Online Appendix

The Interplay of Opinions and Behavior in Social Trading: The Dynamics of Early Cryptocurrency Adoption

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Appendix A Related literature

Our research is related to three research streams. First, we relate to the extensive social learning literature that examines how users learn from neighbors when adopting innovative products. We contribute to this literature by studying conflicting social signals—most notably, the misalignment between the observed trading behavior of neighbors and their expressed opinions—and examine how individuals learn in such a complex and potentially inconsistent informational environment within their social networks. We study cryptocurrency adoption, a context that also enables us to understand the moderating effect of product uncertainty and returns. Second, we engage with the literature on financial technology and cryptocurrency by highlighting the features that distinguish cryptocurrencies from traditional financial assets. Third, we contribute to the literature on social trading platforms by examining how users learn from neighbors through different components of platform design, including social media feeds and trading information disclosures.

A.1 Social learning

Social learning refers to the process through which individuals learn from others when making decisions (Banerjee 1992, Bikhchandani et al. 1992).[1] We adopt a broad definition of social learning that includes all forms of information acquisition, such as observing behaviors (what others do) and listening to word of mouth (what others say). Relying on this broad definition, we are particularly interested in the interplay of possibly confounding signals. How do individuals learn from others when others say one thing but do something else?

Social learning significantly influences decision-making in many contexts (Hu et al. 2019, Qiu et al. 2021, Aral and Walker 2011, Bapna and Umyarov 2015, Dupas 2014, Banerjee et al. 2013). For example, Aral and Walker (2011) show that platform-mediated peer influence can causally drive product adoption through viral design mechanisms, while Bapna and Umyarov (2015) demonstrate that online social connections substantially affect users' willingness to pay and consumption behaviors. Social learning also plays a critical role in influencing the adoption of new products, technologies, and services with limited information, such as healthcare products (Dupas 2014) and microfinance (Banerjee et al. 2013). With the increasing accessibility of data, the recent literature has evolved its focus from understanding social learning based on location-based proximity or crowd behavior to using social network data for a more granular understanding of the

[1] The concept of social learning is defined differently across various disciplines. In the earlier economics literature, it is particularly associated with learning from the outcomes observed among prior adopters, in contrast to social influence, which involves learning from the behaviors of others (Young 2009). Related concepts such as observational learning and herding behavior (Cai et al. 2009, Chen et al. 2011) also emphasize learning based on the actions of others.

social learning process (Hu et al. 2019, Qiu et al. 2021). Recent work suggests that the effectiveness of social learning and peer norms depends critically on the structure and strength of the social network. For example, Liu et al. (2019) show that the influence of social norms on online behavior depends critically on users' social connectivity.

We contribute to the social learning literature by examining cryptocurrency adoption on social trading platforms. Two unique features set our research apart from the literature. First, extending beyond the findings of Ammann and Schaub (2021) that users make investment decisions based on others' posts on social trading platforms, we capture a critical and overlooked aspect of social trading: Users observe not only the opinions of others but also their trading actions. These signals may sometimes be contradictory. How the interplay between the trading actions and expressed opinions of others, especially their alignment, influences an individual's decision to adopt cryptocurrency remains unclear. Investigating the interplay between opinions and actions is particularly important in our cryptocurrency adoption setting, as users may have incentives to share misinformation that does not align with their own trading actions. Second, unlike the extensive literature on product adoption, where the expected value is fixed, cryptocurrency is characterized by high uncertainty, as expressed in its price volatility. While asset volatility affects investment strategy adoption in traditional financial markets (Han et al. 2022), its moderating role in social learning has not been thoroughly explored. Studying the moderating effect of cryptocurrency volatility on the interplay between investors' opinions and actions enriches the literature.

A.2 Technological innovations and cryptocurrency

Our paper is also broadly related to recent research examining the adoption of various technological innovations by investors, such as internet trading, mobile apps, and application programming interfaces (APIs). While the impact of internet trading and mobile apps reduces transaction frictions for retail investors, they may also exacerbate behavioral biases, such as the propensity for active trading (Kalda et al. 2025, Barber and Odean 2000, Arnold et al. 2022), trend-chasing, and myopic trading (Liu et al. 2025). In a similar fashion, APIs reduce information acquisition costs for retailers by allowing them to automate their information acquisition, but APIs may also exacerbate behavioral biases (Havakhor et al. 2025).

As a novel asset class (Gemayel and Preda 2021) that builds on new blockchain technology, cryptocurrencies are another innovation in the context of financial markets that have attracted the attention of many scholars in recent years.[2] Although they share some characteristics with

[2] Fang et al. (2022) and Almeida and Gonçalves (2023) provide comprehensive reviews of recent research on investor behavior in cryptocurrency markets.

traditional assets, cryptocurrencies exhibit at least three unique features. First, cryptocurrencies, built on blockchain technology, operate on a decentralized and near-anonymous network and heavily rely on peer-to-peer exchanges with a lower level of financial institution involvement compared to stock, bond, and mutual funds (Fang et al. 2022). This decentralization raises issues regarding the verification and security of cryptocurrency ownership (Catalini and Gans 2020), which may impose challenges on the scalability of cryptocurrencies (Malik et al. 2022). Second, cryptocurrency prices are highly volatile. This high volatility in prices is attributed to speculative trading (Blau 2017), cryptocurrency mining (Jin et al. 2022), and network effects (Liu and Tsyvinski 2021, Wei and Dukes 2021, Cong et al. 2021). Third, the adoption of cryptocurrency is largely influenced by social factors (Gupta et al. 2021) such as public sentiment (Guégan and Renault 2021, López-Cabarcos et al. 2021). Such social characteristics also result in a pronounced tendency toward herding among investors in cryptocurrency trading (Bouri et al. 2019).

We focus on the social factors driving cryptocurrency adoption. While most of the literature relies on aggregate market-level data (Liu and Tsyvinski 2021, Lyandres et al. 2022), we exploit a unique combination of individual-level social media and trading data to better understand investor behavior related to cryptocurrency with a more granular lens. Closely related to our paper, Kogan et al. (2024) show that retail investors are contrarian in other asset classes but trade on momentum in cryptocurrencies. These authors argue that investors believe that cryptocurrency returns influence the likelihood of future adoption by other investors, which in turn influences future returns. Han et al. (2023) use Bitcointalk data to shed light on the role of peer sentiment in investors' beliefs about the Bitcoin market. These authors show that sentiment is contagious and that investors update their beliefs relative to their peers, which predicts Bitcoin volatility and trading volume. We contribute to this literature by examining the effect of the interplay between the opinions and trading behaviors of neighbors on the cryptocurrency adoption decisions of individual investors and how product/asset uncertainty and returns moderate social learning.

