The End of the Crypto-Diversification Myth*†

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Abstract

We propose a mechanism explaining the recent high positive correlation between cryptocurrencies and the stock market. With a unique dataset of investor-level holdings from a bank offering trading accounts and cryptocurrency wallets, we show that retail investors' net trading volumes of stocks and cryptocurrencies are positively correlated. Theoretically, this micro-level pattern translates into a cross-asset class correlation as long as the two markets are not fully integrated. We provide suggestive evidence showing that this micro-level pattern emerged in March 2020 and that stocks preferred by crypto-traders exhibit a stronger correlation with Bitcoin, especially when the cross-asset retail volume is high.

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I. Introduction

Despite extreme volatility and occasional crashes, large pension providers have recently 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 the inclusion of cryptocurrencies into long-horizon portfolios is the promise of diversification from the stock market. 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, since 2020, the correlation between Bitcoin and the S&P500 has been consistently positive, reaching values as high as 60%.[2]

In this paper, we argue theoretically and empirically that this correlation is largely caused by the trading habits of retail investors. Namely, the fact that crypto-oriented retail investors tend to trade cryptocurrencies and stocks at the same time and in the same direction.

To show this mechanism, we rely on data from *Swissquote*, the leading Swiss platform for online trading. Crypto-friendly Swiss regulation allows *Swissquote* to be one of the few banks worldwide offering both brokerage accounts on traditional securities and cryptocurrency wallets. Thanks to this peculiarity, our database contains: i) 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 ii) crypto-wallets and transactions of 16,483 clients.[3] This setting allows us to observe transactions in cryptocurrencies, not in a vacuum but as part of the retail investors' overall portfolio decisions.[4]

We show that retail investors do engage in cross-asset buying and selling sprees and that this behavior became prominent in early 2020. While identifying this change's causes is outside of the scope of this paper, our data sheds some light on the phenomenon. Indeed, looking at the stocks favored by agents who hold cryptocurrencies, we observe a strong preference for growth stocks and speculative assets. When agents open a cryptocurrency wallet, their overall portfolio becomes riskier, with higher annualized returns which comes at the expense of volatility aggregating into a significantly lower Sharpe Ratio (-10.23%, annualized). Taken together, these results suggest that this recent trading pattern is, at least

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

[2] Daily correlation over a 3 months rolling window. Source: authors calculations using Yahoo Finance data.

[3] Note that this is a representative random subsample of the *Swissquote* customer base.

[4] The *Swissquote* clients exhibit a strong preference for the US stock market, which makes them relevant for the purpose of our study.

in part, explained by the rise of a new breed of crypto-enthusiasts. Unlike early adopters, fans of the technology and its long-term theoretical benefits for society, this new group of traders seems to perceive cryptocurrencies as some kind of tech-stock, well suited for short-term speculation. Given that this regime change coincides with the COVID19 crisis, a possible explanation could be that these new crypto-traders emerged as a consequence of the liquidity shock caused by lockdown policies and state support in the form of partial unemployment benefits (Switzerland/US) and/or COVID19-relief checks (US).

We further defend this new-breed interpretation by looking at the changes in trading habits following the inclusion of cryptocurrencies into retail portfolios. We note that the clients' opening of a cryptocurrency wallet coincides with a growth in attention and activity measured by the number of logins to the *Swissquote* platform and trading volume. In addition, we show that while overall volume increases, a substitution of attention between stocks and cryptocurrencies does exist. The agent's speculative trades on stocks, defined as transactions that are at least half reverted within a month, also diminishes.

We show that these micro-level patterns can cause cross-asset correlation with the help of a simple two-assets extension of the canonical Kyle model (Kyle, 1989), which relies on one key assumption supported by our empirical evidence: while two assets have uncorrelated fundamental values, they have correlated uninformed trading volumes.[5] We extract from the model three testable implications: i) there was a regime change in the cross-asset retail investors' trading habits, coinciding with the change in correlation we observe between cryptocurrencies and the stock market, i.e., in Spring 2020., ii) the correlation between stocks and cryptocurrencies should be stronger when the cross-market uninformed volume from retail investors is large, and iii) this relationship should be stronger for stocks which are preferred by crypto-oriented retail investors.

We test these implications using *Swissquote* data and stock returns. First, we show that the correlation between net trades in stocks and cryptocurrencies jumps from zero to almost 80% in March 2020, and remains high afterward, thus highlighting the regime change. Second, we use the *Swissquote* volume on cryptocurrencies as an estimator of the cross-market uninformed activity and the portfolio of crypto-oriented retail investors to identify stocks where the cross-market retail trading is likely to be stronger. We sort the 3,000 most traded stocks in the US markets in quintiles determined by the preference of crypto-oriented retail investors. The first (fifth) quintile contains the stocks least (most) traded by retail investors who trade both cryptocurrencies and stocks throughout our four-year sample. In

[5] 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 assumptions that these agents cannot be classified as *informed* traders is sound.

panel regressions, we find that for all but the first quintile, the total cryptocurrency's volume of retail investors during a month predicts the correlation between the stock's and Bitcoin's daily return. Furthermore, and as predicted by the model, the magnitude of the effects monotonously increases across quintiles.

Interestingly, the main prediction of the Crypto-Kyle only holds when the markets are not integrated—that is when the two market-makers operate solely on their respective market. We end our analysis with an extension where we relax this assumption. We show that with cross-market integration, the cross-market uninformed volume will create a negative correlation between the assets' return. This suggests that market maturation could, in theory, transform cryptocurrencies into an adequate diversification instrument.

The remainder of this paper is organized as follows. In section II we discuss our link to the extent literature. In section III, we expose our economic rationale and formalize it inside our model. In section IV, we present the dataset in more detail. Section V shows the empirical level validating our model's main hypothesis. Section VI provides macro-level empirical evidence supporting the model's implications. In VII we extend the Crypto-Kyle to verify the effects of integrating the cryptocurrency market with the traditional one. Section VIII concludes.

II. Relevant Literature

Our paper contributes to the growing literature on cryptocurrencies and the one on retail investors. To the best of our knowledge, ours is the first paper attempting to link these two literature and show how retail traders can induce a positive correlation between cryptocurrencies and stock prices.

The Bitcoin, theorized by Nakamoto and Bitcoin (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, Rivera, and Saleh, 2020; Saleh, 2021; Cong, He, and Li, 2021a; Easley, O'Hara, and Basu, 2019). A decentralized design has peculiar economic characteristics, like forks Biais, Bisiere, Bouvard, and Casamatta (2019), and can have positive effects, such as preventing monopolies from arising (Huberman, Leshno, and Moallemi, 2021) and providing firms with new funding channels (Howell, Niessner, and Yermack, 2020). Cryptocurrencies are both a monetary phenomenon (see, e.g., Schilling and Uhlig, 2019; Brunnermeier, James, and Landau, 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, Li, and Wang (2021b) shows 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, Bisiere, Bouvard, Casamatta, and Menkveld, 2020) show that there are multiple possible equilibria, with sharply different prices. Various papers analyze cryptocurrencies' returns from an asset pricing perspective. Liu and Tsyvinski (2021) show that cryptocurrency returns are driven by network factors and that proxies for investor attention strongly forecast future cryptocurrency returns. Liu, Tsyvinski, and Wu (2019) develop a three-factor model to explain cryptocurrency returns, with cryptocurrency market size and momentum. In addition to traditional market forces, Gandal, Hamrick, Moore, and Oberman (2018) and Foley, Karlsen, and Putniņš (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.

