The End of the Crypto-Diversification Myth*†

Antoine Didisheim‡, Luciano Somoza§

November 2022

Abstract

Cryptocurrencies and equities have exhibited a high and positive correlation since March 2020. Without obvious fundamental drivers, we theoretically show that trading flows by retail investors can drive this correlation. Using a unique dataset of investor-level holdings from a bank offering trading accounts and cryptocurrency wallets, we show that retail investors tend to trade equities and cryptocurrencies simultaneously in the same direction. This behavior became prominent in March 2020. We provide suggestive evidence showing that stocks preferred by crypto-traders exhibit a stronger correlation with cryptocurrencies, especially when the cross-asset retail volume is high.

*We thank Viral Acharya, Abhishek Bhardwaj, Peter Bossaerts, Lorenzo Bretscher, Francesco Celentano, Vera Chau, Gilles Chemla, Pierre Collin-Dufresne, Lou Dong, William English, Andreas Fuster, Francisco Gomes, Will Goetzman, Amit Goyal, Hanna Halaburda, Sebastian Hillenbrand, Sabrina Howell, Kose John, Bryan Kelly, Toomas Laarits, Simone Lenzu, Igor Makarov, Semyon Malamud, Roxana Mihet, José-Luis Peydró, Diane Pierret, Ricardo Reis, Robert Richmond, Jean-Charles Rochet, Michael Rockinger, Olivier Scaillet, Philipp Schnabl, Kelly Shue, Roberto Steri, Dacheng Xiu, Constantine Yannelis, David Yermack, Jean-Pierre Zigrand, Irina Zvadiadze, and brownbag participants at NYU Stern, EPFL, HEC Lausanne and the Swiss Finance Institute for their insightful comments and discussions. Any remaining mistakes are our own. Declarations of interest: none.

†We thank Serge Kassibrakis and the Quantitative Asset Management department at *Swissquote* for kindly providing us with the data, and for their invaluable support in our research project.

‡Swiss Finance Institute and HEC, University of Lausanne. Email: antoine.didisheim@unil.ch

§Corresponding author. Swiss Finance Institute and HEC, University of Lausanne. Email: luciano.somoza@unil.ch

I. Introduction

Despite extreme volatility and frequent crashes, some large pension providers have introduced Bitcoin into the investable universe of 401(K)s, arguably completing the transformation of cryptocurrencies from a fringe phenomenon into a mainstream asset class.[1] One of the key rationales for including cryptocurrencies into long-horizon portfolios is the promise of diversification from the stock market. [2] Indeed, since none of the suggested—and much-debated—fundamental values behind crypto-assets have a clear relationship with equity returns, it is reasonable to assume that the two asset classes should be uncorrelated. Or rather, it was, as the correlation between Bitcoin and the S&P500 has been consistently positive after the beginning of the COVID19 crisis in March 2020, reaching heights close to 60% (see Figure 1).

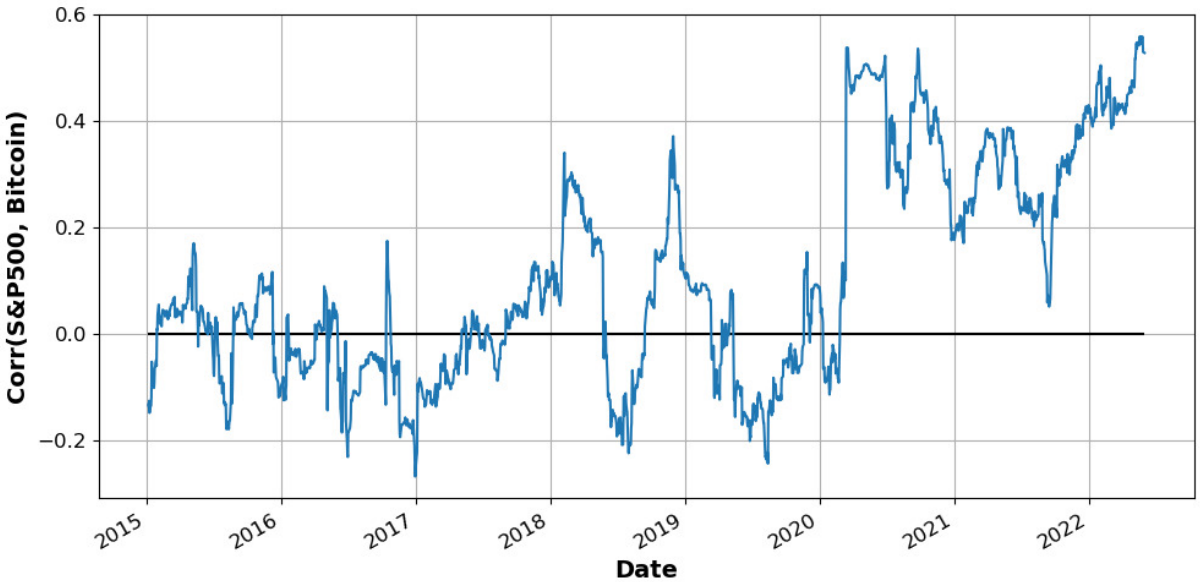


Figure 1. The figure shows the daily correlation estimated with a three month rolling window between Bitcoin's returns and the S&P500. Appendix A shows the same figure for different rolling windows.

In this paper, we argue that the trading habits of retail investors largely drive the correlation. Indeed, without a fundamental driver, correlated trading flows by uninformed investors can theoretically generate cross-asset price correlation. Assuming that retail investors do not

[1]Siegel Bernard, T., *Fidelity's New 401(k) Offering Will Invest in Bitcoin*, The New York Times, April 26th, 2022.

[2]https://www.forbes.com/sites/dantedisparte/2017/11/28/bitcoin-an-asset-currency-or-collectible/?sh=34fa0329300e

carry private information, we test this mechanism using a novel proprietary dataset of retail investors trading equities and cryptocurrencies.

We start with a simple two-asset extension of the canonical Kyle model (Kyle, 1985). Our model relies on three key assumptions: the fundamental values of the two asset classes are uncorrelated, market-making is segmented, and the uninformed investors' order flows on the two assets are correlated. Under these three hypotheses a cross-asset price correlation emerges, and its sign depends on the correlation between uninformed investors' trading flows. The model thus predicts that if there is a positive correlation between two assets with uncorrelated fundamental value, like Bitcoin and equities, there must be a positive correlation between the order flows at the individual investor level.[3] We test this implication in the data along with three corollaries: 1) the correlation at the investor level started at the same time as the one between cryptocurrencies and equities, i.e., March 2020, 2) stocks disproportionately traded by crypto-oriented retail investors show a higher correlation with Bitcoin, and 3) periods with intense retail investors' trading activity are associated with high crypto-equities correlation.

To test our theory, we rely on data from *Swissquote*, the leading Swiss platform for online trading. Crypto-friendly Swiss regulations have allowed *Swissquote* to become one of the first banks worldwide to offer both brokerage accounts on traditional securities and cryptocurrency wallets. Thanks to this peculiarity, our database contains the individual trades and daily portfolios of 77,364 retail investors in classical asset classes—including stocks, indexes, and options—between 2017 and 2020, and crypto-wallet transactions of 16,483 clients.[4] To observe changes in behaviour associated with investing in cryptocurrencies, we only consider investors that opened a cryptocurrency wallet during the sample period. This setting allows us to study transactions in cryptocurrencies, not in a vacuum but as part of the retail investors' overall portfolio decisions.[5]

We show that cryptocurrencies capture the attention of retail investors and partially redirect it away from equities. After opening a cryptocurrency wallet, investors log in twice as often on the platform, trade relatively less in equities, and reduce short-term equity trading. This switch in attention suggests that retail investors consider equities and cryptocurrencies to be partial substitutes. At the same time, we observe that equity and cryptocurrency

[3]While characterizing retail investors as uninformed traders might be seen as a simplification—as the agents may follow predictable patterns akin to trend following—we argue that the implicit assumption that these agents cannot be classified as *informed* traders is sound.

[4]Note that this is a representative random subsample of the *Swissquote* customer base provided by the bank.

[5]The *Swissquote* clients tend to overwhelmingly invest in the US stock market, making them relevant to our study.

trading are correlated. As predicted by the model, this correlation is positive. In other words, retail investors tend to buy equities and cryptocurrencies simultaneously and in the same direction, further corroborating the idea that they consider them similar assets. Note that if investors were selling better-performing assets to buy lower-performing ones the correlation between trading flows would be negative. By contrast, investors tend to change the level of cash they hold with the bank. We find that this phenomenon emerged precisely in Spring 2020, with correlation in net order flows going from roughly zero to almost 80%, thus confirming our first corollary. We hypothesize that this phenomenon might be caused by the COVID19 exogenous shock on investors' liquidity and attention and show suggestive evidence in this direction. While Swiss citizens did not receive stimulus checks, they did retain their salaries. At the same time, lockdown measures significantly reduced opportunities to spend, thus creating the aforementioned liquidity and attention shock. Retail investors started looking into new investment opportunities, leading to a large adoption of cryptocurrencies. Other studies have shown how US investors behaved similarly and invested their stimulus checks in cryptocurrencies (Divakaruni et al., 2021).

Next, we sort US stocks on the trading activity of crypto-oriented *Swissquote* investors and divide them into quintiles. The first (fifth) quintile contains the stocks relatively least (most) traded by crypto-oriented retail investors. We observe that tech and growth stocks are over-represented among their favorites. For each quintile, we run a panel regression where the dependent variable is the correlation in returns between a stock and Bitcoin. The independent variables include the Bitcoin trading volume on global markets, controls, and firm fixed effects. We find that higher global trading volumes on Bitcoin are associated with a higher correlation between equities and Bitcoin. In addition, this relationship is linearly increasing across quintiles, with no significant effect in the first and a strong and positive one in the fifth quintile. This result indicates that stocks disproportionately traded by crypto-oriented retail investors exhibit the highest correlation with Bitcoin, especially when there are high volumes on the global Bitcoin market. In this setting, we add the Bitcoin trading volume on the *Swissquote* platform as a proxy for the retail trading volume. We find that retail trading volume captures all of cross-quintile trend. Furthermore the global Bitcoin trading volume coefficient becomes insignificant or negative. These last empirical results further corroborate the thesis that retail investors drive the crypto-equity correlation.

A natural reaction to our model might be: what will happen if the markets become integrated? To answer this question, we relax the assumption on market segmentation and find that the sign of the correlation changes. When market makers observe both order flows and are aware of the correlation, they are better able to extract information regarding uninformed investors' order flows and adjust prices accordingly.

Our contribution is three-fold. First, we highlight one of the mechanisms driving cryptocurrency prices. This contribution has practical implications. For example, the understanding that retail preferences drive crypto-equity correlation at a stock-specific level would be key to building a stock-derived hedge to crypto-assets. Second, we provide insights into the introduction of cryptocurrencies in individual portfolios and the impact on trading habits and performance. Third, we show how uninformed order flows can drive cross-asset correlation. This notion is particularly relevant for policymakers concerned with spillover effects from the cryptocurrency market to the financial market. Indeed, retail investors act as a bridge between the two markets, and their behaviors could be a source of systemic risk.

The rest of the paper is organized as follows. In Section II, we discuss the link to the extant literature. In Section III, we formalize the economic rationale with the help of a model. In Section IV, we present the dataset in more detail. Sections V and VI provide empirical evidence supporting the model's implications. In Section VII, we extend the model to verify the effects of integrating the cryptocurrency market with the traditional one. Finally, Section VIII concludes.

II. Related Literature

Our paper contributes to the growing literature on cryptocurrencies, the one on retail investors and the recent one studying retail investors' adoption of cryptocurrencies. To the best of our knowledge, our paper is the first to attempt to link retail investors' behavior with price patterns in the cryptocurrency market.

The Bitcoin, theorized by Nakamoto (2008), is the first large-scale application of the decentralized certification algorithm proposed by Haber and Stornetta (1990). Since its launch, a large literature has flourished around cryptography methods, consensus algorithms, and fee structures (see, e.g., John et al., 2020; Saleh, 2021; Cong et al., 2021a; Easley et al., 2019). A decentralized design has peculiar economic characteristics, like forks (Biais et al., 2019), and can have positive effects, such as preventing monopolies from arising (Huberman et al., 2021) and providing firms with new funding channels (Howell et al., 2020). Cryptocurrencies are both a monetary phenomenon (see, e.g., Schilling and Uhlig, 2019; Brunnermeier et al., 2019) and a new kind of financial security. Pricing cryptocurrencies is particularly challenging, as there is no obvious fundamental value nor underlying business, and there are frequent arbitrage opportunities (Makarov and Schoar, 2020). In the literature, there are various approaches to cryptocurrency pricing. For instance, Cong et al. (2021b) show that equilibrium prices of tokens are determined by aggregating heterogeneous users' transactional demand rather than discounted cash flows as in standard valuations models. Pagnotta (2020) and Biais et al. (2022) show that there are multiple possible equilibria, with sharply different equilibrium prices. Various papers analyze cryptocurrencies' returns from an asset pricing perspective. Liu and Tsyvinski (2021) show that network factors drive cryptocurrency returns and that proxies for investor attention strongly forecast future returns. Liu et al. (2019) develop a three-factor model to explain cryptocurrency returns, with cryptocurrency market size and momentum. In addition to traditional market forces, Gandal et al. (2018) and Foley et al. (2019) show that Bitcoin prices have been manipulated with malicious intents, quantifying the number of Bitcoin transactions linked to criminal activities. We contribute to this literature by proposing a mechanism explaining the correlation between cryptocurrency and the stock market, which provides key insight to academics attempting to rationalize cryptocurrency prices.

