Beneath the Crypto Currents: The Hidden Effect of "Crypto Whales"

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Abstract

Cryptocurrency markets are often characterized by market manipulation or, at the very least, by a sharp distinction between large and sophisticated investors and small retail investors. While traditional assets often see a divergence in the success of institutional traders and retail traders, we find an even more pronounced difference regarding the holders of Ethereum (ETH), the second-largest cryptocurrency by volume. We see a significant difference in how large holders of ETH behave compared with smaller holders of ETH relative to price movements and the volatility of the cryptocurrency. We find that large ETH holders tend to increase their ETH holdings prior to a price increase, while small ETH holders tend to reduce their ETH holdings prior to a price increase. In other words, ETH returns tend to move in the direction that benefits crypto "whales" while reducing returns (or increasing loss) to "minnows." Additionally, we find that the volatility of ETH returns seems to be driven by small retail investors rather than by the crypto whales.

Keywords: Cryptocurrency, Ethereum, ETH, crypto whales, blockchain, pump-and-dump
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I. Introduction

Cryptocurrencies and digital assets, although no longer at the forefront of digital innovation, remain both in the public interest as well as on the balance sheets of many investors, traders, and financial institutions. The proliferation of cryptocurrencies in the financial sector has been ubiquitous; both large institutional investors and retail investors often find themselves holding digital assets on their balance sheets. While the widespread adoption of digital assets may promise to increase financial inclusion and transparency, the growth of cryptocurrencies has led to increased concerns about the safety of digital assets and the need for small (and less sophisticated) consumers to be protected when investing in cryptocurrencies. A prominent concern that has emerged is the inability of small retail investors to safely navigate the cryptocurrency space. There has been a growing divide between large and sophisticated investors (crypto "whales") and small retail investors (crypto "minnows") within the cryptocurrency markets.

Cryptocurrency markets are characterized by high volatility, as noted in Brainard (2018) and Hu, Parlour, and Rajan (2019). We suspect that large institutional crypto investors, the crypto whales, may disproportionately benefit from this volatility compared with smaller investors. Additionally, the lack of regulatory oversight in the newly burgeoning cryptocurrency markets makes it a prime venue for manipulative practices that can distort prices as well as undermine investors' trust, as noted in Griffin and Shams (2020); Cong, Li, Tang, and Yang (2023); and Amiram, Lyandres, and Rabetti (2024). Even in the absence of outright manipulation, we suspect that large and sophisticated institutional investors may have a particular advantage over retail investors in crypto markets. This advantage may come from a variety of factors. Crypto markets are newer and may be less efficient at times, as seen in Tran and Leirvik (2020); Al-Yahyaee et al. (2020); and Zhang, Wang, Li, and Shen (2018). Crypto traders may exhibit more significant behavioral biases, such as herding, as noted in Hamurcu (2022) and Gurdgiev and O'Loughlin (2020). Alternatively, these markets may be more prone to bubbles due to sentiment changes, as seen in Chen and Hafner (2019).

Crypto whales could affect the crypto market liquidity and increase price volatility through changes in the supply of cryptoassets. For example, because whales often hold their cryptocurrencies for an extended period of time without any transactions, they create a shortage of supply of cryptocurrencies in circulation. Additionally, whales may cause large price movements when they suddenly become active and start adding a large volume of cryptocurrencies into circulation. More important, as holders of considerable portions of the various cryptocurrency markets, crypto whales could also have significant power to influence the crypto market volatility via strategic transactions that could induce sizable price fluctuations for their own benefit. Although there may be many potential transmission mechanisms for such a phenomenon, we suspect that large and sophisticated institutional investors have been able to capture a large portion of the gains in cryptocurrency markets.

Our goal in this paper is to test this hypothesis using transaction-level data from the Ethereum platform. Large holders of Ethereum (ETH) wield substantial influence in the cryptocurrency markets because of the overwhelming size of their holdings.[1] We shed light on the relationship between ETH price movements and the holdings of ETH by large traders versus retail investors. While "pump-and-dump" schemes are commonplace among newly formed digital assets, such tactics are rare among more well-established digital currencies. We investigate whether cryptocurrencies that have seen more mainstream adoption, such as ETH, the cryptocurrency with the second-largest market cap at the time of this writing, may also display the phenomenon of the market moving most favorably for large traders.

Specifically, we explore whether future (day-ahead) ETH returns may be influenced by the amount of ETH held in the e-wallets of whales versus the amount held in the e-wallets of smaller investors. We examine whether price movements tend to be favorable to large holders of ETH and tend to have an adverse effect on the holdings of smaller investors. This relationship may also be exacerbated by large, market-moving events, such as the collapse of the stablecoin TerraUSD (UST) and digital coin LUNA in May 2022 or the collapse of the cryptocurrency exchange FTX in November 2022.[2] Patel and Rose (2023) examine the 2022 bankruptcies of several cryptocurrency platforms, including Celsius, Voyager Digital, Blockfi, Genesis, and FTX. They identify three shocks that led to runs on these platforms, including the collapse of TerraUSD (UST)/LUNA, the failure of Three Arrows Capital (a hedge fund focusing on cryptoassets), and the failure of FTX itself. In addition, we examine whether whales have influence on the volatility of ETH returns and observe their trading activities in the presence of high market volatility.

Our analysis controls for large events in the crypto space. While our findings may not necessarily imply market manipulation is occurring, they do, at the minimum, suggest a stark difference in the trading and investing strategies of crypto whales and crypto 'minnows' in the ETH space. In undertaking this research, we hope to contribute to the ongoing discourse surrounding

[1] As of October 2023, crypto whales holding millions in ETH accounted for approximately one-third of the total supply of ETH; see Young (2023).

[2] Recent losses from crypto investments were driven by the crypto meltdown period in 2022, resulting in about a 70 percent decline in cryptocurrency valuation. Auer, Cornelli, Doerr, Frost, and Gambacorta (2022) find that nearly three-quarters of retail investors have lost money investing in Bitcoin. They suggest that cryptocurrency adoption is largely influenced by rising digital asset prices.

the regulation and oversight of cryptocurrency markets. By more closely examining how the holdings of different segments of the cryptocurrency markets could influence price dynamics, we seek to inform policy discussions and cultivate a more resilient and transparent cryptocurrency ecosystem.