A.3 Social trading

Owing to the high level of transparency in social communication on social trading platforms, social trading offers an ideal testbed for examining how opinions and trading actions influence the investment decisions of others within a social network. Thus far, the social trading literature reveals a complex interplay between behavioral finance, social network theory, and platform design. Social trading platforms fundamentally alter how investors behave, not only by enabling copying but also by reshaping incentives and informational dynamics. While social learning offers clear benefits, social trading also introduces new risks, especially in the form of herding and other behavioral biases (Gemayel and Preda 2018, Heimer 2016).

For example, social trading can both amplify and mitigate the disposition effect. High transparency may increase bias because of reputational concerns (Pelster and Hofmann 2018), but directed social learning and scrutiny can also reduce it (Jin et al. 2021). Social trading users often react to noninformative signals (e.g., comment frequency), which do not predict returns (Ammann and Schaub 2021). Traders imitate peers and overvalue superficial cues (Shen et al. 2025).

Building on this literature, our paper is the first to examine the interplay between the opinions and trading behaviors of neighbors on social trading platforms, specifically in relation to the decisions of individual investors to adopt new assets (i.e., cryptocurrencies), as well as how market volatility and returns moderate this learning effect.

Appendix B The social trading platform

This appendix provides stylized visualizations of the social trading platform. Figure B.1 shows the "news feed" of the platform (see, e.g., Klocke et al. 2025), which is the first page that appears when a user logs into her account. Figure B.2 displays the main profile page of an investor (user). Figure B.3 shows the performance section of the profile page.

Figure B.2 shows the main profile page of an investor (user). On the social trading platform, each user has a profile page that shows her name, a bio written by the user, the number of followers currently replicating the user's trading strategy, a summary of her financial performance, and the posts that the user has made, along with any comments or likes that those posts have received. The profile page is public, allowing any other user to browse the page and to interact with the posts by leaving comments or likes. If users want to replicate another investor's trading strategy, they can click the "Duplicate Portfolio" icon on the profile page. Once duplicated, the user's (leader's) trades will be replicated in the copier's account in real time. The platform does not disclose the auto-copy network. On a leader's public profile, only the number of followers and the total assets under management are displayed; the identities of followers and followees are not visible to the public.

Also on the profile page, users can visit the performance section of a user, as illustrated in Figure B.3. The performance section provides detailed financial performance metrics based on the user's historical trades on the platform. Users cannot delete or conceal their financial performance metrics on their profile pages. The page also shows the user's current portfolio holdings. On this page, users can easily see whether the focal user is currently holding Bitcoin or not.

