prices. They document that toxicity significantly predicts future price jumps and is correlated with the jump size.

We contribute to this underexplored field by focusing on informed trading during COVID-19. The ongoing pandemic, especially in its first stage, might have led to a large information asymmetry among market participants, since it may become harder to value financial assets. Wei and Zhou (2016) examine informed trading in the bond market prior to earnings announcements. The authors find that the existence of significant pre-event informed trading is not special to 2007–2010 post-crisis period but also valid in the pre-crisis period of 1997–2006. Ormos and Timotity (2016) find lower informed trading in the last quarter of 2008—that is associated with the effects of the collapse of Lehman Brothers—when compared to the first three quarters of the same year. W. X. Li et al. (2017), on the contrary, find significantly higher information asymmetry, informed trading and adverse selection costs in the S&P index options through the 2008 financial crisis when compared to the pre-crisis period. While we may expect larger uncertainty and increased information asymmetry with turbulent periods such as crises (W. X. Li et al., 2017; Ormos & Timotity, 2016), how the prevalence of informed trading evolves through these periods deserves further attention. In addition, while there exist several studies examining the presence of informed trading surrounding the 2008 financial crisis and in the equity, bond, and options market, the role of the recent global crisis of COVID-19 and the case of cryptocurrency market are not conducted yet. Higher probability of trading with informed traders constitutes in itself a crucial information to the rest of the market and should, therefore, be considered in trading decisions. To the best of our knowledge, this is the

first study to investigate informed trading in financial markets throughout the COVID-19 pandemic and one of the very first to analyze informed trading in cryptocurrency markets.

In particular, we compare the levels of informed trading before and during the pandemic and analyze whether (how) the growth rate of confirmed COVID-19 cases and deaths affects informed trading in the Bitcoin market. We find that COVID-19 has a positive impact on the likelihood of informed trading and, thereby, on information asymmetry among market participants. By dividing the pandemic period into two stages, we find that level of informed trading during the COVID-19 stage I (stage II) is higher than (not significantly different from) the level during the pre-COVID period. Our findings can provide important insights for traders and investors alike. They should exert more caution when trading in periods with high uncertainty (such as COVID-19 Stage I), as the likelihood of facing highly informed traders increases.

Documenting the differential presence of informed trading throughout the COVID-19 pandemic would provide various insights to the market participants and regulators. Considering the financial markets as a zero-sum game where the profit-motivated traders (e.g., informed traders) are expected to win and utility traders (e.g., liquidity traders) lose in aggregate (Harris, 2003)³, we may conjecture, by exacerbated informed trading, liquidity traders to face higher trading costs and increased potential losses, which may lead to a crowding-out effect on them.⁴ Thus, uninformed traders may benefit from the findings of this research in timing their trades, and regulators may consider the findings in attempts to reduce the informational disadvantages and to rearrange the mutual benefits of profit-driven and utility-driven traders through such periods.

The rest of the paper is organized as follows. Section 2 describes the data, variables and methodology. Section 3 presents the findings, and Section 4 concludes.

2. Data, Variables and Methodology

We use the BTC/USD tick-by-tick trading data of Bitstamp exchange, which was launched in 2011 and ranks among the top three exchanges with respect to BTC/USD trading volume as of the beginning of our data span.⁵ The data spans a period of 320 days, from 1 November 2019 to 15 September 2020, and comprises 6,693,051 trades in total, with 3,205,310 buyer-initiated trades and 3,487,741 seller-initiated ones.⁶

The data is partitioned in 3 windows: pre-COVID-19 period (1 November 2019–14 February 2020), COVID-19 stage I (15 February 2020–31 May 2020), and COVID-19 stage II (1 June 2020–15 September 2020). The main intuition behind this choice aims to accurately capture the COVID-19 effects in two distinctive stages: an initial stage characterized by extreme uncertainty and strict government measures, and a later stage characterized by reduced uncertainty and lighter restrictions. Several studies, especially those conducted in the first half of 2020, have used the 1st of January 2020 as the starting date of the COVID-19 period to examine the financial effects of the pandemic. However, alternative dates have also been used⁷ such as 20 January (Erdem, 2020; Takahashi & Yamada, 2021), 15 February (Ibrahim et al., 2020; Landier & Thesmar, 2020), 19 February (Thorbecke, 2020), 21 February (Sharif et al., 2020), 24 February (Ramelli & Wagner, 2020) and 11 March (Phan & Narayan, 2020; Salisu et al., 2020). In our study of informed trading in BTC/USD, we utilize 15 February 2020 as the start of the pandemic period. This date witnessed the first death from COVID-19 outside Asia (France), conveying a strong signal that the disease had become a global threat with worldwide scope. While there exist COVID-19 cases in Europe and the U.S. starting from 20th of January, their total number sum up to only 46 by 15th of February. Following this date, the numbers of deaths and non-travel related cases started to significantly increase, and in a widespread fashion. For instance, by the end of February, the number of cases outside Asia had reached around 1500 cases. The start of

COVID-19 stage II is chosen to be the 1st of June 2020. The beginning of June witnessed the easing of various lockdown restrictions in many countries including France, Germany, U.S., Italy, and India. The period between the 1st of June 2020 and the 15th September 2020 is characterized by an increased knowledge and control over the COVID-19 pandemic and looser restrictions. Consequently, we have two subsamples of equal length of 3½ months. For reasons of symmetry, the pre-COVID-19 period also spans 3½ months, resulting in a full sample of 10½ months.

As robustness checks for the choice of the cutoff dates, we redo the analysis for alternative relevant dates. First, instead of 15 February 2020, we select 11 March 2020—the date at which WHO declares COVID-19 as pandemic—as the starting date of COVID-19 stage I. Second, we use 11 May 2020—the date for the very first easing actions on the lockdowns in France—instead of 1 June 2020 as the starting date of COVID-19 stage II⁸. Third, we use the last 3½ months of 2019 as an alternative pre-COVID-19 period. This choice addresses the concerns of observing potential COVID-19 effects in the period between 1 January 2020 and 15 February 2020. The results of these 3 alternative partitioning choices are qualitatively identical to the results reported in the paper. Table A1 in Appendix A lists all dates used in our study as well as their description and importance.

