Accounting for Cryptocurrency Value

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Abstract

Information pertaining to new addresses is highly value-relevant in the cryptocurrency market. Innovations to the number of new addresses explain eight percent of the variations in cryptocurrency returns. Unlike traditional markets, we do not find evidence of pre- or post-drift around the release of new address information. The presence of strong market reactions at the release of new address information and the absence of drifts around the release highlight the distinct features of cryptocurrencies and provide a benchmark case where information is released publicly and continuously. Lastly, we construct the price-to-new address ratios and show that they negatively predict future cryptocurrency returns, which we refer to as the cryptocurrency value effect.

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1 Introduction

Unlike companies that have the Generally Accepted Accounting Principles (GAAP) standards for financial measurements, cryptocurrencies do not have a standardized accounting framework in generating measurements for performance. The lack of such accounting information poses challenges for investors and regulators to determine the intrinsic value of cryptocurrencies. At the same time, economic activities in blockchain are publicly and continuously available, thus providing a rich set of ongoing information that may be used to determine the value of cryptocurrency. We apply accounting and finance valuation frameworks to the cryptocurrency market and, in turn, revisit several classic questions for which the amount and revelation of information are central.

Cryptocurrency is the first asset class that provides a complete history of investment activities recorded on its blockchain. Blockchain data has at least three major advantages. First, the data is widely and easily available compared to trading or pricing information that is often proprietary. Second, the data is verifiable, as anyone can access the public ledger to confirm the data. Third, information is available in real-time, and thus the data is timely for users. These properties of blockchain data echo with the conceptual framework for firms' financial reporting as set by the Financial Accounting Standards Board (FASB) (Financial Accounting Standards Board 2010). FASB defines the fundamental qualitative characteristics of useful financial information to be as follows: "if financial information is to be useful, it must be relevant and faithfully represent what it purports to represent. The usefulness of financial information is enhanced if it is comparable, verifiable, timely, and understandable." Relevant information refers to information that can influence a decision and that has predictive and/or feedback value. Faithful representation, also known as reliability, requires that the information be complete (no transactions excluded), neutral (free from bias), and free from error. The framework is conceptual rather than exact for company financial statements because it can never be exactly achieved in reality.[1] For the data recorded on a blockchain, however, many of these conceptual criteria are exactly achievable.

The theoretical work in network economy and the recent models of dynamic cryptocurrency pricing focus on the role of user adoption and network effect. That is, the value of cryptocurrencies increases when more users join. Motivated by this literature, we propose and comprehensively analyze a measure using on-chain data to value cryptocurrencies – the number of new addresses.

[1]For example, there are subjectivity and estimation involved in preparing financial statements (e.g., estimate uncollectible), and thus the information cannot be truly neutral or free from bias.

Empirically, using the value-relevance tests developed in the accounting and finance literature to establish the role of earnings in the equity market, we find that information pertaining to new addresses is strongly value-relevant for cryptocurrencies. In fact, the value relevance of new addresses to the cryptocurrency market is even higher than that of earnings to the equity market. Furthermore, we show that the price-to-new address ratio negatively predicts future cryptocurrency returns, analogous to the price-to-earnings ratio in the equity market.

We start by testing the usefulness and relevance of information regarding new addresses for the cryptocurrency market. We apply the value-relevance method and examine the cryptocurrency market reactions to the innovations in the number of new addresses. We find that information pertaining to new addresses is highly value-relevant both in the cross-section and in the time-series. In the cross-section, innovations to the number of new addresses can account for more than eight percent of the variations of cryptocurrency returns. The value relevance of new addresses in the cryptocurrency market is higher than that of earnings in the equity market, which is found to be able to explain about five percent of the variations of stock returns (e.g., Lev 1989; Lev and Gu 2016). Moreover, we show that many economic determinants (see, e.g., Kothari 2001, Schipper and Vincent 2003, and Chapter 5.4 of Scott and O'Brien 2019), such as quality, discount rate, and size, of the value-relevance of earnings in the equity market have their counterparts in the cryptocurrency market, and that these counterparts are also central in determining the value-relevance of new addresses in the cryptocurrency market.

One important difference between cryptocurrencies and equities is that, for cryptocurrencies, information of the underlying economic activities is available publicly and continuously on the blockchain. Whereas for equities, public information of firm activities is only available periodically. We draw on this distinction and revisit several classic questions in the equity market.

First, we test potential slow reactions of the cryptocurrency market to the information pertaining to new addresses. In the equity market, it is found that informational events, such as earnings announcements, tend to forecast future returns, a phenomenon known as post-announcement drifts (e.g., Ball and Brown 1968; Bernard and Thomas 1989; Sadka 2006; Daniel, Hirshleifer, and Sun 2020). Among many alternative explanations for this phenomenon, a common view is that the equity market is slow in incorporating earnings information. We find that, unlike the equity market, innovations to the number of new addresses do not forecast cryptocurrency returns in the future, consistent with the view that transparent and timely information revelation facilitates information acquisition.

Second, we test the existence of return drifts prior to the release of new address information. In the equity market, it is found that stock returns tend to precede important informational events such as earnings and Federal Open Market Committee (FOMC) announcements, a phenomenon known as pre-announcement drifts (e.g., Ball and Brown 1968; Lucca and Moench 2015; Cieslak, Morse, and Vissing-Jorgensen 2019). The literature commonly attributes the phenomenon to the discreteness of information releases and information leakages between the discrete announcements. In contrast to the equity market, we find that cryptocurrency returns do not precede releases of new addresses information in the pre-information period, consistent with the view that more frequent new public information reduces potential information leakages.

Next, we use the number of new addresses to construct a financial ratio for cryptocurrencies inspired by the equity research: the price-to-new address ratio. We find that the price-to-new address ratio captures the cross-section of expected returns, which is analogous to the return predictability result of the price-to-earnings ratio in the equity market (e.g., Basu 1977; Campbell and Shiller 1988a; Welch and Goyal 2008). High price-to-new address ratios are followed by low future returns in the cross-section of returns of cryptocurrencies. A zero-investment long-short strategy that buys the portfolio of coins with the lowest price-to-new address ratio and shorts the portfolio of coins with the highest price-to-new address ratio generates an average weekly excess return of 1.9 percent. We show that the return predictability of the price-to-new address ratio is distinct from those documented in the literature. Controlling for the cryptocurrency 3-factor model (see Liu, Tsyvinski, and Wu 2021), the alpha of the long-short strategy remains positive and statistically significant at the 1 percent level. Moreover, the return predictability of the price-to-new address ratio is long-lasting. The long-short strategy based on the price-to-new address ratio remains significant at the 10 percent level 20 weeks after the portfolio formation period. We refer to this return predictability of the price-to-new address ratio as the cryptocurrency value effect, and explore potential mechanisms behind the cryptocurrency value effect.

We discuss the relationship of our paper to the literature. The importance of user adoption is a foundational concept in the literature of network economy (e.g., Rohlfs 1974; Katz and Shapiro 1985; Katz and Shapiro 1994; Rochet and Tirole 2003). Recent theoretical development of cryptocurrency also emphasizes the role of user adoption and network effect in cryptocurrency valuation. Cong, Li, and Wang (2021) is a model about dynamic user adoption, and their main finding is on the endogenous adoption of cryptocurrency and price predictions at the different stages of the life cycles of cryptocurrencies. Sockin and Xiong (2020) show that network externalities in the cryptocurrency market can lead to multiple equilibria. Other studies focusing on user adoption of cryptocurrencies include Pagnotta and Buraschi (2018), Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2020), and Cong, Li, and Wang (Forthcoming).

The vast literature studying market reactions to informational events can be traced back at least to Beaver (1968), Ball and Brown (1968), and Fama, Fisher, Jensen, and Roll (1969). Lev (1989), Kothari (2001), and Dechow, Ge, and Schrand (2010) survey the literature that examines the value-relevance of earnings in the equity market. It is shown that equity returns can both lead information events such as earnings and macroeconomic announcements, known as pre-announcement drifts (e.g., Ball and Brown 1968; Lucca and Moench 2015; Cieslak, Morse, and Vissing-Jorgensen 2019), and lag informational events, known as post-announcement drifts (e.g., Ball and Brown 1968; Bernard and Thomas 1989; Sadka 2006; Daniel, Hirshleifer, and Sun 2020). Using the methods in the value-relevance literature which establishes the role of earnings in the valuation of equities, we find that information pertaining to new addresses is highly value-relevant in the cryptocurrency market. Moreover, we show that, contrary to the equity market, returns of cryptocurrencies do not lead or lag the release of new address information. The findings highlight the distinct feature of cryptocurrencies and provide a benchmark case where information is released both publicly and continuously.

Several recent papers document empirical regularities related to cryptocurrency investment. Liu and Tsyvinski (2021) and Liu, Tsyvinski, and Wu (2021) comprehensively study the valuations of the cryptocurrency market in the aggregate time-series and the cross-section, respectively. Makarov and Schoar (2020), Borri and Shakhnov (2018), and Borri and Shakhnov (2019) find that there are dispersions of Bitcoin prices across different exchange platforms. Hu, Parlour, and Rajan (2019) find that cryptocurrency returns tend to be positively related to Bitcoin returns. Borri (2019) shows that cryptocurrency returns are exposed to the tail-risks within cryptocurrencies but not tail-risks from global assets. Bhambhwani, Delikouras, and Korniotis (2020) show that cryptocurrency exposures to hash rate and network size growths predict cryptocurrency future returns. Cong, Karolyi, Tang, and Zhao (2021) provide another angle on studying the valuation of cryptocurrencies and on the value premium by considering a broad spectrum of variables that may capture value. Cong, He, and Tang (2021) focus on the cryptocurrency staking economy and examine a carry trade strategy. Liu, Sheng, and Wang (2019) construct a technology index from the whitepapers of initial coin offerings. Shams (2020) and Schwenkler and Zheng (2020) study correlations of cryptocurrency pairs. Soska, Dong, Khodaverdian, Zetlin-Jones, Routledge, and Christin (2021) study cryptocurrency derivatives. Griffin and Shams (2020), Cong, Li, Tang, and Yang (2021), and Aloosh and Li (2019) provide evidence of potential manipulations in the cryptocurrency market.

2 Value Relevance and Cryptocurrencies

In this section, we build on a large body of literature on network economy (e.g., Rohlfs 1974; Katz and Shapiro 1985; Katz and Shapiro 1986; Farrell and Saloner 1986; Katz and Shapiro 1994) to discuss its relevance for valuing cryptocurrencies. The basic idea is that the value of a cryptocurrency increases when more users join its blockchain, which is commonly referred to as the network effect. In a network economy, the utility a user derives from a service depends on the overall user adoption of the economy, and therefore the valuation of the network increases when more users join. Markets with network effects such as software, media, payment systems, and Internet are typically two-sided, and thus many recent papers on network economy focus on two-sided, or even multi-sided, markets. Rochet and Tirole (2003) and Armstrong (2006) study platform competition in the two-sided markets, and find that the value of platforms is related to their user base. Mitchell and Skrzypacz (2006) build a dynamic competition model of duopoly platforms featuring network effects, and find a positive relationship between the value of platforms and their current and future user base in their dynamic model. Weyl (2010) and Hagiu and Wright (2015) develop pricing models of multi-sided platforms with network effects. Liebowitz and Margolis (1994), Shy (2001), Rysman (2009), and Shy (2011) discuss and survey the literature of network economy.

The cryptocurrency market can be considered a network economy.[2] Accordingly, the theoretical literature on cryptocurrency valuations also focuses on user adoption and network effect. Cong, Li, and Wang (2021) relate cryptocurrency prices to the user base. In a model of dynamic user adoption, they show that cryptocurrency prices are intimately linked to the endogenous adoption of cryptocurrencies. Sockin and Xiong (2020) feature the network effect in their model and consider the possibility of multiple equilibria. Other studies that relate the network effect to cryptocurrencies include Pagnotta and Buraschi (2018), Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2020), Pagnotta (2020), and Cong, Li, and Wang (Forthcoming).

The early empirical literature on network effects studies the traditional network economy, such

[2] In principle, all cryptocurrencies have the functionality of payment systems even though a significant proportion of them is used primarily for non-payment purposes. Many of these cryptocurrencies also have platforms that serve specific purposes, such as storage, financing, and gaming.

as software, ATM, yellow pages, and payment systems (e.g., Gandal 1994; Saloner and Shepard 1995; Rysman 2004; Rysman 2007). In particular, the value of Internet companies which are considered a classic example of network industry, is found to be strongly increasing when more users join. Trueman, Wong, and Zhang (2000), Rajgopal, Venkatachalam, and Kotha (2003), and Luo, Zhang, and Duan (2013) find that the value of internet companies has a strong and positive relationship with different measures of their user bases. Importantly, they show that traditional accounting numbers such as earnings are not related to the value of these internet companies. In other words, the user base information is highly value-relevant for the internet companies, while traditional accounting information is not.[3] Goldfarb and Tucker (2019) discuss the potential drivers of network effects in digital economies. Levin (2011) survey the literature regarding the economics of Internet markets.

Prior studies of both network economy and cryptocurrencies place a critical role on the network effect induced by user adoption. The utility a cryptocurrency user derives from using the coin depends on the overall level of user adoption of the system, and therefore the valuation of the cryptocurrency would increase when more new users join. Therefore, we seek to empirically test the usefulness and relevance of the information regarding new users for the cryptocurrency market. To do so, we employ the set of methods that is foundational in the accounting literature – the value-relevance tests. The value-relevance tests were pivotal in empirically establishing the role of earnings as the measure of firm fundamentals. The objective of the value-relevance tests is to test whether and how quickly given measures, such as firm earnings, capture changes in the information set that is reflected in security returns over a given period. Such tests are the cornerstones of the vast literature that started with the classic work of Ball and Brown (1968). For related surveys of this vast literature, see Lev (1989), Fama (1998), Kothari (2001), and Scott and O'Brien (2019).

The approach in this literature is to test how investors react to releases of information, such as earnings. In other words, if the market reacts to the release of a piece of information, then this specific piece of information can be considered useful. A common method to test the information content of accounting earnings is to regress contemporaneous stock returns on innovations in earnings. The slope coefficients from these regression specifications are one of the central objects in the accounting literature – *earnings response coefficients*, or ERCs (see, e.g., Chapter 5.4 of Scott and O'Brien 2019 and Exhibit 1 of the survey of Dechow, Ge, and Schrand 2010). Moreover, the

[3]Moreover, this literature links the user base of companies to their revenue and profitability (e.g., Trueman, Wong, and Zhang 2001; Trueman, Wong, and Zhang 2003).

explanatory power, or R-squared, of the regression measures the degree of informativeness of the information.[4]

Besides earnings, the accounting and finance literature also examines the value relevance of other financial statement information as well as of non-accounting information. This so-called fundamental information analysis is another foundational concept in accounting (see recent surveys of Richardson, Tuna, and Wysocki 2010 and Lewellen 2010 for discussions). Early studies of the value relevance of other financial statement information include Lev and Thiagarajan (1993), Lev and Sougiannis (1996), and Chan, Lakonishok, and Sougiannis (2001). Several recent papers (e.g., De Franco, Wong, and Zhou 2011; Patatoukas, Sloan, and Zha 2015) study the value relevance of supplementary information in financial statements. Pakes (1985), Austin (1993), and Hall, Jaffe, and Trajtenberg (2005) study the relation between patents and stock returns. Kogan, Papanikolaou, Seru, and Stoffman (2017) study stock market reactions to different patent announcements. Amir and Lev (1996) study the value-relevance of potential user adoption in the wireless communication industry. Ittner and Larcker (1998) examine the value-relevance of customer satisfaction.

A related line of research that evaluates the usefulness of informational events using market reactions is the event study literature. Fama, Fisher, Jensen, and Roll (1969) examine the stock price reactions to a number of informational events, such as stock splits and dividend adjustments. The literature also examines other informational events of firms, such as merger & acquisition (e.g., Roll 1986; Agrawal and Jaffe 2000; DePamphilis 2019) and IPO (e.g., Ritter and Welch 2002; Loughran and Ritter 2004). The approach is also commonly applied to studying macroeconomic events, such as the announcement of unemployment rates (e.g., Boyd, Hu, and Jagannathan 2005) and federal funds rate (e.g., Bernanke and Kuttner 2005).