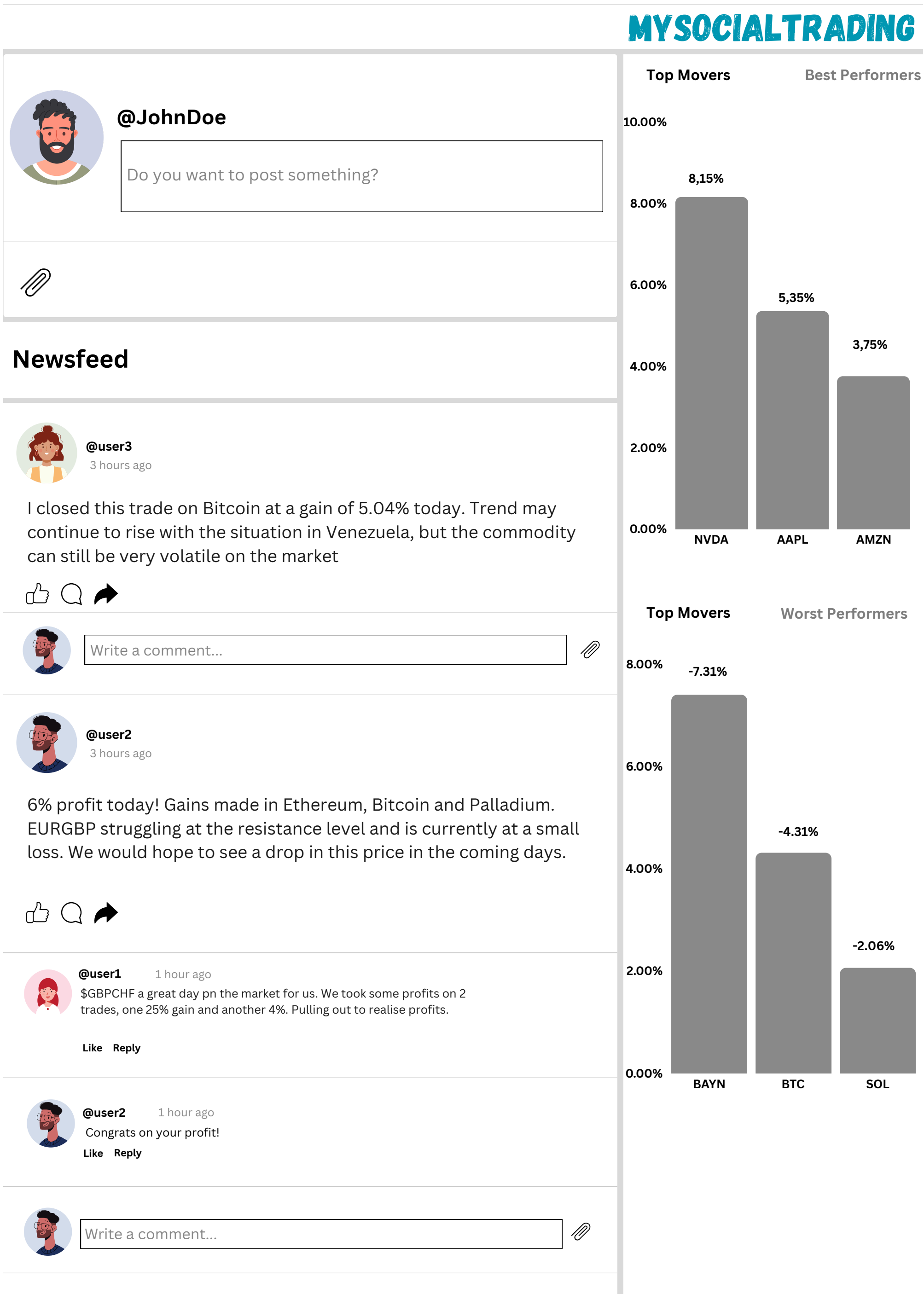


Figure B.1 An illustrative example of the news feed

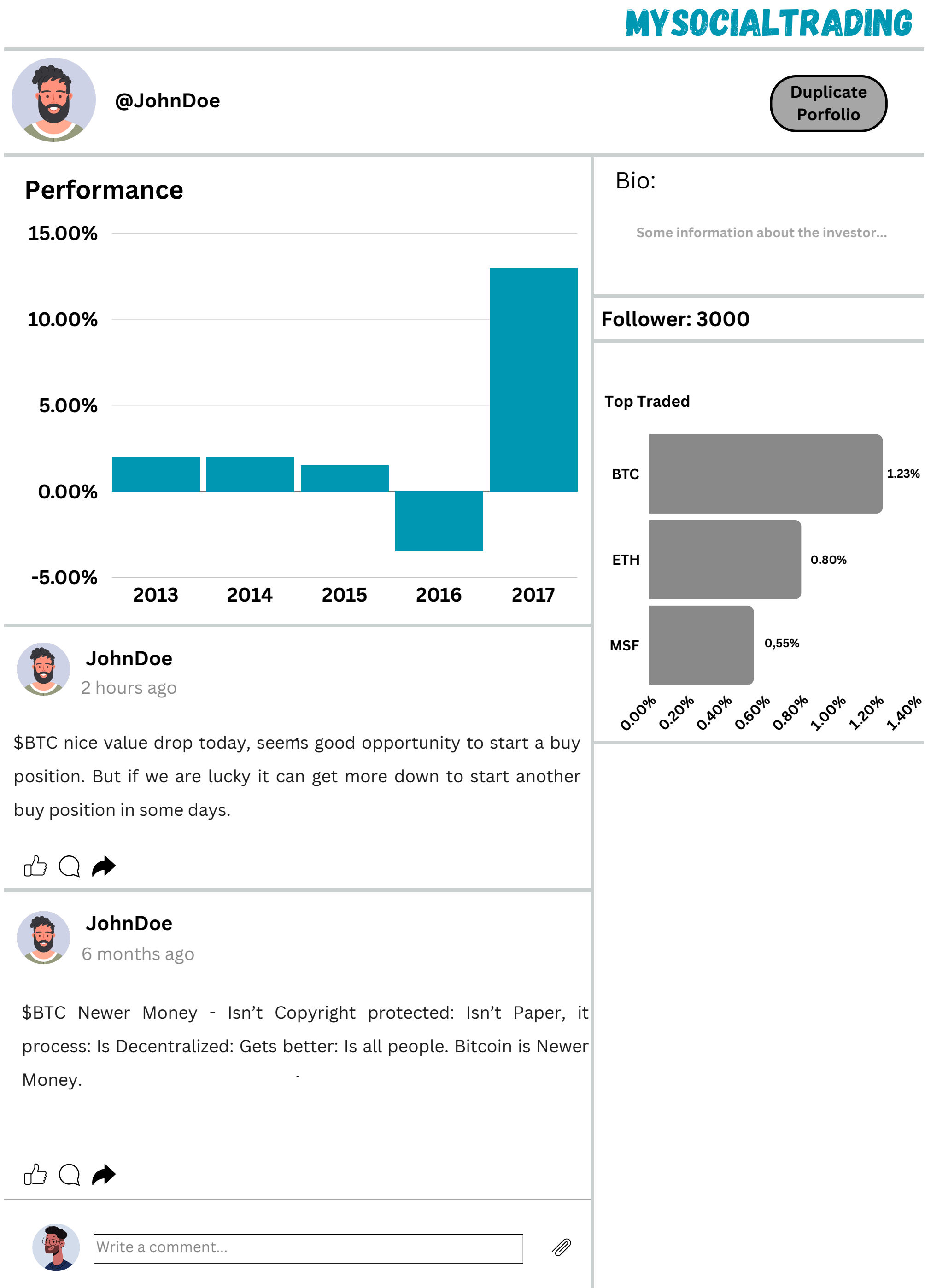


Figure B.2 **Investor main profile page**

Portfolio

Market	Direction	Invested	Profit/Loss	Value	Sell	Buy
BTC	Long	33,33%	21.23%	36,26%	536.78	538.56
Tesla	Long	33,33%	19.35%	32,31%	226.84	227.56

Figure B.3 **Investor performance section**

Appendix C Definitions of the variables and summary statistics

Table C.1 provides an overview of the variables used in our empirical analysis. Table C.2 provides the summary statistics of the demographic variables.

Table C.1 Definitions of variables

Variable	Description
1. Neighbor-related variables	
$\text{NeighborAdopt}_{i,t}$	Fraction of Bitcoin adopters over user *i*'s neighbors in period *t*
$\text{AdoptBTCPositive}_{i,t}$	Fraction of adopters who post positively about Bitcoin over all Bitcoin adopters in user *i*'s neighbors in period *t*
$\text{NonAdoptBTCPositive}_{i,t}$	Fraction of nonadopters who post positively about Bitcoin over all Bitcoin non-adopters from user *i*'s neighbors in period *t*
$\text{Neighbor\_N}_{i,t}$	The total number of user *i*'s neighbors in period *t*
$\text{Post\_N}_{i,t}$	Average number of posts made by user *i*'s neighbors in period *t*
$\text{NeighborBTCReturn}_{i,t}$	Average profitability of Bitcoin trades in user *i*'s neighborhood in period *t*
$\text{NeighborBTCSD}_{i,t}$	Average standard deviation of Bitcoin trades' profitability in user *i*'s neighborhood in period *t*
$\text{NeighborNonBTCReturn}_{i,t}$	Average profitability of non-Bitcoin trades in user *i*'s neighborhood in period *t*
$\text{NeighborNonBTCSD}_{i,t}$	Average standard deviation of non-Bitcoin trades' profitability in user *i*'s neighborhood in period *t*
2. Individuals' trading behavior	
$\text{AccReturn}_{i,t}$	The average profitability of user *i* by period *t*
$\text{AccSD}_{i,t}$	The standard deviations of user *i*'s profitability by period *t*
$\text{AccTrade}_{i,t}$	The total number of trades of user *i* by period *t*
$\text{NTrade}_{i,t}$	The number of trades traded by user *i* in period *t*
$\text{Diversification}_{i,t}$	The total number of unique instruments traded by user *i* by period *t*
$\text{Tenure}_{i,t}$	The number of weeks user *i* has traded on the platform by period *t* since January 2016
3. Individual time-invariant characteristics	
Male_i	1, if male, otherwise, 0
AgeRange_i	Age range of user *i*
Income_i	Annual income of user *i* (in U.S. dollars)
Experience_i	Trading experience of user *i* before joining the platform (in years)
RiskLevel_i	Self-reported risk preference of user *i*

Table C.2 Summary statistics of the demographic variables

Panel A: Gender and age

	Gender		Age range					
	Female	Male	18-24	25-34	35-44	45-54	55-64	≥65
Total	9.0%	91.0%	39.1%	33.4%	14.8%	6.3%	4.3%	2.1%

Panel B: Experience

	< 1 year	1 year	1-3 years	≥3 years
Percent	9.3%	40.1%	29.7%	20.8%

Panel C: Risk level

	Very low	Low	Medium	High	Very high
Percent	9.4%	10.3%	25.2%	27.2%	27.8%

Panel D: Income

	10K	25K	50K	200K	≥500K
Percent	25.6%	1.6%	43.8%	22.8%	6.2%

Note: Panel A reports the gender and age distributions of the users in our dataset. Panel B, C, and D report users' self-reported trading experience, risk level, and income, respectively. Data are collected upon registering with the platform.