II. Literature Review

The rise in the prevalence of digital assets in the financial system has garnered significant attention from researchers and practitioners alike. However, as the popularity and mainstream adoption of cryptocurrencies increases, so do concerns regarding excessive volatility and market manipulation in the digital asset space.

One of the primary problems cryptocurrencies have been facing since 2017 is their unpredictable and extreme volatility. Brainard (2018) notes that the wild fluctuations in Bitcoin's price were ultimately preventing it from being used as a store of value or medium of payment. Brainard goes on to describe how two of the classical qualities of money, serving as a store of value and as a unit of account, are unable to be ascribed to Bitcoin because of its excessive price volatility.

The extreme volatility in Bitcoin prices seems to be correlated with that of other cryptocurrencies. Hu, Parlour, and Rajan (2019) explore the pricing and volatility of Bitcoin and secondary market returns of other cryptocurrencies. They report an overview and summary statistics of the returns of over 200 cryptocurrencies in the digital asset space. Their findings suggest a high degree of skewness and volatility in digital asset returns and identify a high correlation between Bitcoin returns and the returns of most altcoins (other cryptocurrencies) in the study, at both the daily and monthly levels.

In addition to being driven by the supply of cryptocurrencies in circulation and the overall volatility in the cryptoassets space, cryptocurrency returns are also affected by the attacks on proof-of-work cryptocurrencies. Shanaev, Shuraeva, Vasenin, and Kuznetsov (2020) investigate majority attacks (51 percent) on proof-of-work cryptocurrencies using a sample of 14 attacks on 13 cryptocurrencies. They find that following majority attacks on blockchains, coin prices immediately drop by 12 percent to 15 percent in value and do not recover to the preattack levels one week after the event.

Among all the factors that affect cryptocurrency returns, market manipulation has been the main concern for digital asset holders. Griffin and Shams (2020) examine the impact of market manipulation on Bitcoin prices and returns, focusing on Bitcoin that is purchased via the stablecoin Tether (USDT), one of the largest stablecoins in terms of market capitalization at the time of this writing. Specifically, they investigate whether the USDT activities could have impacted the pricing of Bitcoin during the 2017 cryptocurrency boom. Their findings suggest that a large amount of the USDT activities during the time frame analyzed were used to conduct Bitcoin price manipulation. Griffin and Shams (2020) conclude that much of the growth of USDT during the 2017 crypto boom was not driven by investor demand for USDT but instead by the use of USDT by market manipulators to inflate Bitcoin prices, driving the price of Bitcoin up to around $20,000 in December 2017.

Further evidence of market manipulation is provided in Cong, Li, Tang, and Yang (2023). Here, the authors use multiple methods to test for market manipulation across a combination of regulated and unregulated exchanges, including comparing the chi-squared test for Benford's law distribution, the *t*-test for trade-size clustering, and the linear fit for power law. They find that over half of the unregulated exchanges fail at least half of all tests, indicating widespread manipulation. Regulated exchanges pass all tests performed. Amiram, Lyandres, and Rabetti (2024) find that crypto exchanges may be inflating volume numbers, i.e., initiating fake trades, to attract more traders. The ability to fake trades is successful at drawing in traders in the short run, but in the long run, exchanges that fake a large number of trades tend to see significant reputational damage.

One of the more prevalent forms of market manipulation in the cryptocurrency space is the pump-and-dump strategy, in which large and sophisticated investors coordinate to bid up the price of cryptocurrencies before selling them at a profit and crashing the coin prices. There are several research studies on the pump-and-dump strategy. One of the earliest investigations of routinely organized cryptocurrency pump-and-dump activities is found in Xu and Livshits (2019). Here, the authors investigate over 400 schemes organized in Telegram from 2018 to 2019 and find that the pump portion of these schemes results in an artificial trading volume of $6 million USD per month over the time period studied. Li, Shin, and Wang (2022) find that pump-and-dump schemes in the cryptocurrency markets typically last only several minutes and often have no release of false information or company action, as is typical for such schemes in the stock market.

La Morgia, Mei, Sassi, and Stefa (2023) examine over 1,000 different pump-and-dump schemes organized by communities over the internet and take an in-depth look at the online communities that organize them. These pump-and-dump organizers often target digital coins with a particularly small market cap and a net worth that is usually less than a dollar per coin. The authors also attempt to detect fraud in real time and to help investors stay out of the market when a pump-and-dump scheme is in action.

Similarly, Hamrick et al. (2021) attempt to quantify the scope of the pump-and-dump strategy and identify thousands of pumps targeting hundreds of cryptocurrencies. They find that the pump-and-dump strategy is only modestly successful in driving up cryptocurrency prices in the short run. The impact diminishes over time. Interestingly, they find that pumps tend to be most successful when the manipulators are transparent and make their intentions clear.

Kamps and Kleinberg (2018) point out that the pump-and-dump strategy has been around for hundreds of years but that recent advances in technology have identified its scale and scope of operations. They show that information embedded in crypto trading activities could be used to identify and flag potential pump-and-dump trading schemes. Moreover, their findings suggest that these fraudulent pump-and-dump schemes tend to cluster on specific cryptocurrency exchanges and specific coins. The results imply that these fraudulent activities could be identified and that the methodology could be used to help advance crime-prevention programs.

Social media has a role to play in these pump-and-dump schemes. Nghiem, Muric, Morstatter, and Ferrara (2021) use market data and social media signals, along with neural network–based models, to identify and predict the potential targeted cryptocurrency for each pump before its announcement. Their models were also used to forecast the highest price induced by the pump-and-dump strategy. Nizzoli et al. (2020) find that the organizations behind these events often use bots on social media as well. The authors collect data from a large number of messages (more than 50 million messages by almost 7 million users) published on Twitter (now X), Telegram, and Discord over a three-month period. Based on their bot detection, they identify a large number of pump-and-dump schemes and other deceptive strategies. About 93 percent of the invite links shared by Twitter bots point to Telegram pump-and-dump channels.