3 Data Summary

In this section, we discuss the data used in this paper. We obtain on-chain and price data of cryptocurrencies from Glassnode.com, a major blockchain data and intelligence provider.[5] For

[4]Another method to test the usefulness of earnings is to examine the reactions of trading volume or return volatility to earnings news, which is started from Beaver (1968). We also use this approach to empirically test the usefulness of earnings news in Table A.1 in the Online Appendix, and reach similar conclusions. In this paper, we focus on the approach using market price reaction because it is easy to interpret and is believed to provide a stronger test for the decision usefulness than volume or return volatility reaction (see Kim and Verrecchia 1991).

[5]Other popular cryptocurrency on-chain data providers include Coinmetrics and IntoTheBlock.

each coin, Glassnode gathers on-chain data that are recorded in coins' public ledger, which is its record-keeping system of the identities, cryptocurrency balances, and all network transactions of the participants. The data on the public ledgers of cryptocurrencies form the basis of the on-chain data analysis. Because each cryptocurrency has both common and unique features on its blockchain, the number of available on-chain measures varies across the coins. Our main measures are based on the common features of blockchains and thus are available for the maximum amount of coins. The comprehensive sets of the on-chain data are typically available on a daily basis. For our main empirical analyses, we construct the on-chain measures at the weekly frequency. In additional tests, the measures are constructed at different frequencies. Our main variables are discussed below.

To measure the information pertaining to new users of a blockchain, we use the number of new addresses per coin (NA). An address is a unique sequence of numbers and letters that represents a source or a destination of blockchain payments. A new address is a unique address that appears for the first time in a transaction in a week. A high NA for a coin indicates fast user adoption of this cryptocurrency. We then construct the weekly changes in logged NA, or Δna, to measure innovations to the number of new addresses.

Next, we construct the price-to-new address ratio, or pa, defined as $pa = log(\frac{Price}{NA})$, where $Price$ is the end of day price on the last day of a week. In the following section, we empirically show a strong value-relevance of NA in the cryptocurrency market. Moreover, we find that NA has many properties that are similar to earnings in the value-relevance studies. Therefore, pa plays a role similar to the logged price-to-earnings ratio of equities. The definitions of other variables are documented in the Online Appendix.

Our sample starts from February 2018, when the on-chain data became available for most coins, to June 2021. We exclude stablecoins and require the coins to have price data. The final sample consists of 127 cryptocurrencies. Panel A of Table 1 shows the summary statistics of the main variables used in the paper. During the sample period, the average logged coin return is 0.3 percent per week and the weekly standard deviation of the logged coin returns is 0.251. The mean (median) of average growth in new addresses (Δna) is -1.9 percent (-3.2 percent), suggesting that the increase of the number of new users slightly slows down on average in our sample period. The summary statistics of the other variables are also included in Panel A. Panel B shows the correlation matrix of the variables. It shows that cryptocurrency returns are most correlated with the changes in the logged number of new addresses (Δna), with a correlation of 0.252. The correlations between cryptocurrency returns and the other variables are much lower. Table A.11 in the Online Appendix shows the summary statistics of the other variables used in the paper.

Table 1: **Summary Statistics**

This table shows the summary statistics of the main variables used in the paper. Panel A reports the mean, standard deviation, 10% percentile, median and 90% percentile values of the variables. Panel B reports the correlation matrix of the variables.

Panel A	Mean	SD	10%	Median	90%
ret	0.003	0.251	-0.214	-0.000	0.210
Δna	-0.019	0.582	-0.551	-0.032	0.542
na	-13.095	12.362	-17.009	-13.449	-8.787
pa	12.254	1.344	10.844	12.114	13.902

Panel B	ret	Δna	na	pa
ret	1.000			
Δna	0.252	1.000		
na	0.039	0.083	1.000	
pa	0.004	-0.206	-0.167	1.000

4 Value Relevance

Building on the discussion in Section 2, we aim to test the value relevance of information pertaining to new addresses. In other words, we examine if the cryptocurrency returns react to the innovations to the number of new addresses. In our baseline specification, we use the changes in the logged number of new addresses to capture innovations to new addresses, which is analogous to using earnings growth to measure earnings innovations. In summary, we test the value relevance of new addresses in the following baseline form:

$$r_{t,i} = \alpha + \beta \times \Delta na_{t,i} + \epsilon_{t,i} \tag{1}$$

where $r_{i,t}$ is the logged returns of cryptocurrency i at time t, $\Delta na_{t,i}$ is the changes in the logged number of new addresses of cryptocurrency i at time t, and $\epsilon_{t,i}$ is the residual term. The coefficient estimate of interest is β, which measures the cryptocurrency price reactions to the changes in the logged number of new addresses.

Examples

We first examine the time-series properties of the value-relevance of new addresses for three major cryptocurrencies – Bitcoin, Ethereum, and Litecoin. Figure A.1 in the Online Appendix gives a graphical illustration of the relation between prices and the number of new addresses of each coin. The graph shows that the logged prices track well the logged numbers of new addresses for all three cryptocurrencies.

Next, we test the relationship statistically and document the result in Table 2. For each cryptocurrency, we apply two regression specifications, where the first specification only includes changes to logged number of new addresses (Δna) and the second also includes logged new addresses per coin (na) to capture potential level effects (e.g., Collins and Kothari 1989; Lev and Gu 2016). The coefficient estimates of Δna are positive and highly statistically significant for all three cryptocurrencies under the two different specifications. A one-standard-deviation increase of Δna is associated with increases in weekly logged returns of 11.7, 10.1, and 13.1 percent for Bitcoin, Ethereum, and Litecoin, respectively.[6] The adjusted R-squareds in the specifications including only Δna are 4.4 percent, 4.2 percent, and 9.5 percent for Bitcoin, Ethereum, and Litecoin, respectively. To make a comparison, in the equity market, Lev (1989) documents that the R-squared associated with the returns/earnings relation is around 5 percent. More recently, Lev and Gu (2016) survey the literature on value relevance and provide evidence that the value relevance of earnings is decreasing over time as measured by R-squareds. Based on the explanatory power, the value relevance of new addresses in the cryptocurrency market for the three major cryptocurrencies is higher than that of earnings in the equity market.

In columns (2), (4) and (6), we also include na and test whether the level of new addresses provides additional explanatory power. The coefficient estimates of na are significant at the 5-percent level for Bitcoin but not significant for Ethereum and Litecoin. The increases in adjusted R-squareds are smaller than 1 percent. That is, the returns react to new information contained mostly in changes in new addresses instead of the level of new addresses. We systematically test

[6] For example, for Bitcoin, 11.7 percent is calculated as the standard deviation of the sample Δna (0.582) times the coefficient estimate of Δna (0.267). Therefore, a one-standard-deviation increase of Δna is associated with a $0.582 \times 0.267 = 0.117$, or 11.7 percent, increase in weekly logged returns for Bitcoin.

and confirm this phenomenon in the subsequent sections.

Table 2: **Value Relevance Analysis – Time-Series**

This table shows the results for the time-series value relevance tests for the three major cryptocurrencies (Bitcoin, Ethereum, and Litecoin). Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	BTC		ETH		LTC	
	ret	*ret*	*ret*	*ret*	*ret*	*ret*
Δna	0.267***	0.265***	0.150***	0.151***	0.268***	0.267***
	(5.213)	(5.189)	(3.756)	(3.771)	(6.685)	(6.606)
na		-0.010**		-0.003		0.002
		(-2.363)		(-0.632)		(0.303)
Cons	0.021***	-0.009	0.022**	0.001	0.008	0.022
	(3.402)	(-0.654)	(2.240)	(0.030)	(1.043)	(0.467)
Obs	566	566	303	303	419	419
Adj R^2	0.044	0.052	0.042	0.040	0.095	0.093

4.1 Baseline Results

In the previous test, we showed a strong returns/new-addresses relation for the three major cryptocurrencies. In particular, the cryptocurrency market responds strongly to information pertaining to changes to logged number of new addresses. Now, we systematically test the returns/new-addresses relation using all cryptocurrencies with available data. We run cross-sectional regression as the specification (1) for each week, and report the average regression coefficients, the associated Fama and MacBeth (1973) t-statistics, and the average adjusted R-squareds.

The results are documented in Table 3. In column (1) of Table 3, the only independent variable is the changes in the logged number of new addresses (Δna). The coefficient estimate of Δna is positive and highly statistically significant, suggesting that the cryptocurrency market strongly and positively responds to the information contained in Δna. A one-standard-deviation increase in Δna is associated with an increase of 4.9 percent in logged returns. The economic magnitude of the baseline cross-sectional regression is smaller than that based on time-series regressions for

Bitcoin, Ethereum, and Litecoin, suggesting that the value-relevance of new addresses may be higher for larger coins, which we test in Section 4.2. Δna alone already explains 8.5 percent of the variations in cryptocurrency returns, confirming that information about new addresses is highly value-relevant in the cryptocurrency market. Column (2) includes na as an additional explanatory variable to capture the level effects. The coefficient estimate of na is positive and significant at the 10-percent level. The adjusted R-squared increased slightly to 8.8 percent from 8.5 percent in the standalone regression. In Table A.12 of the Online Appendix, we also report the results using other on-chain variables. The coefficient estimates of Δna are stable and remain highly statistically significant. Moreover, none of the control variables is statistically significant. The increases of adjusted R-squareds relative to the baseline specification are small, implying that the incremental explanatory power of these common on-chain variables is limited. Overall, the results show that there is a strong returns/new-addresses relation in the cross-section of cryptocurrencies. The cryptocurrency market responds strongly to information pertaining to changes in the logged number of new addresses.

Market Expectation

One important aspect of value-relevance studies is the proxy for market expectations (see, e.g., Lev 1989, Kothari 2001, and Scott and O'Brien 2019). So far, we have tested whether new addresses are relevant for value. However, in principle, only new information on the market would be incorporated in prices. That is, a more detailed test of the value relevance would need proxies for new information contained in the number of new addresses. In this subsection, we test the value relevance of the *news* in our new address measure.

In the returns/earnings relation studies in equity market research, innovation in earnings is measured as the difference between current earnings and a measure of its expected value. Three methods are commonly employed to estimate the earnings expectations (see, e.g., Chapter 5.2.2 of Scott and O'Brien 2019 for related discussions). The first method uses the last period earnings as the earnings expectations for the current period. This approach implicitly imposes an assumption that earnings are a random walk, and thus earnings growth is the appropriate measure of earnings innovations. The second method uses statistical models to calculate earnings expectations. The third approach uses analysts' forecasts of earnings as the market's earnings expectations. In the cryptocurrency market, both the first and second methods can be applied to proxy for market expectations of new addresses. Because of the lack of analysts' forecasts of new addresses, the third method is not readily applicable to the cryptocurrency market.

So far, we have used the first method to proxy for the market expectations. In our baseline specifications in Panel A of Table 3, the main variable of interest is the change in the logged number of new addresses. Hence, we implicitly assumed that the cryptocurrency market uses the number of new addresses of the last period as the new address expectations for the current period. This approach imposes a relatively strong assumption that the number of new addresses is a random walk or at least the investors believe so. We relax this assumption and use the second method based on statistical models to calculate market expectations of the number of new addresses.

We use two statistical methods: (1) the cross-sectional and (2) the time-series methods.[7] To calculate the expectations of new addresses using the cross-sectional method, we first regress the logged number of new addresses of cryptocurrencies at time $t-1$ on the corresponding logged number of new addresses at time $t-2$ for the cross-section of cryptocurrencies and keep the coefficient estimates. Then, we apply the coefficient estimates to the logged number of new addresses at time $t-1$ to calculate the predicted logged number of new addresses at time t, which is the expectations of new addresses based on the cross-sectional model. Therefore, the innovations to the number of new addresses are the difference between the realized logged number of new addresses and the predicted logged number of new addresses, which we denote as $na\ shock^1$.

To calculate the expectations of new addresses using the time-series method, we first regress the logged number of new addresses of cryptocurrencies on the lagged logged number of new addresses for a cryptocurrency i from the 12 weeks proceeding the current period, and keep the coefficient estimates.[8] Then, we apply the coefficient estimates to the logged number of new addresses for cryptocurrency i at time $t-1$ to calculate the predicted logged number of new addresses for cryptocurrency i at time t, which is the expectation of new addresses based on the time-series model. Similarly, the innovations to the number of new addresses are the difference between the realized logged number of new addresses and the predicted logged number of new addresses, which we denote as $na\ shock^2$.

Panel B and Panel C of Table 4.1 document the results based on $na\ shock^1$ and $na\ shock^2$. We focus our discussion on $na\ shock^1$. The results for $na\ shock^2$ are qualitatively similar. In

[7]See Lev (1989) and Kothari (2001) for discussions.

[8]We use a 12 week window to conduct all rolling estimations in the paper. While there is no consensus on the estimation window, requiring 12 weeks for rolling estimations in the cryptocurrency market balances precision and potential time-varying coefficient estimates. Using longer windows (24 weeks or 36 weeks) generates qualitatively similar results.

the standalone model in column (1), the coefficient estimate of $na\ shock^1$ is positive and highly statistically significant. The point estimate of $na\ shock^1$ is 0.085, which is close in magnitude to that of Δna at 0.084 in Panel A. The adjusted R-squared of the standalone specification is 8.6 percent, which is similar to that based on Δna at 8.5 percent. Column (2) further includes *na* as an explanatory variable. Interestingly, the point estimate of *na* is no longer significant when $na\ shock^1$ is used instead of Δna. This result shows that the cryptocurrency market does not respond to information pertaining to *na* when $na\ shock^1$ is available.

Table 3: **Value Relevance Analysis – Cross-Sectional**

This table shows the results for the cross-sectional value-relevance tests. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	Panel A		Panel B		Panel C	
	(1)	(2)	(1)	(2)	(1)	(2)
	ret	*ret*	*ret*	*ret*	*ret*	*ret*
Δna	0.084***	0.083***				
	(12.060)	(11.823)				
$na\ shock^1$			0.085***	0.087***		
			(13.121)	(12.707)		
$na\ shock^2$					0.076***	0.074***
					(13.115)	(12.905)
na		0.001*		-0.001		0.001
		(1.929)		(-1.335)		(1.419)
Cons	-0.003	0.009	0.099***	0.093***	-0.002	0.007
	(-0.349)	(0.846)	(7.165)	(6.998)	(-0.246)	(0.702)
Obs	13,522	13,522	13,404	13,404	12,163	12,163
Adj R^2	0.085	0.088	0.086	0.094	0.087	0.090

Adjusted for Expected Returns

In the previous analyses, we used raw returns to measure cryptocurrency market reactions. However, the raw returns may include a component of expected returns that measure investor reaction to cryptocurrency market-wide news rather than to coin-specific news. In equity market research, the common method to remove the component of expected returns is to calculate the residual returns using benchmark factor models.[9] The idea is that factor models capture the expected component of returns, and therefore the residual returns would only contain information that is orthogonal to the expected returns.

We apply this method to the cryptocurrency market using the cryptocurrency CAPM and cryptocurrency 3-factor model as in Liu, Tsyvinski, and Wu (2021). Liu, Tsyvinski, and Wu (2021) show that a cryptocurrency three-factor model including the cryptocurrency market factor, cryptocurrency size factor, and cryptocurrency momentum factor is able to capture the cross-section of expected cryptocurrency returns. Therefore, we use the cryptocurrency factor models to remove components that are attributable to the expected returns. We define residual returns as the difference between raw returns and factor model implied expected returns:

$$res_{it} = R_{it} - \left(\hat{\alpha}_{it} + \hat{\beta}'_{ikt} R_{kt}\right)$$

where R_t is either the cryptocurrency market excess return or the three factors including the cryptocurrency market factor, size factor, and momentum factor; $\hat{\alpha}_i$ and $\hat{\beta}_{ik}$ are estimated from the 12 weeks preceding the current period; i indicates the asset, t indicates time, and k indicates the factor.

The results are documented in Table 4. Panel A shows the results adjusting for the cryptocurrency CAPM model. The point estimates of Δna are positive and highly statistically significant. The adjusted R-squared for the specification using only Δna is 7.7 percent, which is similar to the specifications using raw returns at 8.5 percent. Panel B reports the results adjusting for the cryptocurrency 3-factor model. The point estimates of Δna are positive and highly statistically significant. The adjusted R-squared for the specification using only Δna is 5.8 percent. The coefficient estimates of na are not positive and significant in any of the specifications. That is, the cryptocurrency market responds strongly to innovations to new addresses but not to the simple amount of new addresses. Overall, the results based on unexpected returns further support our baseline results that the information pertaining to innovations to new addresses is highly value-relevant in the cryptocurrency market.