Our paper also talks to the literature on retail investors. Retail investors' are extremely heterogeneous (Curcuru, Heaton, Lucas, and Moore, 2010)) because of idiosyncratic financial circumstances (see, e.g., Merton, 1973; Fagereng, Guiso, and Pistaferri, 2018) and a variety of biases, beliefs and individual characteristics. For instance, the extant literature documents heterogeneity across genders (Barber and Odean, 2001), age (Betermier, Calvet, and Sodini, 2017), IQ (Grinblatt, Keloharju, and Linnainmaa, 2012), and political views (Meeuwis, Parker, Schoar, and Simester, 2018). Furthermore, the literature documents a few persistent phenomenons. 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 to consistently underperform the market (Barber and Odean, 2013). They have limited attention (Sicherman, Loewenstein, Seppi, and Utkus, 2016), and often prefer specific stocks or industries (see,e.g., Peng and Xiong, 2006; Balasubramaniam, Campbell, Ramadorai, and Ranish, 2021). Under-diversification is consistent with retail investors' strong preference for positively skewed returns (see,e.g., Astebro, Mata, Santos-Pinto, et al., 2009; Mitton and Vorkink, 2007), and such preference can also partly explain poor returns (see,e.g, Brunnermeier and Parker, 2005; Brunnermeier, Gollier, and Parker, 2007). We contribute to this literature by providing the first insight on how retail investors introduce cryptocurrencies into their portfolios, the effect they have on their performance, and how their trading habits change.

III. Crypto-Kyle

In this section, we provide a mathematical formulation of the key intuition underlying the main thesis of this paper. At its core, the intuition relies on cross-market uninformed trading volumes, which translates into a positive correlation between two asset classes: stocks and cryptocurrencies.

In the model, as in the rest of the paper, we use Bitcoin to represent cryptocurrencies as a whole. This is a reasonable simplification as Bitcoin is by far the most traded cryptocurrency, also in our database. Indeed, the trading volume of Bitcoin is often higher than the one of all other cryptocurrencies combined (excluding stablecoins), and together with Ethereum, they make up for more than 90% of volumes.[6]

Our model is an extension of the Kyle (1989) model with two assets relying on three assumptions:

1. The fundamental values of stocks and Bitcoin are uncorrelated.
2. Market making in the Bitcoin and traditional financial markets is segmented.
3. Uninformed investors engage in cross-assets buying and selling sprees, trading in the same direction in both markets.

We argue that assumption 1 is reasonable. While the matter of a possible Bitcoin fundamental value is a complex one (see, e.g., Härdle, Harvey, and Reule, 2020; Bhambhwani, Delikouras, and Korniotis, 2021), it is safe to say that it is not positively correlated with the stock market, as at the very least it can be said that Bitcoin does not generate any cash flow, nor it represents any claim over real assets.

The structure of the existing market-making institutions suggests that assumption 2 holds. The main firms operating as market makers in the Bitcoin market focus mostly, if not only, on cryptocurrencies.[7] However, this assumption is likely to be relaxed in the future as the market matures. We discuss in section VII the consequences of relaxing this assumption.

Finally, we defend assumption 3 with the results presented in section V. In our model, we consider retail investors as uninformed traders. 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.

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

[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 6th2022.

A. Set-up

We use the set-up of Kyle (1989) and add a second asset, market maker, and informed investor. While this is far from the first extension of the Kyle model with multiple assets (Garcia del Molino, Mastromatteo, Benzaquen, and Bouchaud, 2020), our model differs in the three key hypotheses listed above, i.e., uncorrelated fundamental, segmented markets, and correlated uninformed trading.

The model has two periods. At $t = 0$, both informed traders know the fundamental value of one of the two risky assets and place a market order accordingly. The two fundamental values are not correlated (assumption 1):[8]

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

The informed demand is given by:

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

The uninformed trader submits orders for the two risky assets. The two uninformed orders have a positive correlation $\rho > 0$ (assumption 3). The aggregate inelastic liquidity is distributed as:

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

The two market makers observe the total order flows for the two assets and make the prices. We assume segmented financial markets (assumption 2) so that each market maker observes only one order flow and decides the corresponding price. 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

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:*

$$\max_{x_1} \mathbb{E}\left[(v_1 - p_1)\, x_1 \;\middle|\; v_1\right], \tag{5}$$

$$\max_{x_2} \mathbb{E}\left[(v_2 - p_2)\, x_2 \;\middle|\; v_2\right], \tag{6}$$

- *the price function P when the two market makers don't learn from each other and observe only the total order flow of the asset they have to price:*

$$P = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} \mathbb{E}\left[v_1 \mid y_1\right] \\ \mathbb{E}\left[v_2 \mid y_2\right] \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}. \tag{7}$$

At equilibrium, the insiders' market order $X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ are:

$$x_1 = \frac{\sigma_u}{\sigma_1}\big(v_1 - \mu_1\big), \tag{8}$$

$$x_2 = \frac{\sigma_u}{\sigma_2}\big(v_2 - \mu_2\big), \tag{9}$$

while the market makers' price functions $P = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix}$ are:

$$p_1 = \mu_1 + \frac{\sigma_1}{2\sigma_u}\big(x_1 + u_1\big), \tag{10}$$

$$p_2 = \mu_2 + \frac{\sigma_2}{2\sigma_u}\big(x_2 + u_2\big). \tag{11}$$

The covariance of the two prices is positive for $\rho > 0$:

$$\mathrm{Cov}(p_1, p_2) = \rho\frac{\sigma_1\sigma_2}{4} > 0. \tag{12}$$

For complete proofs, please see Appendix A.

C. *Validation*

Under the assumption that crypto-oriented retail investors as a whole have no private information, our toy model shows that a correlation between Bitcoin and the stock market naturally arises when retail investors engage in cross-asset correlated trading.

This result relies on hypothesis 3, which we will validate empirically in the next sections.

With this assumption validated, the model has three testable implications:

1. We should observe a regime change in the cross-asset retail investors' trading habits. This regime change should coincide with the change in correlation we observe between cryptocurrencies and the stock market, i.e., in Spring 2020.
2. Periods where retail traders are active in the cryptocurrency market, and thus engage in cross-asset trading, are associated with a higher correlation with the stock market.
3. In the cross-section, the effects of testable implication 2 should be stronger on stocks favored by crypto-oriented retail investors.