Perhaps most interesting, Dhawan and Putnins (2023) find that pump-and-dump schemes tend to have negative expected returns for participating small investors. Most pump-and-dump schemes are announced outright to declare the intentions to pump the specific coins, but, surprisingly, people still join in despite the expected negative returns to small retail investors. The authors show how the traders' overconfidence and gambling preferences can explain their participation in these schemes. Pumps generate extreme price distortions of 65 percent on average, abnormal trading volumes in the millions of dollars, and large wealth transfers from small investors to crypto whales.

Feng, Wang, and Zhang (2018) explore profitability in the Bitcoin market using trade-level data of U.S. dollar ($)/Bitcoin exchange rates. They find that in the Bitcoin market, informed traders are likely to build large positions just prior to positive market-moving events and liquidate just prior to negative events, generating considerably large profits. Informed traders tend to build their positions two days before large positive events and one day before large negative events.

There is also a large amount of research that examines potential bubbles and volatility in the cryptocurrency markets.[3] Bouri, Keung, Lau, Lucey, and Roubaud (2019) show that trading volume causes a large amount of volatility in several different cryptocurrencies, including Bitcoin and ETH. Corbet, Lucey, and Yarovaya (2018) classify bubbles from price movements in ETH and Bitcoin prior to 2018, with large ETH bubbles becoming less common toward the end of their study period.

Cong, Karolyi, Tang, and Zhao (2022) conduct an empirical study and construct a five-factor model for over 4,000 cryptocurrencies from 2014 to 2021. They find that in addition to traditional factors, such as market, size, and momentum factors, the cryptocurrency returns analyzed also see explanatory power from two additional factors: the crypto value characteristics and the network adoption premia. When examining return dynamics, the factors we examine are with regard to the holdings of various market segments.

III. The Data

We collect daily data on crypto activities that involve a specific cryptocurrency, ETH, during the period from January 1, 2018, to December 31, 2023. The data are sourced from Coin Metrics,[4] an online data aggregator that compiles various forms of cryptocurrency data, including network metrics from a digital asset's native blockchain, market data on cryptocurrencies, and price information. Our investigative approach takes the form of analyzing whether day-ahead price movement (i.e., future returns) can be predicted by looking at the changes in the cryptocurrency holdings of large versus small investors to explore trading strategies, their returns on investment, and the impact on ETH return volatility.

Investors' wealth and sophistication: We proxy the level of wealth and sophistication of the investors based on the size of their e-wallet (i.e., the amount of ETH held in their e-wallet). Coin Metrics tracks holdings of ETH by e-wallet size. We use these data to track total ETH holdings across our sampled e-wallets, divided into four thresholds. Investors are slotted into four different segments based on the amount of ETH held: (1) more than $1 million USD held in ETH; (2) between

[3] See D'Amato, Levantesi, and Piscopo (2022); Katsiampa (2017); and Catania, Grassi, and Ravazzolo (2018), among others.
[4] See https://coinmetrics.io.

$100,000 USD and $1 million USD held in ETH; (3) between $10,000 USD and $100,000 USD held in ETH; and (4) less than $10,000 USD held in ETH.

Figure 1A shows the average (daily) number of e-wallets within each of the e-wallet–size segments during the study period (2018–2023). Over the years, as the crypto market gained popularity among small investors, the number of e-wallets for the smallest segment (with less than $10,000 in ETH) grew much faster than it did for the other segments. **Figure 1B** shows the average amount of ETH held in each e-wallet for each of the e-wallet–size segments over the study period (2018–2023). The average e-wallet size of the largest segment grew significantly over the years. Overall, the raw data show that while the number of e-wallets grew fastest among the smallest investors, the amount of ETH held in each e-wallet grew fastest among the largest investors.

Changes in ETH holdings and returns on investments: We use the daily percentage change in ETH holdings as our main independent variable of interest. We expect large and sophisticated investors to adjust their ETH holdings such that they would be able to capture good returns from their ETH investments. The daily returns on day $t+1$ (day-ahead returns) are calculated based on changes in the price of ETH from day t to day $t+1$. This allows us to investigate whether the amount of ETH held in the e-wallets of holders of large amounts of ETH can provide insight into price movements the following day.

Figure 2A shows the average net daily change in ETH holdings by year, calculated from trading activities (buys and sells on each day) for each of the e-wallet–size segments in each month. The change in ETH holdings and the change in ETH trading activities vary significantly (often moving in opposite directions) across e-wallet–size segments in the same year. **Figure 2B** shows the daily percentage change in net ETH holdings, calculated from the buy and sell activities for each 30-day moving average window during the sample period for each e-wallet–size segment. We observe the highest volatility among the smallest e-wallet–size segments (i.e., among the smallest investors). In contrast, we observe that the volatility has been declining among the largest investors over the sample period from January 2018 to December 2023.

Current supply of cryptocurrency: Data from Coin Metrics are also used to control for how much ETH is currently actively trading. For this, we use the ratio of one-day active supply[5] to the total current supply of ETH. We calculate the change in this ratio, denoted as *DeltaActCurr*, as a

[5] One-day active supply is defined as the sum of unique native units that see at least a single transaction in the trailing day up to the end of the day in question. Native units that have transacted more than once are counted a single time.

control factor in our regression models to account for changes in ETH price that may be due to changes in the overall market composition.

Key event dates: While the overall sample period covers January 2018 to December 2023, we are paying particularly close attention to the 2022 period, referred to as the “Crypto Winter” by Gorton and Zhang (2023). Note that this period also covers the transition in ETH from proof-of-work to proof-of-stake, as detailed in Kapengut and Mizrach (2023). In addition, we also select a subset of dates to examine if the relationship between returns and the change in holdings from large e-wallets varies based on market conditions. In particular, we look at the collapse of the stablecoin UST/LUNA (May 7–13, 2022), the bankruptcy of the cryptocurrency exchange FTX (November 7–11, 2022), and the collapse of Silicon Valley Bank (March 10–13, 2023). **Table 1** presents a description of the variables, and **Table 2** presents the summary statistics of the data used in this study.