[9] Removing the component of expected returns is a common practice in the literature to separate market-wide effect from firm-specific effect and is used by most existing value relevance studies. see Lev (1989), Kothari (2001), and Chapter 5.2.3 of Scott and O'Brien (2019) for detailed discussions on the merits of using different factor models to capture components of expected returns.

Table 4: **Value Relevance Analysis – Adjusting for Expected Returns with Factor Models**

This table shows the results for the cross-sectional value-relevance tests using returns adjusted for expected returns. The regressions are based on Fama-MacBeth regression method. res^1 is the residual return based on the cryptocurrency CAPM model and res^2 is the residual return based on the cryptocurrency 3-factor model. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	Panel A		Panel B	
	(1)	(2)	(1)	(2)
	res^1	res^1	res^2	res^2
Δna	0.087***	0.086***	0.084***	0.083***
	(11.976)	(12.177)	(11.786)	(12.031)
na		0.000		-0.001
		(0.162)		(-0.911)
Cons	-0.008	-0.007	-0.003	-0.010
	(-1.419)	(-0.862)	(-0.796)	(-1.103)
Obs	12,053	12,053	12,053	12,053
Adj R^2	0.077	0.078	0.058	0.057

4.2 Economic Determinants of Value-Relevance

In the equity market, studies have shown that there are several important determinants of the returns/earnings relation (see, e.g., Kothari 2001; Dechow, Ge, and Schrand 2010; Scott and O'Brien 2019). The first main category is the quality of earnings, measured using both the statistical property of earnings and the property of the accounting system. The second main determinant is companies' discount rates, including both the risk-free component and the risk-based component. Thirdly, the literature also emphasizes the impact of firm size, a common measure of the informativeness of stock prices, on the value relevance of earnings. These three categories of determinants in the returns/earnings relation correspond to the three components of the present value discounting formula – cash-flow (earnings), discount rate, and price. Motivated by the evidence in the equity market, in this subsection, we study these potential economic determinants of value-relevance in the returns/new-addresses relation in the cryptocurrency market.

Persistence and Variability

Research in equities shows that the quality of earnings can differ across companies (see Dechow, Ge, and Schrand 2010 for a comprehensive review). If the quality is high, one may expect the value-relevance of earnings to also be high since investors are better able to assess future firm performance using earnings. There are two main approaches to measuring earnings quality. The first is based on the statistical property of earnings, and the second is based on the attributes of the accounting system.

For the first method, the main measure of earnings quality is earnings persistence. The idea is that the value-relevance of earnings should be high if the good or bad news in current earnings is expected to persist into the future. Kormendi and Lipe (1987) propose and confirm that high earnings persistence is linked to high ERCs in the equity market. The relationship is further confirmed in subsequent studies (e.g., Basu 1997, Ramakrishnan and Thomas 1998, and Li 2011). Another statistical measure of earnings quality is earnings variability. It is proposed that investors prefer earnings with less variability because the business model is not volatile for these companies (e.g., Schipper and Vincent 2003). For the second method, research finds that accounting systems can affect the value-relevance of earnings. Teoh and Wong (1993) find that companies with high quality auditors tend to have larger ERCs. Francis, LaFond, Olsson, and Schipper (2004) show that ERC is linked to the accrual quality of firms, a measure of the quality of a company's accounting system. Leuz and Verrecchia (2000), Bailey, Karolyi, and Salva (2006) and Greenstone, Oyer, and Vissing-Jorgensen (2006) show that stringent accounting standards increase the value-relevance of earnings. The argument based on the persistence and variability of earnings is readily applicable to our setting, while the earnings quality related to the accounting system is not. Therefore, we focus on studying the role of persistence and variability of new addresses growth in its value-relevance in the cryptocurrency market.

We first test the relation between persistence and the value-relevance of new addresses. For each period, we split the cross-section of cryptocurrencies into two groups based on the persistence of Δna in the past 12 weeks. We construct an indicator variable $1_{\{p>Med\}}$ which equals one if the persistence of Δna is above the sample median and zero otherwise. Table 5 shows the results for the high and low persistence of new address growth subsamples.

Columns (1) and (2) of Table 5 show the results for the subsamples of coins with below and above median persistence of Δna, respectively. The point estimate of Δna is 0.105 for the above-median subsample, while the point estimate of Δna is 0.077 for the below-median subsample. That is, the sensitivity between returns and new addresses growth is about 30 percent higher for the high new addresses growth persistence subsample. Column (3) reports the results based on the full sample and includes the cross term between $1_{\{p>Med\}}$ and Δna. The coefficient estimate is positive and statistically significant at the 5-percent level, confirming that the returns/new addresses relation is more pronounced among the coins with above median persistence of Δna. In summary, we find that the returns/new-addresses relation is more pronounced among coins with high persistence of Δna, suggesting that persistence is an important determinant of the value-relevance of new addresses in the cryptocurrency market, similar to related findings in the equity market.

Table 5: **Persistence of New Address Growth and Value Relevance**

This table reports the results of the cross-sectional tests in the subsamples based on the above median and below median persistence of new address growth. $1_{\{p>Med\}}$ is an indicator variable which equals to one if the persistence of new address growth is greater than the sample median and zero otherwise. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)
	ret	ret	ret
Sample	<Med	>Med	Full
Δna	0.077***	0.105***	0.077***
	(7.935)	(11.327)	(7.935)
$1_{\{p>Med\}}$			-0.003
			(-1.042)
$\Delta na * 1_{\{p>Med\}}$			0.026**
			(2.168)
Constant	-0.004	-0.007	-0.004
	(-0.440)	(-0.745)	(-0.440)
Observations	6,644	6,537	13,181
Adj R^2	0.093	0.118	0.119

Table 6: **Variability of New Address Growth and Value Relevance**

This table reports the results of the cross-sectional tests in the subsamples based on the above median and below median variability of new address growth. $1_{\{v>Med\}}$ is an indicator variable which equals to one if the variability of new address growth is greater than the sample median and zero otherwise. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)
	ret	ret	ret
Sample	<Med	>Med	Full
Δna	0.123***	0.073***	0.123***
	(11.511)	(10.026)	(11.511)
$1_{\{v>Med\}}$			0.000
			(0.086)
$\Delta na * 1_{\{v>Med\}}$			-0.044***
			(-4.422)
Constant	-0.005	-0.005	-0.005
	(-0.607)	(-0.572)	(-0.607)
Observations	6,709	6,587	13,296
Adj R^2	0.128	0.080	0.111

Next, we study the relationship between the variability of new address growth and the value-relevance of new addresses. For each period, we split the cross-section of cryptocurrencies into two groups based on the variability of new address growths, measured as the standard deviation of Δna in the past 12 weeks. We construct an indicator variable $1_{\{v>Med\}}$ which equals one if the variability of Δna is above the sample median and zero otherwise. Table 6 shows the results for the high and low variability of new address growth subsamples.

Columns (1) and (2) of Table 6 show the results for the subsamples of coins with below and above median variability of Δna, respectively. The point estimate of Δna is 0.073 for the above-median subsample, while the point estimate of Δna is 0.123 for the below-median subsample. Column (3) reports the results based on the full sample and includes the cross term between $1_{\{v>Med\}}$ and Δna. The coefficient estimate is negative and statistically significant at the 1-percent level, confirming that the returns/new addresses relation is more pronounced among the coins with below median variability of Δna. In summary, we find that the returns/new addresses relation is more pronounced among coins with low variability of Δna, suggesting that variability is an important determinant of the value-relevance of new addresses in the cryptocurrency market, similar to related findings in the equity market.

Discount rate

Another main determinant of the value-relevance of earnings is the discount rate. When the discount rate is high for a stock, the discounted present value of the revisions in expected future earnings would be low. That is, the value relevance of earnings is expected to be lower for companies with high discount rates. Empirically, prior studies test and confirm the negative relationship between discount rates, including the risk-free and risky components, and the value relevance of earnings. Collins and Kothari (1989) show that the value relevance of earnings is low in the equity market when the risk-free rate is high. Easton and Zmijewski (1989) show that the value relevance of earnings is negatively related to the risky components of the discount rates based on single- and multi-beta versions of the CAPM in the cross-section of stocks.

Similarly, if the cryptocurrency valuation also follows a present value discounted formula (e.g., Cong, Li, and Wang Forthcoming; Biais, Bisiere, Bouvard, Casamatta, and Menkveld 2020), we would expect to find a relatively low value relevance of new addresses when the discount rate is high for a cryptocurrency. To measure the discount rate of cryptocurrencies, we use the cryptocurrency 3-factor model as in Liu, Tsyvinski, and Wu (2021). For each cryptocurrency, we estimate the factor loadings on the 3 factors with a rolling 12-week window preceding the current period. The implied discount rate is calculated based on the following formula:

$$\beta_{i,t}^{CMKT} E\left[R^{CMKT}\right] + \beta_{i,t}^{CSMB} E\left[R^{CSMB}\right] + \beta_{i,t}^{CMOM} E\left[R^{CMOM}\right] + R^{f}$$

where $E\left[R^{CMKT}\right]$, $E\left[R^{CSMB}\right]$, and $E\left[R^{CMOM}\right]$ are calculated as the average excess returns of the factors from Liu, Tsyvinski, and Wu (2021).

Table 7 shows the results. For each period, we split the cross-section of cryptocurrencies into two groups based on their implied discount rates. We construct an indicator variable $1_{\{b>Med\}}$ which equals one if the implied discount rate is above the sample median and zero otherwise. Columns (1) and (2) show the results for the subsamples of coins with below and above median discount rates, respectively. The point estimate to Δna is 0.096 for the below-median subsample, while the point estimate to Δna is 0.083 for the above median subsample. That is, the sensitivity between returns and new addresses growth is about 15 percent higher for the low discount rate subsample. Column (3) reports the results based on the full sample and includes the cross term between $1_{\{d>Med\}}$ and Δna. The cross term is negative but statistically insignificant.

Table 7: **Discount Rate and Value Relevance**

This table reports the results of the cross-sectional tests in the subsamples based on high and low discount rate. $1_{\{d>Med\}}$ is an indicator variable which equals to one if the discount rate is greater than the sample median and zero otherwise. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)
	ret	ret	ret
Sample	<Med	>Med	Full
Δna	0.096***	0.083***	0.096***
	(9.843)	(12.249)	(9.843)
$1_{\{d>Med\}}$			0.002
			(0.662)
$\Delta na * 1_{\{d>Med\}}$			-0.013
			(-1.235)
Constant	-0.004	-0.002	-0.004
	(-0.442)	(-0.195)	(-0.442)
Observations	6,022	5,924	11,946
Adj R^2	0.092	0.098	0.107

Size

In the equity market, it is theoretically proposed that the informativeness of firm price, often proxied by firm size, may be negatively related to the value relevance of earnings (e.g., Easton and Zmijewski 1989; Collins and Kothari 1989; Kothari 2001). The argument is that large firms tend to receive more attention and are under more scrutiny by investors, and thus there is less information content in the current accounting earnings, leading to a lower value relevance of earnings at the release of information.[10] A similar argument may be applied to the cryptocurrency market, suggesting a negative relation between size and the value-relevance of new addresses.

On the other hand, there could be a positive relationship between size and the value relevance of new addresses for cryptocurrencies. In the theoretical literature of both the network industries and the cryptocurrencies, models with network externality (e.g., Rohlfs 1974; Katz and Shapiro 1985; Armstrong 2006; Cong, Li, and Wang 2021) imply a potential positive relation. In studying the internet companies in the equity market, Rajgopal, Venkatachalam, and Kotha (2003) show that the value relevance of the number of website users is higher for large e-commerce companies, and they argue that this non-linearity is due to network effects.

To test whether size is a determinant of the value-relevance of new addresses, for each period, we split the cross-section of cryptocurrencies into two groups based on their network sizes measured as the number of addresses.[11] We construct an indicator variable $1_{\{A>Med\}}$ which equals one if the number of address of the cryptocurrency is above the sample median in the previous period and zero otherwise. Table 8 documents the results.

Columns (1) and (2) show the results for the subsamples of coins with below median network size and above median network size, respectively. The point estimate to Δna is 0.080 for the below median subsample, while the point estimate to Δna is 0.103 for the above median subsample. That is, the sensitivity between returns and new addresses growth is about 29 percent higher for the large network size subsample. Column (3) reports the results based on the full sample and includes the cross term between $1_{\{A>Med\}}$ and Δna. The coefficient estimate of the cross term is positive and statistically significant at the 5-percent level, indicating that the returns/new addresses relation is more pronounced among coins with larger network sizes. Overall, we find that the returns/new addresses relation is more pronounced among coins with larger network sizes, consistent with the theoretical argument regarding network effects.

[10]The empirical evidence is mixed between the relationship between size and the value-relevance of earnings. Easton and Zmijewski (1989) do not find support for the relationship. Collins and Kothari (1989) provide support for the claim using an alternative method. Chapter 5.4 of Scott and O'Brien (2019) discusses the mixed results.

[11]Using market cap generates qualitatively similar results

Table 8: **Value Relevance Analysis – Subsample by Network Size**

This table reports the results of the cross-sectional value-relevance tests in the subsamples based on the network size of cryptocurrencies. $1_{\{A>Med\}}$ is an indicator variable which equals to one if the total address of the cryptocurrency is above the sample median in the previous period and zero otherwise. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)
	ret	ret	ret
Sample	<Med	>Med	Full
Δna	0.080***	0.103***	0.080***
	(9.850)	(11.423)	(9.850)
$1_{\{A>Med\}}$			-0.002
			(-0.511)
$\Delta na * 1_{\{A>Med\}}$			0.023**
			(2.136)
Constant	-0.004	-0.006	-0.004
	(-0.450)	(-0.627)	(-0.450)
Observations	6,613	6,906	13,519
Adj R^2	0.085	0.106	0.108

5 Discrete and Continuous Revelation of Information

An important difference between cryptocurrencies and equities is that, for cryptocurrencies, information of the underlying economic activities is available publicly and continuously on the blockchain. This is in striking contrast to the earnings information of public companies. Under the current reporting standards, publicly traded companies are required to report three quarterly earnings and one annual earnings. This quarterly reporting system was not established until 1970. Before the Securities Act of 1933 and the Securities Act of 1934 (Securities Acts), stock exchanges largely governed financial reporting, and there was no homogeneous reporting requirement across exchanges. Since the passage of the Securities Acts, the SEC has played a primary role in regulating financial reporting for public companies. The SEC mandated annual reporting in 1934 and semiannual reporting in 1955. In 1970, the SEC established the current quarterly reporting system.

This discrete nature of corporate earnings is extensively studied in the accounting and finance literature. Theoretically, the net effect of reporting frequency is unclear (e.g., Diamond 1985; Diamond and Verrecchia 1991; Abreu, Milgrom, and Pearce 1991; Easley and O'hara 2004). Empirical studies examine both the benefit and costs associated with more frequent reporting. On the benefit side, studies focus on the additional transparency that more reporting brings. Butler, Kraft, and Weiss (2007) show that stock prices reflect accounting information more quickly when firms voluntarily increase their reporting frequencies. More frequent reporting is also found to be associated with reduced cost of capital and improved liquidity (e.g., Fu, Kraft, and Zhang 2012). On the cost side, both theories (e.g., Gigler, Kanodia, Sapra, and Venugopalan 2014) and empirical studies suggest that higher reporting frequencies can cause managers to myopically prefer short-term performance gains at the expense of overall firm value. Kraft, Vashishtha, and Venkatachalam (2018) claim that increased reporting frequency in the 1970s is associated with a large decline in investments, consistent with managers behaving myopically following increases in reporting frequency. Ernstberger, Link, Stich, and Vogler (2017) show that firms with more frequent reporting exhibit higher real earnings management.

Two important phenomenons in the equity market are attributable to the infrequent release of information and suggest that information is not fully efficiently incorporated into prices. The first phenomenon is referred to as the post-announcement drift. That is, information, such as innovations to earnings, tend to forecast future company returns (e.g., Ball and Brown 1968; Bernard and Thomas 1989; Sadka 2006; Daniel, Hirshleifer, and Sun 2020; Meursault, Liang, Routledge, and Scanlon 2021). Among many alternative explanations for this phenomenon, a common view is that the equity market is slow in incorporating earnings information. The second phenomenon is referred to as the pre-announcement drift. That is, stock returns tend to precede informational events such as earnings and Federal Open Market Committee (FOMC) announcements (e.g., Ball and Brown 1968; Lucca and Moench 2015; Cieslak, Morse, and Vissing-Jorgensen 2019). The literature commonly attributes the phenomenon to the discreteness of information releases and information leakages between the discrete announcements.