Note that because: i) retail investors are not the only uniformed type of investors in the market, and ii) their level of activity is highly heterogeneous across time, we expect the effect described by testable implication 2 to be stronger during periods where retail investors are particularly active.[9] Finally, we stress that the third implication follows from the fact that retail investors tend to specialize in certain stocks (see, e.g., Peng and Xiong, 2006; Balasubramaniam et al., 2021), and that cryptocurrency traders tend to have different socio-economic characteristics from the rest of the investors (see Section IV), we expect their preferred stocks to experience higher correlation with the stock market, especially when retail traders are more active.

IV. Data and Summary Statistics

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. Although it is hard to find data on the Swiss online trading industry, *Swissquote* is often referred to as the market leader. For the purpose of 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. For instance, it has been listed for over 20 years on the SIX stock exchange, and it is the supplier of online brokerage services for *SwissPost*, i.e., the Swiss national postal service and one of Switzerland's largest financial institutions.[10,11] Second, it was one of the first, and probably the only, institutional bank

[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 is highly heterogeneous.

[10] *SwissPost* press release, *Strong partner in e-trading*

[11] *PostFinance* press release, *PostFinance and Swissquote enter into joint venture*, November 11^{th}2020.

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, if not all, traditional banks in the West avoid offering cryptocurrency-related services to their customer, *Swissquote* was able to enter this market as early as 2017. It is worth noting that customers do not trade cryptos indirectly, as *Swissquote* wallets are actual cryptocurrency wallets with similar functionalities to most cryptocurrency wallets provided by specialized cryptocurrency brokers. As of today, there are 28 cryptocurrencies available for trading on the *Swissquote* cryptocurrency exchange, and the bank is the undisputed market leader in Switzerland. This exploit has been possible also thanks to the Swiss policymakers' friendly approach towards cryptocurrencies, which 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 random sub-sample of clients from their bank, which is representative of the whole customer base. We removed from the subsample inactive accounts, resulting in 77,364 unique clients for whom we observe daily holdings, transactions, and portfolio weights between 2017 and 2020 (included) of:

- cash,
- individual stocks,
- index funds (ETFs),
- structured product (derivatives),
- fixed income
- cryptocurrencies.

In addition, we know the clients' gender, age, and the number of daily logins to the *Swissquote* platform.

We present some summary statistics I. The first column shows agents who only trade *traditional* securities, while the second displays the same values for agents who trade both *traditional* assets and cryptocurrencies. This latter sample comprises all of those *Swissquote* customers with a pre-existing securities trading account that opened a cryptocurrency wallet during our sample period. We supplement the data from *Swissquote* with daily prices, market cap, and industry classification from *Thompson Reuters*.

[12] Atkins, R., *Switzerland embraces cryptocurrency culture*, Financial Times, January 25^{th}2018.

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

	Securities only	Securities + crypto
# clients	60,881	16,483
Bank assets - median	34,951	17,228
Bank assets - 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 are, on average poorer, younger, more male, more active, and keener on taking risks. These findings are strongly consistent with anecdotal evidence.

V. Retail Investors and Crytocurrencies

We start our results by exploring how introducing cryptocurrencies changes the retailers' portfolio composition, returns, and trading habits. The purpose of this exploratory analysis is twofold. First, we believe that the information contained in our datasets is both unique and highly relevant. Indeed, to the best of our knowledge, this is the first paper using a dataset containing cryptocurrencies held inside a larger portfolio with traditional assets. Second, this analysis lays the groundwork necessary to test the main assumption behind the model presented in section III: retail investors buy and sell both stocks and cryptocurrencies at the same time and in the same direction.

A. *How do Cryptocurrencies Fit in a Portfolio?*

We perform a simplified version of the variance decomposition method used by Clayton, Dos Santos, Maggiori, and Schreger (2022), which uses changes in portfolio weights to identify substitution between asset classes. This measure includes, altogether, changes in portfolio weights caused by active rebalancing, price effects, and inflows/outflows of cash. In our analysis, we are agnostic about which of those specific effects we capture. Indeed, we interpret the substitution as part of a single overall decision of retail investors. In other words, we assume that, whether through action or inaction, the retail investor is happy, or at least indifferent, to the changes in her portfolio's weights.

For the variance decomposition, we compute $\omega_{i,t}$ for each asset, which is the change in portfolio weight of asset class i between $t-1$ and t, such that mechanically:

$$\omega_{Crypto,t,i} = \omega_{Cash,t,i} + \omega_{Shares,t,i} + \omega_{Structured\,Products,t,i} + \omega_{ETFs,t,i} + \omega_{Fixed,\,income,,it} + \omega_{Others,t,i} \tag{13}$$

It follows that:

$$Var(\omega_{Crypto,t,i}) = \sum_{n=1}^{6} Cov(\omega_{Crypto,t,i}, \omega_{n,t,i}). \tag{14}$$

Mechanically, $1 = \sum_{n=1}^{6} \frac{cov(Crypto,x)}{Var(Crypto)}$, where $\frac{cov(Crypto,x)}{Var(Crypto)}$ is equivalent to the coefficient of ω_n in a OLS regression between ω_n and ω_{Crypto}. When estimating the regression $\omega_{x,t} = \alpha + \beta_x \omega_{crypto,t,i} + \epsilon_{t,i}$, we can interpret β_n as the percentage substitution between cryptocurrencies and asset class n.

More than this substitution rate, we are interested in the abnormal substitution rate with regard to average portfolio weights. To that end, we define the abnormal substitution ratio as the monthly substitution rate divided by the average portfolio rate. A ratio below 1 means that agents under-substitute cryptocurrencies with this particular asset class, a ratio above 1 means that she over-substitute.

Table II shows the results of this exercise.

Table II
The table below shows substitution effects between cryptocurrencies and other asset classes in retail investors' portfolios, monthly and quarterly. The average portfolio weight indicates the weight of the asset class in the average portfolio of cryptocurrency traders before they open a cryptocurrency wallet. The last column shows the abnormal substitution ratio.

	Substitution Monthly	Substitution Quarterly	Average Port. Weights	Relative Substitution Ratio (Monthly)
Cash	59.56%	49.91%	29.76 %	2.00
Stocks	26.99%	34.72%	45.47%	0.59
Structured Prod.	9.63%	10.27%	3.60%	2.67
ETFs	2.67%	3.58%	16.59%	0.16
Fixed Income	0.25%	0.34%	2.71%	0.09
Others	0.90%	1.18%	1.87%	0.48

If the introduction of cryptocurrencies into a portfolio was neutral, we should observe a relative substitution ratio of 1 for all asset classes. Our results paint a very different picture. Cash and structured products have a very high ratio of 2.0 and 2.67, respectively. All other asset classes, including stock, have a ratio below 1. This result holds even when looking at longer time horizons.