IV. The Empirical Analysis

For our regression models, we use day-ahead daily return, *DailyRet*, as the dependent variable, defined as the return from midnight of day t to midnight of day $t+1$.[6] The independent variables include the daily percentage changes in ETH holdings for those investors in each of the e-wallet–size thresholds (as defined in the Data section). Note that the data set does not contain the change in ETH holdings in each account; it reports only the daily change in ETH holdings overall for all the accounts in each e-wallet–size segment. Specifically, *PctDelta_Top1M* represents the daily percentage change in ETH holdings for all accounts with over $1 million in ETH in their e-wallets; *PctDelta_100K* is the percentage change in ETH holdings for all e-wallets that have between $100,000 and $1 million in ETH; *PctDelta_10K* is the percentage change in ETH holdings for e-wallets that hold between $10,000 and $100,000 in ETH; and *PctDelta_LT10K* is the daily percentage change in ETH holdings for e-wallets that hold less than $10,000 in ETH but more than $10 in ETH.[7] The last segment, with e-wallets holding less than $10,000 in ETH, is the one we consider to be small retail investors (the least sophisticated segment of ETH investors).

Our control variables include a measure of the change in the supply of ETH in circulation from day t to day $t+1$. Specifically, we calculate the change in ETH supply, *Delta_Supply_Ratio*, as

[6] Other studies, such as Griffin and Shams (2020), use intraday returns as their dependent variable, but we opt for daily returns to match the data on holding changes.
[7] There were, on average, 16,228,381 holders with under $10 USD in ETH per day during the 2018–2023 period. The results remain the same, both in terms of direction and statistical significance, regardless of whether or not these small e-wallets are excluded from the analysis.

(daily active supply of ETH in circulation as of day *t+1* divided by total supply of ETH as of day *t+1*) minus (daily active supply of ETH in circulation as of day *t* divided by total supply of ETH as of day *t*). We also include dummy variables for each month from January 2018 to December 2023, which we define as *YearMo* in equation (1) below. The results are presented in **Table 3**.

$$DailyRet = PctDelta_{Top1M} + PctDelta_{100K} + PectDelta_{10K} + PctDelta_{LT10K} + Delta\_Supply\_Ratio + YearMo \quad (1)$$

IV.1 Volatility

We conduct additional analysis on the standard deviation of 30-day ETH returns in order to investigate if trading activities in the various segments of the ETH market that we examined previously may also be responsible for driving ETH market volatility. Here, we use the 30-day rolling volatility (standard deviation) of ETH returns, $StdDev_{Ret30d}$, as the dependent variable. The 30-day rolling volatility of ETH holdings (balances) in each of the four e-wallet–size segments is included as the independent variable.[8] Additionally, we used the 30-day active supply, *ActiveSupply_30d*, as a control variable for potential rises in volatility that may come from additional ETH being mined. The regression is given in equation (2) below. The results are presented in **Table 4**.

$$StdDev\_Ret30d = StdDev_{Top1M} + StdDev_{100K} + StdDev_{10K} + StdDev_{LT10K} + ActiveSupply\_30d \quad (2)$$

We also explore an alternative specification, using $Active\ Supply\_30d\_Ratio$ as our control variable in place of the $Active\ Supply\_30d$ variable, as shown in equation (2A) below. The results remain the same, as presented in **Table 4A**.

$$StdDev\_Ret30d = StdDev_{Top1M} + StdDev_{100K} + StdDev_{10K} + StdDev_{LT10K} + Active\ Supply\_30d\_Ratio \quad (2A)$$

IV.2 Market-Moving Events

The digital asset space has experienced a number of market-moving events in the past five years. We investigate three events in particular: the collapse of the stablecoin UST, the bankruptcy of the cryptocurrency exchange FTX, and the collapse of Silicon Valley Bank. First, for the collapse of UST, we chose the May 7 start date to correspond to when UST started losing its peg to the dollar and declined to a low of $0.985. The May 13 end date was chosen as the end date when Binance and

[8] The 30-day window is defined as the 30 days leading up to the day in question. So, for a given day, standard deviations would be calculated using the daily data from the 29 days prior and the day in question.

other exchanges stopped the trading of UST tokens. Second, to examine the effect of the bankruptcy of FTX, November 7 was chosen as the start date, as it coincided with FTX's announcement of its liquidity crisis as well as its attempt to seek a bailout. FTX filed for Chapter 11 bankruptcy on November 11, which was chosen as the end date. Third, Silicon Valley Bank failed after a bank run on March 10, which we used as the start date of the event. The FDIC reopened Silicon Valley Bank as a bridge bank on March 13, which we used as the end date for the event.

These events were denoted as binary variables, where a 1 represents the dates in question, and 0 is assigned otherwise. In addition, we also include interaction terms between the binary variables of each of these events and the holdings of our four e-wallet–size segments, which we include as additional independent variables in the regression models. The extended model is given in equation (3) below. The results are presented in **Table 5**.

$$\begin{aligned} DailyRet = {} & PctDelta_{Top1M} + PctDeltaTop_{100K} + PctDelta_{Top10K} + PctDelta_{LT10K} + \\ & PctDelta_{Top1M} * FTX + PctDelta_{Top100K} * FTX + PctDelta_{Top10K} * FTX + \\ & PctDelta_{LT10K} * FTX + PctDelta_{Top1M} * TERRA + PctDelta_{Top100K} * TERRA + \\ & PctDelta_{Top10K} * TERRA + PctDelta_{LT10K} * TERRA + PctDelta_{Top1M} * SVB + \\ & PctDelta_{Top100K} * SVB + PctDelta_{Top10K} * SVB + PctDelta_{LT10K} * SVB + \\ & Delta\_Supply\_Ratio + YearMo \end{aligned} \tag{3}$$

V. The Empirical Results

The results from our initial regression model are given in **Table 3**, without the inclusion of interaction terms for market-moving events. Here, we see that during the study period (2018–2023), there is a significant positive relationship between ETH returns on the day ahead (day *t+1*) and the increase in ETH holdings in large e-wallets on day t. In contrast, we find a negative relationship between the ETH returns on day *t+1* and the increase in ETH holdings for small e-wallets on day *t*, suggesting that large investors tend to grow their ETH holdings while small retail investors tend to liquidate them just before an increase in ETH prices.