The blockchain information is non-discretionary and continuously available by design. Thus, the cryptocurrency market provides an ideal setting to study frequent reporting where the value-relevant information is revealed continuously. In this section, we revisit these classic information release-related phenomenons in the cryptocurrency market.

5.1 Slow Acquisition of Information

Post-earnings announcement drift (PEAD), first documented by Ball and Brown (1968), is one of the earliest and well-known anomalies in the asset pricing and accounting literature. The PEAD phenomenon can be described as that after earnings are announced, estimated cumulative excess returns drift up for positive earnings innovations (good news) and drift down for negative earnings innovations (bad news). A common explanation of PEAD is the slow acquisition of information (e.g., Bernard and Thomas 1989; Daniel, Hirshleifer, and Sun 2020).

In the cryptocurrency market, information pertaining to new addresses is publicly and continuously available. This environment provides a setting to study investor acquisition of information where the value relevant information can be obtained at any time. It is ex ante unclear whether such an environment would facilitate the information acquisition of investors. On the one hand, attention can be a scarce resource (e.g., Peng and Xiong 2006; DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2009) and continuous revelation of information can lead to severe under-reaction from the investors.[12] On the other hand, it is shown that stock prices reflect accounting information more quickly when firms voluntarily increase their reporting frequencies (e.g., Butler, Kraft, and Weiss 2007).

To study the information acquisition of news pertaining to new addresses in the cryptocurrency market, we use Δna to predict subsequent cryptocurrency returns of the corresponding coins. The results are documented in Table 9. Columns (1) to (3) show the results of using Δna to predict one-, two-, and three-week ahead logged returns, respectively. The point estimates of Δna for the one-, two-, and three-week ahead predictability results are -0.005, 0.005, and -0.005, respectively, which are insignificant and small compared to the contemporaneous response coefficient of 0.055. In columns (4) to (6), we further include the cryptocurrency beta,[13] size and momentum characteristics as controls. The point estimates of Δna remain insignificant and the magnitudes of the coefficients become even smaller. We conclude that, using this metric, the cryptocurrency market is efficient in responding to news pertaining to new addresses, consistent with the idea that frequent revelation of information facilitates information acquisition.

[12] Another plausible explanation of PEAD is based on changes in uncertainty and risks (e.g., Sadka 2006; Francis, Lafond, Olsson, and Schipper 2007).

[13] beta is measured as returns' exposure to cryptocurrency market return in the past 12 weeks

Table 9: **Slow Reaction to New Address Innovations**

This table shows results of predicting one-, two-, three-periods ahead cryptocurrency returns using new address growths. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	ret_{+1}	ret_{+2}	ret_{+3}	ret_{+1}	ret_{+2}	ret_{+3}
Δna	-0.005	0.005	-0.005	-0.006	0.000	-0.000
	(-1.117)	(1.194)	(-1.115)	(-1.039)	(0.097)	(-0.012)
beta				0.001	0.007*	0.007*
				(0.158)	(1.732)	(1.850)
size				-0.001*	-0.001*	-0.001
				(-1.743)	(-1.805)	(-1.399)
mom				0.011	0.042***	-0.023
				(0.537)	(2.684)	(-1.358)
Cons	-0.002	-0.002	-0.002	0.022	0.022	0.012
	(-0.248)	(-0.243)	(-0.250)	(1.137)	(1.141)	(0.643)
Observations	13,517	13,408	13,298	12,486	12,377	12,267
Adj R^2	0.010	0.005	0.006	0.059	0.041	0.040

5.2 Information Leakage

Next, we study the phenomenon of return drift prior to informational events that can also be attributed to the infrequent release of information. Prior studies find that stock returns can precede earnings surprises at earnings announcements by weeks or even months (e.g., Ball and Brown 1968; Scott and O'Brien 2019). That is, firms with positive earnings surprises tend to outperform firms with negative earnings surprises even prior to the release date of earnings. The pre-drift phenomenon is also detected in other informational events. For example, Lucca and Moench (2015) document a sizable pre-FOMC announcement drift. A common explanation for the pre-drift phenomenon is that, because of the discreteness of the events, information gradually leaks to the market prior to the releases (e.g., Collins and Kothari 1989; Cieslak, Morse, and Vissing-Jorgensen 2019). Other proposed explanations include changes in systematic risks and reduction of uncertainty (e.g., Ai and Bansal 2018; Hu, Pan, Wang, and Zhu 2019). Because the on-chain data are publicly and continuously available, the information leakage channel, which depends on the discreteness of information releases, may lose its importance in the cryptocurrency market.

To test whether the pre-drift phenomenon is present in the cryptocurrency market, we regress future changes in the logged number of new addresses on the current logged returns. The results are summarized in Table 10, which uses logged returns to predict future Δna up to three weeks ahead. The results show that cryptocurrency returns do not significantly predict future Δna at the one-week and two-week horizons. At the three-week horizon, cryptocurrency returns predict Δna significantly, but the coefficient estimate is negative, which is inconsistent with the information leakage hypothesis. The economic magnitude is small – a one-standard-deviation (25.1 percent) increase in ret is only associated with a 1.8 percent increase in Δna. Overall, we conclude that returns do not immediately precede information about the new address in the cryptocurrency market, plausibly due to the fact that information is released publicly and continuously in this market.

5.3 Cumulative Return around New Address Information

To further understand the behavior of cryptocurrency returns around the release of new address information, we summarize the evidence in Figure 1. Specifically, we plot the cumulative average logged abnormal return from 6 week before to 6 week after the release of new address information for subgroups of cryptocurrencies based on positive and negative new address growth.

Consistent with the evidence so far, there is a significant market reaction to new address information on the event date 0. However, both pre-announcement and post-announcement drifts are muted in the cryptocurrency market. The return behavior in the cryptocurrency market is in sharp contrast to the return behavior of the equity market around earnings release. Figure A.2 in the Online Appendix shows the celebrated results of pre- and post-announcement drifts around earnings announcements from Ball and Brown (1968). The figure shows a strong pre-announcement drift even 12 months ahead of the announcement date and a post-announcement drift that persist a few months subsequent to the announcement date. The presence of strong market reactions at the release of new address information, the absence of post-announcement drift, and a very muted pre-announcement drift highlight the distinct feature of cryptocurrencies and provide a benchmark case where information is released both publicly and continuously.

Table 10: **Return and Future New Address Growth**

This table shows the results for predicting next period new address growths using current cryptocurrency returns. Time fixed effect is included and standard errors are double clustered at the coin level and time level. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1) Δna_{+1}	(2) Δna_{+2}	(3) Δna_{+3}
ret	0.055	-0.049	-0.071***
	(1.200)	(-1.191)	(-2.633)
Constant	-0.019***	-0.017***	-0.015***
	(-47.404)	(-43.316)	(-37.540)
Obs	13,519	13,451	13,374
Adj R^2	0.052	0.052	0.053

6 Price-to-New Address Ratio and Return Predictability

The price-to-earnings (*pe*) ratio is one of the most studied financial ratios. In this section, we construct the price-to-new address ratio, which we propose as the cryptocurrency counterpart of the price-to-earnings ratio in the equity market. We first describe its properties and determinants. Then, we show that it is a strong cross-sectional cryptocurrency return predictor and that its predictive power is distinct from the existing predictors such as cryptocurrency market, size, and momentum. Lastly, we investigate its other properties.

6.1 The Price-to-New Address Ratio

We first give a graphical illustration of the logged price-to-new address (*pa*) ratios of Bitcoin, Ethereum, and Litecoin from 2018 to 2021. Figure 2 plots the *pa* ratios of these three cryptocurrencies. The *pa* ratios of Bitcoin and Ethereum are close to each other during the period. The sample average *pa* ratio is higher than those of Bitcoin and Ethereum during most of the period. In the time series, the *pa* ratios are relatively low for all three cryptocurrencies at the beginning of 2019 and 2020. In the past two years, the *pa* ratios for all three coins have been steadily increasing.

The *pa* ratios of Bitcoin and Ethereum are at the high points now. The price-to-earnings ratio of the aggregate stock market is also at a high point since the financial crisis.

Figure 1: **Cumulative Abnormal Return around New Address Information**

This figure plots the cumulative average logged abnormal return around the release of new address information for positive and negative new address growth subgroups. Dashed lines represent the 5-percent confidence intervals.

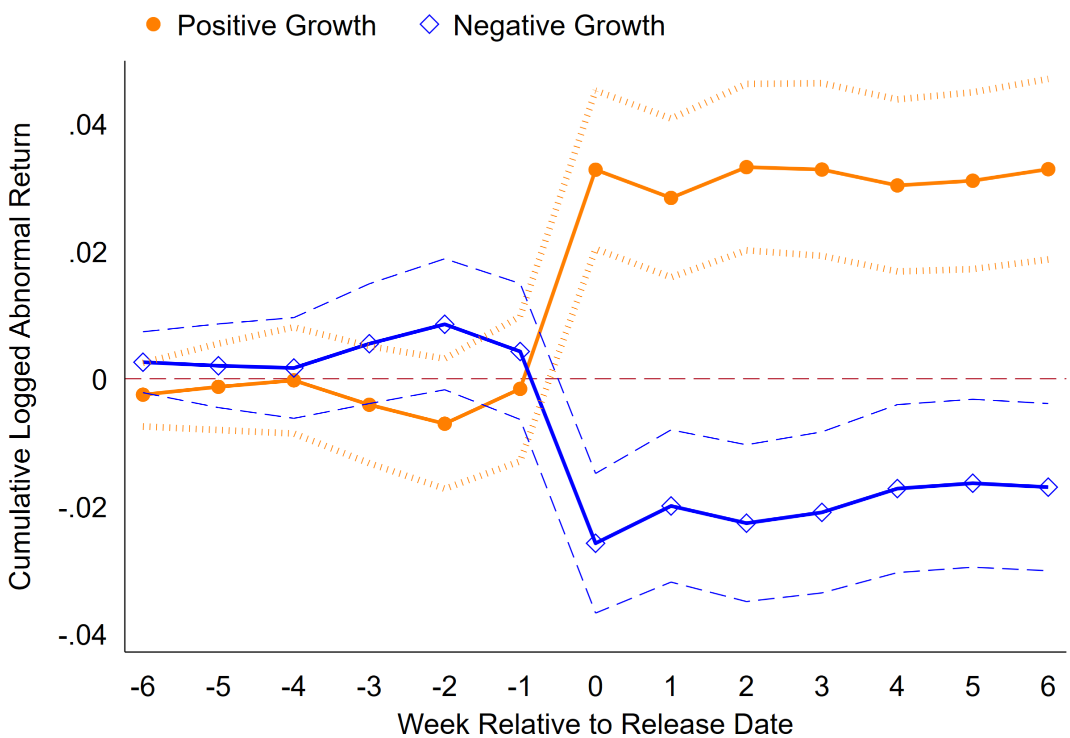
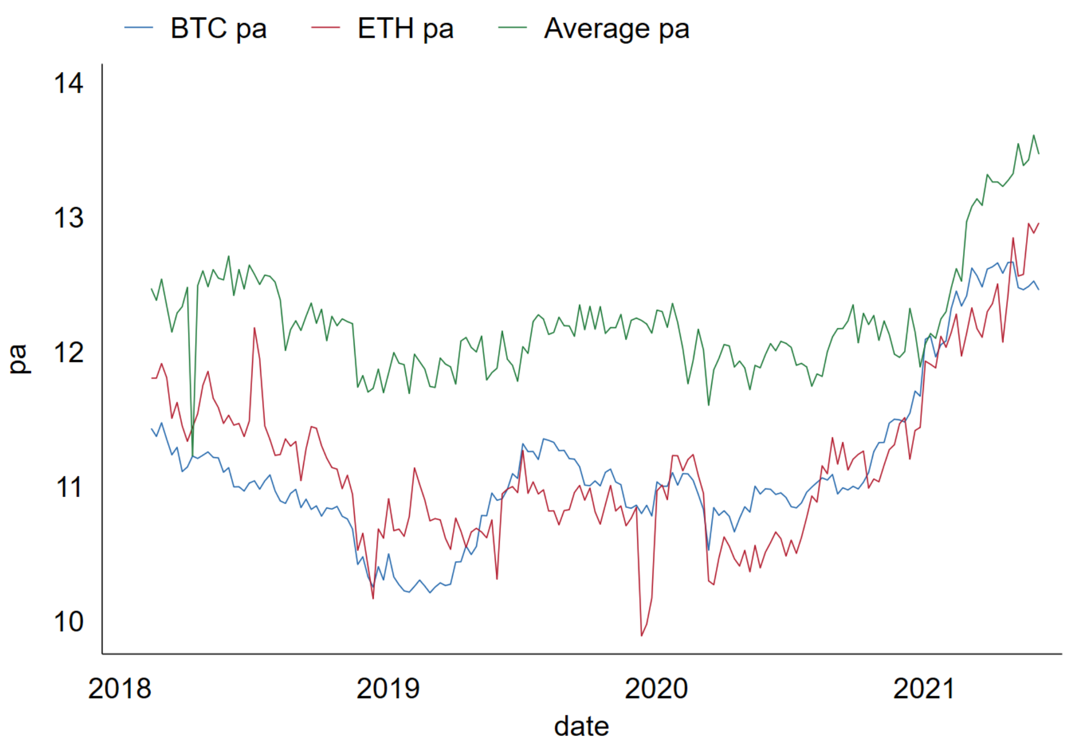


Figure 2: **Price-to-New Address Ratio of Major Coins**

This graph plots the logged price-to-new address ratio of Bitcoin, Ethereum, and Litecoin from 2018 to 2021. The blue line, red line, and green line show the results for Bitcoin, Ethereum, and sample average of the logged price-to-new address ratio, respectively.



6.2 Return Predictability

In the asset pricing literature, a large number of studies (e.g., Basu 1977; Campbell and Shiller 1988a; Welch and Goyal 2008) have documented that the price-to-earnings ratios negatively predict returns in the future. When the price of a stock is high relative to its earnings, the stock tends to have lower returns in the future.

Motivated by the evidence from the equity market, we examine the relationship between cryptocurrency expected returns and price-to-new address ratios. Firstly, we examine this relationship through the standard portfolio sorting method. Secondly, we study the long-horizon performance of the price-to-new address ratios in predicting future cryptocurrency returns. Thirdly, we confirm the return predictability results through the Fama-MacBeth regression method.

Portfolio sorting approach

We analyze the performance of the zero-investment long-short strategy based on the price-to-earnings ratios. Each week, we sort individual cryptocurrencies into quartile portfolios based on the value of price-to-earnings ratios of the corresponding coins.[14] We track the return of each portfolio in the week that follows. Then, we calculate the average excess returns over the risk-free rate of each portfolio, as well as the excess returns of the long-short strategies based on the difference between the fourth and the first quartiles.

Table 11 presents the results based on portfolio sortings. Panel A of Table 11 shows the average excess returns, standard deviations, and Sharpe ratios of the quartile portfolios and the zero-investment long-short strategy. The average mean excess returns decrease monotonically from the lowest *pa* ratio portfolio to the highest *pa* ratio portfolio. The average mean excess return of the lowest *pa* ratio portfolio is 1.5 percent per week, and that of the highest *pa* ratio portfolio is -0.4 percent per week. The difference in the average returns of the lowest quartile and the highest quartile is 1.9 percent per week, which is statistically significant at the 1-percent level. The standard deviations for the lowest quartile portfolio and the highest quartile portfolio are 11.4 percent and 10.5 percent, respectively. The excess returns of the zero-investment long-short strategy have a standard deviation of 6.8 percent. The Sharpe ratios also decrease monotonically from the lowest to the highest *pa* ratio portfolios. The weekly Sharpe ratio for the lowest *pa* ratio portfolio is 0.132 (0.951 annually), and that for the highest *pa* ratio portfolio is -0.038 (-0.274 annually). The weekly Sharpe ratio for the zero-investment long-short strategy is 0.279 (2.012 annually). We refer to the return predictability of the price-to-new address ratio as the cryptocurrency value effect.

[14] We choose quartile portfolios because the average number of cryptocurrencies in the cross-section is about one hundred. Therefore, quartile portfolios ensure that there are about thirty coins in each portfolio. In robustness tests, we find that sorting cryptocurrencies into tercile or quintile portfolios gives qualitatively similar results.