Appendix D Social interactions on the trading platform

This appendix provides an overview of the social interactions on the social trading platform. Social interaction activities on the platform include posts, comments, and likes. Table D.1 presents the summary statistics of the social interaction activities among the 111,083 users in our sample. The statistics (Mean, Std Dev, and Median) are reported at the user level by aggregating the corresponding social interaction activity (posts, comments, or likes) during the observation period. The proportion of users who engage in each activity is defined as the number of users who post, comment, or like at least once divided by the total number of users in our data.

Table D.1 Summary of social interaction activities

	Count	Portion of users engaging	Mean	Std Dev	Median
Posts	218,569	21.7%	1.968	41.946	0
Comments	343,862	26.2%	3.096	35.912	0
Likes	558,602	73.3%	5.029	44.195	1

To provide a clearer sense of how Bitcoin-related posts differ between adopters and nonadopters, as well as between positive and nonpositive posts, Table D.2 provides several examples from our data.

Table D.2 Examples of Bitcoin posts by adoption and sentiment status

User Type	**Sentiment**	**Post**
Adopter	Positive	“$BTC Good chance it will keep trending upwards.”
Adopter	Nonpositive	“BTC has dropped back below $690 overnight and is staying below $650 is looking more likely for the weekend.”
Nonadopter	Positive	“BTC This is exciting... MASSIVE potential.”
Nonadopter	Positive	“BTC Newer Money - Isn’t Copyright Protected : Isn’t Paper, it process : Is Decentralized : Gets better: Is all people. BitCoin is Newer Money.”
Nonadopter	Nonpositive	“$BTC There is some panic at this moment. The price was first like 710 and suddenly dropped to 680. Are the Chinese people in panic modus? Some say that the price can go down fast?”

Appendix E Network statistics

Table E.1 shows the summary statistics of three networks: the network extracted from the social interactions ($SocNet_t$), the network extracted from the leader–copier relationship ($CopyNet_t$), and the combined network of the two (Net_t). The data are weekly.

We model the network as a weekly binary network because most social interactions are sparse and short-lived. Specifically, among all trader pairs with social interactions, 75.6% interact only once, and 12.9% interact only twice. Additionally, 91.4% of interactions occur within a single week.

The network is sparse. To ensure that the sparsity of the network does not alter our conclusions, we obtain a denser network by only including more active users who have been active on the platform for more than one month and executed at least five trades during our observation period. We re-estimate our analysis based on the denser network as a robustness check in Online Appendix J.10. We also investigate how the network structure influences the alignment between neighbors' opinions and actions on the focal user's Bitcoin adoption decision in Online Appendix K.

Table E.1 Summary statistics of the network data

	Net_t	$CopyNet_t$	$SocNet_t$
Overall statistics			
Number of users	21,619	11,988	12,568
Coverage of users	9%	5%	5%
Number of receivers	20,181	10,872	11,368
Number of senders	5,719	1,377	4,820
Number of directed links	75,826	25,369	50,456
Percentage of reciprocal links	15.1%	0.1%	19.3%
Density	0.0002	0.0002	0.0003
Outdegree			
Min	1	1	1
Median	2	2	2
Mean	13	18	10
Max	5,095	3,209	2,349
Indegree			
Min	1	1	1
Median	2	1	1
Mean	4	2	4
Max	848	132	842
Adoption rate			
Senders	12.7%	12.5%	12.7%
Receivers	7.0%	10.9%	4.6%

Note. The table shows the summary statistics of three networks using weekly data. $SocNet_t$ is the network extracted from the social interactions, $CopyNet_t$ is the network extracted from the leader-copier relationship, and Net_t is the combined network of the two. The coverage of users denotes the fraction of users connected with each other relative to the total number of users. The number of receivers denotes the number of users who receive information (identified as a copier from $CopyNet_t$ or a user who comments or likes another user's post from $SocNet_t$). The number of senders denotes the number of users who send information (identified as a leader from $CopyNet_t$ or a user who makes a post from $SocNet_t$). The percentage of reciprocal links denotes the percentage of reciprocal links relative to all the links. The density of a network is calculated as the ratio of the number of existing directed links to the total number of possible links in the network. Outdegree denotes the number of outgoing links; indegree denotes the number of incoming links. Adoption rate denotes the percentage of Bitcoin adoption among senders and receivers, respectively.

Appendix F Summary of hypotheses and results

Table F.1 Summary of hypotheses and results

Hypothesis	Statement	Result
Main Effects		
H1: Observational Learning	Users are more likely to adopt cryptocurrency when their neighbors have adopted.	✓
H2a: Credible Source Dominance	Adoption likelihood increases with the proportion of neighbors whose positive opinions align with their adoption behavior.	✓
H2b: Negative Action Dominance	Adoption likelihood decreases with the proportion of non-adopting neighbors who express positive opinions.	✓
Mechanism: Credibility		
H3a: Post Quality	The effect of neighbors' positive opinions on adoption is stronger when posts are of higher quality.	✓
H3b: Post Arousal	The effect of neighbors' positive opinions on adoption is weaker when posts exhibit higher arousal.	✓
H3c: Forward-Looking Statements	The effect of neighbors' positive opinions is stronger (weaker) when posts are forward-looking and the sender's track record is strong (weak).	✓
Boundary Conditions		
H4: Uncertainty	Under high uncertainty, users rely more on neighbors' opinions and less on alignment between opinions and actions.	✓
H5: Returns	During periods of high returns, users are more responsive to positive opinions, regardless of alignment.	✓
Demographic Heterogeneity		
H6a: Age	Younger users are more responsive to alignment than older users.	×
H6b: Risk Preference	More risk-averse users are more responsive to alignment than more risk-tolerant users.	×
H6c: Experience	More experienced users are more responsive to alignment than less experienced users.	✓
H6d: Income	Higher-income users are more responsive to alignment than lower-income users.	✓

Note: ✓ indicates empirical support for the hypothesis; × indicates that the hypothesis is not supported.

Appendix G Multicollinearity tests

This appendix provides the variance inflation factors (VIFs) and a correlation matrix. Table G.1 indicates that no variable has a VIF score exceeding 10, indicating that multicollinearity does not significantly distort the outcomes of our empirical analysis. Table G.2 suggests that the data do not include variable pairs that exhibit extremely high correlation coefficients.