The largest holders, those with over $1 million in ETH in their e-wallets, tend to have the largest positive relationship with the ETH returns, with the largest statistically significant coefficient (0.6263) for the effect of a 1 percent increase in ETH holdings on the next day's increase in ETH returns. This is followed by a still statistically significant but smaller coefficient of 0.2862 for the effect of a 1 percent increase in holdings in e-wallets with between $100,000 and $1 million in ETH on the market returns of the following day. On the other hand, smaller e-wallets tend to move in the opposite direction, thus small ETH holders tend to be unable to reap the benefits of ETH returns and volatility. For those smaller e-wallets holding between $10,000 and $100,000 in ETH, a

1 percent increase in ETH holdings is associated with a decline in ETH returns — ETH value would be down an additional 0.4847 percent the next day. This effect is even more pronounced for the smallest e-wallets (with less than $10,000 in ETH); when they see a 1 percent increase in holdings, ETH returns are likely to be down 1.8223 percent the following day. There is a clear positive relationship between the size of an investor's holdings (as classified in four different segments) and the next day's returns. ETH returns seem to move in the direction that benefits whales but reduces returns (or increases loss) to small retail investors.

Results of the regression on return volatility are displayed in **Table 4** and **Table 4A**. Volatility in ETH returns has a tendency to move in the opposite direction of the standard deviation in the balances of the largest group of investors (those with more than $1 million in ETH). Conversely, ETH return volatility moves in the same direction as the standard deviation in the balances of the smaller e-wallet segments with less than $1 million in ETH holdings. While ETH is a much larger and more widely held digital coin than the newly minted coins in pump-and-dump schemes, the volatility analysis suggests much the same story. It is the retail investors who are responsible for driving ETH volatility, and it is the whales who profit from it. Large holders of ETH do not make changes in times of market turmoil. Instead, it is the movements of retail traders, and ultimately all holders except the whales, that drive the overall volatility of ETH returns. This is perhaps unsurprising, since it is small investors who may be more likely to enter or exit the market as prices become more dynamic. The largest ETH holders, conversely, appear to be in the market for the long haul. whales may exit a market before a bubble bursts, but they are not making short-term movements based on return volatility.

We also examine if the relationship between ETH holdings and ETH returns changes during the occurrence of market-moving events, as shown in **Table 5**. The results on the relationship between ETH returns and the change in ETH holdings by large versus small investors continue to be significant with the expected signs in **Table 5**, as they were in **Table 3**. In fact, we find even more robust results during the period around the bankruptcy of FTX, in which this relationship became stronger among larger holders of ETH versus smaller holders of ETH.

For the interaction terms, we find the most statistically significant relationship for the FTX event during the FTX collapse (November 7–November 11, 2022), in which we find significantly positive coefficients for all e-wallet–size segments except for the smallest retail investors with less than $10,000 in ETH in their accounts. The coefficient size is in rank order, with the largest positive coefficient (largest positive returns) to the largest group of investors. The results are largely not significant for the interaction terms during the dates for the collapse of UST or the failure of Silicon Valley Bank.

VI. Conclusion

While market manipulation remains an ever-present problem for smaller, niche cryptocurrencies, we find that even for larger, more established digital coins such as ETH, there is still a discernable difference between the holding activities of larger and more sophisticated traders and small retail traders. We find that the holdings in e-wallets with significant amounts of ETH, i.e., the e-wallets of crypto whales, tend to increase as returns are increasing, whereas the holdings of retail ETH investors tend to decline as returns are rising. This difference became even more pronounced during the period around the collapse of FTX. While these results do not necessarily suggest that there is overt market manipulation occurring within the ETH market, they do highlight the stark distinction between the trading activities of large ETH holders and those of small retail investors.

We also find that volatility in the ETH market is not driven by the movements of large ETH holders, whose holdings tend to move against ETH volatility. This pattern of behavior regarding the ETH holdings of crypto whales with regard to volatility and returns is largely consistent with the behavior of informed investors that Feng, Wang, and Zhang (2018) observe in the Bitcoin market.

Acknowledging the nuance between the activities of small and large holders in the ETH ecosystem is crucial for regulators going forward. Small holders remain a significant portion of the market, although their trading activities may be driven by any number of diverse motives. In contrast, large holders seem to command a disproportionate influence on the price dynamics of ETH because of their substantial holdings. Understanding these distinctions is essential for regulators in designing policies and guidelines to discourage such abusive behavior in the cryptocurrency markets and for market participants to better manage risk in the ETH ecosystem and other crypto exchange platforms. As the cryptocurrency landscape continues to mature, ongoing research is imperative to foster a market that is both resilient and transparent. The notable differences between the behaviors of small and large holders in the ETH market underscore the dynamic nature of cryptocurrency markets and the necessity for continued scrutiny.