We use the volume-synchronized probability of informed trading (VPIN) metric introduced by Easley et al. (2012) to estimate the prevalence of informed trading. This metric addresses the high-frequency feature of current financial markets by incorporating the volume and clustering of trades. It differs from the original PIN model (Easley et al., 1996), which relies on the number of trades and constant clock time intervals. The VPIN model is a dynamic econometric model of trading introducing time-varying (GARCH-style) arrival rates of informed and uninformed traders.⁹ Easley et al. (2008) show that, for a particular period of time τ (e.g., days), the expected trade imbalance, $E[V_{\tau}^{Sell} - V_{\tau}^{Buy}]$, approximates the rate of arrival of informed orders while the expected total number of trades, $E[V_{\tau}^{Sell} + V_{\tau}^{Buy}]$, proxies for the arrival of total orders. V_{τ}^{Sell} and V_{τ}^{Buy} stand for seller-initiated volume and buyer-initiated volume, respectively, during the time period τ . Consequently, the ratio of informed activity to the total activity estimates the probability of informed trading.

In contrast to the original PIN model that works on clock-time, VPIN works on volume-time. The first parameter in the VPIN computation is the bar size for which trade aggregation is performed. Following Easley et al. (2012) and Abad and Yagüe (2012), we use a 1 min bar size. For each time bar, trades are aggregated by adding up the volume of all trades, and price change, Δp , is calculated as the price of the final trade minus the price of the initial trade. The second parameter in the computation is volume bucket size (VBS). Volume buckets represent pieces of homogeneous information content that are used to compute order imbalances. In Easley et al. (2012), volume bucket size is calculated by dividing the average daily volume (in Bitcoins) by 50. Buckets are filled by adding the trade volume in consecutive 1 min bars until completing the VBS. If the trade volume of the last time bar needed to complete a bucket is for a size that is greater than required, the excess size is assigned to the next bucket. The final parameter in the computation is sample length, n , that stands for the number of buckets to be included in the computation of each VPIN value. Thus, the VPIN value for a certain volume bucket is driven by the last n buckets' order imbalances. VPIN metric is updated after each volume bucket in a rolling window process, i.e., for the sample length of 50, when bucket #51 is filled, we drop

bucket #1 and calculate the next VPIN based on buckets #2 to #51. VPIN is consequently calculated as below.

$$VPIN = \frac{E \left[\left| V_{\tau}^{Sell} - V_{\tau}^{Buy} \right| \right]}{E \left[V_{\tau}^{Sell} + V_{\tau}^{Buy} \right]} = \frac{\sum_{\tau=1}^n OI_{\tau}}{n \times VBS} \quad (1)$$

where VPIN is the average of order imbalance ratios in the sample length: the result of dividing the sum of order imbalances (OI) for all the buckets in the sample length (proxy for the expected trade imbalance) by the product of volume bucket size (VBS) and the sample length n . In line with Easley et al. (2012) and Abad and Yagüe (2012), we perform our main analysis using the 1-50-50 parameter set—1 min time bars, volume bucket size as 1/50th of the average daily volume, and 50 buckets as a sample length. We utilize 1-50-250 and 1-5-5 as alternative parameter sets for robustness checks.

A key advantage of VPIN is that it provides a high-frequency proxy for order-flow toxicity that is updated in volume time, making it well-suited to environments where trading intensity changes rapidly (Easley et al., 2012). Importantly, VPIN can be computed directly from observable trade and volume data by forming volume buckets and measuring buy–sell volume imbalance without first estimating latent structural quantities (e.g., informed-trade arrival rates or other unobserved model parameters) via numerical optimization, which is the sort of intermediate estimation step that is central to classic PIN-style likelihood approaches (Easley et al., 1996; Easley et al., 2012). At the same time, the VPIN literature highlights two practical caveats. First, VPIN can be sensitive to implementation choices (e.g., bucket size, trade-signing rules, sampling), so robustness across standard parameterizations is important (Abad & Yagüe, 2012). Second, there is a debate about what VPIN captures in extreme episodes: Andersen and Bondarenko (2014), studying S&P 500 futures around the Flash Crash, argue that VPIN is a poor predictor of short-run volatility, that it does not peak prior to the Flash Crash but rather after, and that its apparent predictive content is driven largely by a mechanical relation with trading intensity. Easley et al. (2014) respond that Andersen and Bondarenko’s conclusions hinge on how VPIN is implemented and interpreted, arguing that their critique targets variants and empirical exercises that are not the recommended use of VPIN. Specifically, they emphasize the importance of using the volume-bucket approach rather than the time-bucket and strongly suggest the implementation of alternative parameter sets as robustness. In line with this, in this paper, we employ volume-buckets as well as various robustness checks with altered parameters.

Our main explanatory variables are daily growth rates of the global cumulative number of confirmed COVID-19 cases and deaths. As VPIN is calculated intraday, we obtain the daily VPIN value by taking the time-weighted average of VPIN values on that day, where the weights are the time duration of each bucket within a given day. As an alternative, we use the equally weighted average VPIN as a daily informed trading measure.

The numbers of cumulative confirmed COVID-19 cases and deaths data is downloaded from “Our World in Data” (University of Oxford and Global Change Data Lab) website.¹⁰ We use the differenced natural logarithm of cases and deaths (Ding et al., 2021; Zaremba et al., 2021) to compute their growth rates. The respective growth numbers in cases (C) and deaths (D) on day t are therefore:

$$growthD_t = \ln(D_t) - \ln(D_{t-1}) \quad (2)$$

$$growthC_t = \ln(C_t) - \ln(C_{t-1}) \quad (3)$$

We use two control variables, namely, daily trading volume (*tradVol*) and intraday price volatility (*priceVolat*) (Heflin & Shaw, 2000). Daily trading volume is controlled to address the concern that the informed trading variable may partially capture the effects of liquidity shocks.¹¹ Daily trading volume is calculated in billion USD as the sum of all trade volumes within a given day. Intraday price volatility is calculated using intraday price range (Ersan & Ekinici, 2016; Kirilenko et al., 2017).

$$priceVolat_t = \frac{\max(price)_t - \min(price)_t}{[\max(price)_t + \min(price)_t]/2} \quad (4)$$