Our paper also talks to the literature on retail investors, which is becoming ever more important as their impact on the financial market is becoming apparent, especially since the COVID19 crisis (e.g., Greenwood et al., 2022; van der Beck and Jaunin, 2021; Ozik et al., 2021). Retail investors' are extremely heterogeneous (Curcuru et al., 2010)) because of idiosyncratic financial circumstances (e.g., Merton, 1973; Fagereng et al., 2018) and a variety of biases, beliefs and individual characteristics. The literature documents a few persistent phenomena. Although retail investors' portfolio choices are consistent with their risk aversion (Dorn and Huberman, 2010), they tend to hold under-diversified portfolios (Goetzmann and Kumar, 2008) and consistently underperform the market (Barber and Odean, 2013). They have limited attention (Sicherman et al., 2016), and often prefer specific stocks or industries (e.g., Peng and Xiong, 2006; Balasubramaniam et al., 2021). Under-diversification is consistent with retail investors' strong preference for positively skewed returns (see,e.g., Astebro et al., 2009; Mitton and Vorkink, 2007), and such preference can also partly explain poor returns (see,e.g, Brunnermeier and Parker, 2005; Brunnermeier et al., 2007). We contribute to this literature by providing insights into retail investors' role in the cryptocurrency market and how their trading behavior impacts cross-asset correlation.

Finally, we contribute to the recent literature examining retail investors' cryptocurrency adoption. This phenomenon is recent, and it accelerated during the COVID19 crisis, also thanks to the liquidity shock experienced by many retail investors (Divakaruni et al., 2021). A recent paper by Hackethal et al. (2022) finds that cryptocurrency investors are active, prone to biases, tend to invest in stocks with high media sentiment, and become even more active after the first cryptocurrency purchase. In our dataset, we find similar patterns and provide insights into the aggregate effects of cryptocurrency investors' behavior on financial markets.

III. Crypto-Kyle

In this Section, we provide a theoretical framework to rationalize one of the possible causes of the observed correlation between prices in crypto and stock markets. We extend the asset pricing Kyle (1985) model to include a second asset class representing the crypto markets. In the model, as in the rest of the paper, we use Bitcoin to represent cryptocurrencies as a whole. Bitcoin is by far the most traded cryptocurrency, its trading volume is often higher than the ones of all other cryptocurrencies combined (excluding stablecoins), and, together with Ethereum, they make up for more than 90% of volumes.[6]

In the Kyle model, there are three types of agents: informed investors, uninformed investors, and market makers. The price correlation between the assets must come from spillovers between the two markets. These spillovers could technically originate from correlated fundamental values of the two assets, integration of market makers, or correlated trading flows by uninformed investors.

ASSUMPTION 1: *The fundamental values of stocks and Bitcoin are uncorrelated.*

The matter of Bitcoin's fundamental value is a complex one (see, e.g., Härdle et al., 2020; Bhambhwani et al., 2021). There are different views on the existence and source of a fundamental value, as a Bitcoin does not represent claims over real assets nor entitles the owner to cash flows. The only source of fundamental value where there is widespread consensus is Bitcoin's usefulness as a mean of payment for illegal transactions (Foley et al., 2019). Regardless of one's view on the issue, it is safe to say that there is no apparent link between Bitcoin's fundamental value and the stock market. The Bitcoin algorithm adapts its difficulty to maintain the duration of blocks relatively stable regardless of competition between miners, therefore even semiconductors or other technologies affecting the supply side of Bitcoin do not obviously translate into a fundamental mechanism (Nakamoto, 2008). We argue that Assumption 1 is realistic as there is no obvious fundamental mechanism linking Bitcoin's value to stock market fluctuations.

ASSUMPTION 2: *Market making in crypto and traditional financial markets is segmented.*

By segmented, we mean that each market maker is only observing the order flow on his own asset. The current structure of market-making suggests that Assumption 2 holds. Indeed, the leading firms operating as market makers in the Bitcoin market focus mainly, if

[6]CoinMarketCap.com, Monthly Volume Rankings (Currency).

not only, on cryptocurrencies.[7] In Section VII we discuss the implications of relaxing this assumption. While market-making in Bitcoin is not as developed as the one in financial markets, the Kyle model remains a good fit, as in the Bitcoin market there are many small specialized investors and algorithmic DeFi protocols. Vayanos (2001) demonstrates that in the Kyle model a continuum of small risk-neutral investors is equivalent to a single market maker.

ASSUMPTION 3: *Trading flows of uninformed investors are correlated because they engage in cross-asset trading.*

Retail traders are the uninformed investors in the model. While they have many reasons to trade, such as liquidity shocks, hype, and sentiment, we feel confident in excluding the hypothesis that their trades contain information that is not already available to the market. We assume that their cross-asset flows are correlated, but we do not take a stance on the direction of this correlation. There are two possible reasons for a correlation to emerge. First, retail investors might rebalance their portfolio due to wealth effects. For instance, if Bitcoin is performing particularly well, they might sell some Bitcoins to buy shares or vice versa. In this case, we should observe negatively correlated trading flows. The second potential reason is sentiment. In periods of optimism, they might leverage up by reducing cash or borrowing, thus buying different assets at the same time and in the same direction, and vice-versa in periods of pessimism. This second explanation implies a positive correlation in cross-asset trading flows. In Section V, we assess Assumption 3 and study the direction of the correlation of retail investments.

A. Set-up

We use the same set-up as in Kyle (1989) add a second asset. While this is far from the first extension of the Kyle model with multiple assets (Garcia del Molino et al., 2020), our model differs in the three key assumptions listed previously, i.e., uncorrelated fundamental values, segmented markets, and correlated uninformed trading.

The model has two periods. At $t = 0$, each informed trader learns the fundamental value of one of the two risky assets and places a market order accordingly. Following Assumption

[7] "The most active traders and market makers in the nearly \$3tn digital asset space include Alameda Research, B2C2, Cumberland, and Genesis Trading, none of them well-known names in traditional financial markets." Szalay, E. *Battle for dominance heats up in cryptocurrency trading*, Financial Times, Jan 6^{th}2022.

1, the two fundamental values are not correlated:[8]

$$V = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} \right). \tag{1}$$

Accordingly, the informed demand is given by:

$$X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \beta_{11} & 0 \\ 0 & \beta_{22} \end{bmatrix} \left(\begin{bmatrix} v_1 \\ v_2 \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \right) = \begin{bmatrix} \beta_{11} (v_1 - \mu_1) \\ \beta_{22} (v_2 - \mu_2) \end{bmatrix}, \tag{2}$$

meaning that informed investors trade only the asset for which they learned the fundamental value. Assuming one single informed trader receiving private information and trading on both assets would not change the economics of the model. Since markets are segmented and market makers do not observe each other's order flows, the optimal trade by the informed investor on a given asset is independent of the order on the other asset.

At the same time, the uninformed trader submits correlated orders for the two risky assets because of Assumption 3. The aggregate inelastic liquidity is distributed as:

$$U = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \sigma_u^2 \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right). \tag{3}$$

At $t = 1$, the two market makers observe the total order flows for the two assets and make the prices. In line with Assumption 2, we consider segmented financial markets so that each market maker observes only one order flow and decides the corresponding price. The two market makers don't learn from each other. The total order flow is:

$$Y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = X + U = \begin{bmatrix} x_1 + u_1 \\ x_2 + u_2 \end{bmatrix} = \begin{bmatrix} \beta_{11} (v_1 - \mu_1) + u_1 \\ \beta_{22} (v_2 - \mu_2) + u_2 \end{bmatrix}. \tag{4}$$

B. *Sequential equilibrium*

We define a sequential equilibrium for the Kyle model with two asset classes taking into consideration the Assumptions 1, 2, and 3.

DEFINITION 1: *The sequential equilibrium is defined by*

[8]We indicate vectors and matrices with upper case letters and scalars with lower case letters.

- *the market order X that solves the maximization problem of the two informed traders:*

$$X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \arg\max_{x_1} & \mathbb{E}\left[(v_1 - p_1)\, x_1 \mid v_1\right] \\ \arg\max_{x_2} & \mathbb{E}\left[(v_2 - p_2)\, x_2 \mid v_2\right] \end{bmatrix}, \tag{5}$$

- *the price function P considering segmented markets:*

$$P = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} \mathbb{E}\left[v_1 \mid y_1\right] \\ \mathbb{E}\left[v_2 \mid y_2\right] \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}. \tag{6}$$

Solving the sequential equilibrium, we find that the informed investors' market orders are:

$$x_1 = \frac{\sigma_u}{\sigma_1}\big(v_1 - \mu_1\big), \qquad\qquad x_2 = \frac{\sigma_u}{\sigma_2}\big(v_2 - \mu_2\big), \tag{7}$$

while the market makers' price functions are:

$$p_1 = \mu_1 + \frac{\sigma_1}{2\sigma_u}\big(x_1 + u_1\big), \qquad\qquad p_2 = \mu_2 + \frac{\sigma_2}{2\sigma_u}\big(x_2 + u_2\big). \tag{8}$$

PROPOSITION 1: *The covariance between the two equilibrium prices is positive if and only if the correlation of the uninformed investors' trading is positive:*

$$\mathrm{Cov}(p_1, p_2) > 0 \qquad \Longleftrightarrow \qquad \rho > 0. \tag{9}$$

Proof. Combining the equilibrium prices in equation (8) with the equilibrium orders of informed investors in equation (7), and applying the distributions of the fundamental values in equation (1) and the uninformed investors' trading flows in equation (3), we obtain the following covariance between prices:

$$\mathrm{Cov}(p_1, p_2) = \rho \frac{\sigma_1 \sigma_2}{4}. \tag{10}$$

It is trivial to show that this covariance is positive for positive values of ρ. □

Since the correlation between Bitcoin and the stock market is positive, as shown in Figure 1, we expect to observe a positive correlation in cross-asset trading at the individual retail investor level.

COROLLARY 1: *There is a change in the cross-asset retail investors' trading habits when we observe a change in the correlation between cryptocurrencies and the stock market.*

Figure 1 shows a substantial change in the correlation between Bitcoin and S&P500 in

Spring 2020 as it jumps from around zero to strictly positive. If our model captures the right mechanism we must observe in the data a substantial change in the retail investors' behaviour around the same time.

COROLLARY 2: *Retail investors engage more in cross-asset trading in periods when they are more active the cryptocurrency market. In these periods, we observe a stronger correlation between cryptocurrencies and the stock market because the magnitude of* ρ *is higher.*

It is worth noting that retail investors are not the only uninformed investors in the market, and their level of activity is highly heterogeneous across time.[9] For these reasons, we expect a stronger correlation in uninformed investors' trading, where retail investors are particularly active. We also expect a stronger correlation between Bitcoin and the stock market prices in the same periods because of Proposition 1.

COROLLARY 3: *There is a stronger correlation between the prices of Bitcoin and stocks favored by crypto-oriented retail investors because cross-asset trading is higher for these stocks. Similarly, there is a weaker correlation between the prices of Bitcoin and stocks less favored by crypto-oriented retail investors for the same reasons.*

Retail investors tend to specialize in certain stocks (see, e.g., Peng and Xiong, 2006; Balasubramaniam et al., 2021), and cryptocurrency traders tend to have different socio-economic characteristics from the rest of the investors (see Section IV). We expect the preferred stocks to experience a stronger correlation with the crypto-market, especially when retail traders are more active.

IV. Data

A. Institutional Details

Swissquote is a Swiss bank established in 1999, offering various online banking services. It is particularly famous in Switzerland for its trading platform and is often referred to as the market leader for online trading. For our paper, *Swissquote* has two key characteristics that make it an ideal laboratory. First, although it is an online bank, it is well-established, trusted, and widely used by all segments of the population. It has been listed for over 20 years on the SIX stock exchange, and it is the supplier of online brokerage services for *SwissPost*, the Swiss

[9] While we can not show in this paper the levels of retail activity in our database across time because of data confidentiality, we observe that it is highly heterogeneous.

national postal service and one of Switzerland's largest financial institutions.[10,11] Second, it was one of the first, and among the few, institutional banks to offer cryptocurrency wallets and operate a cryptocurrency exchange. This is one of their selling points, as highlighted by their slogan "Trade crypto with a real bank".

While most traditional banks avoid offering cryptocurrency-related services to their customer, *Swissquote* was able to enter this market as early as 2017. Moreover, customers do not indirectly trade cryptos but exchange real tokens. *Swissquote* offers actual cryptocurrency wallets similar to the ones in most specialized cryptocurrency platforms. Currently, there are 28 cryptocurrencies available for trading on the *Swissquote* cryptocurrency exchange at the time of writing. This exploit has been possible also thanks to the Swiss policymakers' friendly approach toward cryptocurrencies, that has fueled a burgeoning growth across the entire Swiss blockchain and cryptocurrency ecosystems.[12]

B. Sample Description

The Quantitative Asset Management department at *Swissquote* generously provided us with the data from a representative random sub-sample of clients from their bank. The sub-sample consists of 77,364 unique active clients and their daily holdings, transactions, and portfolio weights between 2017 and 2020. For each feature, we distinguish between cash, individual stocks, index funds (ETFs), structured product (derivatives), fixed income, and cryptocurrencies. In addition, we know the clients' gender, age, and the number of daily logins to the *Swissquote* platform.