This analysis shows that investors are not likely to sell stocks in order to buy cryptocurrencies. Instead, they tend to trade cryptocurrencies by increasing and decreasing their cash balance or, for the small minority, using structured products as risky assets.

B. *What is the Impact on Retail Investors' Portfolio Performance?*

To answer this question, we look at the changes occurring around the opening of a cryptocurrency wallet and use a staggered difference-in-difference design. Deciding to trade cryptocurrencies is highly endogenous, and as such, the effect can not be interpreted as causal. Nevertheless, this design allows us to isolate the relative differences in returns and observe which changes are correlated with the opening of a cryptocurrency wallet. We start with the following regression:

$$y_{i,t} = \beta_0 + \beta_1 * Crypto\_User_{i,t} + \beta_2 * Bank\_Assets_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{15}$$

where $Crypto\_User_{i,t}$ 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 held by investor i at time

t with *Swissquote*. α_i is a vector of investors' fixed effects, and γ_t is a vector of time fixed effects. For the dependent variable, we estimate various specifications, all concerning the stock portfolio: monthly returns, Sharpe ratios of the overall portfolio, and monthly return and Sharpe ratio of the portfolio excluding cryptocurrencies. We cluster standard errors at the investor level. Table III shows the results for the overall portfolio, while table IV shows the results for the hypothetical portfolio without cryptocurrencies, i.e. the non-crypto part of a crypto-traders' portfolio. In Appendix B we shows the same results, along with the main others from this section, when using a Callaway Sant'Anna estimator (Callaway and Sant'Anna, 2021), to address concerns regarding heterogeneous treatment effects (Goodman-Bacon, 2021; Baker, Larcker, and Wang, 2022). The results remain unchanged in both the sign and their significance.

Table III

The table below shows the results of estimating equation (15). The first line indicates the dependent variable, and $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t has an active cryptocurrency wallet. $Bank\_Assets_{i,t}$ is the total amount of assets held by an investor at *Swissquote*. Observations are monthly, and we cluster standard errors at the investor level.

	Return	Return	Sharpe	Sharpe
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

Investors trading cryptocurrencies have significantly higher returns than others, up to 11.69% on an annual basis. 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, benefiting from a sharp increase in cryptocurrency prices. Nevertheless, these high returns come with even higher volatility, leading to a Sharpe ratio that is significantly lower than other investors, casting a shadow over narratives concerning diversification, as increased returns do not compensate for the additional variance.

Table IV

The table below shows the results of estimating equation (15) for the part of an investor's portfolio that is not invested in cryptocurrencies. The first line indicates the dependent variable, and $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t has an active cryptocurrency wallet. $Bank\_Assets_{i,t}$ is the total amount of assets held by an investor at Swissquote. Observations are monthly, and standard errors are clustered at the investor level.

	Return ex	Return ex	Sharpe ex	Sharpe ex
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

Considering only the part of the portfolio not invested in cryptocurrencies yields interesting results. Retail investors with an active cryptocurrency wallet have significantly higher returns and Sharpe ratios. While they tend to have higher returns overall because they are less risk-averse, their Sharpe ratio is generally lower than average. Nevertheless, the Sharpe ratio of their non-crypto portfolio increases with the opening of a cryptocurrency wallet. A potential reason is that they tend to trade more frequently, and frequent trading for retail investors leads to sub-par returns (Barber and Odean, 2000). Thus, if cryptocurrency trading reduces stock trading, returns on their stock portfolio should increase. In the next subsection, we explore changes in trading habits.

C. How do Trading Habits Change?

First, we note that the opening of a cryptocurrency wallet coincides with a Sharpe rise in investors' attention. Indeed, when we compute the number of logins to the *Swissquote* platform in the year around the date when an investor opens a cryptocurrency wallet, we see a significant increase in this proxy for investor attention. Figure 1 shows the results.

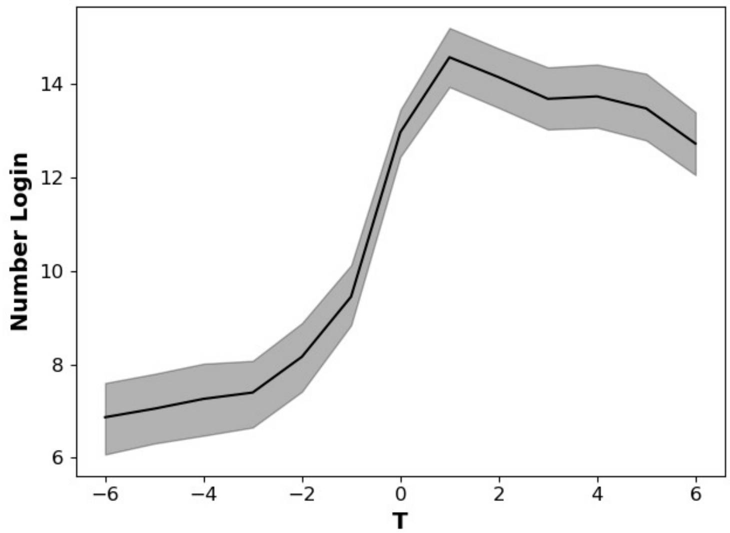


Figure 1. The figure above shows the number of logins in the 6 months before and after the opening of a cryptocurrency wallet, where 0 is the date of the opening. The highlighted area show the 5% confidence interval.

Next, we look at how investors' stock trading behavior changes after they introduce cryptocurrencies into their asset universe. We use a setting similar setting to the one in the previous subsection and estimate the following regression:

$$y_{i,t} = \beta_0 + \beta_1 * Crypto\_User_{i,t} + \beta_2 * Crypto\_Turnover_{i,t} + \beta_3 * Bank\_Assets_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{16}$$

where $Crypto\_User_{i,t}$ is a dummy equal to 1 if investor i holds cryptocurrencies at time t. $Crypto\_Turnover_{i,t}$ the turnover of the cryptocurrency wallet, defined as trading volume in cryptocurrencies divided by average cryptocurrencies holdings. $Bank\_Assets_{i,t}$ is the total amount of assets held by investor i at time t with *Swissquote*. α_i and γ_t are, respectively, investor and time fixed effects. As a dependent variable, we consider the turnover of the trading account, defined as monthly trading volume in shares divided by average shares holdings over the month. We cluster standard errors at the investor level. Table V shows the results:

Table V

The table shows the results of estimating equation (16). The dependent variable is the monthly turnover of individual investors' stock portfolios. $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t holds cryptocurrencies. $Crypto\_Turnover_{i,t}$ is the turnover of the cryptocurrency portfolio. $Bank\_Assets_{i,t}$ is the total amount of assets held by an investor at *Swissquote*. Standard errors are clustered at the investor level.