We use 3 models in examining the impacts of the growth rate of confirmed COVID-19 cases and deaths on informed trading in cryptocurrency markets. These regression models with the growth in COVID-19 cases as dependent variable are presented in Equations (5)–(7). Same models are used to estimate the effect of growth rate of COVID-19-related deaths. The first model (Equation (5)) runs the univariate regression while the second model (Equation (6)) controls for two variables: daily trading volume and price volatility. The last model (Equation (7)) additionally controls for day-of-the-week dummies.

$$VPIN_t = \alpha + \beta growthC_t + \varepsilon_t \quad (5)$$

$$VPIN_t = \alpha + \beta_1 growthC_t + \beta_2 tradVol_t + \beta_3 priceVolat_t + \varepsilon_t \quad (6)$$

$$VPIN_t = \alpha + \beta_1 growthC_t + \beta_2 tradVol_t + \beta_3 priceVolat_t + \sum_{j=2}^7 \gamma_j dayOfWeek_j + \varepsilon_t \quad (7)$$

The VPIN construction follows the volume-synchronized framework introduced by Easley et al. (2012), where order-flow toxicity is measured from volume imbalances computed in “volume time (bulk volume, BV)” and updated at high frequency. The same BV/VPIN methodology has been adopted and discussed in the subsequent literature, including Abad and Yagüe (2012) who provide a detailed exposition of the VPIN procedure and its key innovations relative to PIN, as well as empirical applications linking VPIN to market conditions in traditional assets (e.g., Kang et al. (2020) for equity-index futures and Yildiz et al. (2020) for U.S. equities). More recently, VPIN-type measures have also been used in crypto market settings; for example, Kitvanitphasu et al. (2025) study VPIN and its relation to discontinuous price movements. Recent crypto-specific microstructure evidence also adopts VPIN as a central informational-asymmetry proxy; for example, Easley et al. (2024) explicitly include VPINs (alongside Roll’s measure and other liquidity proxies) to characterize and predict market dynamics across major cryptocurrencies.

3. Findings

Figure 1 depicts the time series of the probability of informed trading on Bitstamp exchange for the study period. Cutoff days partitioning the study period are represented by 2 vertical lines. Figure 1 suggests an overall rise in information asymmetry during the COVID-19 stage I.

Table 1 presents descriptive statistics for the main variables. The average daily VPIN over the whole sample is 23.7% and varies substantially among different subsamples. For instance, COVID-19 stage I is associated with relatively higher VPIN values when compared to the pre-COVID-19 period. The difference in means between stage I and the pre-COVID-19 period is 4.2% and it is both statistically and economically meaningful. The difference corresponds to an increase in the average VPIN of roughly 19% relative to the pre-crisis benchmark. In addition, VPIN during the first stage of pandemic has a relatively wide dispersion (SD = 6.6%) and values ranging from 14.8% to as high as 51.4%. In the pre-COVID-19 period, standard deviation of 5% and the range of 11.4% to 33.4% implies a

tighter dispersion. However, COVID-19 stage II does not (on average) exhibit a significantly different level of informed trading when compared to the pre-COVID-19 period. This is consistent with the normalization of information asymmetry as the market and public health conditions begin to stabilize. These findings are robust to various alternative choices of subsamples.¹²

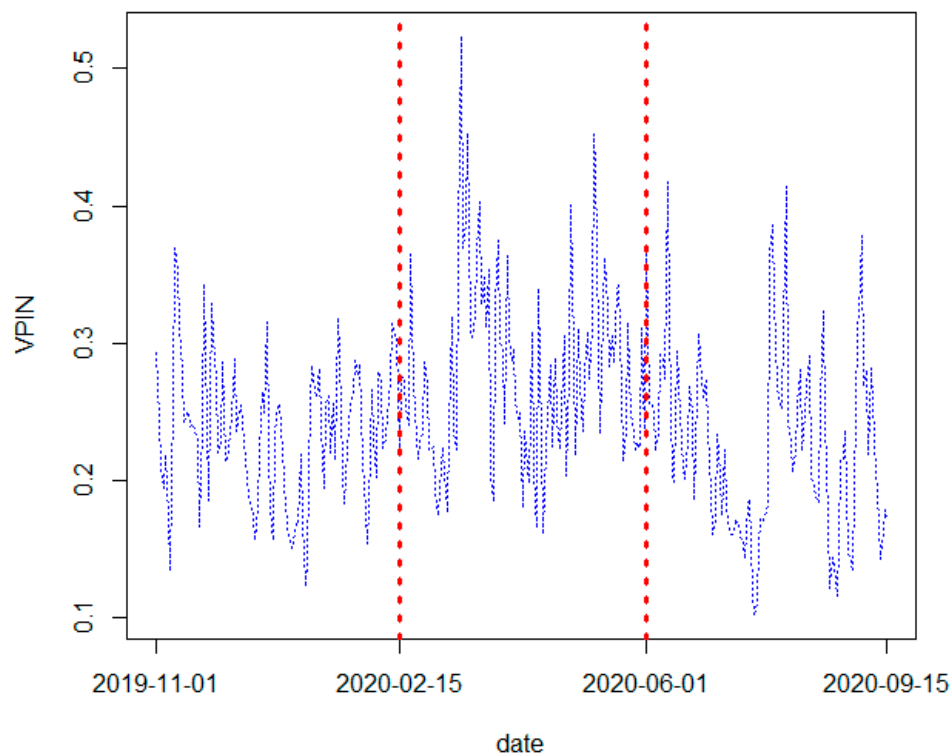


Figure 1. Daily VPIN for 320 days between 1 November 2019 and 15 September 2020. Notes: Two vertical lines divide the sample into three periods: 1 November 2019 to 14 February 2020 (pre-COVID-19), 15 February 2020 to 31 May 2020 (COVID-19 stage I), and 1 June 2020 to 15 September 2020 (COVID-19 stage II). Daily VPIN utilizes the 1-50-50 parameter set and the calculation details are as in Section 2.

Table 1. Descriptive statistics.