We present some summary statistics in Table I. The first column shows agents who only trade traditional securities, while the second displays agents who trade both traditional securities and cryptocurrencies, which we call crypto-oriented retail investors. We define as crypto-oriented all *Swissquote* customers with a pre-existing securities trading account that opened a cryptocurrency wallet and kept at least 1% of cryptocurrencies. We complete the data from *Swissquote* with daily prices, market cap, and industry classification from *Thomson Reuters*.

[10] *SwissPost* press release, *Strong partner in e-trading.*
[11] *PostFinance* press release, *PostFinance and Swissquote enter into joint venture*, November 11$^{\text{th}}$ 2020.
[12] Atkins, R., *Switzerland embraces cryptocurrency culture*, Financial Times, January 25$^{\text{th}}$ 2018.

Table I

The table shows descriptive statistics of our random sample of *Swissquote* clients. We split the sample into two groups: those who trade only traditional assets and those who trade both traditional assets and cryptocurrencies. We define agents as crypto-oriented if at one point in time their portfolio contained at least 1% of cryptocurrencies.

	Securities only	Crypto-oriented
# clients	60,881	16,483
Investor assets (CHF) - median	34,951	17,228
Investor assets (CHF) - mean	181,680	115,425
% daily-traded wealth	0.8%	2.0%
Age - mean	54	47
% female	18.0%	8.8%
Portfolio return - mean	6.7%	11.2%
Portfolio return - std	17.4%	30.6%
Portfolio return - Sharpe	0.57	0.53

These statistics suggest that crypto-oriented retail investors, on average, have fewer assets and are younger, more male, more active, and keener on taking risks. These findings are consistent with anecdotal evidence and the literature (Hackethal et al., 2022).

V. Retail Investors

In this Section, we look at the investment behaviour of those retail investors that also trade cryptocurrencies. First, we provide empirical evidence at the individual portfolio level to assess whether there is cross-asset trading, confirming Assumption 3 in our theoretical model. Then, we verify whether the correlation in cross-asset trading flows is positive (Proposition 1) and if this behaviour started at the same time as the positive correlation between Bitcoin and equities (Corollary 1).

A. *Cross-Asset Trading*

To assess the existence of cross-asset trading, we study the changes around the opening month a cryptocurrency wallet and observe how trading habits change. Opening a cryptocurrency wallet is a non-trivial event, as the investor accesses a novel asset class with which she is not necessarily familiar. As Figure 2 shows, the number monthly of logins to the Swissquote platform after opening a cryptocurrency wallet significantly increases, suggesting a sizable impact on investors' attention.

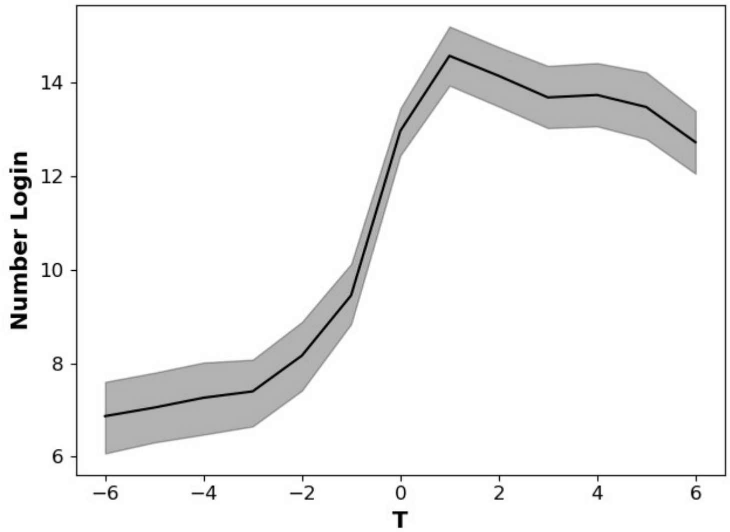


Figure 2. The figure shows the average number of monthly logins of crypto-oriented investors in the 6 months before and after opening a cryptocurrency wallet, where $T = 0$ is opening date. The grey area shows the 5% confidence interval.

We do not have a complete overview of an investor's total wealth, which likely includes real estate and pension funds. Nevertheless, we can affirm that we observe most of an investor's active trades. *Swissquote* is the market leader in Switzerland for online trading, and investors tend to open accounts with this primary purpose in mind. Since frequent trading activity and cash level changes make portfolio weights hard to evaluate, we focus on trading patterns and use a staggered difference-in-difference design around the opening of a cryptocurrency wallet. Deciding to trade cryptocurrencies is highly endogenous, and the effect can not be interpreted as causal. Nevertheless, the staggered difference-in-difference design allows us to isolate the relative differences and observe which changes are correlated with the opening of a cryptocurrency wallet.

We start by looking at whether crypto trading is correlated with stock trading to provide empirical evidence for Assumption 3. We estimate the following regression:

$$y_{i,t} = \beta_0 + \beta_1 Crypto\_User_{i,t} + \beta_2 Crypto\_Turnover_{i,t} + \beta_3 Bank\_Assets_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}. \quad (11)$$

The dependent variable $y_{i,t}$ is the turnover of the trading account, defined as monthly trading volume in shares divided by average shares holdings over the month. $Crypto\_User_{i,t}$ is a dummy equal to 1 if investor i holds cryptocurrencies at time t. $Crypto\_Turnover_{i,t}$

represents the turnover of the cryptocurrency wallet, defined as trading volume in cryptocurrencies divided by average cryptocurrencies holdings over the month. $Bank\_Assets_{i,t}$ is the total amount of assets investor i holds at time t with *Swissquote*. We include investor and time fixed effects and cluster standard errors at the investor level.

Table II

The table shows the results of regression (11) with the monthly turnover of individual investors' stock portfolios as the dependent variable. $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t holds cryptocurrencies. $Crypto\_Turnover_{i,t}$ is the monthly turnover of the cryptocurrency portfolio. $Bank\_Assets_{i,t}$ is the total amount of assets the investor holds with *Swissquote*. Standard errors are clustered at the investor level.

Dep.: Stock_Turnover	(1)	(2)	(3)	(4)	(5)	(6)
Crypto_User	0.1129***	-0.0092***			0.0088***	-0.0772***
	(0.0033)	(0.0035)			(0.0028)	(0.0035)
Crypto_Turnover			0.2657***	0.1337***	0.2621***	0.1499***
			(0.0037)	(0.0023)	(0.0036)	(0.0023)
Bank_Assets	0.0588***	0.1189***	0.0564***	0.1150***	0.0566***	0.1144***
	(0.0007)	(0.0014)	(0.0006)	(0.0013)	(0.0006)	(0.0013)
Intercept	-0.3615***		-0.3383***		-0.3411***	
	(0.0066)		(0.0064)		(0.0065)	
FE investor	NO	YES	NO	YES	NO	YES
FE time	NO	YES	NO	YES	NO	YES
# Obs	2,695,478	2,695,478	2,695,478	2,695,478	2,695,478	2,695,478
Adj-R^2	0.0366	0.3685	0.0495	0.3715	0.0495	0.3720

Table II reports the estimated coefficients of regression (11). We find that crypto and stock turnovers are positively and significantly correlated in columns (3) to (6), meaning that there exists cross-asset trading for crypto-oriented retail investors (Assumption 3 in our model). The positive coefficients for the crypto dummy in columns (1) and (5) suggest that cryptocurrency investors trade more shares on average. Without fixed effects, the $Crypto_User$ dummy captures the average trading when an investor has a cryptocurrency wallet. However, the same coefficients are negative in columns (2) and (6), showing that once taking in account that they do trade more on average, we find that they trade relatively less on stocks after opening a cryptocurrency wallet. This effect is not caused by the relative lower weight of shares in the portfolio nor by the amount invested, as the dependent variable is scaled by stock holdings. A possible interpretation is that investors pay less attention to shares once they trade cryptocurrencies, thus trading them less often. This switch in attention would indicate that retail investors consider the two asset classes to be sustitutes in their trading activity on the platform. To test this interpretation, we run three separate test. In Subsection V.A.1, we look at short-term trading in equities, as frequent trading requires more attention. In Subsection V.A.2, we look at the risk-adjusted performance of equity portfolios, as retail investors are highly biased, and lower attention should translate into superior performance. In Subsection V.A.3, we look at the weight of stocks in the non-crypto part of a portfolio to assess how their relative importance changes after opening a cryptocurrency wallet.

A.1. Short-term trading

Short-term trades in equities require a high level of attention, and thus a decrease in the amount of short-term trades might indicate a reduction in attention. We define short-term trades as those trades for which we observe a reversion within a month. We consider a reversion only when the investor trades in the opposite direction on the same security for at least 50% of the original position. We estimate regression (11) with the percentage of short-term trades as the dependent variable. Table III shows the results.

Table III

The table shows the results of estimating regression (11) with the percentage of short-term trades in stocks as the dependent variable. Short-term trades are trades for which we observe a transaction with the opposite sign on the same security within a month for at least 50% of the original position. $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t holds cryptocurrencies. $Crypto\_Turnover_{i,t}$ is the monthly turnover of the cryptocurrency portfolio. $Bank\_Assets_{i,t}$ is the total amount of assets the investor holds with *Swissquote*. Standard errors are clustered at the investor level.

Dep.: %Short_Term	(1)	(2)	(3)	(4)	(5)	(6)
Crypto_User	0.0109***	-0.0039***			-0.0040***	-0.0116***
	(0.0005)	(0.0007)			(0.0004)	(0.0007)
Crypto_Turnover			0.0359***	0.0145***	0.0375***	0.0169***
			(0.0009)	(0.0005)	(0.0009)	(0.0005)
Bank_Assets	0.0052***	0.0153***	0.0050***	0.0149***	0.0049***	0.0148***
	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)
Intercept	-0.0338***		-0.0321***		-0.0309***	
	(0.0011)		(0.0011)		(0.0011)	
FE investor	NO	YES	NO	YES	NO	YES
FE time	NO	YES	NO	YES	NO	YES
# Obs	2,695,478	2,695,478	2,695,478	2,695,478	2,695,478	2,695,478
Adj-R^2	0.0076	0.2688	0.0143	0.2697	0.0144	0.2699

In Table III, we observe coefficients with the same sign as the ones in Table II. The positive coefficients for the crypto dummy in columns (1) and (5) suggest that cryptocurrency investors make more short-term stock trades on average. However, the same coefficients are negative in columns (2) and (6), showing that they make fewer short-term trades after opening a cryptocurrency wallet. Moreover, short-term trades on stocks are positively correlated with high activity in cryptocurrency trading, as in columns (3) to (6). These results corroborate the idea that after opening a cryptocurrency wallet, an investor pays relatively less attention to the stocks in her portfolio.

A.2. Equity Portfolio Performance

Previous literature has shown that the relationship between trading and performance is strong and negative for retail investors (Barber and Odean, 2000). The reason is that retail investors are subject to numerous biases that affect their trading behavior (Barber and Odean, 2013). By the same logic, paying less attention to their equities portfolio should improve their performance, as they would be less subject to biases. To test this mechanism, we look at the impact of cryptocurrencies on the performance of both the overall portfolio and the equities-only part. We estimate the following regression:

$$y_{i,t} = \beta_0 + \beta_1 Crypto\_User_{i,t} + \beta_2 Bank\_Assets_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \quad (12)$$

where the dependent variable is the portfolio performance in terms of annualized monthly returns or Sharpe ratio. $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i has an active cryptocurrency wallet at times t. $Bank\_Assets_{i,t}$ is the total amount of assets investor i holds at time t with *Swissquote*. We include investors and time fixed effects. We cluster standard errors at the investor level.

Table IV

The table shows the results of estimating regression (12) with the performance of the overall portfolio as dependent variable. The performance is measured in terms of annualized monthly returns or Sharpe ratio. $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t holds cryptocurrencies. $Bank\_Assets_{i,t}$ is the total amount of assets the investor holds with *Swissquote*. Standard errors are clustered at the investor level.

	Dep.: Return		Dep.: Sharpe	
	(1)	(2)	(3)	(4)
Crypto_User	0.2125***	0.1169***	-0.3876***	-0.1023***
	(0.0040)	(0.0041)	(0.0075)	(0.0117)
Bank_Assets	0.0045***	0.0241***	0.1509***	0.1403***
	(0.0004)	(0.0013)	(0.0014)	(0.0038)
Intercept	0.1585***		-0.2444***	
	(0.0040)		(0.0153)	
FE investor	NO	YES	NO	YES
FE time	NO	YES	NO	YES
#Obs	2,695,478	2,695,478	2,695,478	2,695,478
Adj R^2	0.0070	0.2635	0.0078	0.3749

Table IV shows the results for the overall portfolio. Investors trading cryptocurrencies have significantly higher returns, i.e., 11.69% more on an annual basis in column (2). This result is not surprising, given the performance of cryptocurrencies over the sample period. Many investors opened a cryptocurrency account in the spring of 2020 and benefited from the sharp price increase. Nevertheless, these high returns come with even higher volatility, leading to a Sharpe ratio that is significantly lower in columns (3) and (4). These results casts a shadow over narratives concerning diversification, as increased returns do not compensate for the additional variance. Moreover, lower portfolio performances are consistent with the increased overall attention of crypto-oriented retail investors.