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

Cryptocurrency investors trade more stocks on average but less so after opening a crypto-wallet. This effect is not caused by the relative lower weight of stocks 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 stocks once they trade cryptocurrencies and thus trade them less often. This result might explain part of the higher Sharpe ratios documented in Table IV. In addition, we find that trading in stocks is correlated with trading in cryptocurrencies. In other words, once they open a wallet, investors trade fewer stocks, and they trade them at the same time as cryptocurrencies.

To corroborate this analysis, we look at the percentage of short-term trades. We define short-term trades as those for which we observe a trade with the opposite sign on the same security within a month, for at least 50% of the original position. We estimate equation (16), with the percentage of short-term trades as the dependent variable. Table VI shows the results.

Table VI

The table shows the results of estimating equation (16). The dependent variable is the percentage of short-term trades in stocks. $Crypto\_User_{i,t}$ is a dummy variable equal to 1 if investor i at time t holds cryptocurrencies. $Crypto\_Turnover_{i,t}$ is the turnover of the cryptocurrency portfolio. $Bank\_Assets_{i,t}$ is the total amount of assets held by an investor at *Swissquote*. The dependent variable is the % of trades for which we observe a trade with the opposite sign on the same security within a month, for at least 50% of the original position. Standard errors are clustered at the investor level.

	Short term	Short term	Short term	Short term	Short term	Short term
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

We observe similar patterns as in Table V. Cryptocurrency investors do make more short-term stock trades on average, but less so after opening a cryptocurrency wallet. Short-term trades on stocks are correlated with high activity in cryptocurrency trading. These results further corroborate the idea that there is a significant change in trading behavior once an investor introduces cryptocurrencies into her investable universe.

D. Correlated Trading

We now move to assumption 3 of the Crypto-Kyle model: retailers' net trading volume is correlated across asset classes. The results presented in Table V show that a large trading volume in cryptocurrencies is associated with a large trading volume in equities. But this does not necessarily imply that the net trading volumes are positively correlated. The positive correlation between the turnovers can be explained by one of two following hypotheses:

1. Retail investors reallocate funds from one asset class to another because their objec-

tive is to keep their cross-asset class portfolio weights somewhat stable. Under this hypothesis, we should observe investors selling the high-performing assets in order to buy the low-performing ones to restore their preferred weights. Thus, net flows in cryptocurrencies and stocks should be negatively correlated.

2. Retail investors are 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. Under this hypothesis, the agent would tend to buy and sell both asset classes in the same direction. The correlation between the net trading volume of cryptocurrencies and stocks should be positive.

We distinguish between these two alternative explanations with the following regression:

$$y_{i,t} = \beta_0 + \beta_1 * Crypto\_Pos_{i,t} + \beta_2 * Crypto\_Neg_{i,t} + \beta_3 * Bank\_Assets_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{17}$$

where $Crypto\_Pos_{i,t}$ is the ratio of buy orders to cryptocurrency holdings, $Crypto\_Neg_{i,t}$ is the ratio of buy orders to crypto-holdings. $Bank\_Assets_{i,t}$ is the total amount of assets held by investor i at time t with *Swissquote*. α_i and γ_t are, respectively, investor and time fixed effects. As a dependent variable, we consider net trades by investor i at time t in stocks over stocks holdings. We use monthly frequency and cluster the standard errors at the investor level. Table VII shows the results:

Table VII

The table shows the results of estimating equation (17). 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 buy orders to crypto-holdings. $Bank\_Assets_{i,t}$ is the total amount of assets held by investor i at time t with *Swissquote*. α_i and γ_t are, respectively, investor and time fixed effects. The dependent is net trades in stocks over stocks holdings of investor i at time t. We use monthly frequency and standard-error cluster at the investor level.

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

Regardless of the specification and the combination of fixed effects, the direction of the trading flows between stocks and cryptocurrencies are positively correlated. We reject hypothesis 1 in favor of hypothesis 2. The results in this table are, therefore in line with assumption 3 presented in section III.

VI. Suggestive Evidence

In this section, we use *Swissquote* data to test the three implication for the Crypto-Kyle model presented in sectionIII.C.

A. *Implication 1: Regime Change*

We stated in section III that our model implies a regime change in the cross-asset retail investors' trading habits. Namely, the correlation between the retail net trading volume on cryptocurrencies and stocks should coincide with the change in correlation we observe between cryptocurrencies and the stock market, i.e., in Spring 2020. In figure 2 we illustrate this regime change by showing the daily correlation estimated with a three months rolling window between the S&P500 and Bitcoin.

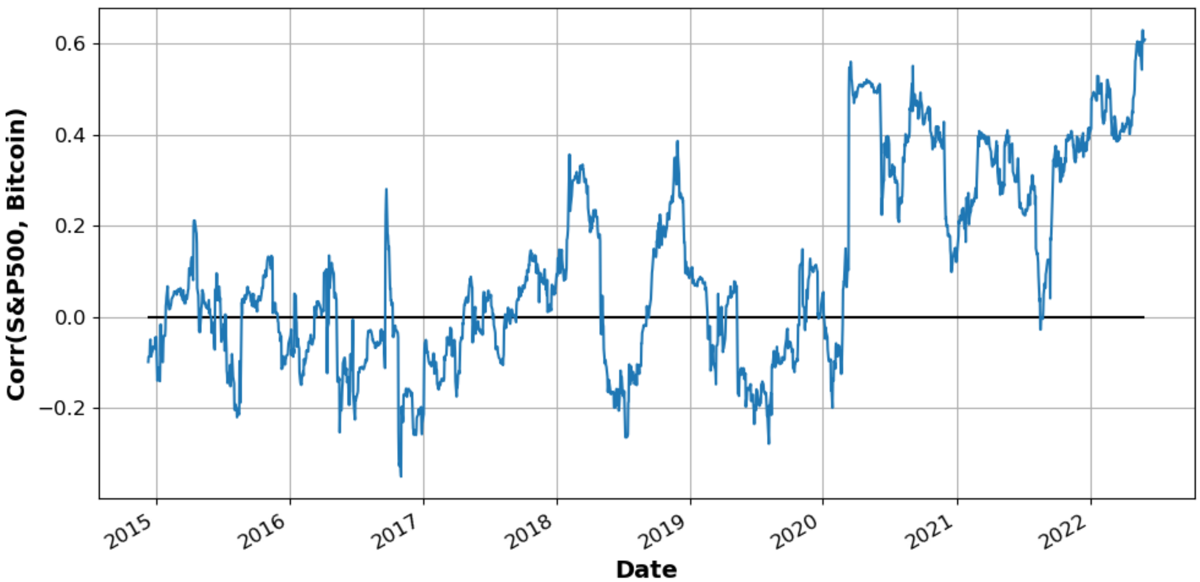
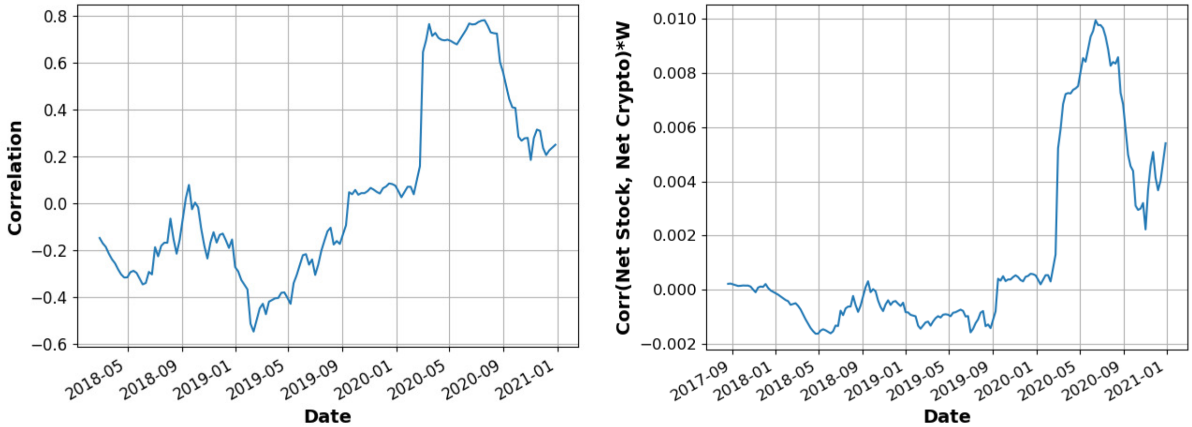