Table 11: **Portfolio Sorts Based on Cryptocurrency Price-to-New Address Ratio**

This table shows portfolio sorting results based on cryptocurrency price-to-new address ratios. Panel A reports the means, standard deviations, and Sharpe ratios of the value-weighted portfolios excess returns. Panel B reports the factor exposures of the portfolios sorted on price-to-new address ratios. The factor models in include the cryptocurrency market factor and the cryptocurrency three factor model. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A	Low	2	3	High	Low–High
Mean	0.015*	0.008	0.006	-0.004	0.019***
	(1.682)	(0.769)	(0.550)	(-0.553)	(3.638)
SD	0.114	0.142	0.135	0.105	0.068
SR	0.132	0.056	0.044	-0.038	0.279

Panel B	Alpha		CMKT		CSIZE		CMOM		R^2
Low	0.003	(1.481)	1.025***	(46.655)					0.927
2	-0.003	(-0.382)	1.057***	(17.088)					0.632
3	-0.004	(-0.645)	0.970***	(15.572)					0.588
High	-0.013***	(-2.819)	0.810***	(19.179)					0.684
Low–High	0.016***	(3.387)	0.218***	(4.789)					0.119
Low	0.004	(1.559)	1.029***	(47.160)	0.058*	(1.971)	-0.051**	(-2.439)	0.933
2	-0.007	(-1.254)	1.153***	(22.615)	0.637***	(9.271)	-0.023	(-0.472)	0.767
3	-0.009*	(-1.684)	1.073***	(21.704)	0.681***	(10.215)	-0.027	(-0.559)	0.758
High	-0.015***	(-3.934)	0.865***	(24.291)	0.390***	(8.127)	-0.062*	(-1.802)	0.790
Low–High	0.019***	(4.131)	0.169***	(3.937)	-0.322***	(-5.580)	0.009	(0.215)	0.271

Panel B of Table 11 reports results controlling for either the cryptocurrency CAPM model or the cryptocurrency 3-factor model (see Liu, Tsyvinski, and Wu 2021). In the first part of Panel B, we use the cryptocurrency CAPM model, where cryptocurrency market excess returns are included. The beta loadings to the cryptocurrency market factor decrease monotonically from the lowest to the highest *pa* ratio portfolios. The zero-investment long-short strategy significantly loads on the cryptocurrency market factor. However, the alpha of the long-short strategy remains positive and significant at the 1-percent level. The economic magnitude of the alpha is 1.6 percent per week, suggesting that the cryptocurrency CAPM model cannot explain a sizable portion of the excess returns. In the second part of Panel B, we use the cryptocurrency 3-factor model from Liu, Tsyvinski, and Wu (2021). The long-short strategy loads positively and significantly on the cryptocurrency market factor, while negatively and significantly on the cryptocurrency size factor. The long-short strategy does not significantly expose to the cryptocurrency momentum factor. The alpha of the long-short strategy remains positive and significant at the 1-percent level after controlling for the cryptocurrency 3-factor model. The economic magnitude of the alpha is 1.9 percent per week. These results show that the return predictability cannot be subsumed and is distinct from those of the cryptocurrency market, size, and momentum effect.

Different horizons

We have shown that the price-to-new address ratios negatively and significantly predict next period cryptocurrency returns. We further examine the persistence of the return predictability power of the price-to-new address ratio.

To study the long-term return predictability of the price-to-new address ratio, we calculate the weekly average excess returns, the cryptocurrency CAPM alphas, and the cryptocurrency 3-factor alphas for the zero-investment long-short strategy from 1-week to 28-week after the formation of the portfolios. The results are summarized in Table 12. The return predictability of *pa* ratios is relatively long-lasting. The average excess returns of the long-short strategy are positive throughout the different horizons, and are significant at the 5-percent level up to 12-week ahead. The cryptocurrency CAPM model adjusted alphas remain positive and significant at the 10-percent level up to 12-week ahead at 0.9 percent per week. The cryptocurrency 3-factor model adjusted alphas stay positive and significant at the 5-percent level at 1.0 percent per week up to 12-week ahead. The cryptocurrency 3-factor model adjusted alphas remain positive throughout the 28 weeks.

In summary, we find evidence that the *pa* ratios negatively and significantly predict future cryptocurrency returns over a relatively long horizon.

Table 12: **Cryptocurrency Price-to-New Address Effect – Different Horizon**

This table shows portfolio sorting results over different horizons based on cryptocurrency price-to-new address ratios. The Low–High row reports the average long-short strategy returns based on cryptocurrency price-to-new address ratios. The C1 Alpha and C3 Alpha rows report the cryptocurrency market factor and the cryptocurrency three-factor model adjusted alphas, respectively. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Weeks	+1	+4	+8	+12	+16	+20	+24	+28
Low	0.015*	0.017**	0.018**	0.014	0.016*	0.019**	0.017*	0.017*
	(1.682)	(1.990)	(2.033)	(1.541)	(1.787)	(2.106)	(1.887)	(1.891)
2	0.008	0.009	0.005	0.008	0.014	0.016	0.005	0.017
	(0.769)	(0.853)	(0.509)	(0.787)	(1.363)	(1.379)	(0.447)	(1.644)
3	0.006	0.006	0.015	0.011	0.011	0.011	0.019*	0.012
	(0.550)	(0.616)	(1.380)	(1.018)	(0.984)	(1.032)	(1.691)	(1.102)
High	-0.004	0.000	0.005	0.001	0.008	0.009	0.008	0.012
	(-0.553)	(0.030)	(0.627)	(0.112)	(1.004)	(1.083)	(0.928)	(1.469)
Low–High	0.019***	0.018***	0.013**	0.012**	0.009	0.010*	0.010	0.005
	(3.638)	(3.170)	(2.322)	(2.214)	(1.502)	(1.660)	(1.585)	(0.843)
C1 Alpha	0.016***	0.015***	0.009*	0.009*	0.004	0.005	0.005	-0.000
	(3.387)	(2.819)	(1.758)	(1.785)	(0.797)	(0.928)	(0.941)	(-0.050)
C3 Alpha	0.019***	0.017***	0.010**	0.010**	0.006	0.008*	0.009*	0.004
	(4.131)	(3.458)	(2.131)	(2.280)	(1.420)	(1.816)	(1.830)	(0.772)

6.3 Investigating Mechanism

This subsection explores the potential mechanism for the return predictability of the price-to-new address ratio. The asset pricing literature has proposed various potential explanations for the return predictability related to price-to-fundamental ratios, such as price-to-earnings, price-to-dividend, and market value-to-fundamental value ratios. The explanations can be largely categorized into either risk-based explanations or behavioral explanations.

Risk-based explanation

The literature has at least proposed three main risk-based explanations. The first proposed risk-based explanation is based on the distressed risk mechanism (e.g., Fama and French 1996). The idea is that certain assets have an elevated probability of failing or persistently weak performance, referred to as distressed assets. The returns of these distressed assets tend to move together, so their risk cannot be diversified away, and thus investors demand a premium to bear the risk, leading to high average returns. However, Lakonishok, Shleifer, and Vishny (1994) find that the strategies based on valuation ratios, which may capture relative distress, do not underperform during business downturns. Moreover, Campbell, Hilscher, and Szilagyi (2008) directly measure the distress risks of companies and show that distressed companies have relatively low returns on average.

Motivated by this explanation, we test if cryptocurrencies with low price-to-new address ratios perform poorly during business or market downturns. In Table A.2 of the Online Appendix, we show the average daily cryptocurrency long-short strategy returns based on the *pa* ratio for each month, as well as the NBER recession indicators, an indicator that equal to one if the cumulative excess return of the coin market is less than –20 percent in the month, and an indicator that equal to one if the cumulative excess return of the stock market is less than –5 percent in the month. In the sample period, there is an important recession period related to the recent pandemic. The corresponding NBER recession indicators are for March and April of 2020. There are three months in the sample where the coin market excess returns are less than –20 percent and five months in the sample where the stock market excess returns are less than –5 percent. For the two NBER recession months, the average daily return of the strategy is slightly negative for March but strongly positive for April. For the three months with large negative cumulative coin market excess returns and the five months with large negative cumulative stock market excess returns, there are also no discernible pattern in the strategy excess returns. Our results in the cryptocurrency market are largely consistent with Lakonishok, Shleifer, and Vishny (1994) for the equity market that the strategies based on valuation ratios do not underperform during business or market downturns.

Two other risk-based theories are commonly referred to in explaining the return predictability of the valuation ratios. The first theoretical mechanism is formalized by Zhang (2005). Zhang (2005) argues that costly reversibility makes it difficult to reduce assets in place, and thus firms with growth options are less risky in bad times when reducing assets is preferred. The second theoretical mechanism is based on the concept of investment-specific shocks, or *ist* shocks (e.g., Papanikolaou 2011; Kogan and Papanikolaou 2014). It is argued that there are *ist* shocks that improve investment opportunities, which increase the representative household's marginal utility. The *ist* shocks benefit firms with more growth options, and increase the value of growth opportunities relative to that of existing assets, leading to the return predictability of valuation ratios. The important implications of these two theories are that the long-short strategy returns based on valuation ratios should comove with macroeconomic shocks.

In Table 13, we test the exposures of the cryptocurrency long-short strategy excess returns based on the *pa* ratio on several macroeconomic shocks. We use four different macroeconomic variables to capture innovations to the aggregate economy. The first three variables, including consumption growths, durable consumption growths, and industrial production growths, are designed to capture the first-order aggregate innovations. The last variable, changes in the logged investment to consumption ratio similar to Papanikolaou (2011) and Kogan and Papanikolaou (2014), is designed to capture the *ist* shocks. Table 13 shows that the excess returns of the long-short strategy based on the price-to-new address ratios do not significantly expose to these macroeconomic variables, inconsistent with the predictions of these two risk-based theories.

In summary, we show that the long-short strategy excess returns based on the price-to-new address ratio are not concentrated in business or market downturns. The strategy excess returns are also not significantly exposed to the macroeconomic, including consumption growth, durable consumption growth, industrial production growth, and investment-specific shocks.

Behavioral explanation

The behavioral explanations of the return predictability of the valuation ratios are largely based on the idea of over-reaction. The theories of over-reaction state that investors may over-react to the news or performance of certain assets, leading to the predictability of valuation ratios. (e.g., Daniel, Hirshleifer, and Subrahmanyam 1998; Hong and Stein 1999; Barberis, Greenwood, Jin, and Shleifer 2015).

Table 13: **Strategy Exposures**

This table reports the results of regressing the excess returns of the long-short strategy based on the price-to-new address ratios on different macro variables. Δc is the changes in the logged consumption. Δdc is the changes in the logged durable consumption. Δip is the changes in the logged industrial production. ist is the changes in the logged investment to consumption ratio similar to Papanikolaou (2011) and Kogan and Papanikolaou (2014). The table reports the point estimates, t-statistics, and the R-squareds of the regressions. The data are from the St louis Fed website and are monthly.

	ret	ret	ret	ret
Δc	-0.412			
	(-0.568)			
Δdc		-0.032		
		(-0.087)		
Δip			-0.136	
			(-0.171)	
ist				0.231
				(0.300)
R-squared	0.008	0.000	0.001	0.002

An implication of the over-reaction explanation is that assets with high valuation ratios and low growths tend to underperform, because these assets are overpriced due to investor over-reaction and would converge to the fundamental value over time. Motivated by the prediction, we study the interaction between the price-to-new address ratio and the address growth of cryptocurrencies. Panel A of Table 14 reports the subsample results based on the coins' address growth of the long-short strategies. For each week, coins are first sorted into the low and high groups based on the address growths of the coins. Then, within each group, the coins are further sorted into four portfolios based on their price-to-new address ratios. We find that the return predictability of the pa ratio largely concentrates in the low address growth subsample. Within the low address growth subsample, the long-short strategy that longs the coins with low pa ratios and shorts the coins with high pa ratios generates an average excess return of 2.68 percent per week that is statistically significant at the 1-percent level. For the coins with high valuation ratios and low address growth, the average excess returns is -0.94 percent per week in the future. The subsample result is consistent with the notion that investors over-react to certain coins with low growth whose prices gradually converge to the correct value, leading to lower average returns for these coins.

Another implication that is common to behavioral theories is that the return predictability should be stronger among the assets with relatively high costs of arbitrage (e.g., Shleifer and Vishny 1997; Pontiff 2006; Atilgan, Bali, Demirtas, and Gunaydin 2020). Similar to Liu, Tsyvinski, and Wu (2021), we construct the cost of arbitrage index for each coins and test the long-short strategy in the subsamples based on the coins' cost of arbitrage indexes. High index value corresponds to high cost of arbitrage. For each week, coins are first sorted into the low and high groups based on the cost of arbitrage index. Then, within each group, the coins are further sorted into four portfolios based on their price-to-new address ratios. In Panel B of Table 14, we find that the average excess returns is larger for the high cost of arbitrage subsample, relative to the low cost of arbitrage subsample, which is consistent with the implications of behavioral explanations. Overall, the evidence is potentially in line with behavioral explanation of over-reaction. We note that although we provide evidence to support some plausible mechanisms behind the return predictability of valuation ratios in the cryptocurrency market, the channels are possible mechanisms and not conclusive.

Table 14: **Subsample Results**

This table reports the subsample results of the long-short strategy based on the price-to-new address ratios. For each week, coins are first sorted into the low and high groups based on the address growths or the cost of arbitrage index of the coins. Then, within each group, the coins are further sorted into four portfolios based on their price-to-new address ratios. The table reports the average excess returns and the t-statistics associated with the excess returns.

Panel A: $\Delta Address$					
	1	2	3	4	1–4
Low	1.74	0.97	-0.01	-0.94	2.68***
	(1.62)	(0.84)	(-0.01)	(-1.05)	(3.52)
High	0.18	1.75	0.55	0.00	0.18
	(0.25)	(1.51)	(0.55)	(0.00)	(0.33)
Panel B: Cost of Arbitrage Index					
	1	2	3	4	1–4
Low	1.49*	0.81	0.38	-0.00	1.49***
	(1.69)	(0.80)	(0.36)	(-0.00)	(2.64)
High	2.72**	2.03*	1.66	0.03	2.69***
	(2.24)	(1.73)	(1.58)	(0.03)	(2.71)

6.4 Robustness of the Predictability

Fama-MacBeth regression method

We further test the robustness of the relation between price-to-new address ratios and future cryptocurrency returns from the cross-sectional regressions using the Fama-MacBeth method. Table 15 shows the results.

Column (1) of Table 15 only includes the *pa* ratio as the cryptocurrency return predictor. Consistent with the portfolio sorting results, the coefficient estimate to *pa* ratio is negative and significant at the 1-percent level, confirming that a high *pa* ratio is associated with low expected returns. The economic magnitude of the effect is large. The point estimate is -0.004, suggesting that a one-standard-deviation increase in the *pa* ratio is associated with a 0.6 percent decrease in the next week's cryptocurrency returns. Columns (2) and (4) include beta, size, and momentum as controls, respectively. Column (4) includes all of beta, size and momentum as controls. The magnitude of the point estimates to the *pa* ratio decrease, but the estimates remain negative and statistically significant at the 1-percent level when beta, size, and momentum are entered separately and at the 5-percent level when all of beta, size, and momentum are controlled.

Alternative portfolio formation

In our baseline portfolio sorting results, we sort cryptocurrencies into quartile portfolios based on their price-to-new address ratios. This choice is due to the fact that the average number of cryptocurrencies in the cross-section is about one hundred. Therefore, quartile portfolios ensure that there are about thirty coins in each portfolio.

To test the robustness of the portfolio sorting results, we further sort cryptocurrencies into tercile and quintile portfolios based on their price-to-new address ratios and examine the average future value-weighted returns of the portfolios. The results based on these alternative portfolio formations are summarized in Table A.4 in the Appendix.

Table 15: **Fama-MacBeth Regression Results**

This table shows the results for predicting next period returns using the price-to-new address ratios. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1) RET_{+1}	(2) RET_{+1}	(3) RET_{+1}	(4) RET_{+1}	(5) RET_{+1}
pa	-0.004***	-0.003***	-0.003***	-0.003**	-0.003**
	(-2.805)	(-2.696)	(-2.674)	(-2.563)	(-2.554)
beta		0.004			0.003
		(0.877)			(0.755)
size			-0.002***		-0.002**
			(-2.679)		(-2.065)
mom				0.014	0.019
				(0.862)	(1.138)
Constant	0.054**	0.051**	0.089***	0.045**	0.073**
	(2.539)	(2.468)	(3.015)	(2.142)	(2.530)
Observations	13,455	12,449	13,455	13,455	12,449
R-squared	0.017	0.049	0.031	0.058	0.102

The results based on tercile and quintile portfolios confirm the baseline results based on quartile portfolios. For the results based on tercile portfolios, the zero-investment long-short strategy generates an average weekly excess return of 1.6 percent that is statistically significant at the 1 percent level. The weekly Sharpe ratio of the excess returns of the long-short strategy is 0.242. For the results based on quintile portfolios, the zero-investment long-short strategy also generates an average weekly excess return of 1.6 percent, which is significant at the 1 percent level. The weekly Sharpe ratio of the excess returns of the long-short strategy is 0.219.