Table V

The table shows the results of estimating regression (12) with the performance of the portfolio excluding cryptocurrencies as dependent variable. The performance is measured in terms of annualized monthly returns or Sharpe ratio. $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t holds cryptocurrencies. $Bank\_Assets_{i,t}$ is the total amount of assets the investor holds with *Swissquote*. Standard errors are clustered at the investor level.

	Dep.: Return		Dep.: Sharpe	
	(1)	(2)	(3)	(4)
Crypto_User	0.1190***	0.0829***	-0.1732***	0.1583***
	(0.0021)	(0.0031)	(0.0080)	(0.0120)
Bank_Assets	0.0105***	0.0365***	0.1611***	0.1548***
	(0.0003)	(0.0010)	(0.0014)	(0.0038)
Intercept	0.0958***		-0.3489***	
	(0.0033)		(0.0154)	
FE investor	NO	YES	NO	YES
FE time	NO	YES	NO	YES
#Obs	2,695,478	2,695,478	2,695,478	2,695,478
Adj R^2	0.0026	0.2690	0.0074	0.3757

Table V shows the results for the portfolio without cryptocurrencies, i.e., the equities-only part of the crypto-traders portfolio. As expected, considering only the part of the portfolio not invested in cryptocurrencies yields different results. Crypto-oriented retail investors have significantly higher returns and Sharpe ratios on the equity part of their portfolio, as in columns (2) and (4). While they tend to have higher returns overall because they are less risk-averse, column (3) shows that their Sharpe ratio is generally lower than average. Nevertheless, the Sharpe ratio of their equities-only portfolio increases when opening a cryptocurrency wallet in column (4). These results are consistent with retail investors switching their attention from equities to cryptocurrencies.

A.3. Equities in the Portfolio

Third, we look at the relative weight of equities inside a portfolio. While adding an asset class mechanically reduces the weights of all of the others, looking at the relative weights, excluding cryptocurrencies, can provide insights into investors' rationale. In particular, a decrease in the relative weight of equities would indicate that investors' consider cryptocurrencies and equities to play a similar role. To test it, we estimate the following regression:

$$y_{i,t} = \beta_0 + \beta_1 Crypto_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{13}$$

where the dependent variable is the equities' weight into an investor's non-crypto portfolio, i.e. her total assets at Swissquote excluding cryptocurrencies. *Crypto* is the cryptocurrencies' weight in the overall portfolio of investor i at time t and and γ are relatively investors and time fixed effects. We cluster standard errors at the investor level. Table VI shows the results.

Table VI

The table shows the results of estimating regression (13). The dependent variable is the weight of equities in the non-crypto part of an investor's portfolio, i.e. the total assets held at Swissquote excluding cryptocurrencies. *Crypto* is the cryptocurrencies' weight in the overall portfolio. Standard errors are clustered at the investor level.

	(1)	(2)	(3)	(4)
crypto	-0.3951***	-0.396***	-0.1787***	-0.2409***
	(0.0009)	(0.001)	(0.001)	(0.002)
Constant	YES	NO	NO	NO
Time FE	NO	YES	NO	YES
Client FE	NO	NO	YES	YES
Observations	1,244,148	1,244,148	1,244,148	1,244,148
R^2	0.1274	0.1281	0.7396	0.7376

We find that 1% increase in cryptocurrencies' portfolio weight leads to a 0.24% decrease in the relative weight of equities. Note that this decrease is not mechanic, as the relative weights are computed excluding cryptocurrencies. In addition, we find that a 1% increase in cryptocurrencies' portfolio weight is associated with a 0.3% increase in cash and a reduction in structured products and index funds (see Appendix D). In other words, investing in cryptocurrencies is associated with a relative reduction in risk on the remaining part of the portfolio, achieved by increasing cash and reducing equities.

These results further corroborate the idea that investors perceive equities and cryptocurrencies as similar assets. We hypothesise that the reason lies in the belief that the price of cryptocurrencies is a function of their success as a technology, and thus retail investors consider cryptocurrencies akin to (tech) stocks. This partial substitution provides a rationale for the existence of a persistent correlation in trading between equities and cryptocurrencies. Overall, the empirical evidence presented in this section supports Assumption 3 in the model presented in Section III.

In Appendix C, we show the main results of this Section using a Callaway-Sant'Anna estimator (Callaway and Sant'Anna, 2021) to address concerns regarding heterogeneous treatment effects (Goodman-Bacon, 2021; Baker et al., 2022). The estimates remain significant and unchanged in terms of sign and magnitude. This is not surprising as most of the investors started trading cryptocurrencies around March 2020, alleviating concerns regarding time-varying treatment effects.

B. Positively Correlated Trading

The model presented in Section III assumes a correlation in cross-asset trading at the individual retail investor level (Assumption 3). We observe in the data that a large trading volume in cryptocurrencies is associated with a large trading volume in equities (Table II), confirming our theoretical assumption. However, this empirical result does not necessarily imply the sign (positive or negative) of the correlation in net trading volumes.

A priori, the correlation between turnovers could be either positive or negative. Retail investors could reallocate funds from one asset class to another because of wealth effects with the objective to keep their cross-asset class portfolio weights relatively stable. In this case, we should observe investors selling high-performing assets to buy low-performing ones to restore their preferred weights. Thus, net flows in cryptocurrencies and stocks should be negatively correlated. On the other hand, retail investors could be driven by idiosyncratic factors that lead them to change the total amount of capital invested. These factors could be liquidity shocks, attention, or personal belief. In this case, the trader would tend to buy and sell both asset classes in the same direction. Thus, the correlation between the net trading volume of cryptocurrencies and stocks should be positive.

Given the positive correlation between Bitcoin and stock prices (Figure 1), our model predicts that the correlation in retail cross-asset trading must be positive (Proposition 1). We empirically test the sign of the micro-level correlation by estimating the following regression:

$$y_{i,t} = \beta_0 + \beta_1 Crypto\_Pos_{i,t} + \beta_2 Crypto\_Neg_{i,t} + \beta_3 Bank\_Assets_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \quad (14)$$

in which we distinguish between the two alternative explanations for the sign of the correlation state above. The dependent variable is the net trades by investor i at time t in stocks over total stocks holdings. $Crypto\_Pos_{i,t}$ is the ratio of buy orders to cryptocurrency holdings, while $Crypto\_Neg_{i,t}$ is the ratio of sell orders to crypto-holdings. $Bank\_Assets_{i,t}$ is the total amount of assets investor i holds at time t with *Swissquote*. α_i and γ_t are, respectively, investor and time fixed effects. We use monthly frequency and cluster the standard errors at the investor level.

We also estimate the regression:

$$y_{i,t} = \beta_0 + \beta_1 Net\_Crypto_{i,t} + \beta_2 Bank\_Assets_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \quad (15)$$

where $Net\_Crypto_{i,t}$ is the ratio of net orders flows to cryptocurrency holdings. Everything else remains the same as in regression (14).

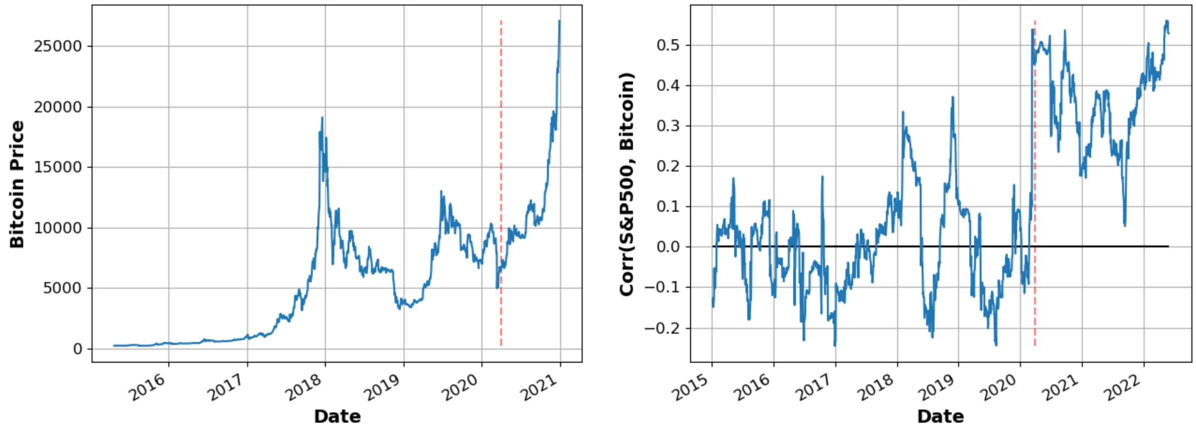
Table VII

The table shows the results of estimating regressions (14) and (15). The dependent variable is the net monthly trading flow in stocks of each individual investor. $Crypto\_Pos_{i,t}$ is the ratio of buy orders to cryptocurrency holdings. $Crypto\_Neg\_i, t$ is the ratio of sell orders to crypto-holdings. $Net\_Crypto_{i,t}$ is the ratio of net orders flows to cryptocurrency holdings. $Bank\_Assets_{i,t}$ is the total amount of assets the investor holds with *Swissquote*. Standard errors are clustered at the investor level.

Dep.: Net_Stock	(1)	(2)	(3)	(4)	(5)	(6)
Crypto_Pos	0.0182***	0.0200***	0.0223***			
	(0.0031)	(0.0033)	(0.0033)			
Crypto_Neg	-0.0274***	-0.0331***	-0.0265***			
	(0.0029)	(0.0030)	(0.0031)			
Net_Crypto				0.0237***	0.0277***	0.0246***
				(0.0027)	(0.0028)	(0.0028)
Bank_Assets	0.0048***	0.0129***	0.0137***	0.0044***	0.0113***	0.0133***
	(0.0006)	(0.0020)	(0.0020)	(0.0005)	(0.0020)	(0.0020)
Intercept	-0.0060***			-0.0046***		
	(0.0050)			(0.0050)		
FE investor	NO	YES	YES	NO	YES	YES
FE time	NO	NO	YES	NO	NO	YES
# Obs	250,752	250,752	250,752	250,752	2,695,478	250,752
Adj-R^2	0.0010	0.0459	0.0526	0.0009	0.0458	0.0526

Table VII shows the estimates of regressions (14) and (15). Regardless of the specification and the combination of fixed effects, the trading flows between stocks and cryptocurrencies are positively correlated. Retail investors tend to trade cryptos and stocks in the same direction and at the same time. The results strengthen the hypothesis that retail cross-asset trading is driven by liquidity shocks, attention, or personal beliefs. The positive correlation at the individual investor level is consistent with the pattern observed at the price level, providing empirical evidence for Proposition 1.

As depicted in Figure 3, we observe a change in the correlation between Bitcoin and stock market prices. The correlation jumps to strictly positive in Spring 2020 and maintains high levels, months before the explosion in Bitcoin price. According to Corollary 1, the change in the correlation between prices should coincide with a change in the retail traders' investment behaviour. In particular, we should observe a change in the correlation between the retail net trading volume on cryptocurrencies and stocks in Spring 2020.

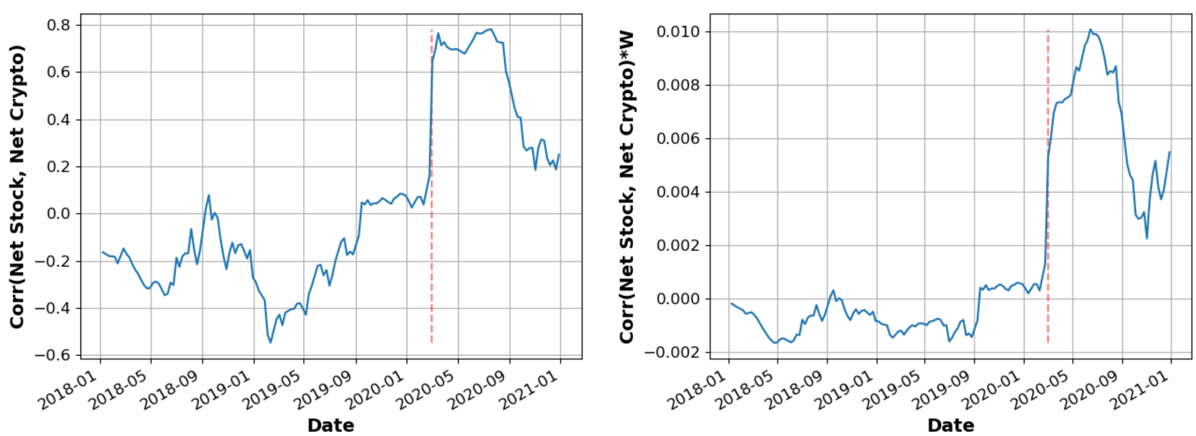


(a) Bitcoin

(b) Correlation

Figure 3. The figures show: (a) the Bitcoin price, and (b) the correlation between Bitcoin and the S&P500 estimated with a 3-month rolling window.

To test this implication, we compute the average correlation between stock and cryptocurrency net flows across investors with a 25-week rolling window. We show the results in Panel (a) of Figure 4. Consistently with our model, we observe that in the spring of 2020, there was a drastic and sudden change in the correlation between net cryptocurrencies and stock trading flows.