Table G.1 VIF results

Variable	VIF score
AccTrade	7.76
Diversification	5.74
Tenure	2.59
NTrade	2.35
AccSD	1.58
NeighborBTCSD	1.21
NeighborAdopt	1.15
AdoptBTCPositive	1.11
NeighborNonBTCSD	1.10
AccReturn	1.10
NeighborBTCReturn	1.08
Post_N	1.02
NeighborNonBTCReturn	1.01
NonAdoptBTCPositive	1.01
Mean VIF score	2.34

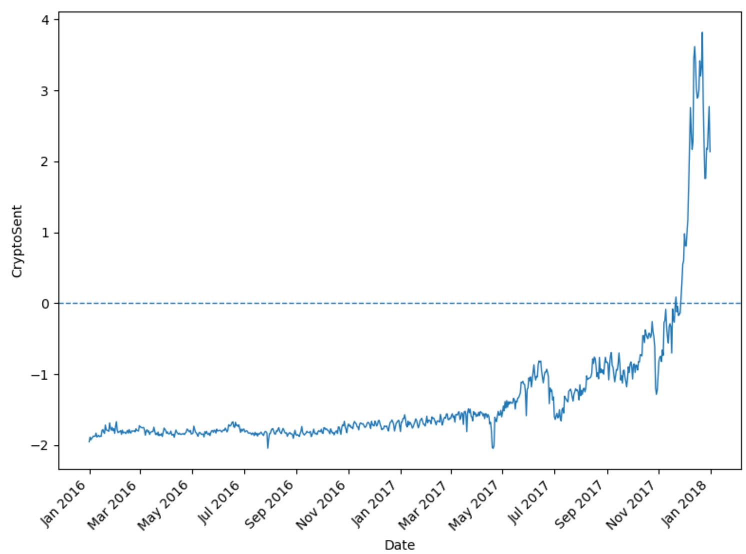
Table G.2: Correlation matrix

	Adopt	NeighborAdopt	Post_N	AdoptBTCPositive	NonAdoptBTCPositive	NeighborBTCReturn	NeighborBTCSD	NeighborNonBTCReturn	NeighborNonBTCSD	AccReturn	AccSD	Tenure	AccTrade	NTrade	Diversification
Adopt	1.000	0.193	-0.013	0.062	0.009	0.026	0.048	0.013	0.015	-0.002	0.079	0.023	0.145	0.209	0.216
NeighborAdopt	0.193	1.000	0.001	0.244	0.000	0.074	0.281	-0.011	0.154	0.014	-0.036	-0.098	-0.063	0.017	-0.025
Post_N	-0.013	0.001	1.000	0.006	0.031	-0.002	0.003	0.019	0.020	0.012	-0.057	-0.111	-0.106	-0.040	-0.078
AdoptBTCPositive	0.062	0.244	0.006	1.000	0.008	0.059	0.248	0.002	0.059	0.005	-0.011	-0.040	-0.025	0.014	-0.008
NonAdoptBTCPositive	0.009	0.000	0.031	0.008	1.000	0.003	0.005	0.001	0.017	-0.002	-0.001	-0.049	-0.003	0.040	0.033
NeighborBTCReturn	0.026	0.074	-0.002	0.059	0.003	1.000	0.264	-0.004	0.005	0.002	-0.003	-0.002	-0.002	0.004	0.001
NeighborBTCSD	0.048	0.281	0.003	0.248	0.005	0.264	1.000	-0.001	0.074	0.002	-0.012	-0.033	-0.029	-0.003	-0.018
NeighborNonBTCReturn	0.013	-0.011	0.019	0.002	0.001	-0.004	-0.001	1.000	0.021	0.068	0.017	-0.013	0.029	0.066	0.041
NeighborNonBTCSD	0.015	0.154	0.020	0.059	0.017	0.005	0.074	0.021	1.000	0.018	0.035	-0.231	-0.106	0.088	-0.008
AccReturn	-0.002	0.014	0.012	0.005	-0.002	0.002	0.002	0.068	0.018	1.000	-0.234	0.023	-0.011	0.045	-0.024
AccSD	0.079	-0.036	-0.057	-0.011	-0.001	-0.003	-0.012	0.017	0.035	-0.234	1.000	0.129	0.493	0.427	0.551
Tenure	0.023	-0.098	-0.111	-0.040	-0.049	-0.002	-0.033	-0.013	-0.231	0.023	0.129	1.000	0.598	0.112	0.230
AccTrade	0.145	-0.063	-0.106	-0.025	-0.003	-0.002	-0.029	0.029	-0.106	-0.011	0.493	0.598	1.000	0.634	0.830
NTrade	0.209	0.017	-0.040	0.014	0.040	0.004	-0.003	0.066	0.088	0.045	0.427	0.112	0.634	1.000	0.736
Diversification	0.216	-0.025	-0.078	-0.008	0.033	0.001	-0.018	0.041	-0.008	-0.024	0.551	0.230	0.830	0.736	1.000

Appendix H Descriptive analysis of public sentiment

In this appendix, we provide a descriptive analysis of a market-level sentiment index (CryptoSent; John et al. 2025) during our observation period. CryptoSent is a top-down sentiment index, similar to the established stock market sentiment index by Baker and Wurgler (2007). CryptoSent contains data on cryptocurrency market performance, news, Twitter/X discussions, social media attention, blockchain activity, and the number of active wallets on blockchains, which proxy for overall market sentiment. Notably, in 2016, both public attention, as measured by the Google Trends in Figure 2 of the main paper, and public sentiment, as captured by CryptoSent, exhibit limited variation and remain persistently low and predominantly negative, as shown in Figure H.1. This finding provides additional evidence that during our observation period, Bitcoin remained a niche market in which users were more likely to rely on information from neighbors than to rely on aggregate public signals.

Figure H.1 CryptoSent from 2016 to 2017



Note: This figure plots market-level sentiment related to Bitcoin from 2016 to 2017. It shows the daily CryptoSent sentiment index for the same period, with positive (negative) values indicating net positive (negative) sentiment.

Appendix I Details of ML-IV implementation and the first-stage estimation results

In this appendix, we provide the implementation details of the machine learning-based instrumental variable (ML-IV) approach. We first conceptually explain why one may use ML-IV methods and then describe the specific approach that we adopt. We also perform additional robustness tests using the standard 2SLS instrumental variable (IV) procedure without machine learning steps.

IV estimation relies on two fundamental assumptions: the relevance (correlation) condition and the exclusion condition. The recent ML-IV literature primarily addresses the relevance problem, namely, the issue of weak instruments (Bound et al. 1995). When instruments are only weakly correlated with the endogenous regressor, the resulting first-stage F-statistic is low, leading to biased estimates in the second stage (Bound et al. 1995). While machine learning techniques can improve the predictive strength of instruments, importantly, similar to the standard IV approach, the exclusion restriction is untestable (Bound et al. 1995).