	Mean	SD	Min	25%	Median	75%	Max
VPIN, whole period	0.237	0.066	0.100	0.188	0.234	0.279	0.514
VPIN, pre-COVID-19 period	0.227	0.050	0.111	0.195	0.231	0.259	0.334
VPIN, COVID-19 stage I	0.269	0.068	0.148	0.218	0.259	0.310	0.514
VPIN, COVID-19 stage II	0.214	0.067	0.100	0.162	0.201	0.252	0.418
diff1 (COVID-19 stage I—pre-COVID-19 period)	0.042 ***						
diff2 (COVID-19 stage II—pre-COVID-19 period)	−0.013						
priceVolat	0.055	0.054	0.010	0.027	0.040	0.062	0.501
tradVol (billion USD)	0.081	0.057	0.012	0.044	0.065	0.105	0.360
COVID-19 Deaths	4335	2280	38	3377	4813	5850	10,491
COVID-19 Cases	136,938	94,783	523	72,909	110,998	225,031	305,691

Notes: VPIN is calculated with the parameter set of 1-50-50. Differences in means of VPIN are tested using a two-sided *t*-test with the null hypothesis of equal means in subperiods. Each of the two COVID-19 stages are compared with the pre-COVID-19 period. Intraday price volatility (*priceVolat*) captures the price range, daily trading volume (*tradVol*) is the total of all trade volumes in billion USD on any given day. Statistics on the explanatory variables are calculated for the 15 February 2020–15 September 2020 period. Computation details for VPIN and for other variables are as in Section 2. (***) represents significance at 1% level.

Overall, the descriptive evidence suggests a transitory elevation in VPIN during the initial phase of the COVID-19 period. VPIN increases in COVID-19 stage I and the mean-comparison test indicates that it differs significantly from the pre-COVID benchmark. In COVID-19 stage II, VPIN moves back toward its pre-COVID range and the difference no longer meets conventional significance thresholds. While these comparisons remain descriptive, they are consistent with a narrative in which the pandemic was characterized by heightened uncertainty and heterogeneous information processing, temporarily widening information asymmetries between better-informed and less-informed market participants. Once the initial wave of uncertainty receded and market participants gradually learned to interpret pandemic-related news, informed trading pressures appear to have normalized. This time variation in VPIN aligns with the interpretation of VPIN as a real-time measure of order-flow toxicity and adverse-selection risk (Easley et al., 2012; Abad & Yagüe, 2012).

In Table 2, we find that the daily growth rate for both cases and deaths positively affects the level of information asymmetry on the Bitcoin market. Informed trading, measured by VPIN, is an increasing function of daily information about new cases and deaths, captured through their respective growth rates (Models 1–2). The finding is robust to the use of alternative models such as multivariate models that control for trading volume and price volatility, as well as day-of-the-week effects (Models 3–6). The magnitude of the impact is economically significant. Based on the results of Model 5 (6), as reported in Table 2, a 10% increase in the growth rate of confirmed cases (deaths) leads to an 8.17% (6.6%) increase in VPIN. In our unreported subsample analysis, we confirm a positive effect of daily COVID-19 variables on informed trading in both COVID-19 stage I and II. Alternatively, a 3-day growth rate of confirmed cases (and deaths) is shown to significantly affect informed trading prevalence.

The regression results in Table 2 further corroborate this pattern and link it directly to the dynamics of the pandemic. When the daily growth in confirmed cases (growthC) is the only explanatory variable (Model 1), its coefficient is positive and highly significant (1.047***), and the specification explains around 13% of the variation in VPIN ($\text{Adj-R}^2 = 0.134$). A similar picture emerges when using the daily growth in deaths (growthD) instead (Model 2), with a slightly smaller but still economically large coefficient of 0.747*** and comparable explanatory power ($\text{Adj-R}^2 = 0.126$). These results suggest that both dimensions of the pandemic, its spread and its severity, are associated with an increased incidence of informed trading in the Bitcoin market.

Adding control variables for market conditions in Models 3–6 substantially increases the explanatory power of the regressions while leaving the estimated effects of pandemic growth largely intact. In Models 3 and 5, the coefficients on growthC remain positive and strongly significant (0.786*** and 0.817***, respectively), even after including trading volume, intraday price range and day-of-the-week dummies. Models 4 and 6 show an analogous robustness for growthD, with coefficients of 0.622*** and 0.660***. Adjusted R^2 rises to the 0.57–0.60 range once controls are added, indicating that contemporaneous market activity accounts for a material fraction of VPIN variation but does not subsume the predictive content of COVID-19 growth rates. The consistently positive and significant coefficients across all specifications thus support the interpretation that pandemic-related information is an independent driver of informed trading, rather than merely a proxy for increased trading activity or volatility.

The control variables themselves yield additional insights into the microstructure of the Bitcoin market. Trading volume (tradVol) is positively and strongly associated with VPIN in all specifications where it is included, with coefficients between 0.819 and 0.966 in Table 2, suggesting that periods of heavy trading are also periods when the probability of facing an informed counterparty is elevated. Price volatility (priceVolat), measured by the high–low

range, is mostly insignificant, implying that order-flow toxicity is not mechanically driven by contemporaneous price swings once volume and pandemic conditions are controlled for. The day-of-the-week effects are generally small, with only Sunday occasionally displaying a weak positive impact on VPIN, which is consistent with the 24/7 nature of cryptocurrency trading and suggests that the COVID-19 information channel dominates any residual calendar anomalies over the sample period.

Table 2. Regression results.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
growthC	1.047 *** (0.196)		0.786 *** (0.205)		0.817 *** (0.189)	
growthD		0.747 *** (0.134)		0.622 *** (0.133)		0.660 *** (0.121)
priceVolat			0.051 (0.191)	0.034 (0.191)	−0.018 (0.184)	−0.047 (0.184)
tradVol			0.819 *** (0.094)	0.845 *** (0.098)	0.928 *** (0.104)	0.966 *** (0.106)
Tuesday					−0.007 (0.011)	−0.005 (0.011)
Wednesday					−0.012 (0.011)	−0.013 (0.011)
Thursday					−0.015 (0.013)	−0.015 (0.013)
Friday					−0.011 (0.012)	−0.008 (0.012)
Saturday					0.006 (0.012)	0.007 (0.012)
Sunday					0.023 * (0.012)	0.026 ** (0.012)
Intercept	0.212 *** (0.007)	0.219 *** (0.006)	0.150 *** (0.007)	0.152 *** (0.006)	0.146 *** (0.011)	0.147 *** (0.011)
Adj-R	0.134	0.126	0.569	0.579	0.584	0.598
F-Stat	33.96 ***	31.67 ***	94.66 ***	98.73 ***	34.16 ***	36.20 ***
Observations	214	214	214	214	214	214