(a) Retail volumes correlation

(b) Weighted retail volumes correlation

Figure 4. Panel (a) shows the correlation between net retail trading volumes of cryptocurrencies and equities. We compute the correlation at the weekly level, using a 25-week rolling window. Panel (b) shows the same numbers weighted by cryptocurrencies trading volumes on the *Swissquote* platform.

he t-stat for the difference in mean before and after March 2020 is 21.62, indicating that the increase in correlation is highly significant. Before the regime change in Spring 2020, we observe a negative correlation. These values are consistent with the idea that agents substitute stocks for cryptocurrencies. However, we argue that this pattern is not as important as the post-2020 pattern, as the volume of retail traders and the number of cryptocurrency traders were much lower. In Panel (b) of Figure 4 we show the rolling correlation multiplied by the total volume of cryptocurrencies trading during the week and divided by the total trading volume throughout the sample. These numbers suggest that the pre-2020 period coincides with low cross-asset trading volumes.

We propose an interpretation for the regime change in March 2020. In that month, due to COVID19 and the subsequent lockdown measures, households were subject to two shocks. First, they had more time available, as they were forced to stay home. This led many of them to pay closer attention to their investment portfolio. We clearly observe this phenomenon in our sample. Figure 5 shows the median number of logins to the Swissquote platform in the months around March 2020.

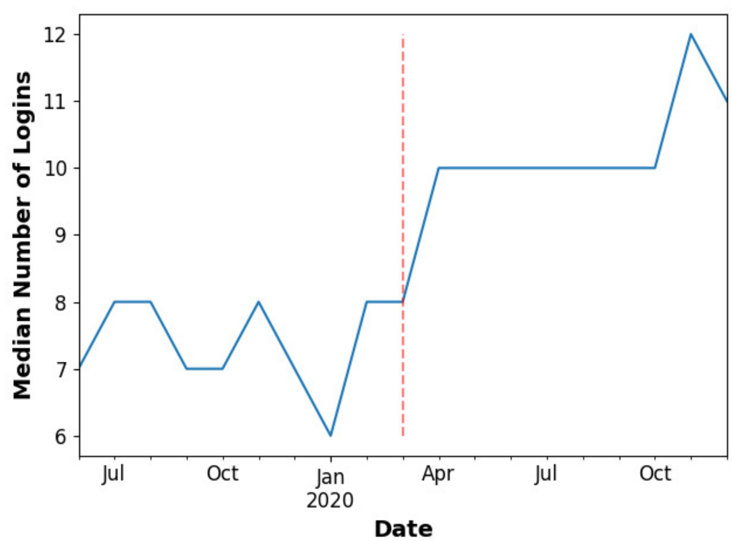


Figure 5. The figure shows the median number of monthly logins for the users in our sample around March 2020.

Second, they had a liquidity shock. Even though Switzerland did not implement stimulus check programs like the US, the vast majority of the population was able to retain their primary source of income or rely on unemployment benefits. At the same time, Swiss people could not spend the money on leisure activities due to the lockdown measures. The combination of these two shocks led to a boom in online trading. On the *Swissquote* platform trading volumes skyrocketed in Spring 2020, increasing by an order of magnitude, and remained high for various months. In addition, cryptocurrencies started to become mainstream, with increasing attention from the press and the launch of many crypto-trading platforms. Previous literature has documented similar patterns in the US and other countries, with the boom in retail trading impacting equity market prices (Greenwood et al., 2022). Furthermore, Divakaruni et al. (2021) have found that many individuals in the US used their stimulus checks to invest in cryptocurrencies, consistently with what we observe in the Swissquote platform.

VI. Global Markets

This Section extends the empirical analysis to study the relationship between cryptocurrencies and stocks in global markets. We provide evidence that Bitcoin trading volumes matter for the price correlation (Corollary 2) and that this effect is stronger for the stocks that crypto-oriented retail investors prefer (Corollary 3).

We select the 3000 most traded US stocks throughout the sample.[13] We group stocks in quintiles based on the relative weight of trading by crypto-oriented investors over trading on global markets. The first quintile contains the least traded stocks by crypto-oriented traders on the *Swissquote* platform, and the fifth quintile contains the most preferred.

We start by looking at the characteristics of the stocks. Table VIII shows the industry distribution of the stocks in each quintile. For each industry, we compute the total trading volume and normalize it by quintile. We observe that crypto-oriented retail investors prefer companies in tech and healthcare, while they tend to avoid utilities, real estate, and financial firms. This pattern is consistent with anecdotal evidence suggesting that cryptocurrency traders are more likely to be wary of traditional financial institutions and enthusiastic about new technologies.

[13] All the patterns shown in this Section remain when reducing the sample to 1000 stocks.

Table VIII

The table shows the industry distribution of the stocks. We sort the 3,000 most traded US stocks into five quintiles based on the trading volume of crypto-oriented investors on the *Swissquote* platform. The first (last) quintile contains the stocks with the least (most) trading volume. For each industry, we compute the total trading volume and normalize it by quintile. We show the average market cap in millions of USD.

	Q1	Q2	Q3	Q4	Q5
Industries:					
Technology	9.40%	12.80%	17.00%	13.50%	18.20%
Health Care	16.40%	24.00%	27.20%	29.20%	28.40%
Consumer Discretionary	11.90%	16.10%	12.60%	18.80%	17.20%
Basic Materials	5.40%	3.10%	4.20%	3.20%	5.40%
Telecommunications	2.90%	2.80%	3.70%	3.70%	2.90%
Consumer Staples	4.70%	5.10%	2.90%	4.40%	3.90%
Industrials	12.70%	12.20%	11.20%	11.90%	9.40%
Energy	9.20%	7.60%	6.00%	5.80%	6.10%
Financials	14.50%	8.90%	8.90%	5.40%	5.50%
Real Estate	8.70%	4.70%	3.90%	2.30%	2.50%
Utilities	4.20%	2.50%	2.40%	1.90%	0.50%
Av. market cap (M USD)	3 256	3 698	4 728	5 930	7 570
Av. price-to-book ratio	3.03	3.13	3.48	3.51	3.70

As suggested by Corollary 2 and Panel (b) of Figure 4, the retail investors' trading volume in cryptocurrencies plays a role in determining the cross-trading correlation. The strengthening of the correlation at the retail investor level, in turn, increases the correlation at the price level between Bitcoin and stocks (Proposition 1 and Table VII). The effect should be stronger for the stocks preferred by crypto retail investors because of Corollary 3.

For these reasons, we estimate the following regression for each quintile:

$$y_{i,t} = \beta_0 + \beta_1 Volume\_Bit_t + \beta_2 Vix_t + \beta_3 Mom_{i,t} + \beta_4 Ret_{i,t} + \beta_5 Volume_{i,t} + \gamma_i + \epsilon_{i,t}, \quad (16)$$

where the dependent variable $y_{i,t}$ is the correlation between the daily returns of stock i and Bitcoin during month t. $Volume\_Bit_t$ is the monthly trading volume of Bitcoin in the global market, obtained from Yahoo Finance. Vix_t is the VIX index. $Mom_{i,t}$ is the momentum, defined as the lagged monthly return of the stock i. $Ret_{i,t}$ is the monthly return of stock i

to control for retailers' tendency to buy stocks exhibiting extreme returns (see, e.g., Odean, 1999; Barber and Odean, 2008). $Volume_{i,t}$ is the monthly trading volume of stock i on the global market. γ_i is a set of stock fixed effects to control for stock-level heterogeneity. We cluster standard errors at the stock level. Table IX reports the estimates.

Table IX

The table shows the results of the estimation of regression (16). Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The first quintile contains the stocks with the least trading volume. The fifth quintile contains the stocks with the most trading volume. The dependent variable is the monthly correlation between stock and Bitcoin daily returns. $Volume\_Bit_t$ is the monthly trading volume of Bitcoin in the global market. Vix_t is the VIX index. $Mom_{i,t}$ is momentum of the stock, $Ret_{i,t}$ the monthly return, and $Volume_{i,t}$ its monthly global trading volume. Standard errors are clustered at the stock level.

Dep.: Corr	Q1	Q2	Q3	Q4	Q5
Volume_Bit	0.0070***	0.0122***	0.0109***	0.0126***	0.0145***
	(0.0018)	(0.0017)	(0.0017)	(0.0018)	(0.0018)
Vix	0.0197***	0.0223***	0.0228***	0.0228***	0.0207***
	(0.0016)	(0.0015)	(0.0014)	(0.0014)	(0.0015)
Mom	0.3836*	0.6365**	1.0788***	0.2068	0.3361***
	(0.2173)	(0.2570)	(0.3067)	(0.1830)	(0.1252)
Ret	-0.3378*	-0.6216***	-0.0191***	-0.4013***	-0.3322***
	(0.2050)	(0.1607)	(0.0009)	(0.1272)	(0.1254)
Volume	0.0209***	0.0230***	0.0243***	0.0276***	0.0319***
	(0.0037)	(0.0036)	(0.0036)	(0.0034)	(0.0035)
FE firm	YES	YES	YES	YES	YES
# Obs	23,112	24,581	24,385	24,947	23,504
Adj-R^2	0.0332	0.0331	0.0359	0.038	0.0398

Global volumes include activity by algorithms, hedge funds, specialized investors, and other actors. While it is correlated with the Bitcoin trading volume on the *Swissquote* platform, they are not the same. We argue that the volume on the *Swissquote* platform is a proxy only for the retail investors' volume. We estimate the following regression:

$$\begin{aligned} y_{i,t} = \beta_0 + \beta_1 Volume\_Bit_t + \beta_2 Volume\_Sq\_Bit_t + \beta_3 Vix_t + \\ + \beta_4 Mom_{i,t} + \beta_5 Ret_{i,t} + \beta_6 Volume_{i,t} + \gamma_i + \epsilon_{i,t}, \end{aligned} \tag{17}$$

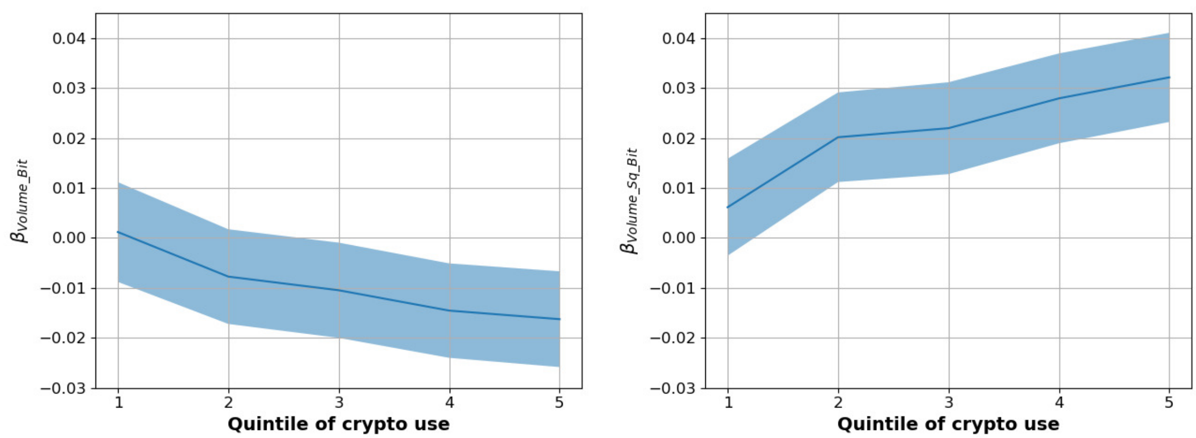
where everything is as in regression (16) with the addition of the variable $Volume\_Sq\_Bit_t$ that is the monthly trading volume in Bitcoin on the *Swissquote* platform. Including both the crypto-volumes in the regression does not pose multicollinearity problems. Table X shows the estimates.

Table X

The table shows the results of the estimation of regression (17). Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The first (last) quintile contains the stocks with the least (most) trading volume. The dependent variable is the monthly correlation between stock and Bitcoin daily returns. $Volume\_Bit_t$ is the monthly trading volume of Bitcoin in the global market. $Volume\_Sq\_Bit_t$ is the monthly trading volume in Bitcoin on the *Swissquote* platform. Vix_t is the VIX index. $Mom_{i,t}$ is momentum of the stock, $Ret_{i,t}$ the monthly return, and $Volume_{i,t}$ its monthly global trading volume. Standard errors are clustered at the stock level.