Figure 2. In the figure above we show the daily correlation estimated with a three month rolling window between Bitcoin's returns and the S&P500.

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 3.



(a) (b)

Figure 3. Figure (a) shows the correlation between the net retail trading volumes of cryptocurrencies and equities. We compute the correlation at the weekly level, using a 25-week rolling window. Figure (b) shows the same numbers weighted by trading volumes in cryptocurrencies on the *Swissquote* platform.

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.

Before the regime change, 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 was much lower, as well as the number of cryptocurrency traders. In Figure 3(b), 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 negative correlation coincides with a time period with very low cross-asset trading volumes.

Understanding the cause of this regime change is outside the scope of this paper, but we nonetheless propose an interpretation. In March 2020, there was a significant liquidity shock that left households with more money to invest. Even though Switzerland did not implement stimulus check programs like the US, a vast majority of the population was able to retain their main source of income or, at least, rely on unemployment benefits. This leads to almost constant earning flows, with a sudden drop in expenses, due to lockdown measures. Retail trading activities boomed, with significant effects on stock markets (Greenwood, Laarits, and Wurgler, 2022). We also observe a similar pattern in the *Swissquote* data, where trading volumes skyrocketed in spring 2020 and remained high for various months. In addition, cryptocurrencies started to become mainstream in 2020, with an increasing number of retail investors opening a cryptocurrency wallet. This new wave of more mainstream investors is likely to have different characteristics than previous, more ideological ones. In fact, in the next section, we provide anecdotal evidence arguing that this new breed of retail traders views crypto-currencies as something close to a tech stock.

B. *Implication 2-3: Cross-Asset Trading Volumes and Correlation.*

We now turn toward the last two implications of the Crypto-Kyle model:

2. Periods where retail traders are active in the cryptocurrency market, and thus engage in cross-asset trading, are associated with a higher correlation with the stock market.
3. In the cross-section, the effects of testable implication 2 should be stronger on stocks favored by crypto-oriented retail investors.

We select the 3000 most traded US stocks throughout the sample.[13] We group stocks in quintiles based on the total trading volume of crypto-oriented investors—that is, the first quintile contains the stocks least preferred by crypto-oriented traders on the *Swissquote* platform, and the fifth quintile contains the most traded.

First, we look at the characteristics of the stocks in each quintile. Table VIII shows that crypto-oriented retail investors prefer larger 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 that are enthusiastic about new technologies. A Fama-French regression (Fama and French, 2015) with three factors highlights that crypto-oriented traders prefer growth to values stocks.

For each of the five subsamples, we estimate the following regression:

$$\begin{aligned} y_{i,t} = \beta_0 + \beta_1 * Volume\_Bit_t + \beta_2 * Volume\_sq\_Bit_t + \beta_3 * Vix_t + \\ + \beta_4 * Mom_{i,t} + \beta_5 * Ret_{i,t} + \beta_6 * Volume_{i,t} + \gamma_i + \epsilon_{i,t}, \end{aligned} \tag{18}$$

where $y_{i,t}$ is the correlation between the daily returns of stock i and Bitcoin during month t. $Volume\_Bit_t$ is the monthly trading volume in the Bitcoin global market, obtained from Yahoo Finance. $Volume\_sq\_Bit_t$ the monthly trading volume in Bitcoin on the *Swissquote* platform. Vix_t is the VIX index. $Mom_{i,t}$ is the lagged monthly return of the stock i. $Ret_{i,t}$ is the monthly return of stock i to control for the tendency of retailers to buy stocks exhibiting

[13] All of the patterns shown in this section are present even when reducing the sample to 1000 stocks.

Table VIII

In the table below, we sort the 3,000 most traded US stocks into 5 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. We report the average β of a three factor regression (Fama and French, 2015) at the stock level: $r_{i,t} = \alpha + \beta_{mkt}M_t + \beta_{smb}SmB_t + \beta_{hml}HmL_t + \varepsilon_{i,t}$ and the annualized standard deviation of the idiosyncratic risks for each quintile. In the second panel, we report the industry breakdown. We compute the total trading volume per quintile and industry and normalize it by quintile. The last column shows the difference between the fifth and first quintile normalized by the sum of the percentage by the industry. This ratio captures the abnormal weight of the industry.

	Q1	Q2	Q3	Q4	Q5	**diff_norm**
Market cap	3256	3698	4728	5930	7570	
Fama-French:						
alpha	0.00	0.00	0.00	0.00	0.00	
mkt	1.00	1.03	1.06	1.06	1.02	
smb	0.86	0.96	0.97	0.97	1.02	
hml	0.26	0.01	-0.16	-0.23	-0.25	
std(epsilon)	0.64	0.69	0.61	0.69	0.70	
Industries:						
Technology	9.40%	12.80%	17.00%	13.50%	18.20%	0.13
Health Care	16.40%	24.00%	27.20%	29.20%	28.40%	0.10
Consumer Discretionary	11.90%	16.10%	12.60%	18.80%	17.20%	0.07
Basic Materials	5.40%	3.10%	4.20%	3.20%	5.40%	0.00
Telecommunications	2.90%	2.80%	3.70%	3.70%	2.90%	0.00
Consumer Staples	4.70%	5.10%	2.90%	4.40%	3.90%	-0.03
Industrials	12.70%	12.20%	11.20%	11.90%	9.40%	-0.06
Energy	9.20%	7.60%	6.00%	5.80%	6.10%	-0.09
Financials	14.50%	8.90%	8.90%	5.40%	5.50%	-0.21
Real Estat	8.70%	4.70%	3.90%	2.30%	2.50%	-0.28
Utilities	4.20%	2.50%	2.40%	1.90%	0.50%	-0.33

extreme returns (see, e.g., Odean, 1999; Barber and Odean, 2008). $Volume_{i,t}$ is the monthly trading volume on stock i on the global market. γ_i is a set of firm fixed effects, to control for firm-level heterogeneity. We clusters standard errors by firm. Table IX reports the results. Q1-5 indicate the quintile of preference by cryptocurrency traders.