Top 30 coins

In our baseline portfolio sorting results, we use the full cross-section of cryptocurrencies where on-chain and price information is available. We further investigate the behavior of the portfolio sorting results by restricting our sample to the largest and most liquid coins in the market and test the performances of the return predictability of *pa*. Each period, we restrict our sample to the largest 30 coins at the time based on the market capitalization of the cryptocurrencies. We form tercile portfolios based on their price-to-new address ratios. The results are summarized in Table A.5.

The results based on the top 30 largest coins confirm the baseline results based on the full cross-section of cryptocurrencies. The long-short strategy that buys the tercile with the lowest price-to-new address ratios and shorts the tercile with the highest price-to-new address ratios generates an average weekly excess return of 1.5 percent that is statistically significant at the 1 percent level. The weekly Sharpe ratio of the excess returns of the long-short strategy is 0.217, which is economically large. Adjusting for the cryptocurrency CAPM model, the alpha of the long-short strategy decreases slightly to 1.3 percent per week, which is significant at the 5 percent level. Adjusting for the cryptocurrency 3-factor model, the alpha of the long-short strategy remains at 1.5 percent per week and is significant at the 1 percent level.

Portfolio sorting excluding Bitcoin

The cryptocurrency market has a clear level factor – Bitcoin. Because of the dominant position of Bitcoin in the cryptocurrency market, the returns of the portfolios including Bitcoins would strongly comove with Bitcoin return. We repeat our portfolio sorting analysis based on the price-to-new address ratio excluding Bitcoin. The results are summarized in Table A.6 in the Online Appendix.

The zero-investment long-short strategy that buys the portfolio with the lowest price-to-new address ratios and shorts the portfolio with the highest price-to-new address ratios generates an average excess return of 1.3 percent per week and is statistically significant at the 5 percent level. Adjusting for the cryptocurrency CAPM model, the alpha of the long-short strategy decreases slightly to 1.2 percent per week, which is significant at the 5 percent level. Adjusting for the cryptocurrency 3-factor model, the alpha of the long-short strategy remains at 1.3 percent per week and is significant at the 1 percent level.

Equal-Weighted

For our main portfolio sorting results, we report the performance of the strategy based on value-weighted results. We further test whether the results are robust under equal-weighted portfolios. The results based on equal-weighted portfolios are reported in Table A.7 in the Online Appendix.

We find that the results based on equal-weighted portfolios are qualitatively similar to those based on value-weighted portfolios. The average long-short strategy excess return is 1.6 percent per week, compared to 1.9 percent per week under the value-weighted portfolios. The alphas adjusted for the cryptocurrency CAPM model and the cryptocurrency 3-factor model remain positive and statistically significant at the 1 percent level.

6.5 Additional Results

We provide additional results regarding the price-to-new address ratio of the cryptocurrency market.

Short Sample

Because the data on the number of new addresses are only available starting from 2018, we only have about four years of the cross-section of cryptocurrencies. The short sample is a potential barrier to studying the return predictability of the price-to-new address ratio we cannot avoid. Moreover, as discussed above, there is likely a great deal of uncertainty and investor learning about cryptocurrencies during the period. As argued in Pástor and Veronesi (2009), it can take time for investors to learn and understand emerging technologies, which may lead to the departure between prices and the fundamental of the technology.

We partially address these concerns by breaking the sample into two halves and checking whether the return predictability results of the price-to-new address ratio are stable for these two subsamples. These two subsamples both feature important events, which can facilitate the test of the robustness of our results. In the first half of the sample, the cryptocurrency market witnessed one of the largest declines in prices since its debut. The second half of the sample contains the COVID-19 period. The results are summarized in Table A.3 in the Online Appendix.

For the first half of the sample, the average excess return of the zero-investment long-short strategy is 1.8 percent per week, while that for the second half of the sample is 1.9 percent per week. The average excess returns for both subsamples are positive and statistically significant at the 5-percent level. The standard deviations of excess returns for the long-short strategy are 7.0 percent and 6.5 percent for the first half and the second half of the sample, respectively. The weekly Sharpe ratios for these two subsamples are 0.257 and 0.292, respectively. We conclude that the performance of the long-short strategy is stable and consistent across the two subsamples.

Exposures to equity factors

Additionally, we test whether the equity factor models can account for the long-short strategy excess returns based on the *pa* ratio. In terms of the equity factor models, we use the CAPM, Fama-French 3-factor, and Fama-French 5-factor models. The results are summarized in Table A.8 in the Appendix.

We find that the quartile portfolio excess returns are positive and significantly exposed to the equity market factor. This result highlights a recent development of the cryptocurrency market that the market excess return is significantly exposed to the equity market excess returns.[15] However, the excess returns of the zero-investment long-short strategy based on the *pa* ratio do not significantly expose to the equity market factor. The excess returns of the strategy also do not significantly expose to the Fama-French 3 factors and the Fama-French 5 factors. The alphas of the strategy remain positive and statistically significant at the 1-percent level. The magnitudes of the alphas are about 1.9 percent per week. Overall, the results suggest that the equity market factors do not account for the excess returns of the strategy.

Controlling for coin market factor excluding Bitcoin

Similar to the currency market, where U.S. dollar is a dominant level factor, Bitcoin is the level factor for the cryptocurrency market. We construct an alternative coin market factor measured as the value-weighted return of all coins excluding Bitcoin and test whether this alternative coin market factor can explain the long-short strategy excess returns generated by the price-to-new address ratios. We document the results in Table A.9 in the Online Appendix.

We denote this alternative cryptocurrency market factor as CMKT2. We regress the level portfolio returns and the long-short strategy spread on cryptocurrency CAPM and 3-factor models using CMKT2. Similar to the results using CMKT, the alphas of the long-short strategies remain positive and statistically significant adjusting for both factor models. The alpha is 1.8 percent per week adjusting for the cryptocurrency CAPM model using CMKT2, and the alpha is 2.0 percent per week adjusting for the cryptocurrency 3-factor model using CMKT2.

[15] The cryptocurrency market excess returns do not significantly expose to the equity market excess returns between 2011 and 2018 (see Liu and Tsyvinski 2021).

Predicting future new address growth

A number of studies (e.g., Campbell and Shiller 1988a; Campbell and Shiller 1988b; Vuolteenaho 2002) find that valuation ratios such as price-to-earnings ratios and price-to-dividend ratios can be decomposed and have to predict future returns or earnings (dividend) growths or both. Campbell and Shiller (1988b) and Campbell and Shiller (1988a), among others, find that the price-to-earnings (price-to-dividend) ratios predict future equity excess returns but not future earnings (dividend) growths in the time series. On the other hand, Vuolteenaho (2002) shows that the valuation ratios predict both future returns and earnings in the cross-section.

A similar decomposition can be applied to the price-to-new address ratio. We have shown that the price-to-new address ratio predicts future cryptocurrency returns. However, in a dynamic cryptocurrency pricing model with the network effect, cryptocurrency prices not only capture current cryptocurrency adoption but also contain information about expected future adoption (e.g., Cong, Li, and Wang 2021). Therefore, we further test whether the price-to-new address ratio predicts future new address growth. Table A.10 in the Online Appendix shows the cross-sectional results of regressing next period logged new address growths on current *pa* ratios using the Fama-MacBeth method.

Column (1) reports the result of the specification with only the *pa* ratio. The coefficient estimate to the *pa* ratio is positive and statistically significant at the 1-percent level. In other words, high *pa* ratios are on average followed by high new address growths next period. The magnitude of the point estimate is 0.090. That is, a one-standard-deviation increase in the *pa* ratio is associated with an increase of about 12 percent in the logged new address growth of the next period. In Columns (2) to (5), we control for the beta, size, and momentum characteristics. The coefficient estimates to the *pa* ratio stay positive and statistically significant at the 1-percent level when these additional controls are included. The magnitude of the point estimate remains similar to the standalone specification. The results strongly support the idea that the *pa* ratios of the cryptocurrencies are related to expected new address growths in the cross-section, which is consistent with cryptocurrency pricing models featuring dynamic user adoption.

7 Conclusion

The importance of user adoption and network effect is a foundational concept in the theoretical literature of both the network economy (e.g., Rohlfs 1974; Katz and Shapiro 1985; Katz and Shapiro 1994; Rochet and Tirole 2003) and the cryptocurrency valuation (e.g., Cong, Li, and Wang Forthcoming; Sockin and Xiong 2020; Biais, Bisiere, Bouvard, Casamatta, and Menkveld 2020). In this paper, we empirically evaluate whether investors react to the information pertaining to new addresses and show that the information is highly value-relevant in the cryptocurrency market. In fact, the value relevance of new addresses in the cryptocurrency market is higher than that of earnings in the equity market.

One important difference between cryptocurrencies and equities is that, for cryptocurrencies, information of the underlying economic activities is available publicly and continuously on the blockchain. While for equities, public information of firm activities is only available periodically. Two important phenomenons in the equity market are commonly attributed to the infrequent release of information: pre-announcement drift and post-announcement drift. We show that pre- and post-drifts are absent around the release of new address information. The presence of strong market reactions at the release of new address information and the absence of pre- and post-drifts highlight the distinct features of cryptocurrencies and provide a benchmark case where information is released both publicly and continuously.

Lastly, we construct the price-to-new address ratio of each cryptocurrency. We show that, similar to the price-to-earnings ratio in the equity market, the price-to-new address ratios negatively predict future cryptocurrency returns in the cross-section. A long-short strategy that buys the coins with the lowest price-to-new address ratios and shorts the coins with the highest price-to-new address ratios generates positive and statistically significant excess returns of 1.9 percent per week. The excess returns of the long-short strategy cannot be subsumed by existing cryptocurrency factor models or equity factor models.

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Online Appendix

Figure A.1: **Cryptocurrency Prices and New Addresses**

This figure gives a graphical illustration of the relationship between prices and new addresses for Bitcoin, Ethereum, and Litecoin.

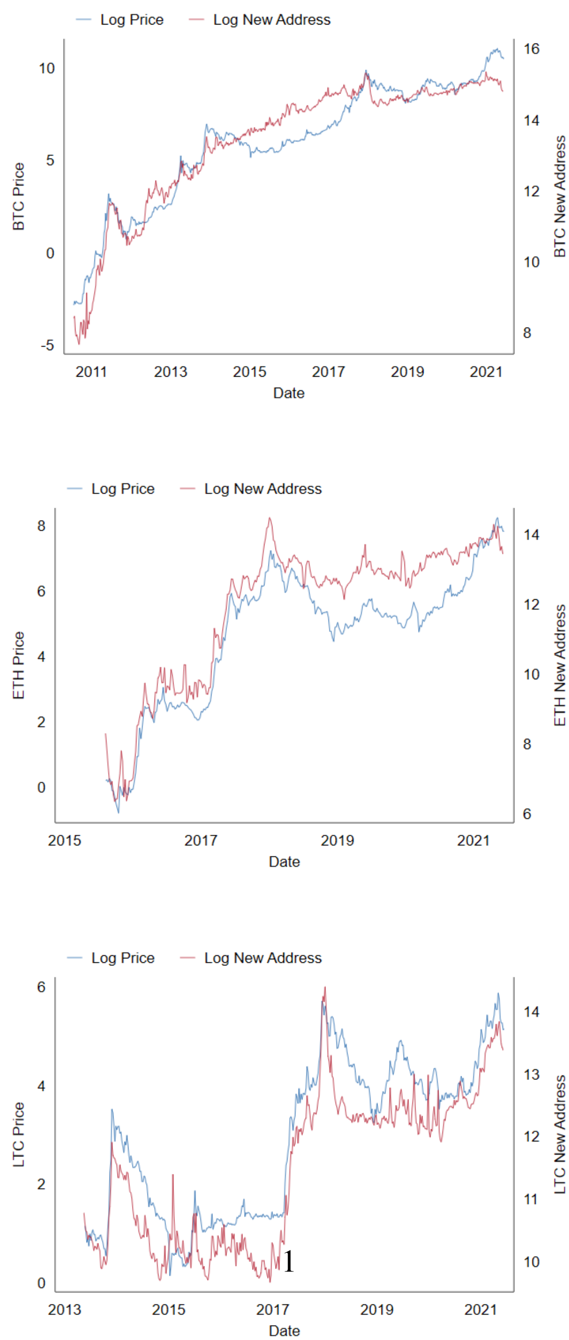

Figure A.2: **Ball and Brown (1968) Graph**

The source of the graph is Ball and Brown (1968).

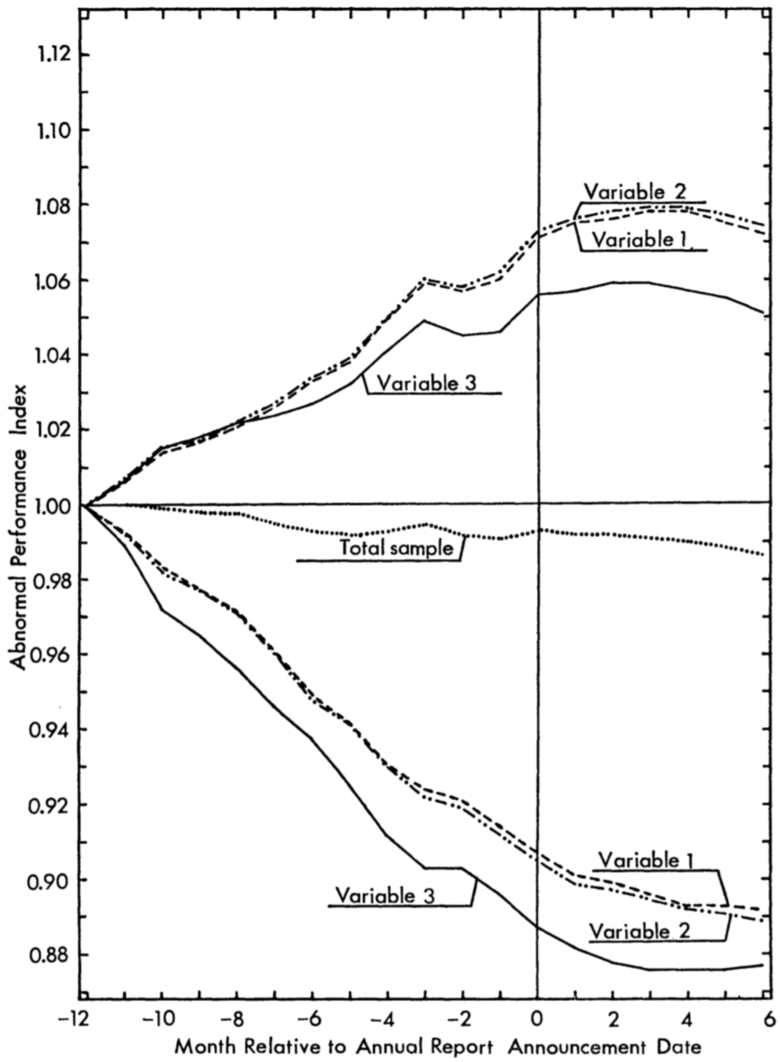

Figure A.3: **Cumulative Abnormal Return around New Address Information – Controlling Transfer Volume Growth**

This figure plots the cumulative average logged abnormal return around the release of new address information for positive and negative new address growth subgroups controlling for changes in logged transfer volume. Dashed lines represent the 5-percent confidence intervals.