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Table 1
Data Definitions and Variable Descriptions

Variable	Definition
DailyRet	The day-ahead log return from midnight of day *t* to midnight of day *t+1*
StdDev_Ret30d	The 30-day volatility, measured as the standard deviation of the natural log of daily returns over the past 30 days
PctDelta_Top1M	The daily percent change in ETH holdings for any accounts with over $1 million
PctDelta_100K	The daily percent change in ETH holdings for e-wallets holding between $100,000 and $1 million
PctDelta_10K	The daily percent change in ETH holdings for e-wallets holding between $10,000 and $100,000
PercDelta_LT10K	The daily percent change in ETH holdings for e-wallets holding less than $10,000 but more than $10
StdDev_Top1M	The 30-day rolling standard deviation in ETH holdings for any accounts with over $1 million
StdDev_100K	The 30-day rolling standard deviation in ETH holdings for e-wallets holding between $100,000 and $1 million
StdDev_10K	The 30-day rolling standard deviation in ETH holdings for e-wallets holding between $10,000 and $100,000
StdDev_LT10K	The 30-day rolling standard deviation in ETH holdings for e-wallets holding less than $10,000 but more than $10
Delta_Supply Ratio	The change in the ratio of daily active supply over current supply from that of the prior day
Active Supply_30d	The sum of unique native units that transacted at least once in the trailing 30 days up to the end of that interval
Active Supply_30d_Ratio	The sum of unique native units that transacted at least once in the trailing 30 days up to the end of that interval, divided by the current supply
N_ETH Wallet_Top 1M	The number of e-wallets in the largest segment, in which all e-wallets hold more than $1 million in ETH
N_ETH Wallet_100K-1M	The number of e-wallets in the second-largest segment, in which all e-wallets hold between $100,000 and $1 million in ETH
N_ETH Wallet_10K-100K	The number of e-wallets in the third-largest segment, in which all e-wallets hold between $10,000 and $100,000 in ETH
N_ETH_Wallet_LT 10K	The number of e-wallets in the smallest segment, in which all e-wallets hold between $10 and $10,000 in ETH
YearMo	Dummy variables for each year and month combination
D_TERRA	Dummy flagging 2022-05-07 to 2022-05-13
D_FTX	Dummy flagging 2022-11-07 to 2022-11-11
D_SVB	Dummy flagging 2023-03-10 to 2023-03-13

Data Source: Coin Metrics, available at https://coinmetrics.io.

Table 2
Summary Statistics of the Data

Variable	Obs N	Mean	Min	Max	Median	Std. Dev
DailyRet	2191	0.002	-0.432	0.277	0.000	0.047
StdDev_Ret30d	2191	0.044	0.008	0.130	0.042	0.018
Delta_Supply_Ratio	2191	-4.54E-07	-0.071	0.086	0.000	0.016
Delta_ActiveSupply	2191	1141.3	-7883206	9582015	-35245.2	1788002.9
Delta_TotalSupply	2191	13647.3	-58283.5	390246.8	13512.9	18288.3
Active Supply_30d	2191	30726634	19318763	46336569	30021979	6174082
PctDelta_Top1M	2191	1.42E-04	-0.057	0.037	1.30E-04	0.0045
PctDelta_100K	2191	3.40E-05	-0.065	0.093	-1.09E-04	0.0112
PctDelta_10K	2191	2.88E-04	-0.083	0.128	1.27E-04	0.0145
PercDelta_LT10K	2191	4.35E-04	-0.112	0.238	1.91E-04	0.0211
StdDev_Top1M	2191	695147	47689	2828550	572619	480138
StdDev_100K	2191	262596	11686	1156224	198235	219966
StdDev_10K	2191	201476	16522	805861	165972	140135
StdDev_LT10K	2191	218052	23396	1022326	177679	151642
N_ETH E-Wallet_Top 1M	2191	7639.8	888	23203	7719	5551.8
N_ETH E-Wallet_100K-1M	2191	44275.0	5444	132116	38783	32692.5
N_ETH E-Wallet_10K-100K	2191	1.07E+08	9.42E+07	1.23E+08	1.10E+08	8.15E+06
N_ETH E-Wallet_LT 10K	2191	1.59E+07	2.23E+06	3.55E+07	9.11E+06	1.23E+07

Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io

Table 3
Regression Results Based on Equation (1)
The Impact of ETH Trading by Large Investors on Future ETH Returns

$$DailyRet = PctDelta_{Top1M} + PctDelta_{100K} + PctDelta_{10K} + PctDelta_{LT10K} + Delta\_Supply + YearMo \quad (1)$$

Coefficient	Estimate	Std. Error	Pr(>|t|)
(Intercept)	0.0128	0.0027	1.61e-06 ***
PctDelta_Top1M	0.6263	0.1928	0.001176 ***
PctDelta_100K	0.2862	0.0747	0.000130 ***
PctDelta_10K	-0.4847	0.0624	1.24e-14 ***
PctDelta_LT10K	-1.8223	0.0452	< 2e-16 ***
Delta_Supply_Ratio	0.0353	0.0198	0.074799 *
YearMo Dummies	--Yes--		

Multiple R-squared: 0.9057, Adjusted R-squared: 0.9024

Note: The *** and * represent statistical significance at the 1 percent and 10 percent levels, respectively.

Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io

Table 4
Regression Results Based on Equation (2)
The Impact of ETH Trading by Large Investors on ETH Return Volatility

$$StdDev\_Ret30d = StdDev_{Top1M} + StdDev_{100K} + StdDev_{10K} + StdDev_{LT10K} + Active\ Supply\_30d \quad (2)$$

Coefficient	Estimate	Std. Error	Pr(>|t|)
(Intercept)	-3.21E-03	1.48E-03	0.0305 **
StdDev_Top1M	-2.13E-08	2.57E-09	2.36e-16 ***
StdDev_100K	5.61E-08	3.47E-09	< 2e-16 ***
StdDev_10K	2.16E-08	5.31E-09	4.74e-05 ***
StdDev_LT10K	5.07E-08	4.54E-09	< 2e-16 ***
Active Supply_30d	1.05E-09	4.71E-11	< 2e-16 ***

Multiple R-squared: 0.5345, Adjusted R-squared: 0.5334

Note: The *** and ** represent statistical significance at the 1 percent and 5 percent levels, respectively.
Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io

Table 4A
Regression Results Based on Equation (2A)
The Impact of ETH Trading by Large Investors on ETH Return Volatility

$$StdDev\_Ret30d = StdDev_{Top1M} + StdDev_{100K} + StdDev_{10K} + StdDev_{LT10K} + Active\ Supply\_30d\_Ratio \quad (2A)$$