Notes: The dependent variable (VPIN) is calculated using the parameter set of 1-50-50. *GrowthC* and *GrowthD* are the daily differences in the natural logarithm of COVID-19 cases and deaths, respectively. Intraday price volatility (*priceVolat*) captures the price range; daily trading volume (*tradVol*) is the total of all trade volumes in billion USD on any given day. Data sample is 15 February 2020–15 September 2020. Computation details for VPIN and for other variables are as in Section 2. Robust standard errors are presented in parenthesis. (*), (**), and (***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The positive and statistically significant coefficients on the case and death growth variables suggest that pandemic-related information is not only reflected in prices and volumes but is also systematically incorporated into the order flow via unbalanced trading. In other words, when the global health situation deteriorates more rapidly, the probability that trades are information-driven increases, consistent with investors trading on superior information or on superior ability to process public and semi-public pandemic news. This result is in line with prior work which documents that VPIN tends to increase in periods of market stress and heightened uncertainty, such as the Flash Crash of 2010 and other episodes of extreme volatility.

We conduct various robustness checks of the calculation method for the dependent variable (VPIN) and report the results in Table 3. We consider three alternative ways of calculating VPIN: a daily time-weighted average VPIN using parameter sets (1-50-250) and (1-5-5), and daily equally weighted VPIN using the initial parameter set (1-50-50).

While the first alternative parameter set (1-50-250) incorporates a larger rolling window in the calculation, the latter set (1-5-5) utilizes large volume buckets, and, thus, a lower frequency of intraday calculation. Performing the regression models using the alternatively calculated dependent variable leads to results reported in Table 3. These results provide further evidence supporting a positive and significant impact of the growth rates of cases and deaths on the prevalence of informed trading. Both growthC and growthD retain positive and statistically significant coefficients across all models. Although the magnitude of the estimated effects varies somewhat across VPIN specifications, the signs and significance levels are stable and the adjusted R^2 remain in a relatively high range (0.38–0.66), underscoring that the documented relationship between pandemic dynamics and informed trading is a pervasive feature of the data rather than an artifact of a particular modeling choice. Taken together, the descriptive statistics, baseline regressions and robustness tests point to a sharp, but largely transitory, increase in information asymmetry in the Bitcoin market during the early phase of the COVID-19 pandemic, tightly linked to the acceleration of reported cases and deaths.

Table 3. Robustness checks I—VPIN specifications.

	VPIN 1-50-250	VPIN 1-50-250	VPIN 1-5-5	VPIN 1-5-5	VPIN 1-50-50 (Equal Weight)	VPIN 1-50-50 (Equal Weight)
growthC	0.823 *** (0.143)		0.222 ** (0.095)		0.715 *** (0.166)	
growthD		0.582 *** (0.101)		0.220 *** (0.065)		0.588 *** (0.104)
priceVolat	0.095 (0.139)	0.108 (0.146)	0.051 (0.071)	0.023 (0.070)	0.152 (0.124)	0.121 (0.124)
tradVol	0.566 *** (0.106)	0.579 *** (0.109)	0.379 *** (0.065)	0.403 *** (0.067)	0.937 *** (0.102)	0.974 *** (0.104)
Tuesday	0.008 (0.012)	0.010 (0.012)	−0.003 (0.008)	−0.003 (0.008)	−0.006 (0.012)	−0.005 (0.011)
Wednesday	−0.002 (0.011)	−0.002 (0.012)	−0.005 (0.008)	−0.006 (0.008)	−0.010 (0.011)	−0.011 (0.011)
Thursday	−0.018 (0.011)	−0.018 (0.011)	−0.014 * (0.008)	−0.015 * (0.008)	−0.011 (0.014)	−0.011 (0.013)
Friday	0.002 (0.012)	0.004 (0.011)	−0.009 (0.008)	−0.009 (0.008)	−0.016 (0.012)	−0.014 (0.011)
Saturday	0.020 (0.012)	0.022 * (0.012)	0.002 (0.008)	0.002 (0.008)	0.008 (0.012)	0.010 (0.012)
Sunday	0.017 (0.011)	0.019 * (0.011)	0.014 (0.010)	0.014 (0.010)	0.025 ** (0.012)	0.028 ** (0.012)
Intercept	0.184 *** (0.009)	0.187 *** (0.009)	0.061 *** (0.008)	0.061 *** (0.008)	0.143 *** (0.011)	0.144 *** (0.011)
Adj-R	0.423	0.419	0.379	0.393	0.645	0.657
F-Stat	18.36 ***	18.06 ***	15.37 ***	16.26 ***	40.09 ***	42.35 ***
Obs	214	214	214	214	214	214