Dep.: Corr	Q1	Q2	Q3	Q4	Q5
Volume_Bit	0.0007	-0.0066	-0.0088*	-0.0142***	-0.0166***
	(0.0051)	(0.0047)	(0.0048)	(0.0048)	(0.0049)
Volume_Sq_Bit	0.0065	0.0195***	0.0205***	0.0279***	0.0324***
	(0.0049)	(0.0045)	(0.0046)	(0.0046)	(0.0046)
Vix	0.0202***	0.0238***	0.0244***	0.0249***	0.0232***
	(0.0016)	(0.0016)	(0.0015)	(0.0014)	(0.0015)
Mom	0.3858*	0.6400**	1.0939***	0.2110	0.3406***
	(0.2179)	(0.2580)	(0.3109)	(0.1859)	(0.1254)
Ret	-0.3399*	-0.6224***	-0.0193***	-0.3995***	-0.3359***
	(0.2056)	(0.1612)	(0.0009)	(0.1272)	(0.1255)
Volume	0.0210***	0.0233***	0.0246***	0.0283***	0.0327***
	(0.0038)	(0.0036)	(0.0036)	(0.0034)	(0.0036)
FE firm	YES	YES	YES	YES	YES
# Obs	23,112	24,581	24,385	24,947	23,504
Adj-R^2	0.0332	0.0336	0.0364	0.0389	0.0411

In both Table IX and Table X, we observe that the correlation between stock and Bitcoin prices is positively associated with market volatility, momentum, and overall trading volume, while it is negatively related to returns. These effects are relatively stable across quintiles and specifications. The trading volume coefficients always exhibit the same sign but different magnitude across quintiles. The retail trading volume is always positively associated with the macro correlation between prices, according to Corollary 2. Nevertheless, we observe that the stocks preferred by cryptocurrency traders (Q5) correlate more with Bitcoin when retail trading volumes on Bitcoin are high. The magnitude of the coefficients grows monotonically across quintiles, consistent with Corollary 3. Finally, we notice that the overall Bitcoin trading volume coefficients pass from positive in Table IX to negative in Table X. These results highlight retail investors' volume's role in increasing the correlation between Bitcoin and stock prices.



(a) Total

(b) Retail

Figure 6. The figures show the coefficients of the total Bitcoin trading volume and the Swissquote platform Bitcoin trading volume from regression (17) for each quintile. The dependent variable is the monthly correlation of daily returns between stocks and Bitcoin.

Figure 6 shows the coefficients from Table X obtained estimating regression (17). These results support Corollaries 2 and 3 of the model presented in Section III. The stocks preferred by crypto-traders exhibit a higher correlation with Bitcoin, especially when Bitcoin volumes are high. Intuitively, the channel that we highlight in the model only works when there is cross-asset trading by retail investors. The fact that this mechanism is associated with the retail trading activity in the Bitcoin market and not the total Bitcoin trading further corroborates our thesis. Retail traders are the drivers of the correlation between cryptocurrencies and equities.

For robustness, we estimate the results in Table IX and X without fixed effects, and the results in Table X including only the *Swissquote* volume. The estimates are in Appendix E.

VII. Market Integration

This Section explores the theoretical consequences of integrating cryptocurrencies into mainstream financial institutions. Our model predictions are based on the hypothesis of market segmentation, but this will not necessarily be always the case in the future. We consider the same set-up as in Section III and relax the assumption of segregated market makers, thus allowing the same market maker to operate in both markets. The market maker observes the total order flows for the two risky assets $Y = X + U$ and competitively sets the prices:

$$P = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} \mathbb{E}\left[v_1 \mid y_1, y_2\right] \\ \mathbb{E}\left[v_2 \mid y_1, y_2\right] \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}. \tag{18}$$

The parameters λ_{ij} are the slope coefficients in the linear regression of v_i on y_j:

$$\lambda_{11} = \frac{\mathrm{Cov}(v_1, y_1)\mathrm{Var}(y_2) - \mathrm{Cov}(v_1, y_2)\mathrm{Cov}(y_1, y_2)}{\mathrm{Var}(y_1)\mathrm{Var}(y_2) - \left(\mathrm{Cov}(y_1, y_2)\right)^2}, \tag{19}$$

$$\lambda_{12} = \frac{\mathrm{Cov}(v_1, y_2)\mathrm{Var}(y_1) - \mathrm{Cov}(v_1, y_1)\mathrm{Cov}(y_1, y_2)}{\mathrm{Var}(y_1)\mathrm{Var}(y_2) - \left(\mathrm{Cov}(y_1, y_2)\right)^2}, \tag{20}$$

$$\lambda_{21} = \frac{\mathrm{Cov}(v_2, y_1)\mathrm{Var}(y_2) - \mathrm{Cov}(v_2, y_2)\mathrm{Cov}(y_1, y_2)}{\mathrm{Var}(y_1)\mathrm{Var}(y_2) - \left(\mathrm{Cov}(y_1, y_2)\right)^2}, \tag{21}$$

$$\lambda_{22} = \frac{\mathrm{Cov}(v_2, y_2)\mathrm{Var}(y_1) - \mathrm{Cov}(v_2, y_1)\mathrm{Cov}(y_1, y_2)}{\mathrm{Var}(y_1)\mathrm{Var}(y_2) - \left(\mathrm{Cov}(y_1, y_2)\right)^2}. \tag{22}$$

We define the sequential equilibrium as in Section III. The informed traders' market order at equilibrium is:

$$X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \sqrt[4]{1-\rho^2}\ \frac{\sigma_u}{\sigma_1}\left(v_1 - \mu_1\right) \\ \sqrt[4]{1-\rho^2}\ \frac{\sigma_u}{\sigma_2}\left(v_2 - \mu_2\right) \end{bmatrix}, \tag{23}$$

while the market maker's equilibrium price function is:

$$P = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \frac{\sqrt[4]{1-\rho^2}}{1-\rho^2+\sqrt{1-\rho^2}} \begin{bmatrix} (1+\sqrt{1-\rho^2})\frac{\sigma_1}{2\sigma_u} & -\rho\frac{\sigma_1}{2\sigma_u} \\ -\rho\frac{\sigma_2}{2\sigma_u} & (1+\sqrt{1-\rho^2})\frac{\sigma_2}{2\sigma_u} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}. \tag{24}$$

We can rewrite the prices as:

$$p_1 = \mu_1 + \frac{\sqrt[4]{1-\rho^2}}{1-\rho^2+\sqrt{1-\rho^2}}\Big((1+\sqrt{1-\rho^2})y_1 - \rho\, y_2\Big)\frac{\sigma_1}{2\sigma_u}, \tag{25}$$

$$p_2 = \mu_2 + \frac{\sqrt[4]{1-\rho^2}}{1-\rho^2+\sqrt{1-\rho^2}}\Big((1+\sqrt{1-\rho^2})y_2 - \rho\, y_1\Big)\frac{\sigma_2}{2\sigma_u}. \tag{26}$$

PROPOSITION 2: *The covariance between the two equilibrium prices when the markets are integrated is negative if and only if the correlation of the uninformed investors' trading is positive:*

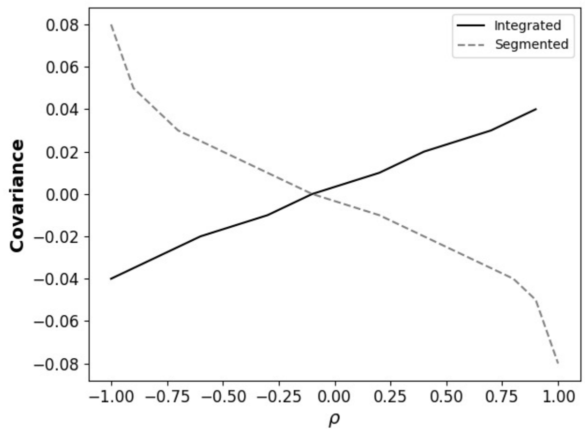
$$\mathrm{Cov}(p_1, p_2) < 0 \qquad \Longleftrightarrow \qquad \rho > 0. \tag{27}$$

Proof. Combining the equilibrium prices in equation (24) with the equilibrium orders of informed investors in equation (23), and applying the distributions of the fundamental values in equation (1) and the uninformed investors' trading flows in equation (3), we obtain the following covariance between prices:

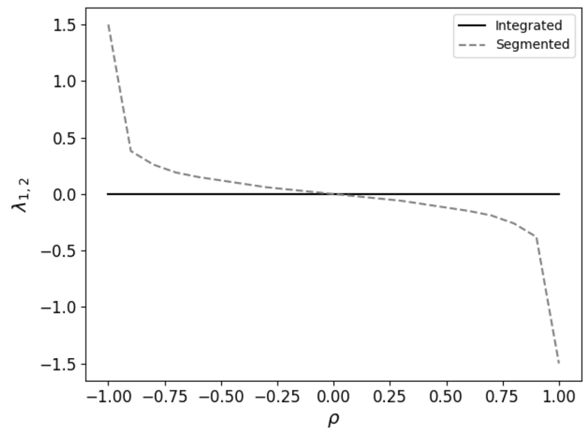
$$\mathrm{Cov}(p_1, p_2) = -\rho\,\frac{\sqrt{1-\rho^2}}{1-\rho^2+\sqrt{1-\rho^2}}\,\frac{\sigma_1\sigma_2}{2}. \tag{28}$$

Therefore the covariance is negative for positive values of ρ. □

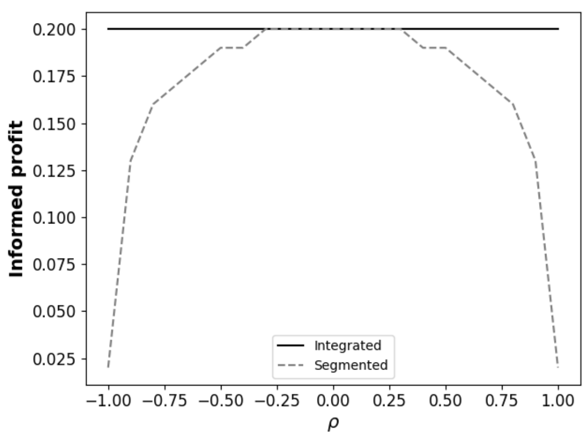
If markets become fully integrated, our model predicts that the correlation between cryptocurrencies and equities should become negative. The driving force behind this mechanism is the additional information received by the market maker that allows him to better identify the informed investor's activity. To fully grasp the intuition, one can consider the extreme case where $\rho = 1$. In this case, any difference between y_1 and y_2 is necessarily due to the activity of the informed investor, leading the market maker to adjust the prices accordingly. In this extreme scenario, the informed investors can not hide behind the uninformed investors' and halt trading altogether (see Appendix B). Outside this extreme scenario, the higher the correlation between uninformed investor's trading flows, the more the market maker will infer that any difference between y_1 and y_2 is due to the informed investors' activity. The obvious reaction is to adjust the price of the asset with the highest demand upward and the other downwards, assuming that the informed investor is long on the first and short (or less long) on the second. Figure 9 shows how the correlation between the two assets changes with ρ for both segmented and integrated market. The negative correlation is driven $\lambda_{1,2}$ (and $\lambda_{2,1}$), because the higher the order flow on asset 2 (1), the less likely an informed investor is long on asset 1 (2). Also, the further ρ is from zero, the more the market maker is able to exploit the second data-point, the less the informed investor profits from her information. Conversely, uninformed investor's losses are decreasing with correlation, as they mirror informed investors' profit. In the model, market makers make zero profits on average, and the profit pocketed by informed investors comes from uninformed investors.



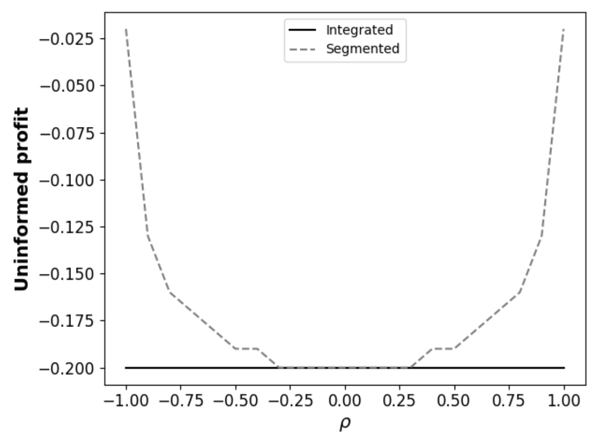
(a) Covariance between p_1 and p_2



(b) Price impact of y_2 on p_1



(c) Informed investor's profit



(d) Uninformed investor's profit

Figure 7. The figures show the relationship between the model's main metrics and ρ,i.e., the correlation between uninformed trading flows on asset 1 and 2.

As an illustrative example, consider a city where the municipality needs to build a new junkyard. The city only has two districts, District 1 and District 2, and there are two types of households: those who already know the municipality's decision and those who do not. Realtors do not know the decision in advance but are aware that certain households do. The demand for houses is positive in both districts, but the demand in District 1 is much higher than in District 2. If there are two separate realtors, each one observing only their district, they will both increase prices because they both see a positive demand and infer that the junkyard will go to the other district. Instead, if a single realtor is observing both districts, she will increase the price in District 1 and reduce it in District 2. Even if the demand in District 2 is positive, she infers that informed households are likely selling in District 2 and buying in District 1. In this scenario, realtor market integration leads to a negative price correlation between District 1 and District 2, while market segmentation leads to a positive correlation.

This insight suggests that if cryptocurrencies become more integrated into the mainstream financial market, the positive price correlation might disappear or even become negative, as market makers can better tell informed and uninformed trading flows apart. In this scenario, crypto assets could become a diversification tool. It is worth noting that while our model is non-crypto-specific, this mechanism is magnified by the absence of an obvious fundamental value. Correlated fundamental values would make additional information coming from the second asset less valuable.

VIII. Conclusion

The fast rise of cryptocurrencies from an obscure technology to a multi-trillion dollar market has been followed by rapid legitimization: cryptocurrencies are often included in the portfolios of long-established hedge funds, well-known investors, and households' 401(K)s. Yet, we do not have a full understanding of the economic mechanisms driving this new asset class.