The correlation between a stock and Bitcoin is positively correlated with market volatility, momentum, and overall trading volume, while it is negatively correlated with returns. These effects are fairly stable across quintiles and specifications. Conversely, we observe that the

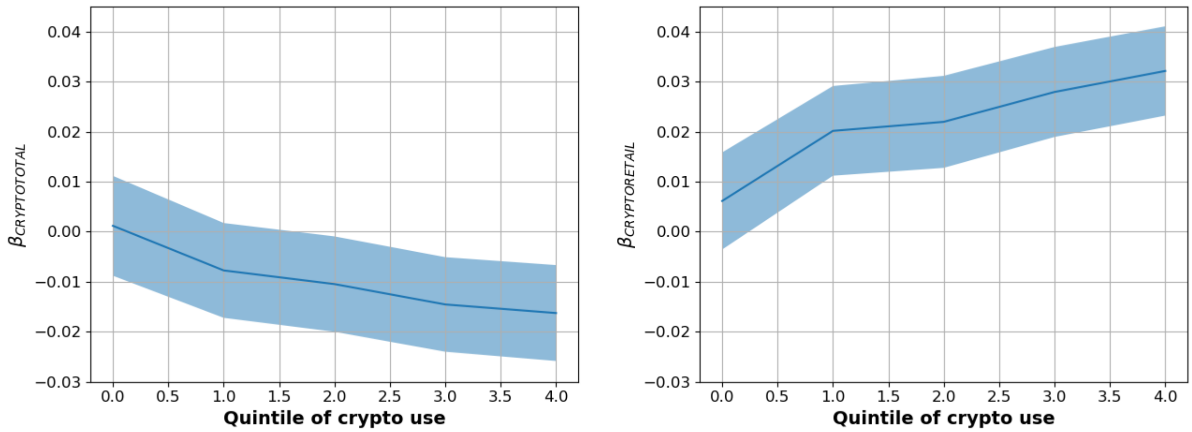
Table IX

This table shows the results of the estimation of equation 18. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The dependent variable is monthly correlation between stock i and Bitcoin daily returns. $Volume\_Bit_t$ is the monthly trading volume of Bitcoin on 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_t is momentum in the subsample. $Ret_{i,t}$ is the monthly return of stock i. $Volume_{i,t}$ is the monthly global trading volume on stock i. Standard errors are clustered at the stock level.

	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

stocks which are preferred by cryptocurrency traders on the *Swissquote* platform exhibit a higher level of correlation with Bitcoin when retail trading volumes on Bitcoin are high. The relationship is growing monotonically across the quintiles, consistently with the mechanism we propose. This pattern holds both when considering the global Bitcoin trading volume or the one on the *Swissquote* platform only (see appendix B.

Looking at the overall crypto-volume yields a further interesting result. While it is correlated with Bitcoin trading volumes on the *Swissquote* platform, the two measures are not the same. The volume on the *Swissquote* platform is a proxy for retail investors' volume on the Bitcoin market, while the total volume also includes institutional investors, hedge funds, and other large players. In Table IX we include both crypto-volumes in the regression. The results show that while there is no clear pattern across the beta associated with total crypto-volume, the trend of the beta associated with *Swissquote* crypto-volume is even



(a) Global (b) Swissquote

Figure 4. These figures show the coefficients of the global Bitcoin trading volume and the Swissquote platform Bitcoin trading volume from equation 18. The dependent variable is the monthly correlation of daily return between stocks in subsample Q1-Q5 and Bitcoin returns.

sharper. These numbers highlight the role of retail investors' volume and the cross-asset class correlation. Figure 4 shows the coefficients associated to the *Swissquote* and total crypto-volume from Table IX.

Together, the results presented in this section strongly support the last two implications of the Crypto-Kyle model. Stocks that are preferred by crypto-traders exhibit a higher correlation with Bitcoin, and more so 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 retail trading activity in the Bitcoin market and not total global Bitcoin trading further points in the direction of retail traders as the drivers of the correlation between cryptocurrencies and stocks.

For robustness, we estimate the results in Table XIV, XV, and IX without fixed effects. Appendix B shows the results.

VII. Market Integration and Correlation

In this section, we explore the theoretical consequences of integrating cryptocurrencies into mainstream financial institutions. We consider the same set-up as in Section III and relax the assumption on segregated market makers, thus allowing the same market maker to operate in both markets. The market maker observes both the total order flows $Y = X + U$

and competitively sets the prices for the risky assets:

$$P = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} \mathbb{E}\left[v_1 \mid y_1, y_2\right] \\ \mathbb{E}\left[v_2 \mid y_1, y_2\right] \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}. \tag{19}$$

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

$$\lambda_{11} = \frac{\mathrm{Cov}(v_1, y_1)\mathrm{Var}(y_2) - \mathrm{Cov}(v_1, y_2)\mathrm{Cov}(y_1, y_2)}{\mathrm{Var}(y_1)\mathrm{Var}(y_2) - \left(\mathrm{Cov}(y_1, y_2)\right)^2}, \tag{20}$$

$$\lambda_{12} = \frac{\mathrm{Cov}(v_1, y_2)\mathrm{Var}(y_1) - \mathrm{Cov}(v_1, y_1)\mathrm{Cov}(y_1, y_2)}{\mathrm{Var}(y_1)\mathrm{Var}(y_2) - \left(\mathrm{Cov}(y_1, y_2)\right)^2}, \tag{21}$$

$$\lambda_{21} = \frac{\mathrm{Cov}(v_2, y_1)\mathrm{Var}(y_2) - \mathrm{Cov}(v_2, y_2)\mathrm{Cov}(y_1, y_2)}{\mathrm{Var}(y_1)\mathrm{Var}(y_2) - \left(\mathrm{Cov}(y_1, y_2)\right)^2}, \tag{22}$$

$$\lambda_{22} = \frac{\mathrm{Cov}(v_2, y_2)\mathrm{Var}(y_1) - \mathrm{Cov}(v_2, y_1)\mathrm{Cov}(y_1, y_2)}{\mathrm{Var}(y_1)\mathrm{Var}(y_2) - \left(\mathrm{Cov}(y_1, y_2)\right)^2}. \tag{23}$$