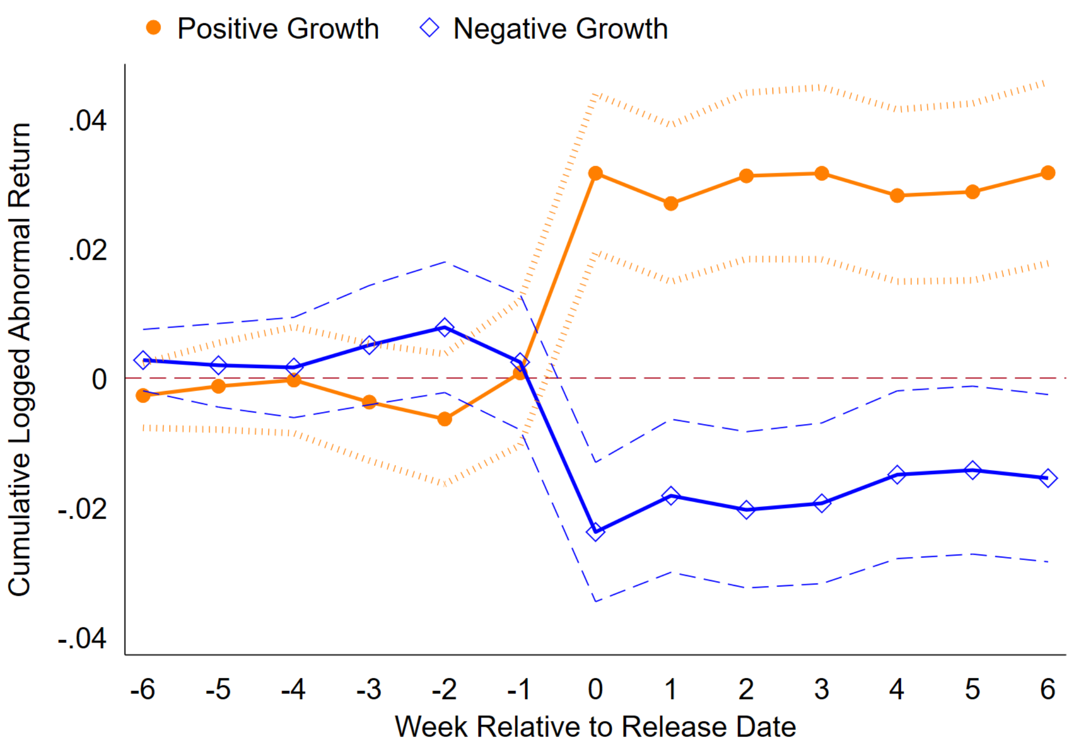

Table A.1: **Abnormal Volatility**

This table shows the results for the cross-sectional abnormal volatility tests. Panel A reports results where the abnormal return volatility is calculated using raw returns and Panel B reports results where the abnormal return volatility is calculated using the CAPM model adjusted returns. Abnormal return volatility is calculated as the difference of the logged standard deviation of returns of the week and the logged average standard deviation of returns of the previous four weeks. Time fixed effects are included for all specifications. Standard errors are double clustered at the coin level and time level. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	$avar^1$	$avar^1$	$avar^1$	$avar^1$	$avar^1$	$avar^1$
$\|\Delta na\|$	0.081***	0.082***	0.085***	0.077***	0.081***	0.081***
	(4.330)	(4.321)	(4.728)	(4.027)	(4.103)	(4.352)
$\|\Delta balance1\|$		0.110				0.085
		(0.678)				(0.536)
$\|\Delta balance2\|$			0.052***			0.050***
			(3.805)			(3.770)
$\|\Delta trans\|$				0.008		0.010
				(0.805)		(1.028)
$\|\Delta current\|$					0.002	-0.032
					(0.018)	(-0.175)
Cons	-0.114***	-0.116***	-0.118***	-0.117***	-0.114***	-0.123***
	(-17.575)	(-17.402)	(-18.713)	(-14.095)	(-17.531)	(-14.027)
Obs	13,137	12,765	12,671	13,115	13,137	12,481
Adj R^2	0.283	0.277	0.286	0.283	0.283	0.283

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
	$avar^2$	$avar^2$	$avar^2$	$avar^2$	$avar^2$	$avar^2$
$\|\Delta na\|$	0.124***	0.124***	0.123***	0.116***	0.122***	0.115***
	(4.861)	(4.828)	(4.681)	(4.607)	(4.757)	(4.349)
$\|\Delta balance1\|$		0.203				0.155
		(0.873)				(0.686)
$\|\Delta balance2\|$			0.075***			0.071***
			(2.883)			(2.800)
$\|\Delta trans\|$				0.013		0.013
				(1.284)		(1.268)
$\|\Delta current\|$					0.112	0.036
					(0.446)	(0.133)
Cons	-0.137***	-0.139***	-0.140***	-0.143***	-0.137***	-0.148***
	(-15.773)	(-15.510)	(-15.616)	(-14.442)	(-15.800)	(-14.142)
Obs	11,597	11,255	11,244	11,592	11,597	11,086
Adj R^2	0.146	0.141	0.146	0.147	0.146	0.143

Table A.2: **Distribution of Strategy Returns**

This table shows the average daily long-short strategy returns based on the price-to-new address ratio for each month in the sample. The Recession column shows the NBER recession indicators, where the data are from the St Louis Fed website. The "Coin<-20%" column is an indicator variable that equals one if the cumulative excess return of the coin market is less than 20 percent in the month and zero otherwise. The "Stock<-5%" column is an indicator variable that equals one if the cumulative excess return of the stock market is less than 5 percent in the month and zero otherwise.

Year-Mon	Strategy (d)	NBER	Coin<-20%	Stock<-5%	Year-Mon	Strategy (d)	NBER	Coin<-20%	S
201802	1.83%	0	0	0	201911	-0.29%	0	0	
201803	0.12%	0	1	0	201912	0.16%	0	0	
201804	1.11%	0	0	0	202001	-0.04%	0	0	
201805	0.43%	0	0	0	202002	-0.59%	0	0	
201806	0.68%	0	0	0	202003	-0.08%	1	1	
201807	1.08%	0	0	0	202004	0.59%	1	0	
201808	0.47%	0	0	0	202005	0.08%	0	0	
201809	-0.08%	0	0	0	202006	-0.41%	0	0	
201810	-0.39%	0	0	1	202007	0.51%	0	0	
201811	-0.14%	0	1	0	202008	-0.18%	0	0	
201812	0.18%	0	0	1	202009	0.30%	0	0	
201901	-0.14%	0	0	0	202010	1.47%	0	0	
201902	-0.37%	0	0	0	202011	1.15%	0	0	
201903	0.33%	0	0	0	202012	0.40%	0	0	
201904	0.72%	0	0	0	202101	-0.07%	0	0	
201905	0.58%	0	0	1	202102	-0.07%	0	0	
201906	0.16%	0	0	0	202103	0.74%	0	0	
201907	0.58%	0	0	0	202104	1.00%	0	0	
201908	0.46%	0	0	0	202105	-0.13%	0	0	
201909	-0.11%	0	0	0	202106	0.41%	0	0	
201910	-0.11%	0	0	0					

Table A.3: **Portfolio Sorts – First Half and Second Half**

This table shows portfolio sorting results based on cryptocurrency price-to-new address ratios for the first half and the second half of the sample. Mean is the average weekly excess returns of the portfolios and the long-short strategy. SD is the standard deviation of the weekly excess returns of the portfolios and the long-short strategy. SR is the weekly Sharpe ratio of the excess returns of the portfolios and the long-short strategy. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A: First Half					
	Low	2	3	High	Low–High
Mean	-0.002	-0.020	-0.016	-0.021*	0.018**
	(-0.212)	(-1.589)	(-1.291)	(-1.965)	(2.619)
SD	0.104	0.123	0.121	0.107	0.070
SR	-0.019	-0.163	-0.132	-0.196	0.257

Panel B: Second Half					
	Low	2	3	High	Low–High
Mean	0.036**	0.045**	0.034*	0.017	0.019**
	(2.572)	(2.456)	(1.978)	(1.531)	(2.525)
SD	0.123	0.157	0.148	0.098	0.065
SR	0.293	0.287	0.230	0.173	0.292

Table A.4: **Portfolio Sorts – Tercile and Quintile**

This table shows portfolio sorting results based on cryptocurrency price-to-new address ratios using tercile and quintile portfolios. Mean is the average weekly excess returns of the portfolios and the long-short strategy. SD is the standard deviation of the weekly excess returns of the portfolios and the long-short strategy. SR is the weekly Sharpe ratio of the excess returns of the portfolios and the long-short strategy. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A: Tercile

	Low	2	High	Low–High
Mean	0.013	0.012	-0.003	0.016***
	(1.552)	(1.111)	(-0.316)	(3.122)
SD	0.113	0.137	0.106	0.066
SR	0.115	0.088	-0.028	0.242

Panel B: Quintile

	Low	2	3	4	High	Low–High
Mean	0.012	0.008	0.016	0.005	-0.004	0.016***
	(1.422)	(0.868)	(1.464)	(0.456)	(-0.451)	(2.841)
SD	0.114	0.128	0.143	0.134	0.107	0.073
SR	0.105	0.063	0.112	0.037	-0.037	0.219

Table A.5: **Portfolio Sorts – Top 30 Cryptocurrencies**

This table shows portfolio sorting results based on cryptocurrency price-to-new address ratios using the largest 30 cryptocurrencies by market capitalization. Mean is the average weekly excess returns of the portfolios and the long-short strategy. SD is the standard deviation of the weekly excess returns of the portfolios and the long-short strategy. SR is the weekly Sharpe ratio of the excess returns of the portfolios and t0he long-short strategy. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A				
	Low	2	High	Low–High
Mean	0.012	0.006	-0.003	0.015***
	(1.400)	(0.544)	(-0.402)	(2.814)
SD	0.111	0.141	0.107	0.069
SR	0.108	0.043	-0.028	0.217

Panel B	Alpha		CMKT		CSIZE		CMOM		R^2
Low	0.001	(0.579)	1.028***	(86.532)					0.978
2	-0.005	(-0.664)	1.014***	(15.720)					0.592
High	-0.012**	(-2.418)	0.815***	(18.082)					0.658
Low–High	0.013**	(2.520)	0.215***	(4.583)					0.110
Low	0.001	(0.654)	1.027***	(83.809)	-0.000	(-0.017)	-0.010	(-0.814)	0.978
2	-0.009	(-1.639)	1.117***	(21.231)	0.678***	(9.565)	-0.022	(-0.444)	0.747
High	-0.014***	(-3.355)	0.873***	(22.036)	0.394***	(7.382)	-0.038	(-0.987)	0.754
Low–High	0.015***	(3.382)	0.157***	(3.721)	-0.387***	(-6.790)	0.027	(0.661)	0.326

Table A.6: **Portfolio Sorts – Exclude Bitcoin**

This table shows portfolio sorting results based on cryptocurrency price-to-new address ratios excluding Bitcoin. Mean is the average weekly excess returns of the portfolios and the long-short strategy. SD is the standard deviation of the weekly excess returns of the portfolios and the long-short strategy. SR is the weekly Sharpe ratio of the excess returns of the portfolios and the long-short strategy. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A	Low	2	3	High	Low–High
Mean	0.009	0.013	0.008	-0.004	0.013**
	(0.886)	(1.170)	(0.726)	(-0.537)	(2.424)
SD	0.133	0.147	0.138	0.105	0.072
SR	0.068	0.088	0.058	-0.038	0.181

Panel B	Alpha		CMKT		CSIZE		CMOM		R^2
Low	0.004	(1.181)	1.096***	(42.285)					0.913
2	0.008	(1.309)	1.076***	(20.984)					0.721
3	0.003	(0.469)	1.002***	(20.480)					0.712
High	-0.008*	(-1.958)	0.771***	(21.554)					0.732
Low–High	0.012**	(2.494)	0.325***	(8.057)					0.276
Low	0.006**	(2.002)	1.086***	(45.745)	-0.054	(-1.548)	-0.151***	(-5.975)	0.928
2	0.006	(1.024)	1.066***	(23.157)	0.430***	(6.374)	-0.001	(-0.019)	0.779
3	0.001	(0.230)	0.989***	(22.764)	0.400***	(6.286)	-0.056	(-1.218)	0.776
High	-0.007*	(-1.859)	0.760***	(22.322)	0.110**	(2.216)	-0.116***	(-3.214)	0.761
Low–High	0.013***	(2.786)	0.326***	(8.202)	-0.164***	(-2.820)	-0.035	(-0.816)	0.309

Table A.7: **Portfolio Sorts Based on Cryptocurrency Price-to-New Address Ratio – Equal Weighted**

This table shows portfolio sorting results based on cryptocurrency price-to-new address ratios with equal-weighting. Panel A reports the means, standard deviations, and Sharpe ratios of the value-weighted portfolios excess returns. Panel B reports the factor exposures of the portfolios sorted on price-to-new address ratios. The factor models in include the cryptocurrency market factor and the cryptocurrency three factor model. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A	Low	2	3	High	Low–High
Mean	0.016	0.013	0.013	-0.001	0.016***
	(1.601)	(1.218)	(1.329)	(-0.118)	(3.636)
SD	0.129	0.138	0.125	0.108	0.059
SR	0.124	0.094	0.104	-0.009	0.271

Panel B	Alpha		CMKT		CSIZE		CMOM		R^2
Low	0.006	(0.907)	0.907***	(14.893)					0.565
2	0.002	(0.372)	1.002***	(16.194)					0.607
3	0.003	(0.543)	0.919***	(16.487)					0.615
High	-0.009*	(-1.936)	0.817***	(18.069)					0.658
Low–High	0.016***	(3.449)	0.092**	(2.194)					0.028
Low	-0.001	(-0.145)	1.028***	(28.373)	0.842***	(17.384)	-0.024	(-0.678)	0.856
2	-0.004	(-1.261)	1.146***	(37.961)	0.939***	(23.089)	-0.011	(-0.366)	0.913
3	-0.002	(-0.767)	1.045***	(35.447)	0.823***	(20.721)	-0.013	(-0.471)	0.900
High	-0.012***	(-4.105)	0.898***	(31.431)	0.572***	(14.843)	-0.088***	(-3.194)	0.872
Low–High	0.013***	(3.018)	0.143***	(3.581)	0.301***	(5.596)	0.060	(1.554)	0.180

Table A.8: **Equity Factors Exposures**

This table shows exposures to the equity factor models for the portfolios based on cryptocurrency price-to-new address ratios. The equity factor models are the CAPM, Fama-French 3-factor, and the Fama-French 5-factor models. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	Alpha		MKTRF		SMB		HML		RMW		CMA		R^2
Low	0.012	(1.388)	0.855**	(2.563)									0.037
2	0.004	(0.360)	1.480***	(3.614)									0.071
3	0.001	(0.146)	1.373***	(3.515)									0.068
High	-0.007	(-0.940)	0.963***	(3.168)									0.056
Low–High	0.019***	(3.669)	-0.110	(-0.543)									0.002
Low	0.012	(1.450)	0.749**	(2.177)	0.652	(1.098)	0.234	(0.586)					0.051
2	0.003	(0.313)	1.352***	(3.192)	0.891	(1.219)	-0.282	(-0.573)					0.080
3	0.002	(0.206)	1.376***	(3.395)	-0.079	(-0.113)	0.297	(0.630)					0.070
High	-0.007	(-0.839)	0.918***	(2.919)	0.234	(0.431)	0.342	(0.936)					0.065
Low–High	0.019***	(3.611)	-0.170	(-0.815)	0.419	(1.162)	-0.110	(-0.455)					0.010
Low	0.014	(1.566)	0.629*	(1.689)	0.393	(0.575)	0.679	(1.148)	-0.550	(-0.552)	-1.084	(-0.864)	0.057
2	0.004	(0.393)	1.352***	(2.946)	0.596	(0.707)	0.001	(0.001)	-0.904	(-0.732)	-0.001	(-0.001)	0.083
3	0.003	(0.269)	1.238***	(2.820)	-0.159	(-0.198)	0.600	(0.859)	0.030	(0.025)	-1.241	(-0.838)	0.074
High	-0.005	(-0.653)	0.839**	(2.471)	-0.146	(-0.234)	0.835	(1.546)	-1.004	(-1.099)	-0.713	(-0.622)	0.074
Low–High	0.019***	(3.515)	-0.213	(-0.943)	0.547	(1.318)	-0.163	(-0.454)	0.479	(0.788)	-0.384	(-0.504)	0.015

Table A.9: **Cryptocurrency Market Factor Excluding Bitcoin**

This table shows portfolio sorting results controlling for the cryptocurrency CAPM model and the cryptocurrency 3-factor model, where the cryptocurrency market factor is constructed as the value-weighted cryptocurrency returns excluding bitcoin over the risk-free rate (CMKT2). Mean is the average weekly excess returns of the portfolios and the long-short strategy. SD is the standard deviation of the weekly excess returns of the portfolios and the long-short strategy. SR is the weekly Sharpe ratio of the excess returns of the portfolios and t0he long-short strategy. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	Alpha		CMKT2		CSIZE		CMOM		R^2
Low	0.009**	(2.211)	0.850***	(23.482)					0.763
2	0.003	(0.534)	1.005***	(18.769)					0.674
3	0.001	(0.157)	0.990***	(20.944)					0.721
High	-0.008**	(-1.994)	0.771***	(21.613)					0.733
Low–High	0.018***	(3.581)	0.090**	(2.045)					0.024
Low	0.012***	(3.176)	0.851***	(25.642)	-0.278***	(-5.746)	-0.120***	(-3.388)	0.805
2	0.003	(0.510)	0.992***	(19.480)	0.265***	(3.549)	-0.099*	(-1.828)	0.711
3	0.000	(0.026)	0.976***	(22.863)	0.334***	(5.341)	-0.092**	(-2.031)	0.776
High	-0.008*	(-1.895)	0.760***	(22.398)	0.110**	(2.220)	-0.117***	(-3.243)	0.763
Low–High	0.020***	(4.422)	0.098**	(2.485)	-0.376***	(-6.515)	-0.006	(-0.135)	0.231

Table A.10: **Fama-MacBeth Regression Results – New Address Growth**

This table shows the results for predicting next period new address growths using the price-to-new address ratios. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)
	Δna_{+1}	Δna_{+1}	Δna_{+1}	Δna_{+1}	Δna_{+1}
pa	0.090***	0.078***	0.091***	0.088***	0.078***
	(16.205)	(13.516)	(15.988)	(15.951)	(13.081)
beta		0.006			0.007
		(0.588)			(0.732)
size			0.002		0.002
			(1.031)		(0.812)
mom				0.063	0.043
				(1.554)	(0.950)
Constant	-1.116***	-0.973***	-1.173***	-1.081***	-1.005***
	(-16.455)	(-14.054)	(-12.322)	(-15.969)	(-10.341)
Obs	13,343	12,337	13,343	13,343	12,337
R-squared	0.074	0.080	0.087	0.099	0.117

Table A.11: **Summary Statistics of Other Variables**

This table shows the summary statistics of the other on-chain variables. Panel A reports the mean, standard deviation, 10% percentile, median and 90% percentile values of the variables. Panel B reports the correlation matrix of the variables.