In this paper, we focus on the recent persistent positive correlation between cryptocurrencies and equities and propose a possible explanation. We show theoretically that uninformed trading flows can generate a correlation in prices in the absence of a clear relationship between the fundamental values. We use a proprietary dataset containing the portfolio choices and transactions of Swiss retail investors on traditional assets and cryptocurrencies. With it, we show that the retail investors' trading habits can explain this recent shift in correlation between the two assets.

Our findings are relevant for academics and practitioners alike. We highlight a novel economic mechanism where correlation in uninformed trading and a lack of market integration can introduce a correlation between two unrelated assets. This is an important piece of information for anybody considering the introduction of cryptocurrency into their portfolio. For instance, the impact of retail investors is more likely to be larger in times of market euphoria or generalized panic when they are more active. Risk managers should consider this information and be ready for the correlation to spike during extreme market movements.

Finally, our findings speak to the policymaker community evaluating potential systemic risks stemming from cryptocurrency markets. Indeed, we highlight a channel that could lead to contagion mechanisms, with retail investors acting as a power transmission chain between the two markets.

REFERENCES

Astebro, Thomas, José Mata, and Luís Santos-Pinto, 2009, Preference for skew in lotteries: Evidence from the laboratory, HEC Paris.

Baker, Andrew C, David F Larcker, and Charles CY Wang, 2022, How much should we trust staggered difference-in-differences estimates?, *Journal of Financial Economics* 144, 370–395.

Balasubramaniam, Vimal, John Y Campbell, Tarun Ramadorai, and Benjamin Ranish, 2021, Who owns what? A factor model for direct stock holding, Technical report, National Bureau of Economic Research.

Barber, Brad M, and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *The Journal of Finance* 55, 773–806.

Barber, Brad M, and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *The Review of Financial Studies* 21, 785–818.

Barber, Brad M, and Terrance Odean, 2013, The behavior of individual investors, in *Handbook of the Economics of Finance*, volume 2, 1533–1570 (Elsevier).

Bhambhwani, Siddharth, Stefanos Delikouras, and George M Korniotis, 2021, Blockchain characteristics and the cross-section of cryptocurrency returns, Available at SSRN 3342842.

Biais, Bruno, Christophe Bisiere, Matthieu Bouvard, and Catherine Casamatta, 2019, The blockchain folk theorem, *The Review of Financial Studies* 32, 1662–1715.

Biais, Bruno, Christophe Bisiere, Matthieu Bouvard, Catherine Casamatta, and Albert J Menkveld, 2022, Equilibrium bitcoin pricing, *Journal of Finance, forthcoming* .

Brunnermeier, Markus K, Christian Gollier, and Jonathan A Parker, 2007, Optimal beliefs, asset prices, and the preference for skewed returns, *American Economic Review* 97, 159–165.

Brunnermeier, Markus K, Harold James, and Jean-Pierre Landau, 2019, The digitalization of money, Technical report, National Bureau of Economic Research.

Brunnermeier, Markus K, and Jonathan A Parker, 2005, Optimal expectations, *American Economic Review* 95, 1092–1118.

Callaway, Brantly, and Pedro HC Sant'Anna, 2021, Difference-in-differences with multiple time periods, *Journal of Econometrics* 225, 200–230.

Cong, Lin William, Zhiguo He, and Jiasun Li, 2021a, Decentralized mining in centralized pools, *The Review of Financial Studies* 34, 1191–1235.

Cong, Lin William, Ye Li, and Neng Wang, 2021b, Tokenomics: Dynamic adoption and valuation, *The Review of Financial Studies* 34, 1105–1155.

Curcuru, Stephanie, John Heaton, Deborah Lucas, and Damien Moore, 2010, Heterogeneity and portfolio choice: Theory and evidence, in *Handbook of financial econometrics: Tools and techniques*, 337–382 (Elsevier).

Divakaruni, Anantha, Peter Zimmerman, et al., 2021, Uncovering retail trading in bitcoin: The impact of covid-19 stimulus checks, Technical report, Federal Reserve Bank of Cleveland.

Dorn, Daniel, and Gur Huberman, 2010, Preferred risk habitat of individual investors, *Journal of Financial Economics* 97, 155–173.

Easley, David, Maureen O'Hara, and Soumya Basu, 2019, From mining to markets: The evolution of bitcoin transaction fees, *Journal of Financial Economics* 134, 91–109.

Fagereng, Andreas, Luigi Guiso, and Luigi Pistaferri, 2018, Portfolio choices, firm shocks, and uninsurable wage risk, *The Review of Economic Studies* 85, 437–474.

Foley, Sean, Jonathan R Karlsen, and Tālis J Putniņš, 2019, Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies?, *The Review of Financial Studies* 32, 1798–1853.

Gandal, Neil, JT Hamrick, Tyler Moore, and Tali Oberman, 2018, Price manipulation in the bitcoin ecosystem, *Journal of Monetary Economics* 95, 86–96.

Garcia del Molino, Luis Carlos, Iacopo Mastromatteo, Michael Benzaquen, and Jean-Philippe Bouchaud, 2020, The multivariate kyle model: More is different, *SIAM Journal on Financial Mathematics* 11, 327–357.

Goetzmann, William N, and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

Goodman-Bacon, Andrew, 2021, Difference-in-differences with variation in treatment timing, *Journal of Econometrics* 225, 254–277.

Greenwood, Robin, Toomas Laarits, and Jeffrey Wurgler, 2022, Stock market stimulus, Technical report, National Bureau of Economic Research.

Haber, Stuart, and W Scott Stornetta, 1990, How to time-stamp a digital document, in *Conference on the Theory and Application of Cryptography*, 437–455, Springer.

Hackethal, Andreas, Tobin Hanspal, Dominique M Lammer, and Kevin Rink, 2022, The characteristics and portfolio behavior of bitcoin investors: Evidence from indirect cryptocurrency investments, *Review of Finance* 26, 855–898.

Härdle, Wolfgang Karl, Campbell R Harvey, and Raphael CG Reule, 2020, Understanding cryptocurrencies, *Journal of Financial Econometrics* 18, 181–208.

Howell, Sabrina T, Marina Niessner, and David Yermack, 2020, Initial coin offerings: Financing growth with cryptocurrency token sales, *The Review of Financial Studies* 33, 3925–3974.

Huberman, Gur, Jacob D Leshno, and Ciamac Moallemi, 2021, Monopoly without a monopolist: An economic analysis of the bitcoin payment system, *The Review of Economic Studies* 88, 3011–3040.

John, Kose, Thomas J Rivera, and Fahad Saleh, 2020, Economic implications of scaling blockchains: Why the consensus protocol matters, Available at SSRN.

Kyle, Albert S, 1985, Continuous auctions and insider trading, *Econometrica: Journal of the Econometric Society* 1315–1335.

Kyle, Albert S, 1989, Informed speculation with imperfect competition, *The Review of Economic Studies* 56, 317–355.

Liu, Yukun, and Aleh Tsyvinski, 2021, Risks and returns of cryptocurrency, *The Review of Financial Studies* 34, 2689–2727.

Liu, Yukun, Aleh Tsyvinski, and Xi Wu, 2019, Common risk factors in cryptocurrency, Technical report, National Bureau of Economic Research.

Makarov, Igor, and Antoinette Schoar, 2020, Trading and arbitrage in cryptocurrency markets, *Journal of Financial Economics* 135, 293–319.

Merton, Robert C, 1973, An intertemporal capital asset pricing model, *Econometrica: Journal of the Econometric Society* 867–887.

Mitton, Todd, and Keith Vorkink, 2007, Equilibrium underdiversification and the preference for skewness, *The Review of Financial Studies* 20, 1255–1288.

Nakamoto, Satoshi, 2008, A peer-to-peer electronic cash system, *Bitcoin.–URL: https://bitcoin. org/bitcoin. pdf* 4.

Odean, Terrance, 1999, Do investors trade too much?, *American Economic Review* 89, 1279–1298.

Ozik, Gideon, Ronnie Sadka, and Siyi Shen, 2021, Flattening the illiquidity curve: Retail trading during the covid-19 lockdown, *Journal of Financial and Quantitative Analysis* 56, 2356–2388.

Pagnotta, Emiliano, 2020, Decentralizing money: Bitcoin prices and blockchain security, *Review of Financial Studies (forthcoming)* .

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Saleh, Fahad, 2021, Blockchain without waste: Proof-of-stake, *The Review of Financial Studies* 34, 1156–1190.

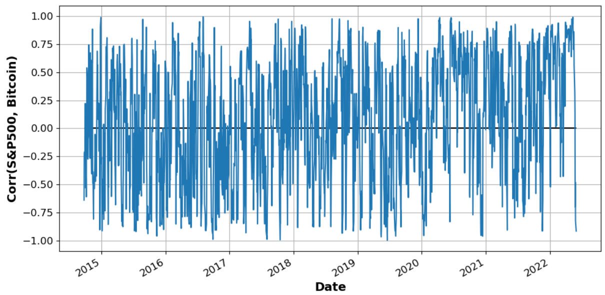
Schilling, Linda, and Harald Uhlig, 2019, Some simple bitcoin economics, *Journal of Monetary Economics* 106, 16–26.

Sicherman, Nachum, George Loewenstein, Duane J Seppi, and Stephen P Utkus, 2016, Financial attention, *The Review of Financial Studies* 29, 863–897.

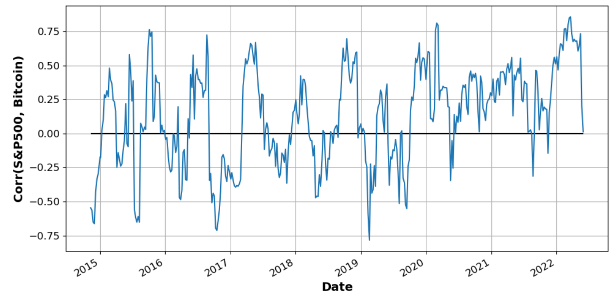
van der Beck, Philippe, and Coralie Jaunin, 2021, The equity market implications of the retail investment boom, Available at SSRN 3776421.

Vayanos, Dimitri, 2001, Strategic trading in a dynamic noisy market, *The Journal of Finance* 56, 131–171.

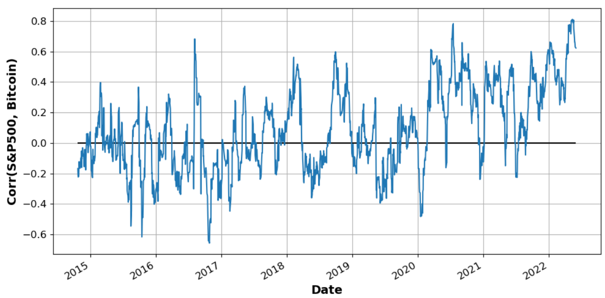
Appendix A. March 2020



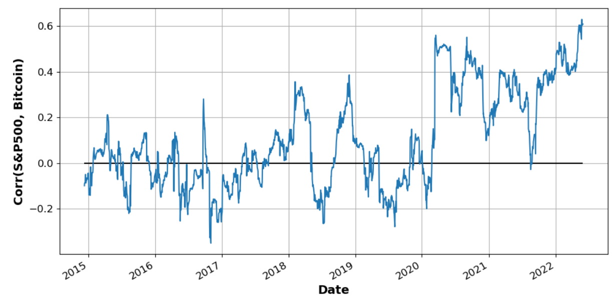
(a) 5



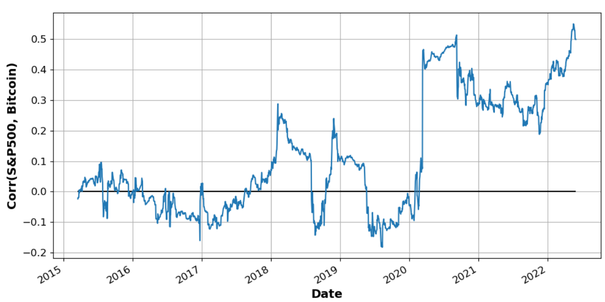
(b) 10



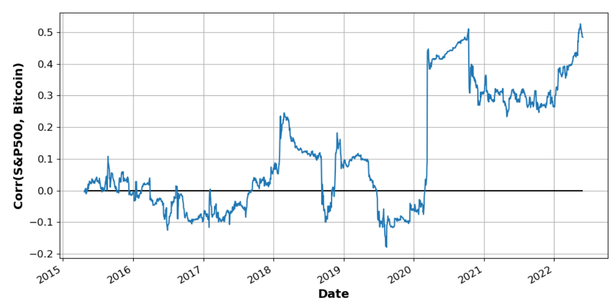
(c) 25



(d) 60



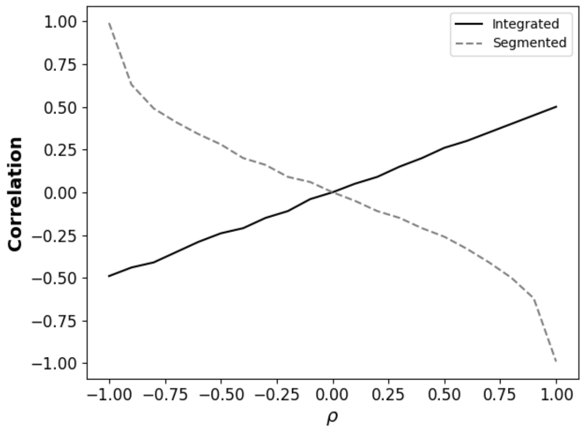
(e) 120



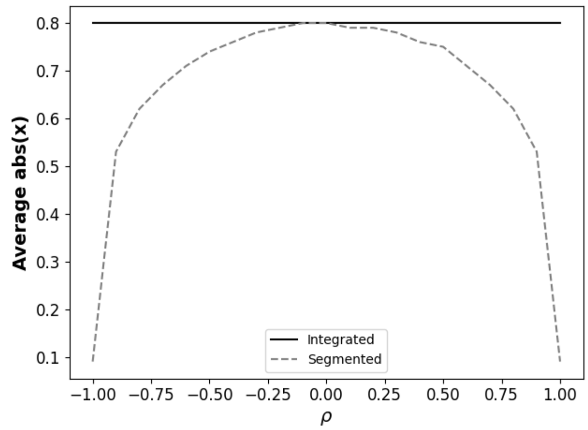
(f) 150

Figure 8. These figures show the correlation between the returns of the S&P500 index and Bitcoin computed with different rolling windows. The labels indicate the number of trading days included in the rolling window.