Coefficient	Estimate	Std. Error	Pr(>|t|)
(Intercept)	-5.59E-03	1.49E-03	0.000173 ***
StdDev_Top1M	-1.74E-08	2.53E-09	7.19e-12 ***
StdDev_100K	4.13E-08	3.33E-09	< 2e-16 ***
StdDev_10K	1.93E-08	5.24E-09	0.000239 ***
StdDev_LT10K	5.33E-08	4.49E-09	< 2e-16 ***
Active Supply_30d_Ratio	1.31E-01	5.47E-03	< 2e-16 ***

Multiple R-squared: 0.5472, Adjusted R-squared: 0.5462

Note: The *** represents statistical significance at the 1 percent level, respectively.
Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io

Table 5
Regression Results Based on Equation (3)
The Impact of ETH Trading by Large Investors on Future ETH Returns

$$DailyRet = PctDelta_{Top1M} + PctDeltaTop_{100K} + PctDelta_{Top10K} + PctDelta_{LT10K} + PctDelta_{Top1M} * FTX + PctDelta_{Top100K} * FTX + PctDelta_{Top10K} * FTX + PctDelta_{LT10K} * FTX + PctDelta_{Top1M} * TERRA + PctDelta_{Top100K} * TERRA + PctDelta_{Top10K} * TERRA + PctDelta_{LT10K} * TERRA + PctDelta_{Top1M} * SVB + PctDelta_{Top100K} * SVB + PctDelta_{Top10K} * SVB + PctDelta_{LT10K} * SVB + Delta\_Supply + YearMo \quad (3)$$

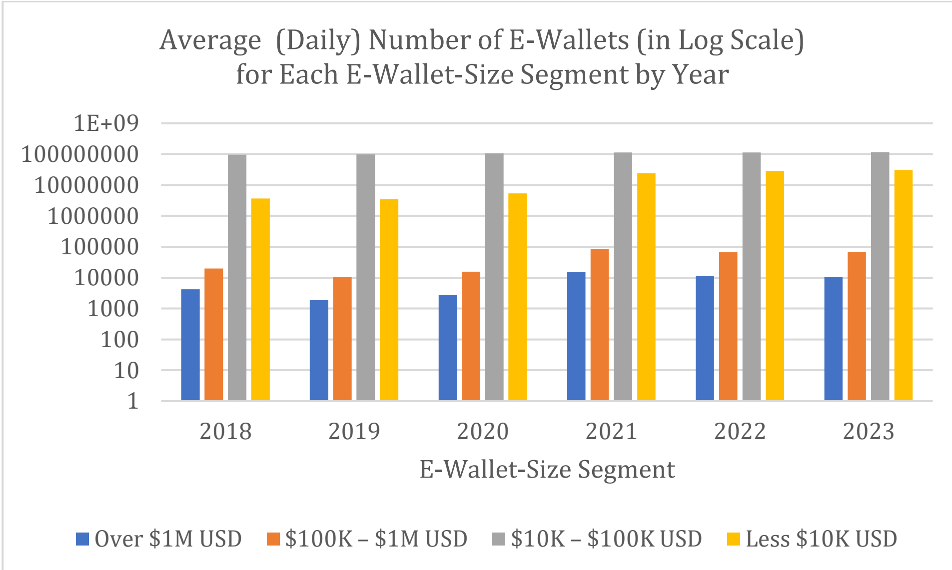
Coefficient	Estimate	Std. Error	Pr(>|t|)
(Intercept)	0.0127	0.0026	1.51e-06 ***
PctDelta_Top1M	0.6412	0.1925	0.000881 ***
PctDelta_100K	0.2789	0.0746	0.000189 ***
PctDelta_10K	-0.4956	0.0625	3.53e-15 ***
PctDelta_LT10K	-1.8040	0.0457	< 2e-16 ***
PctDelta_Top1M*FTX	73.4100	42.6800	0.085589 *
PctDelta_100K*FTX	11.8200	6.3280	0.061992 *
PctDelta_10K*FTX	5.4560	1.9910	0.006190 **
PctDelta_LT10K*FTX	2.0220	2.7810	0.467203
PctDelta_Top1M*TERRA	-60.2300	44.5400	0.176481
PctDelta_100K*TERRA	-3.2290	5.3320	0.544794
PctDelta_10K*TERRA	-7.4800	2.3690	0.001613 **
PctDelta_LT10K*TERRA	-0.9357	1.7500	0.592951
PctDelta_Top1M*SVB	-21.0000	228.1000	0.926645
PctDelta_100K*SVB	-0.5284	24.8800	0.983056
PctDelta_10K*SVB	-3.9540	21.1900	0.851977
PctDelta_LT10K*SVB	-0.8034	10.5800	0.939464
Delta_Supply_Ratio	0.0363	0.0197	0.065675 *
YearMo	--Yes--		

Multiple R-squared: 0.9074, Adjusted R-squared: 0.9036

Note: The ***, **, and * represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

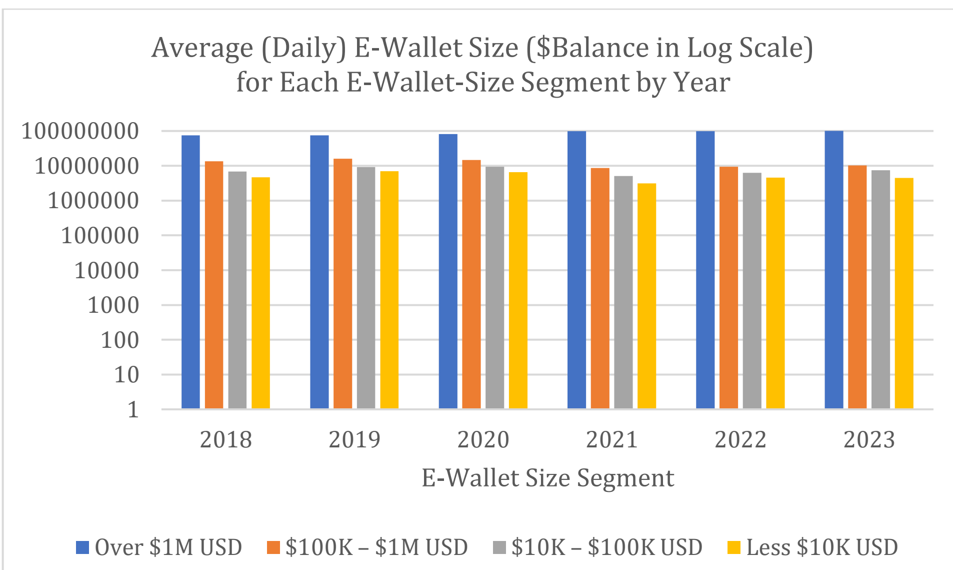
Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io