Notes: Dependent variable *VPIN* is calculated using alternative specifications. The first two columns present results of regressions using *VPIN* (1-50-250). The third and fourth columns stand for the results when the dependent variable is *VPIN* (1-5-5). The last two columns report regression results of models using daily *VPIN* by equally weighted average of intraday values. *GrowthC* and *GrowthD* are the daily difference in natural logarithm of COVID-19 cases and deaths, respectively. Intraday price volatility (*priceVolat*) captures the price range; daily trading volume (*tradVol*) is the total of all trade volumes in billion USD on any given day. Data sample is 15 February 2020–15 September 2020. Computation details for *VPIN* and for other variables are as in Section 2. Robust standard errors are presented in parenthesis. (*), (**), and (***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 reports a set of complementary robustness checks and verify that the main pandemic-VPIN results are not driven by a particular control set or timing convention. Models R1–R2 repeat the baseline COVID-stage regressions but replace the contemporaneous price volatility and trading volume with their lagged counterparts. The estimated coefficients on GrowthC and GrowthD remain positive and statistically significant. Moreover, the magnitude of the coefficients is close to the ones in our baseline analyses (Models 5–6 in Table 2), implying that the economic meaning remains qualitatively similar. This indicates that the pandemic–growth association with VPIN is not tied to same-day movements in these market-condition variables. Models R3–R4 replace the main intraday range volatility proxy (*priceVolat*) with an alternative high-frequency measure, realized volatility (*RealizedVolat*) computed from 5 min returns, i.e., the sum of squared 5 min log returns within each day.¹³ Our main results remain unchanged, suggesting that the findings are not driven by the particular volatility proxy used. Both GrowthC and GrowthD retain similar magnitudes and strong statistical significance. Finally, Models R5–R6 add a mortality control (calculated as the ratio of daily number of deaths to number of cases) capturing the severity dimension of COVID-19; mortality enters positively and significantly, yet the GrowthC and GrowthD coefficients remain positive and statistically significant, suggesting that the primary growth-related results are not subsumed by this additional epidemiological channel. In our unreported analyses, we also use the 3-day growth rate of confirmed cases (and deaths) instead of the baseline 1-day growth rates obtaining qualitatively similar results. Although Bitcoin trading occurs continuously (24/7), broader market participation and liquidity conditions may still shift on days when major traditional markets are closed. Accordingly, as an additional robustness check, we include a market-holiday dummy that equals one on dates corresponding to official exchange holidays in the United States (NYSE) and Europe (Euronext) during our sample window, and zero otherwise.¹⁴ Including this holiday indicator in our models leaves the estimated pandemic–growth coefficients and the overall inference unchanged (with almost identical coefficients), indicating that our results are not driven by holiday-related disruptions in broader market activity.

An important feature of our findings is that the impact of COVID-19 dynamics on informed trading is stronger in the early pandemic phase. In our subsample analysis (not reported in full for brevity), the growth in cases and deaths exerts a more pronounced and statistically significant effect on VPIN during COVID-19 stage I, while the effect weakens in stage II. This asymmetry across stages implies that the information content of pandemic news is state-dependent: in the early phase, when the virus, the policy response, and the macroeconomic consequences were largely unknown, new information was more likely to convey private or difficult-to-process signals, thereby providing scope for informed trading. In the later phase, market participants seem to have partially adjusted their expectations and trading strategies, leading to a more muted response from VPIN to changes in the pandemic trajectory. This pattern echoes evidence from other asset classes that the COVID-19 shock had its most disruptive effects on trading behavior and volatility in the early months of the pandemic.

Our findings suggest a significant increase in informed trading during COVID-19 stage I, and a positive impact of COVID-19 cases and deaths on informed trading prevalence. They provide supporting evidence to the argument that informed traders tend to increase their trading activity during periods characterized by high uncertainty, in order to exploit its associated effects such as more prevalent behavioral biases among uninformed traders (Kumar, 2009). The findings of our study are also in line with the studies suggesting that sophisticated traders benefit from uncertainties, i.e., government policy uncertainties (Gao & Huang, 2016; Nagar et al., 2019).

Table 4. Robustness checks II—Alternative independent variable specifications.

	Model R1	Model R2	Model R3	Model R4	Model R5	Model R6
growthC	0.666 *** (0.194)		0.772 *** (0.148)		0.767 *** (0.190)	
growthD		0.546 *** (0.129)		0.614 *** (0.092)		0.643 *** (0.122)
Mortality					0.536 ** (0.223)	0.641 *** (0.214)
priceVolat					0.041 (0.188)	0.010 (0.185)
tradVol			0.882 *** (0.078)	0.902 *** (0.077)	0.870 *** (0.106)	0.904 *** (0.107)
priceVolat (t − 1)	0.197 (0.147)	0.171 (0.138)				
tradVol (t − 1)	0.702 *** (0.121)	0.734 *** (0.122)				
RealizedVolat			0.486 (0.504)	0.448 (0.518)		
Tuesday	−0.045 *** (0.012)	−0.045 *** (0.012)	−0.007 (0.011)	−0.005 (0.011)	−0.006 (0.011)	−0.005 (0.010)
Wednesday	−0.035 *** (0.012)	−0.037 *** (0.012)	−0.005 (0.011)	−0.006 (0.011)	−0.010 (0.011)	−0.011 (0.010)
Thursday	−0.014 (0.015)	−0.015 (0.014)	−0.015 (0.013)	−0.015 (0.013)	−0.015 (0.013)	−0.015 (0.012)
Friday	−0.058 *** (0.012)	−0.057 *** (0.012)	−0.012 (0.012)	−0.009 (0.012)	−0.011 (0.012)	−0.009 (0.011)
Saturday	−0.059 *** (0.012)	−0.059 *** (0.012)	0.005 (0.012)	0.006 (0.012)	0.005 (0.012)	0.006 (0.011)
Sunday	0.002 (0.014)	0.003 * (0.014)	0.022 * (0.012)	0.025 ** (0.012)	0.022 * (0.012)	0.025 ** (0.012)
Intercept	0.185 *** (0.010)	0.186 *** (0.010)	0.149 *** (0.012)	0.150 *** (0.011)	0.124 *** (0.014)	0.119 *** (0.014)
Adj-R	0.517	0.527	0.585	0.599	0.592	0.611
F-Stat	26.23 ***	27.23 ***	34.40 ***	36.36 ***	31.89 ***	34.47 ***
Obs	213	213	214	214	214	214

Notes: Model R1 and Model R2 repeat our baseline analyses for *GrowthC* and *GrowthD* after altering contemporaneous values of two independent variables (*priceVolat* and *tradVol*) with their lagged values. Model R3 and Model R4 replace our main volatility variable (*priceVolat*) with an alternative high-frequency variable: Realized volatility (*RealizedVolat*). Model R5 and Model R6 include an additional variable capturing the mortality dimension of COVID-19 (*Mortality*). Dependent variable (VPIN) is calculated using the parameter set of 1-50-50. *GrowthC* and *GrowthD* are the daily differences in the natural logarithm of COVID-19 cases and deaths, respectively. Intraday price volatility (*priceVolat*) captures the price range; daily trading volume (*tradVol*) is the total of all trade volumes in billion USD on any given day. *RealizedVolat* is calculated as the daily sum of squared returns on 5 min intervals. *Mortality* is the ratio of daily number of COVID-19 deaths to COVID-19 cases. Data sample is 15 February 2020–15 September 2020. Computation details for VPIN and for other variables are as in Section 2. Robust standard errors are presented in parenthesis. (*), (**), and (***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Our main evidence, positive and robust associations between pandemic intensity (case/death growth) and daily VPIN, accords with the broader interpretation in the VPIN literature that information asymmetry tends to rise in periods of heightened uncertainty and market stress. In the original framework, VPIN is presented as a real-time measure of flow toxicity designed to capture adverse-selection risk faced by liquidity providers in a high-frequency environment. Empirical studies in other markets similarly document informative links between VPIN, liquidity, and return volatility in U.S. equities (Yildiz et al., 2020). In crypto markets, recent evidence also connects VPIN to stress-like outcomes such as Bitcoin price jumps (Kitvanitphasu et al., 2025), providing a complementary context in