Panel A	Mean	SD	10%	Median	90%
$\Delta bal1$	0.002	0.046	-0.007	0.000	0.011
$\Delta bal2$	0.022	0.591	-0.014	0.000	0.077
$\Delta trans$	0.008	1.002	-0.889	-0.000	0.931
$\Delta curr$	0.012	0.105	-0.000	0.000	0.013
nvt	5.050	2.245	2.617	4.916	7.556

Panel B	$\Delta bal1$	$\Delta bal2$	$\Delta trans$	$\Delta curr$	nvt
$\Delta bal1$	1.000				
$\Delta bal2$	0.008	1.000			
$\Delta trans$	0.010	0.040	1.000		
$\Delta curr$	0.034	0.043	-0.001	1.000	
nvt	-0.015	-0.035	-0.253	-0.100	1.000

Table A.12: **Value Relevance Analysis – Additional Results**

This table shows the results for the cross-sectional value-relevance tests. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A	(1)	(2)	(3)	(4)
	ret	ret	ret	ret
$\Delta balance1$	0.170			
	(1.501)			
$\Delta balance2$		-0.013		
		(-0.981)		
$\Delta trans$			0.025***	
			(6.558)	
$\Delta current$				-0.039
				(-0.407)
Cons	-0.005	-0.003	-0.004	-0.003
	(-0.490)	(-0.374)	(-0.387)	(-0.327)
Obs	14,394	14,293	14,148	15,503
Adj R^2	0.017	0.017	0.031	0.018

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ret	ret	ret	ret	ret	ret	ret	ret
Δna	0.084***	0.083***	0.081***	0.091***	0.101***	0.087***	0.079***	0.078***
	(12.060)	(11.823)	(12.500)	(7.733)	(4.299)	(12.514)	(13.085)	(12.865)
na		0.001*						0.001
		(1.929)						(1.456)
$\Delta balance1$			0.199				0.310**	0.350**
			(1.532)				(2.065)	(2.327)
$\Delta balance2$				-0.027			-0.034	-0.034
				(-1.505)			(-1.596)	(-1.579)
$\Delta trans$					-0.005		0.009***	0.008***
					(-0.340)		(4.152)	(3.912)
$\Delta current$						-0.605	-0.006	-0.004
						(-0.816)	(-0.045)	(-0.031)
Cons	-0.003	0.009	-0.004	-0.003	-0.005	-0.003	-0.005	0.007
	(-0.349)	(0.846)	(-0.446)	(-0.310)	(-0.546)	(-0.331)	(-0.528)	(0.623)
Obs	13,522	13,522	13,139	13,027	13,418	13,522	12,759	12,759
Adj R^2	0.085	0.088	0.092	0.106	0.095	0.103	0.143	0.149

Table A.13: **Value Relevance Analysis – ERC20**

This table shows the results for the cross-sectional value-relevance tests. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ret	ret	ret	ret	ret	ret	ret	ret
Δna	0.079***	0.078***	0.078***	0.079***	0.079***	0.080***	0.077***	0.076***
	(12.140)	(12.058)	(12.161)	(11.757)	(12.031)	(14.052)	(13.094)	(12.777)
na		0.001						0.001
		(0.905)						(1.312)
$\Delta balance1$			0.193				0.256	0.298*
			(1.468)				(1.644)	(1.891)
$\Delta balance2$				-0.031			-0.038*	-0.036
				(-1.625)			(-1.680)	(-1.585)
$\Delta trans$					0.013***		0.013***	0.012***
					(4.731)		(5.291)	(5.033)
$\Delta current$						0.120	0.002	0.012
						(0.869)	(0.013)	(0.082)
Cons	-0.005	0.004	-0.005	-0.006	-0.005	-0.006	-0.006	0.006
	(-0.543)	(0.294)	(-0.552)	(-0.609)	(-0.541)	(-0.655)	(-0.616)	(0.472)
Obs	11,867	11,867	11,851	11,567	11,772	11,867	11,479	11,479
Adj R^2	0.081	0.091	0.094	0.096	0.099	0.105	0.141	0.148

Table A.14: **Subsample with Controls**

This table reports the results of the cross-sectional tests in the subsamples based on the above median and below median persistence, variability, discount rate, and size with controls. $1_{\{X>Med\}}$ is an indicator variable which equals to one if the $X \in \{Persistence, Variability, Discount, Size\}$ is greater than the sample median and zero otherwise. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
	ret	ret	ret	ret
X	Persistence	Variability	Discount	Size
Δna	0.075***	0.106***	0.090***	0.075***
	(11.250)	(11.206)	(10.525)	(11.250)
$1_{\{X>Med\}}$	-0.005*	-0.000	0.001	-0.002
	(-1.676)	(-0.011)	(0.474)	(-0.586)
$\Delta na * 1_{\{X>Med\}}$	0.025**	-0.039***	-0.013	0.022**
	(2.458)	(-4.199)	(-1.503)	(2.441)
$\Delta balance1$	0.359**	0.316**	0.298	0.267*
	(2.168)	(2.022)	(1.508)	(1.742)
$\Delta balance2$	-0.038*	-0.035	-0.017	-0.036*
	(-1.800)	(-1.560)	(-0.708)	(-1.700)
$\Delta trans$	0.007***	0.007***	0.007***	0.008***
	(3.353)	(3.330)	(3.245)	(3.762)
$\Delta current$	-0.043	-0.007	-0.089	0.032
	(-0.255)	(-0.053)	(-0.709)	(0.230)
Constant	-0.002	-0.006	-0.003	-0.005
	(-0.217)	(-0.624)	(-0.347)	(-0.499)
Observations	12,553	12,655	11,444	12,758
Adj R^2	0.161	0.154	0.150	0.166

Table A.15: **Value Relevance Analysis – Growth**

This table shows the results for the cross-sectional value-relevance tests. The regressions are based on Fama-MacBeth regression method. The variables are in growth rates instead of logged growth rates. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ret	*Ret*	*Ret*	*Ret*	*Ret*	*Ret*
gNA	0.079***	0.075***	0.088***	0.098***	0.081***	0.074***
	(13.010)	(14.372)	(6.302)	(3.424)	(11.565)	(13.551)
$gBalance1$		0.098				0.186
		(0.711)				(1.226)
$gBalance2$			-0.007			-0.016
			(-0.326)			(-0.714)
$gTrans$				-0.012		0.007***
				(-0.583)		(3.852)
$gCurrent$					-0.780	0.070
					(-0.807)	(0.629)
Cons	0.006	0.005	0.007	0.003	0.006	0.004
	(0.631)	(0.527)	(0.731)	(0.386)	(0.658)	(0.491)
Obs	13,522	13,139	13,027	13,418	13,522	12,759
Adj R^2	0.116	0.122	0.137	0.127	0.123	0.162

Table A.16: **Value Relevance Analysis – with Attention Growth**

This table shows the results for the cross-sectional value-relevance tests controlling for changes in logged Google attention. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ret	ret	ret	ret	ret	ret	ret
Δna	0.084***	0.084***	0.083***	0.085***	0.083***	0.087***	0.081***
	(12.060)	(13.444)	(13.571)	(13.147)	(13.288)	(13.867)	(12.905)
$\Delta \log(Google+1)$		0.013	0.003**	0.012	0.012	0.013	0.003**
		(1.361)	(2.145)	(1.318)	(1.320)	(1.389)	(2.316)
$\Delta balance1$			0.271*				0.340**
			(1.864)				(1.978)
$\Delta balance2$				-0.030			-0.044*
				(-1.412)			(-1.714)
$\Delta trans$					0.012***		0.012***
					(4.908)		(4.828)
$\Delta current$						0.155	0.053
						(1.246)	(0.419)
Cons	-0.003	-0.001	-0.003	-0.001	-0.001	-0.003	-0.004
	(-0.349)	(-0.106)	(-0.334)	(-0.150)	(-0.146)	(-0.261)	(-0.477)
Obs	13,522	11,710	11,521	11,435	11,621	11,710	11,181
Adj R^2	0.085	0.099	0.106	0.125	0.121	0.118	0.163

Table A.17: **Value Relevance Analysis – Subsamples**

This table reports the results of the cross-sectional value-relevance tests for each year from 2018 to 2021 and for each quarter. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A	(1) 2018	(2) 2019	(3) 2020	(4) 2021
Δna	0.058***	0.040***	0.106***	0.183***
	(4.599)	(6.426)	(7.679)	(12.439)
Cons	-0.040*	-0.007	0.013	0.041
	(-1.830)	(-0.670)	(0.818)	(1.373)
Obs	2,434	3,832	4,733	2,523
Adj R^2	0.068	0.056	0.102	0.144

Panel B	(1) Q1	(2) Q2	(3) Q3	(4) Q4
Δna	0.108***	0.089***	0.067***	0.065***
	(7.097)	(8.448)	(5.181)	(3.991)
Cons	0.023	-0.003	-0.015	-0.024
	(1.017)	(-0.174)	(-0.919)	(-1.255)
Obs	3,622	3,727	2,932	3,241
Adj R^2	0.112	0.101	0.062	0.055

Table A.18: **Predicting Price-to-New Addresses Ratio**

This table shows results of predicting future period price-to-address ratios. Panel A and Panel B report results for predicting one-period-ahead price-to-address ratios. Panel A does not include the current period price-to-address ratio as an explanatory variable and Panel B includes the current period price-to-address ratio as an explanatory variable. Panel C reports results for predicting two-period-ahead price-to-address ratios. Panel D reports results for predicting three-period-ahead price-to-address ratios. The regressions are based on Fama-MacBeth regression method. Variable definition is documented in the Online Appendix. *, **, and *** represent significance level at the 10%, 5%, and 1% level.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}
$\log(size)$	0.019**						-0.588***
	(2.291)						(-5.340)
gini		1.345***					4.101***
		(4.381)					(5.403)
bom1			-0.146***				-0.742***
			(-20.357)				(-6.843)
bom2				-0.008			0.065***
				(-0.375)			(7.341)
nvt					0.380***		0.373***
					(19.425)		(50.465)
com						-0.016	-0.145***
						(-1.207)	(-13.659)
Constant	11.877***	11.001***	11.664***	12.598***	10.287***	12.599***	15.008***
	(75.735)	(37.329)	(318.710)	(147.437)	(129.920)	(148.633)	(17.966)
Observations	13,398	13,050	13,011	12,889	13,392	13,398	12,717
Adj R^2	0.010	0.008	0.030	0.009	0.320	-0.002	0.432

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)
	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}	pa_{+1}
pa	0.883***	0.872***	0.869***	0.868***	0.881***	0.860***	0.885***	0.822***
	(97.389)	(75.484)	(84.154)	(86.998)	(94.362)	(74.970)	(98.801)	(66.375)
$\log(size)$		0.002						-0.121
		(0.419)						(-1.596)
gini			0.267					0.726
			(1.471)					(1.294)
bom1				-0.015***				-0.136*
				(-4.051)				(-1.786)
bom2					-0.004***			0.011**
					(-3.579)			(2.406)
nvt						0.029***		0.046***
						(5.601)		(8.798)
com							-0.005***	-0.029***
							(-3.183)	(-4.567)
Constant	1.432***	1.487***	1.354***	1.564***	1.534***	1.558***	1.482***	3.125***
	(13.083)	(10.466)	(7.229)	(12.575)	(13.110)	(12.951)	(13.283)	(5.385)
Observations	13,325	13,323	12,947	12,945	12,825	13,324	13,323	12,653
Adj R^2	0.777	0.778	0.758	0.758	0.771	0.783	0.777	0.780

Panel C	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	pa_{+2}	pa_{+2}	pa_{+2}	pa_{+2}	pa_{+2}	pa_{+2}	pa_{+2}	pa_{+2}
pa	0.847***	0.836***	0.829***	0.828***	0.848***	0.822***	0.849***	0.786***
	(88.710)	(71.279)	(77.152)	(79.595)	(87.007)	(69.996)	(90.479)	(60.716)
$\log(size)$		-0.002						-0.076
		(-0.374)						(-0.900)
gini			0.308					0.450
			(1.465)					(0.732)
bom1				-0.015***				-0.086
				(-3.887)				(-1.042)
bom2					-0.005***			0.013**
					(-3.675)			(2.302)
nvt						0.033***		0.047***
						(5.845)		(8.235)
com							-0.005***	-0.034***
							(-3.513)	(-4.648)
Constant	1.888***	2.011***	1.819***	2.068***	1.950***	2.016***	1.938***	3.290***
	(16.449)	(13.472)	(8.418)	(16.029)	(15.930)	(16.253)	(16.715)	(4.782)
Observations	13,208	13,205	12,833	12,830	12,715	13,207	13,205	12,544
Adj R^2	0.731	0.733	0.711	0.709	0.729	0.738	0.732	0.740

Panel D	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	pa_{+3}	pa_{+3}	pa_{+3}	pa_{+3}	pa_{+3}	pa_{+3}	pa_{+3}	pa_{+3}
pa	0.839***	0.828***	0.821***	0.820***	0.838***	0.818***	0.842***	0.781***
	(87.117)	(70.396)	(74.646)	(77.963)	(86.015)	(69.178)	(89.105)	(62.611)
$\log(size)$		-0.003						-0.002
		(-0.582)						(-0.026)
gini			0.231					-0.120
			(1.139)					(-0.193)
bom1				-0.014***				-0.012
				(-3.087)				(-0.137)
bom2					-0.004***			0.016***
					(-3.237)			(2.612)
nvt						0.027***		0.040***
						(5.264)		(7.680)
com							-0.005***	-0.037***
							(-3.162)	(-4.749)
Constant	1.992***	2.131***	2.002***	2.178***	2.075***	2.105***	2.030***	2.962***
	(17.128)	(13.926)	(9.323)	(16.628)	(17.223)	(16.675)	(17.858)	(4.267)
Observations	13,090	13,087	12,718	12,715	12,606	13,089	13,087	12,436
Adj R^2	0.714	0.717	0.691	0.691	0.707	0.718	0.715	0.717

Variable Definitions

- ret: Logged cryptocurrency return
- na: Logged number of new address per coin
- Δna: Weekly changes in logged number of new address per coin
- pa: Logged price-to-address ratio, or $\log\left(\frac{Price}{NA}\right)$
- $balance1$: Logged percentage of supply held by the top 1% addresses
- $balance2$: Logged total amount of coins held on exchange addresses
- $trans$: Logged transaction volume
- $current$: Logged total amount of circulating supply
- $\log(size)$: Logged market capitalization
- $gini$: Gini index of coin holding