The informed traders' market order $X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ at equilibrium is:

$$x_1 = \sqrt[4]{1-\rho^2}\ \frac{\sigma_u}{\sigma_1}\left(v_1 - \mu_1\right), \tag{24}$$

$$x_2 = \sqrt[4]{1-\rho^2}\ \frac{\sigma_u}{\sigma_2}\left(v_2 - \mu_2\right). \tag{25}$$

The market maker's equilibrium price function is:

$$P = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \frac{\sqrt[4]{1-\rho^2}}{1-\rho^2+\sqrt{1-\rho^2}} \begin{bmatrix} (1+\sqrt{1-\rho^2})\frac{\sigma_1}{2\sigma_u} & -\rho\frac{\sigma_1}{2\sigma_u} \\ -\rho\frac{\sigma_2}{2\sigma_u} & (1+\sqrt{1-\rho^2})\frac{\sigma_2}{2\sigma_u} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}, \tag{26}$$

so that the prices are:

$$p_1 = \mu_1 + \frac{\sqrt[4]{1-\rho^2}}{1-\rho^2+\sqrt{1-\rho^2}}\Big((1+\sqrt{1-\rho^2})y_1 - \rho\, y_2\Big)\frac{\sigma_1}{2\sigma_u}, \tag{27}$$

$$p_1 = \mu_1 + \frac{\sqrt[4]{1-\rho^2}}{1-\rho^2+\sqrt{1-\rho^2}}\Big((1+\sqrt{1-\rho^2})y_2 - \rho\, y_1\Big)\frac{\sigma_2}{2\sigma_u}. \tag{28}$$

The covariance of the prices is negative for $\rho > 0$:

$$\mathrm{Cov}(p_1, p_2) = -\rho\,\frac{\sqrt{1-\rho^2}}{1-\rho^2+\sqrt{1-\rho^2}}\,\frac{\sigma_1\sigma_2}{2} < 0. \tag{29}$$

We find that with fully integrated markets, the correlation between cryptocurrencies and the stock market is negative. The driving force is the additional information received by the market maker about the trading activity of uninformed traders that allows the market maker to better identify the nature of the order flow. This insight suggests that if cryptocurrency markets become more integrated into the mainstream financial system, the cross-asset positive correlation might disappear or even become negative. In this sense, it is plausible that, over the long run, cryptocurrencies will become a valid hedging instrument as long as retail investors will continue to treat them as an asset akin to (growth) stocks.

VIII. Conclusions

In this paper, we propose an economic mechanism explaining the recent persistent high positive correlation between Bitcoin's and S&P500's returns: retail investors' trading habits. Specifically, the fact that crypto-oriented retail investors tend to engage in cross-assets buying or selling sprees, thus creating cross-asset uninformed trading flows. With the Crypto-Kyle model, an extension of the canonical Kyle model, we show under which conditions a correlation in uninformed trading between two assets with uncorrelated fundamental value can translate into a positive correlation in returns.

We use a proprietary dataset by *Swissquote*, the Swiss leader in online trading, to empirically support our thesis. First, we validate our model's hypothesis by showing that retail investors' net volumes on crypto-assets do correlate strongly with their net trading volumes on equities. Second, we test our model's implications and show that this cross-asset trading volume correlation only started in March 2020. Furthermore, we show that the correlation between stocks and cryptocurrencies is higher in periods of high cross-asset retail trading and that this cross-asset class correlation is higher for those stocks which are preferred by crypto-oriented investors.

This recent correlation between stocks and cryptocurrency markets is more than an interesting asset pricing puzzle. The fast rise of cryptocurrencies from an obscure technology to a multi-trillion dollar market has been followed by a fast legitimization. We now see cryptocurrencies being included in the portfolios of long-established hedge funds, well-known investors, and households' 401(K)s. Yet, the economic channel we show in this paper highlights how little we know about this asset class. The very fact that the correlation between cryptocurrencies and the stock market can suddenly change from 0 to 60% is already troubling. The idea that such a major regime change might be caused by something as unpredictable as retail investors' liquidity shocks and trading habits adds a layer of concerns surrounding the systematic risks stemming from the mainstream adoption of this new asset class.

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Appendix A. Callaway Sant'Anna Estimator

Table X

This table presents the main results from section V computed with a Callaway Sant'Anna estimator (Callaway and Sant'Anna, 2021). *Ret* is the monthly return of an individual investor's portfolio. *Sharpe* is its Sharpe ratio. *Ret ex* is the monthly return of a portfolio computed on the non-crypto assets only. *Sharpe ex* is the Sharpe ratio of a portfolio computed on the non-crypto assets only. *Stocks Turn* is the monthly turnover of an investor's stock portfolio, computed as the total trading volume divided by the average stock holding. $Short - Term$ is an investor's percentage of short-term trades, defined as those trades for which the investors completed an opposite trade on the same stock within a month for at least 50% of the original amount. $Crypto\_User$ is a dummy variable equal to 1 if investor i has an active cryptocurrency wallet at time t.

	Ret	Sharpe	Ret ex	Sharpe ex	Stocks Turn.	Short-Term
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 B. Robustness Checks

Table XI

This table shows the results of the estimation of equation 18. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The dependent variable is monthly correlation between stock i and Bitcoin daily returns. $volume\_bit_t$ is the monthly trading volume of Bitcoin on the global market. vix_t is the VIX index. mom_t is momentum in the subsample. ret is the monthly return of stock i. $volume_{i,t}$ is the monthly global trading volume on stock i. Standard errors are clustered at the stock level.

	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 XII

This table shows the results of the estimation of equation 18. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The dependent variable is monthly correlation between stock i 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_t is momentum in the subsample. $Ret_{i,t}$ is the monthly return of stock i. $Volume_{i,t}$ is the monthly global trading volume on stock i. Standard errors are clustered at the stock level.

	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 XIII

This table shows the results of the estimation of equation 18. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The dependent variable is monthly correlation between stock i and Bitcoin daily returns. $Volume\_Bit_t$ is the monthly trading volume of Bitcoin on 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_t is momentum in the subsample. $Ret_{i,t}$ is the monthly return of stock i. $Volume_{i,t}$ is the monthly global trading volume on stock i. Standard errors are clustered at the stock level.

	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 XIV

This table shows the results of the estimation of equation 18. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The dependent variable is monthly correlation between stock i and Bitcoin daily returns. $Volume\_Bit_t$ is the monthly trading volume of Bitcoin on the global market. Vix_t is the VIX index. Mom_t is momentum in the subsample. $Ret_{i,t}$ is the monthly return of stock i. $Volume_{i,t}$ is the monthly global trading volume on stock i. Standard errors are clustered at the stock level.

	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

Table XV

This table shows the results of the estimation of equation 18. Q1 to Q5 refer of the quintiles of stocks, ranked by the relative weight of cryptocurrency investors' trading activity. The dependent variable is monthly correlation between stock i 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_t is momentum in the subsample. $Ret_{i,t}$ is the monthly return of stock i. $Volume_{i,t}$ is the monthly global trading volume on stock i. Standard errors are clustered at the stock level.

	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