Figure 1A
Average (Daily) Number of E-Wallet Observations for Each E-Wallet–Size Segment by Year



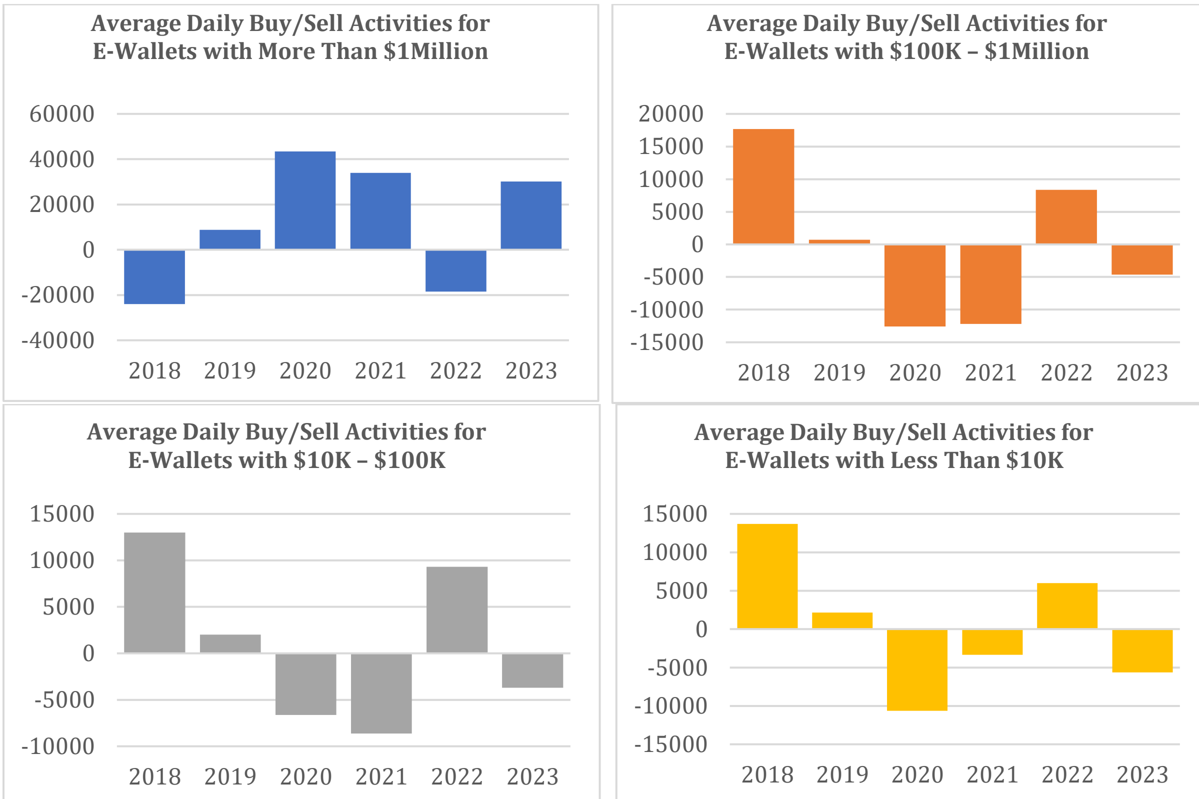
Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io

Figure 1B
Average Amount of ETH (shown in log scale) Held in Each E-Wallet
for Each of the E-Wallet–Size Segments by Year



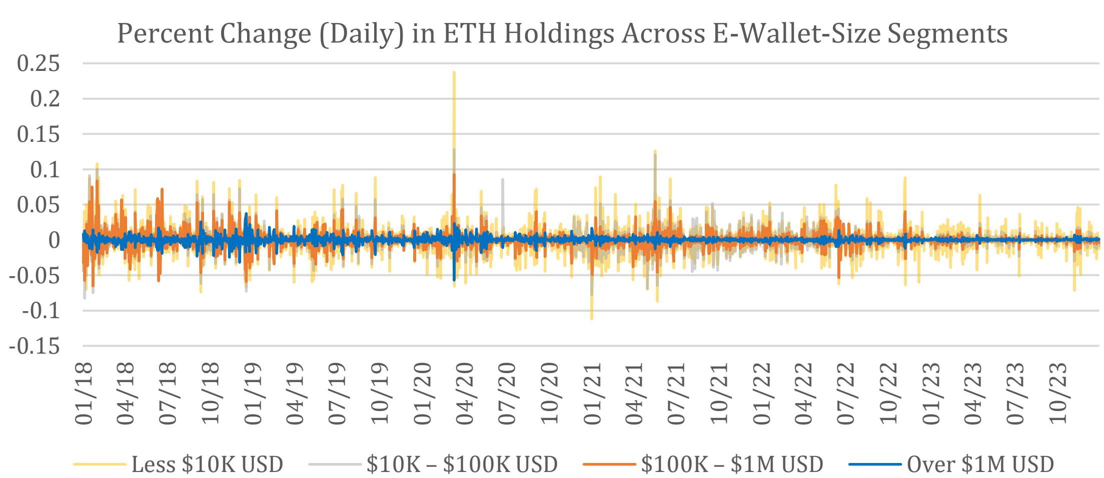
Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io

Figure 2A
Average Net Daily Change in ETH Holdings



Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io
Note: It is calculated from buy and sell activities on each day for each of the e-wallet–size segments in each month.

Figure 2B
The Daily Percentage Change in Net ETH Holdings (based on buy and sell activities) During the Sample Period (January 2018 to December 2023)



Source: Authors' calculations based on data from Coin Metrics, available at https://coinmetrics.io