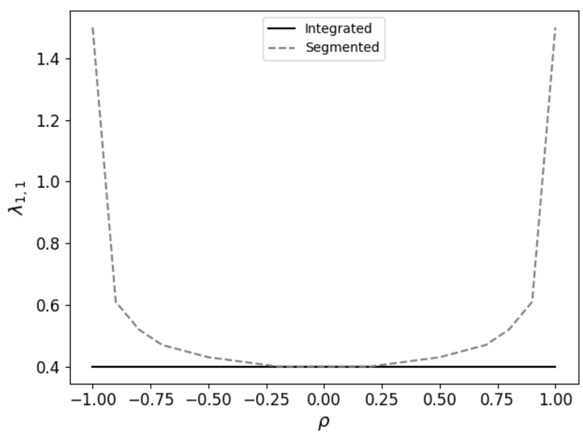
Appendix B. Additional Model Figures



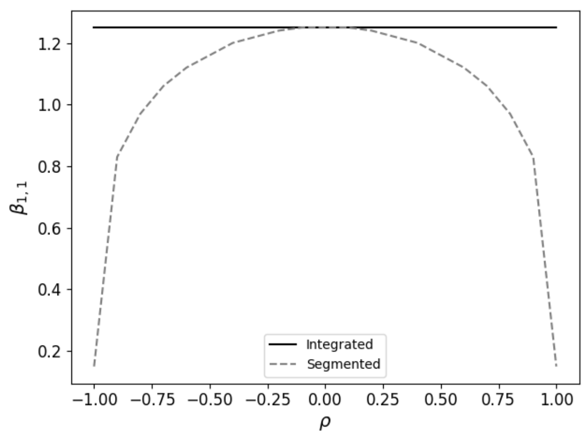
(a) Correlation between p_1 and p_2



(b) Informed investor's average order, in absolute value.



(c) Price impact of y_1 on p_1.



(d) Informed investor's trade aggressiveness.

Figure 9. The figures show the relationship between the model's main metrics and ρ, i.e., the correlation between uninformed trading flows on asset 1 and 2.

Appendix C. Callaway Sant'Anna Estimator

Table XI

The table presents the main results from Section V.A computed with a Callaway Sant'Anna estimator (Callaway and Sant'Anna, 2021). The dependent variables are: the annualized monthly return and Sharpe ratio of the overall portfolio in columns (1) and (2) respectively, the annualized monthly return and Sharpe ratio of the equities-only portfolio in columns (3) and (4) respectively, the monthly turnover of the stock portfolio in column (5), the percentage of short-term trades in column (6). The turnover of the stock portfolio is computed as the total trading volume divided by the average stock holdings. The short-term trades are defined as those trades for which we observe a transaction with the opposite sign on the same security within a month for at least 50% of the original position. $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t holds cryptocurrencies.

	(1)	(2)	(3)	(4)	(5)	(6)
Crypto_User	0.0556**	-0.1241**	0.0438**	0.0535**	-0.1543**	-0.0101**
	(0.0154)	(0.0656)	(0.0151)	(0.0148)	(0.0662)	(0.0042)
Bank Assets	YES	YES	YES	YES	YES	YES
FE investor	YES	YES	YES	YES	YES	YES
FE time	YES	YES	YES	YES	YES	YES
# Obs	2,695,478	2,695,478	2,695,478	2,695,478	2,695,478	2,695,478

Appendix D. Ex-Crypto Portfolio Weights

Table XII

The table shows the results of estimating regression (13). The dependent variable is the weight of cash in the non-crypto part of an investor's portfolio, i.e. the total assets held at Swissquote excluding cryptocurrencies. *Crypto* is the cryptocurrencies' weight in the overall portfolio. Standard errors are clustered at the investor level.

	(1)	(2)	(3)	(4)
crypto	0.5126***	0.5183***	0.2151***	0.2959***
	(0.001)	(0.001)	(0.0011)	(0.0027)
Constant	YES	NO	NO	NO
Time FE	NO	YES	NO	YES
Client FE	NO	NO	YES	YES
Observations	1,244,148	1,244,148	1,244,148	1,244,148
R^2	0.1893	0.1912	0.7128	0.7107

Table XIII

The table shows the results of estimating regression (13). The dependent variable is the weight of index funds in the non-crypto part of an investor's portfolio, i.e. the total assets held at Swissquote excluding cryptocurrencies. *Crypto* is the cryptocurrencies' weight in the overall portfolio. Standard errors are clustered at the investor level.

	(1)	(2)	(3)	(4)
crypto	-0.0692***	-0.071***	-0.0225***	-0.0291***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Constant	YES	NO	NO	NO
Time FE	NO	YES	NO	YES
Client FE	NO	NO	YES	YES
Observations	1,244,148	1,244,148	1,244,148	1,244,148
R^2	0.0204	0.0207	0.7462	0.7462

Table XIV

The table shows the results of estimating regression (13). The dependent variable is the weight of structured products in the non-crypto part of an investor's portfolio, i.e. the total assets held at Swissquote excluding cryptocurrencies. *Crypto* is the cryptocurrencies' weight in the overall portfolio. Standard errors are clustered at the investor level.

	(1)	(2)	(3)	(4)
crypto	-0.0425***	-0.0459***	-0.0384***	-0.0476***
	(0.0004)	(0.0004)	(0.0005)	(0.0006)
Constant	YES	NO	NO	NO
Time FE	NO	YES	NO	YES
Client FE	NO	NO	YES	YES
Observations	1,244,148	1,244,148	1,244,148	1,244,148
R^2	0.0089	0.0119	0.5387	0.542

Appendix E. Robustness Checks

Table XV

The table shows the results of the estimation of regression (16) with no fixed effects. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The first (last) quintile contains the stocks with the least (most) trading volume. The dependent variable is the monthly correlation between stock and Bitcoin daily returns. $Volume\_Bit_t$ is the monthly trading volume of Bitcoin in the global market. Vix_t is the VIX index. $Mom_{i,t}$ is momentum of the stock, $Ret_{i,t}$ the monthly return, and $Volume_{i,t}$ its monthly global trading volume. Standard errors are clustered at the stock level.

Dep.: Corr	Q1	Q2	Q3	Q4	Q5
Volume_Bit	0.0070***	0.0122***	0.0109***	0.0126***	0.0145***
	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0020)
Vix	0.0197***	0.0223***	0.0228***	0.0228***	0.0207***
	(0.0018)	(0.0017)	(0.0017)	(0.0017)	(0.0018)
Mom	0.3836***	0.6365***	1.0788***	0.2068***	0.3361***
	(0.0808)	(0.0790)	(0.1464)	(0.0736)	(0.0735)
Ret	-0.3378***	-0.6216***	-0.0191**	-0.4013***	-0.3322***
	(0.0776)	(0.0732)	(0.0089)	(0.1286)	(0.0737)
Volume	0.0209***	0.0230***	0.0243***	0.0276***	0.0319***
	(0.0031)	(0.0029)	(0.0029)	(0.0030)	(0.0030)
FE firm	NO	NO	NO	NO	NO
# Obs	23,112	24,581	24,385	24,947	23,504
Adj-R^2	0.0332	0.0331	0.0359	0.038	0.0398

Table XVI

The table shows the results of the estimation of regression (17) with no fixed effects. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The first (last) quintile contains the stocks with the least (most) trading volume. The dependent variable is the monthly correlation between stock and Bitcoin daily returns. $Volume\_Bit_t$ is the monthly trading volume of Bitcoin in the global market. $Volume\_Sq\_Bit_t$ is the monthly trading volume in Bitcoin on the *Swissquote* platform. Vix_t is the VIX index. $Mom_{i,t}$ is momentum of the stock, $Ret_{i,t}$ the monthly return, and $Volume_{i,t}$ its monthly global trading volume. Standard errors are clustered at the stock level.

Dep.: Corr	Q1	Q2	Q3	Q4	Q5
Vol_Bit	0.0007	-0.0066	-0.0088	-0.0142**	-0.0166***
	(0.0058)	(0.0056)	(0.0057)	(0.0056)	(0.0058)
Volume_Sq_Bit	0.0065	0.0195***	0.0205***	0.0279***	0.0324***
	(0.0057)	(0.0055)	(0.0056)	(0.0055)	(0.0057)
Vix	0.0202***	0.0238***	0.0244***	0.0249***	0.0232***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Mom	0.3858***	0.6400***	1.0939***	0.2110***	0.3406***
	(0.0808)	(0.0790)	(0.1465)	(0.0736)	(0.0734)
Ret	-0.3399***	-0.6224***	-0.0193**	-0.3995***	-0.3359***
	(0.0776)	(0.0731)	(0.0089)	(0.1286)	(0.0736)
Volume	0.0210***	0.0233***	0.0246***	0.0283***	0.0327***
	(0.0031)	(0.0029)	(0.0029)	(0.0030)	(0.0030)
FE firm	NO	NO	NO	NO	NO
# Obs	23,112	24,581	24,385	24,947	23,504
Adj-R^2	0.0332	0.0336	0.0364	0.0389	0.0411

Table XVII

The table shows the results of the estimation of regression (17) with no overall trading volume and no fixed effects. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The first (last) quintile contains the stocks with the least (most) trading volume. The dependent variable is the monthly correlation between stock and Bitcoin daily returns. $Volume\_Sq\_Bit_t$ is the monthly trading volume in Bitcoin on the *Swissquote* platform. Vix_t is the VIX index. $Mom_{i,t}$ is momentum of the stock, $Ret_{i,t}$ the monthly return, and $Volume_{i,t}$ its monthly global trading volume. Standard errors are clustered at the stock level.

Dep.: Corr	Q1	Q2	Q3	Q4	Q5
Volume_Sq_Bit	0.0072***	0.0135***	0.0124***	0.0148***	0.0171***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Vix	0.0203***	0.0233***	0.0238***	0.0239***	0.0221***
	(0.0018)	(0.0017)	(0.0017)	(0.0017)	(0.0018)
Mom	0.3858***	0.6407***	1.0913***	0.2110***	0.3405***
	(0.0808)	(0.0790)	(0.1464)	(0.0736)	(0.0734)
Ret	-0.3399***	-0.6237***	-0.0192**	-0.4034***	-0.3361***
	(0.0776)	(0.0731)	(0.0089)	(0.1286)	(0.0736)
Volume	0.0210***	0.0230***	0.0242***	0.0274***	0.0317***
	(0.0031)	(0.0029)	(0.0029)	(0.0029)	(0.0030)
FE firm	NO	NO	NO	NO	NO
# Obs	23,112	24,581	24,385	24,947	23,504
Adj-R^2	0.0332	0.0336	0.0363	0.0387	0.0408

Table XVIII

The table shows the results of the estimation of regression (17) with no overall trading volume. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The first (last) quintile contains the stocks with the least (most) trading volume. The dependent variable is the monthly correlation between stock and Bitcoin daily returns. $Volume\_Sq\_Bit_t$ is the monthly trading volume in Bitcoin on the *Swissquote* platform. Vix_t is the VIX index. $Mom_{i,t}$ is momentum of the stock, $Ret_{i,t}$ the monthly return, and $Volume_{i,t}$ its monthly global trading volume. Standard errors are clustered at the stock level.

Dep.: Corr	Q1	Q2	Q3	Q4	Q5
Volume_Sq_Bit	0.0072***	0.0135***	0.0124***	0.0148***	0.0171***
	(0.0018)	(0.0016)	(0.0017)	(0.0017)	(0.0017)
Vix	0.0203***	0.0233***	0.0238***	0.0239***	0.0221***
	(0.0016)	(0.0015)	(0.0014)	(0.0014)	(0.0015)
Mom	0.3858*	0.6407**	1.0913***	0.2110	0.3405***
	(0.2179)	(0.2582)	(0.3100)	(0.1855)	(0.1256)
Ret	-0.3399*	-0.6237***	-0.0192***	-0.4034***	-0.3361***
	(0.2056)	(0.1613)	(0.0009)	(0.1275)	(0.1257)
Volume	0.0210***	0.0230***	0.0242***	0.0274***	0.0317***
	(0.0037)	(0.0036)	(0.0036)	(0.0034)	(0.0035)
FE firm	YES	YES	YES	YES	YES
# Obs	23,112	24,581	24,385	24,947	23,504
Adj-R^2	0.0332	0.0336	0.0363	0.0387	0.0408