which our pandemic-based results can be interpreted as a macro-stress channel associated with higher order-flow toxicity. Consistent with the interpretation of VPIN as an order-flow toxicity measure that becomes more informative in stress/uncertainty episodes, [Easley et al. \(2024\)](#) show that VPIN-type metrics carry substantial explanatory and predictive content.

4. Conclusions

We use the BTC/USD tick-by-tick trading data of Bitstamp exchange for the period from 1 November 2019 to 15 September 2020. The sample includes 6,693,051 trades in total, with 3,205,310 buyer-initiated trades and 3,487,741 seller-initiated ones. We divide the period in three subperiods: pre-COVID-19 period, COVID-19 stage I, and COVID-19 stage II. VPIN values vary substantially between COVID-19 stage I and pre-COVID-19 period. In contrast, COVID-19 stage II does not exhibit a significantly different level of informed trading when compared to the pre-pandemic period. We find that both the daily growth rate of cases and deaths positively affect the magnitude of information asymmetry in cryptocurrency markets. Our findings are robust to the use of alternative models that control for trading volume and price volatility, as well as for day-of-the-week dummies; or use of alternative calculation methods of informed trading metric, VPIN.

The significant increase in information asymmetry level in the COVID-19 stage I (from 15 February 2020 to 1 June 2020) implies that traders should be vigilant when taking trading decisions during highly uncertain periods. As increasing growth rates in cases and deaths exacerbate the prevalence of informed trading, they can be perceived as precautionary signals of unfavorable timing of trades. Further research is needed to investigate if such findings extend to informed trading in other financial markets, and whether it is priced throughout the COVID-19 pandemic.

Our results contribute to, and are broadly consistent with, recent studies that document a substantial increase in Bitcoin volatility and a change in the role of Bitcoin in investors' portfolios during the COVID-19 period ([Nguyen, 2022](#); [Panyagometh, 2024](#); [Su, 2025](#)). Several papers report that Bitcoin volatility rose sharply in the initial months of the pandemic and that the correlation between Bitcoin and major stock indices increased, at least temporarily, as investors reassessed Bitcoin's hedging and diversification properties ([Nguyen, 2022](#); [Panyagometh, 2024](#); [Su, 2025](#)). While these studies focus primarily on return dynamics and volatility transmission, our VPIN-based analysis highlights the microstructure channel through which pandemic-related information was impounded into Bitcoin prices. Specifically, we show that the pandemic affected not only the second moment of returns, but also the composition of order flow and the prevalence of informed trading. In this sense, our paper complements prior work on informed trading in Bitcoin around major crypto-specific events, by showing that a global, non-crypto shock can also generate distinct episodes of elevated informed trading in the Bitcoin market ([Feng et al., 2018](#)).

Moreover, the documented increase in VPIN during COVID-19 stage I underscores the sensitivity of cryptocurrency markets to large-scale macro-health shocks. Bitcoin is often portrayed as an asset that is largely disconnected from traditional macroeconomic fundamentals. Our results suggest that, at least during extreme events, this view is incomplete: informed trading in Bitcoin appears to respond strongly to global health and policy developments. For example, [Assaf et al. \(2025\)](#) show that return and volatility spillovers among DeFis and cryptocurrencies increase in uncertain, turbulent periods. This has implications for the interpretation of Bitcoin as a "safe haven" or "diversifier" asset and suggests that measures of order-flow toxicity such as VPIN can be informative for monitoring stress and information asymmetry in crypto markets during future crisis episodes (e.g., [Bouri et al., 2017](#)).

One limitation of our study is that our microstructure evidence is based on a single trading venue, which may not fully capture the fragmented nature of Bitcoin trading across many spot exchanges, derivatives venues, and OTC activity. However, we work with a large data (around 6.7 million trades) from an exchange with one of the largest market shares in Bitcoin trading (see, for example Feng et al., 2018; X. Li et al., 2020; Wang et al., 2020 for other analyses with Bitstamp data). A further limitation is that, although VPIN is constructed from intraday order flow, our main empirical specifications are at the daily level: we aggregate intraday VPIN to a daily measure (via both time-weighted and equal-weighted averaging across buckets within the day), which is appropriate for aligning with daily COVID-19 indicators but may mask finer intraday lead-lag dynamics between information arrival, trading activity, and order-flow toxicity. Finally, our sample window is intentionally concentrated on the pandemic onset and the subsequent normalization phase (November 2019–September 2020), so the external validity of the estimated relationships to other stress episodes, or to later, structurally different crypto market regimes, should be interpreted with appropriate caution.

Future research can extend our framework beyond BTC to other large cryptoassets (e.g., ETH and other majors) to test whether the positive association between pandemic (or broader stress) dynamics and VPIN generalizes across assets with different liquidity and trader composition. A second natural direction is to apply the same VPIN-based methodology to traditional asset classes where order-flow toxicity was originally developed and widely studied (e.g., equities or equity index futures), enabling a direct comparison of how pandemic-related information effects alter in those asset classes. Finally, future work could move from daily regressions to an intraday design, especially in settings where pandemic proxies are available at high frequency (e.g., pandemic-news feeds, intraday announcements) and relate intraday VPIN to intraday realized volatility and other microstructure outcomes to map short-horizon lead-lag dynamics more precisely.

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Appendix A

Table A1. Cutoff dates and intervals associated with COVID-19.

Intervals, Dates	Description	Explanation
1 November 2019–15 September 2020	Full sample window	Overall observation period used for VPIN estimation and regressions.
1 November 2019–14 February 2020	Pre-COVID subsample	Benchmark period before the COVID-19 shock period defined in the study.