In terms of our implementation, rather than relying on "deep" (such as neural networks) ML-IV estimators (discussed in Wu et al. 2025), we adopt a more conservative approach that uses LASSO for first-stage estimation. The LASSO estimator performs variable selection, enabling us to identify the most predictive instruments among a potentially large set. However, since the LASSO estimator may introduce bias because of shrinkage, the prior literature has proposed the post-LASSO estimator (Belloni et al. 2012) to alleviate such bias by re-estimating the model using only the selected variables. More recently, the double/debiased machine learning (DML) framework (Chernozhukov et al. 2018) has provided a general approach for conducting valid inference when flexible or high-dimensional machine learning methods are used in structural estimation. One key innovation in this framework is cross-fitting, a sample-splitting procedure that trains and predicts disjointed data folds to mitigate overfitting and remove regularization bias. Applied to the IV setting, Singh et al. (2026) extend this framework and prove that cross-fitted ML-based IV estimators achieve asymptotic normality under standard regularity conditions. We adopt the same estimation strategy and use the same specification as in their Monte Carlo simulations—LASSO regression with 3-fold cross-validation—which has been shown to perform robustly in synthetic settings. Specifically, we perform the following steps to construct the ML-IV model:

- **Step 1: Data partition.** We randomly split the dataset, $\mathcal{D}$, into two disjoint partitions, each denoted as $D_l, l \in \{1, 2\}$. For each partition, we define its complement set, D_l^c, as the subset of $\mathcal{D}$ excluding D_l (i.e., $D_1^c = D_2, D_2^c = D_1$).

- **Step 2: Cross-fitting.** For each partition l, we estimate a linear model on the complement dataset, D_l^c, using the LASSO method with hyperparameters tuned via 3-fold cross-validation. We then use the trained model to generate out-of-sample predictions of each endogenous variable for D_l. We denote these fitted values as $\hat{f}_l$, which serve as the ML-IVs.

- **Step 3: First-stage regression.** For each endogenous variable, we estimate the first-stage regression using the ML-IV as the predictor. We report the corresponding F-statistics in Table I.1.

Table I.1 First-stage estimation results

	(1) NeighborAdopt	(2) AdoptBTCPositive	(3) NonAdoptBTCPositive
ML-IV	1.019***	0.991***	1.036***
	(0.013)	(0.021)	(0.024)
User-level FE	Yes	Yes	Yes
Week-level FE	Yes	Yes	Yes
F-statistics	6,639.74***	2,152.51***	1,794.41***
Observations	1,600,598	1,600,598	1,600,598

Note: Standard errors (in parentheses) are clustered at the user-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In standard 2SLS IV estimation, researchers typically report the first-stage F-statistic and, when possible, an overidentification test (e.g., Hansen J statistics). Because our ML-IV specification is just identified, no overidentification test can be performed; thus, we report only the first-stage F-statistics to validate the relevance condition. To address potential concerns that our main results may be driven by flexible, high-dimensional modeling or algorithmic choices rather than the underlying economic structure, we also estimate a benchmark model using a conventional 2SLS specification without machine learning in the first stage. The results remain qualitatively consistent with those obtained from our ML-IV estimation (see Table I.2), indicating that our findings are not driven by the machine learning procedure itself. Notably, the first-stage F-statistics increase by approximately two to three times for each endogenous regressor under the ML-IV specification compared with the standard 2SLS benchmark (Tables I.1 and I.2), indicating that the ML-IV approach substantially strengthens the first-stage predictive power.

Table I.2 Estimation results with standard 2SLS IV procedures

	First Stage			Second Stage
	NeighborAdopt (1)	AdoptBTCPositive (2)	NonAdoptBTCPositive (3)	Adopt (4)
$\widehat{NeighborAdopt}$				0.089** (0.043)
$\widehat{AdoptBTCPositive}$				1.159*** (0.251)
$\widehat{NonAdoptBTCPositive}$				-0.261*** (0.069)
Post_N	-0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000* (0.000)
AccTrade	-0.002*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.017*** (0.001)
Tenure	-0.004*** (0.001)	-0.001*** (0.000)	0.002*** (0.000)	-0.011*** (0.001)
NTrade	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.012*** (0.000)
Diversification	0.002* (0.001)	0.001*** (0.000)	0.005*** (0.000)	0.043*** (0.002)
AccReturn	-0.000 (0.000)	0.000 (0.000)	-0.000*** (0.000)	-0.000 (0.000)
AccSD	-0.000 (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
N2Gender	-0.012*** (0.003)	-0.002*** (0.001)	0.006*** (0.001)	
N2Age	-0.002*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	
N2Risk	0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)	
N2Experience	0.022*** (0.001)	0.002*** (0.000)	-0.007*** (0.000)	
N2Income	0.003*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	
N2Tenure	0.015*** (0.001)	0.003*** (0.000)	-0.009*** (0.000)	
N2NTrades	-0.003*** (0.001)	0.001*** (0.000)	0.001*** (0.000)	
N2Profit	0.000*** (0.000)	0.000** (0.000)	-0.000*** (0.000)	
N2SD	0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)	
F-statistic	597.7***	172.4***	198.6***	–
User-level FE	Yes	Yes	Yes	Yes
Week-level FE	Yes	Yes	Yes	Yes
Observations	1,600,598	1,600,598	1,600,598	1,600,598

Notes: Columns (1)–(3) report first-stage regressions for the endogenous variables. Column (4) reports the second-stage IV estimates. All specifications include user and week fixed effects. Standard errors (in parentheses) are clustered at the user level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix J Robustness checks

In this appendix, we present a series of robustness checks of our main results.

J.1 Extension of time and scope

To address concerns about the generalizability of our findings beyond Bitcoin's early adoption in 2016, we now (1) extend the analysis of Bitcoin adoption to November 2017 and (2) expand the scope to Ethereum adoption, utilizing data from February 2017 (when the platform introduced Ethereum) to November 2017. These alternative contexts allow us to test whether the social learning effects are unique to Bitcoin in 2016 or are indicative of broader trends in cryptocurrency adoption.

Cryptocurrencies can differ along multiple dimensions, including technical aspects, market characteristics, and community norms. The heterogeneity in these dimensions may, in principle, influence adoption dynamics. To assess whether our results generalize beyond Bitcoin, we extend our analysis to Ethereum. This extension is meant to provide evidence on the robustness and generalizability of our results rather than to make claims about differences across cryptocurrencies. We also note that cross-cryptocurrency differences appear limited in practice within our setting. In particular, we find that 79.6% of investors who trade ETH also trade Bitcoin. This substantial overlap indicates that Bitcoin and Ethereum adoption largely occurs within a common user base, alleviating concerns that our findings are driven by fundamentally different investor communities across cryptocurrencies.