Table A1. Cont.

Intervals, Dates	Description	Explanation
15 February 2020–31 May 2020	COVID-19 stage I subsample	Initial COVID-19 phase intended to capture the period of high uncertainty and strict government measures.
1 June 2020–15 September 2020	COVID-19 stage II subsample	Later COVID-19 phase intended to capture reduced uncertainty and the easing of restrictions relative to stage I.
15 February 2020	Cutoff: start of stage I	Chosen because it coincides with the first reported COVID-19 death outside Asia (France), signaling broader international spread.
1 June 2020	Cutoff: start of stage II	Used to mark the beginning of widespread easing of lockdown restrictions and a shift toward lighter restrictions in many countries.
11 March 2020	Alternative cutoff: start of stage I	WHO characterized COVID-19 as a pandemic on this date.
11 May 2020	Alternative cutoff: start of stage II	Date associated with the first easing actions of lockdown restrictions in Europe (France).
16 September 2019–31 December 2019	Alternative window: pre-COVID subsample	Used to avoid potential early COVID-related effects already present in early-2020 data.

Notes: The table presents the dates and intervals used in the study as well as the descriptions and explanations for selecting each of them.

Notes

- ¹ Thus, informed trading is not only about access to superior information; it can also arise from investors' superior ability to process information, faster access to the market, or superior trading skills, each of which can generate informational asymmetry among investors (see, e.g., [Ahn et al., 2008](#), for a careful definition).
- ² See, e.g., [J. Goodell and Goutte \(2021\)](#) for a recent review of the research on how cryptocurrencies have been affected by the COVID-19 pandemic.
- ³ By the term utility trader, [Harris \(2003\)](#) refers to any trader with a trading motivation other than trading profits, e.g., liquidity purposes, asset exchange, hedging.
- ⁴ Market microstructure commonly distinguishes between informed traders and liquidity (or "noise") traders. Informed traders trade because they believe they have an advantage about value—through private information, superior information-processing, faster reaction, or better execution, whereas liquidity traders trade mainly for non-informational reasons such as rebalancing, hedging, meeting cash needs, or implementing longer-horizon portfolio decisions ([Kyle, 1985](#)). These motives interact: liquidity trading creates a steady background of order flow, and informed traders can trade within that flow (often gradually) so their information-based orders are less identifiable (e.g., [Kyle, 1985](#)). Because liquidity suppliers (e.g., market makers/passive limit-order traders) cannot perfectly observe who is informed, they face adverse-selection risk: trading at unfavorable prices against better-informed counterparties. Classic models show that this risk is reflected in wider bid-ask spreads and/or reduced displayed depth, and that transaction prices adjust as trades reveal information (e.g., [Glosten & Milgrom, 1985](#); [Easley & O'Hara, 1987](#)). More broadly, market microstructure views these mechanisms such as quote revisions, spread/depth choices, and price impact as the way markets translate heterogeneous trading goals into observed prices, volumes, and trading costs ([Madhavan, 2000](#)).
- ⁵ <https://blog.kaiko.com/tether-vs-usd-is-a-dollar-a-dollar-when-it-comes-to-trading-4632380f4284> (accessed on 1 September 2020). Bitstamp data is commonly used in the literature ([X. Li et al., 2020](#); [Wang et al., 2020](#)).
- ⁶ The side of trade initiation information is already available in the data urging no need for the use of trade-initiation-identifying algorithms such as the algorithm of [Lee and Ready \(1991\)](#).
- ⁷ See studies such as [Takahashi and Yamada \(2021\)](#) and [Erdem \(2020\)](#) for findings and discussion on the lack of significant COVID-19 impacts prior to mid-February.
- ⁸ Note that the resulting COVID-19 subsamples have unequal lengths.

- ⁹ See Ari (2020), and Dyhrberg (2016) on the use of GARCH specifications in addressing volatility clustering in the markets.
- ¹⁰ <http://www.ourworldindata.org/covid-deaths> (accessed on 1 September 2020).
- ¹¹ For example, Duarte and Young (2009) argue for the liquidity shock component in the PIN model of Easley et al. (1996).
- ¹² Multivariate regression analysis that controls for the effects of trading volume and price volatility provides identical results, i.e., positive and significant (insignificant) coefficient for stage I (II) dummy variable. The results are not reported for the sake of brevity.
- ¹³ The measure is firmly grounded in the literature measuring the within-day price variation using high-frequency data (Andersen et al., 2003). At the same time, using very high sampling frequencies (e.g., tick-by-tick) can make realized variance sensitive to market microstructure noise, motivating the use of coarser sampling such as 5 min intervals (Hansen & Lunde, 2006). Consistent with this practice, Liu et al. (2015) provide large-scale evidence across many assets and many realized measures that 5 min realized variance is a strong benchmark and is rarely outperformed, supporting its use as a robust volatility control. In our checks, the 5 min realized volatility exhibits materially lower collinearity with the pandemic growth variables ($\text{corr} \approx 0.25$). Alternatively, we also obtain a daily volatility variable from a standard GARCH(1,1) model (Engle, 1982; Bollerslev, 1986), but in our COVID-stage sample it is highly correlated with the pandemic growth variables ($\text{corr} \approx 0.85$). A plausible reason is that GARCH volatility is designed to capture persistent volatility clustering, and during the pandemic this volatility regime co-moves tightly with the evolution of pandemic news and uncertainty; in a short crisis window, that leaves limited independent variation to separately identify “pandemic growth” effects once conditional volatility is included. In linear regressions, multicollinearity can inflate variances and destabilize inference (O’Brien, 2007). For this reason, we do not rely on the GARCH-based volatility control in our robustness set and instead use an intraday realized volatility proxy constructed from 5 min returns.
- ¹⁴ There are seven dates associated with holidays in our sample: 17 February 2020 (NYSE—Washington’s Birthday/Presidents’ Day), 10 April 2020 (NYSE & Euronext—Good Friday), 13 April 2020 (Euronext—Easter Monday), 1 May 2020 (Euronext—Labor Day), 25 May 2020 (NYSE—Memorial Day), 3 July 2020 (NYSE—Independence Day), and 7 September 2020 (NYSE—Labor Day).

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