For the Ethereum analysis, we construct variables that are analogous to those of our main analysis. $NeighborAdoptETH_{i,t}$ measures the percentage of user i's neighbors who adopt Ethereum at time t, $AdoptETHPositive_{i,t}$ captures the percentage of user i's neighboring adopters who post positively about Ethereum at time t, and $NonAdoptETHPositive_{i,t}$ represents the percentage of user i's neighboring nonadopters who post positively about Ethereum at time t.

We present the estimation results in Columns (1) and (2) of Table J.3. The results are consistent with our main findings, demonstrating that social learning persists across different cryptocurrencies and time periods. This finding suggests generalizable patterns of social influence in cryptocurrency adoption. Overall, these results support the broader theoretical implications for understanding new technology adoption through social learning processes.

J.2 Complete sample

In our main analysis, we focus on understanding social learning dynamics by restricting the sample to users who have at least one connection during our observation period, thereby addressing

Table J.3 Results of robustness checks I

	(1) 2-year BTC	(2) ETH	(3) Complete Sample	(4) 2-week	(5) 8-week	(6) Omit Top 1%
$\widehat{NeighborAdopt}$	0.211***		0.125***	0.087*	0.208***	0.111*
	(0.012)		(0.041)	(0.033)	(0.041)	(0.044)
$Adopt\widehat{BTCPositive}$	0.146***		1.067***	0.685***	0.350	0.911***
	(0.035)		(0.218)	(0.182)	(0.242)	(0.246)
$NonAdo\widehat{ptBTCP}ositive$	-1.950***		-0.185**	-0.169**	-0.374***	-0.240***
	(0.093)		(0.070)	(0.071)	(0.084)	(0.073)
$\widehat{NeighborAdoptETH}$		0.012				
		(0.012)				
$Adopt\widehat{ETHP}ositive$		0.563***				
		(0.032)				
$NonAdo\widehat{ptETHP}ositive$		-2.394***				
		(0.325)				
Post_N	0.00007***	0.00001***	-0.000	-0.00001	-0.00000	-0.00001
	(0.00000)	(0.00000)	(0.000)	(0.00000)	(0.00000)	(0.00000)
AccTrade	-0.006***	0.016***	-0.014***	-0.018***	-0.018***	-0.018***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	-0.021***	-0.031***	-0.012***	-0.015***	-0.013***	-0.013***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
NTrade	0.044***	0.049***	0.009***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diversification	0.061***	0.053***	0.038***	0.043***	0.044***	0.043***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
AccReturn	-0.0004***	0.002***	0.000	0.00001	0.00000	-0.00001
	(0.0001)	(0.000)	(0.000)	(0.00005)	(0.00005)	(0.00005)
AccSD	-0.002***	-0.006***	-0.000***	-0.0004***	-0.0004***	-0.0004***
	(0.0001)	(0.0002)	(0.000)	(0.00006)	(0.00006)	(0.00006)
User-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,446,503	2,379,675	2,709,761	1,600,598	1,600,598	1,583,917

Note: Standard errors (in parentheses) are clustered at the user level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

concerns about network sparsity. As a robustness check, we now expand the analysis to include the entire active user base. Again, the results (Column (3) of Table J.3) remain consistent with our main findings.

J.3 Alternative time windows

Next, we ensure that our findings are not sensitive to the specific time window used for constructing the social network. Thus, we repeat our analysis using alternative window sizes. We define network connections based on 2-week and 8-week interaction periods, in contrast to our baseline specification of a 4-week window, and summarize the results in Columns (4) and (5) of Table J.3, respectively. Our main findings remain substantively consistent across these different temporal specifications. Positive opinions are less relevant in our 8-week specification, which might be explained by the fact that an 8-week window might be too long in the fast-moving world of financial markets.

J.4 Excluding highly connected users

To address the concern that highly connected users drive our findings, we conduct a robustness check and remove the top 1% of users with the highest outdegree centrality and re-estimate our model.

This approach ensures that our findings are not unduly influenced by a small group of particularly influential users who could skew network-wide adoption patterns. Our key results remain robust to this exclusion, as shown in Column (6) of Table J.3.

J.5 Network constructed from only social interactions

When defining the neighbors of a focal user, i.e., the network capturing the information flow among users, we consider both the leader–copier network and social interactions. In terms of social interactions, a link is established when a user comments on or likes another user's post. This behavior indicates that the focal user has noticed her neighbor's behavior. While the literature (Pelster and Hofmann 2018) argues that users also closely monitor the behaviors of the leaders whom they copy, it is possible that they do not notice all activities of their leaders. To ensure that our results are not driven by unnoticed activities, we conduct an additional robustness check and consider only a network based on social interactions. Using this stricter network definition, we reconstruct all relevant variables and re-estimate our model. The estimation results show that our main findings remain qualitatively unchanged (see Column (1) of Table J.4).

Table J.4 Results of robustness checks II

	(1) Social Net Only	(2) Funds Allocated to BTC	(3) Nonrepetitive Adoption	(4) Measure by Count	(5) Alt. Senti.
$\widehat{NeighborAdopt}$	0.043	0.027	0.380***	0.171***	-0.116
	(0.105)	(0.081)	(0.074)	(0.034)	(0.060)
$\widehat{AdoptBTCPositive}$	1.244***	1.262***	0.787**	0.254***	1.315***
	(0.438)	(0.437)	(0.367)	(0.076)	(0.197)
$\widehat{NonAdoptBTCPositive}$	-0.164	-0.661***	-0.816***	-0.072**	-0.384***
	(0.468)	(0.144)	(0.238)	(0.033)	(0.070)
Post_N	-0.00001	-0.00001	-0.000***	-0.000	-0.00001**
	(0.00001)	(0.00001)	(0.000)	(0.000)	(0.00000)
AccTrade	-0.017***	-0.010***	-0.020***	-0.010***	-0.017***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Tenure	-0.014***	-0.018***	-0.010***	-0.018***	-0.014***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
NTrade	0.012***	0.003***	0.012***	0.003***	0.011***
	(0.0004)	(0.001)	(0.001)	(0.001)	(0.000)
Diversification	0.043***	0.042***	0.042***	0.042***	0.043***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)
AccReturn	-0.00000	-0.00019*	-0.000	-0.000*	-0.00000
	(0.00005)	(0.00011)	(0.000)	(0.000)	(0.00005)
AccSD	-0.00039***	-0.00050***	-0.001***	-0.001***	-0.00039***
	(0.00006)	(0.00011)	(0.000)	(0.000)	(0.00006)
User-level FE	Yes	Yes	Yes	Yes	Yes
Week-level FE	Yes	Yes	Yes	Yes	Yes
Observations	1,600,598	1,600,598	633,182	1,600,598	1,600,598

Note: Standard errors (in parentheses) are clustered at the user level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

J.6 Proportion of funds allocated to Bitcoin

We address concerns regarding the binary dependent variable measuring whether the focal user adopts Bitcoin or not. Instead of using a binary outcome (adoption or not), we now employ the portfolio weight that the user allocated to Bitcoin as a more precise measure of Bitcoin adoption. A higher portfolio weight indicates that a greater proportion of funds is allocated to the adoption decision. Thus, the continuous variable provides a more granular view of investment decisions, capturing not only whether users adopt Bitcoin but also the extent of their investment, including partial investments or withdrawals. Again, the results remain consistent with our main findings (see Column (2) of Table J.4).

J.7 Subsample excluding users with repetitive adoption behavior

Our main analysis includes users who may have adopted Bitcoin at some point in the past, discontinued trading the cryptocurrency, and readopted Bitcoin. One may argue that these users do not provide the cleanest identification because of the potentially confounding effects of the first adoption. We now address this concern and explicitly focus on a subsample of users who adopt Bitcoin for the very first time. This restriction rules out any potential effects from prior Bitcoin adoption experience in our data. We summarize the estimation results in Column (3) of Table J.4. These results are consistent with our main results.

J.8 Alternative measure of AdoptBTCPositive and NonAdoptBTCPositive

In our main model, the two key variables $AdoptBTCPositive$ and $NonAdoptBTCPositive$ are defined as the percentage of adopters and nonadopters who make positive Bitcoin-related posts. To further validate the robustness of our findings, we employ one alternative measure for these two key variables. In particular, we simply count the number of positive Bitcoin-related posts by adopters ($AdoptBTCPositive$) and nonadopters ($NonAdoptBTCPositive$) in the neighborhood, respectively. Thus, this measure relies on the absolute number rather than the percentage of positive Bitcoin-related posts. We re-estimate our model using these alternative measures and present the estimation results in Column (4) of Table J.4. The estimation results are consistent with our main results.

J.9 Alternative sentiment measurement

To ensure that our findings are not dependent on the specific sentiment classification approach, we additionally estimate sentiment using a LLM rather than our baseline lexicon-based method. This alternative approach leverages the contextual understanding capabilities of modern language models to capture more nuanced sentiment expressions that may be missed by dictionary-based approaches. We re-estimate our main models using the LLM-derived sentiment measures. Column (5) of Table J.4 indicates that our main results remain consistent.

J.10 Subsample comprising more active users

We conduct a robustness test using a focused subsample comprising more active users. Specifically, we select those users who have been active for more than one month on the platform and executed at least five trades during our observation period. This criterion ensures that our analysis accurately represents the behaviors of traders who consistently engage on the platform, as opposed to those who participate occasionally or only once. We estimate the model based on this subsample and present the estimation results in Column (1) of Table J.5. The results align with the major findings from the main model.

J.11 Model without user-level fixed effects

In our main model, we include user-level fixed effects to account for unobserved heterogeneity at the user level. However, including these fixed effects may introduce information from the future into the model. This may occur during the demeaning of variables when the mean considers the future behavior of users. This potentially contaminates the analysis with information not available at the time of decision-making. To address this concern, we re-estimate our main model without user-level fixed effects. The results remain consistent (see Column (2) of Table J.5).

J.12 Conditional logit

In our main analysis, we use a linear probability model. We have verified that the predicted likelihoods from our LPM model remain within a reasonable range, with 89.5% of predictions falling within [0,1] and the most extreme values extending to -0.52 on the lower bound (the upper bound remains within [0,1]). To further ensure that the model specification is appropriate, we conduct a robustness check using a conditional logit model (Chamberlain 1980) in which we account for user-level fixed effects by conditioning on each user's choice set and include week fixed effects as dummy variables. To address potential endogeneity in the nonlinear setting, we employ a control function approach rather than the 2SLS approach, using the same set of instruments as in our main model. This method ensures consistent estimation within the logit framework. The results remain consistent with our main findings (see Column (3) of Table J.5).

Table J.5 Results of robustness checks III

	(1) More Active Users	(2) No User FE	(3) Conditional Logit	(4) Double Clustering
$\widehat{NeighborAdopt}$	0.159*	0.141***	2.641***	0.104
	(0.082)	(0.044)	(0.050)	(0.080)
$\widehat{AdoptBTCPositive}$	1.245***	0.825***	0.475***	0.955*
	(0.450)	(0.251)	(0.067)	(0.504)
$\widehat{NonAdoptBTCPositive}$	-0.216***	-0.349***	0.041	-0.260
	(0.083)	(0.080)	(0.115)	(0.201)
Post_N	-0.000	0.000	0.00006	-0.00001
	(0.000)	(0.000)	(0.00017)	(0.00001)
AccTrade	-0.017***	-0.016***	-0.593***	-0.018***
	(0.001)	(0.000)	(0.033)	(0.002)
Tenure	-0.014***	-0.002**	-0.114**	-0.013***
	(0.001)	(0.001)	(0.043)	(0.002)
NTrade	0.012***	0.099***	0.361***	0.012***
	(0.0004)	(0.0004)	(0.009)	(0.001)
Diversification	0.043***	0.002***	0.987***	0.044***
	(0.002)	(0.002)	(0.058)	(0.004)
AccReturn	-0.000	0.000*	0.0027*	-0.00000
	(0.000)	(0.000)	(0.0015)	(0.00010)
AccSD	-0.000***	-0.001**	-0.0050**	-0.00039**
	(0.000)	(0.000)	(0.0017)	(0.00019)
User-level FE	Yes	No	Yes	Yes
Week-level FE	Yes	Yes	Yes	Yes
Observations	1,600,598	1,600,598	487,387	1,600,598

Note: Standard errors (in parentheses) are clustered at the user level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

J.13 Double-clustered standard errors

Finally, we address concerns regarding potential serial correlation in the error term, which may arise along both the individual and time dimensions. To account for this potential correlation, we implement a two-way clustering approach, clustering standard errors at both the user and time levels. This method allows for arbitrary correlation within users over time and across users within a given week. However, multiway clustering following Cameron et al. (2011) may yield a nondefinite variance matrix. Such a matrix is generally not a problem since it is forced to be semidefinite by setting negative eigenvalues to zero in these cases and the variance estimator is asymptotically correct. However, in a setting where the number of clusters is small, single-clustered standard errors may be preferred. We summarize the results in Column (4) of Table J.5. The results remain qualitatively consistent with our main findings.

Appendix K Moderating effect of network centrality

In this appendix, we investigate how the network structure influences the effect of the alignment between neighbors' opinions and actions on the focal user's Bitcoin adoption decision. Specifically, we focus on the outdegree centrality of information senders to distinguish users with broader reach from those on the network's periphery. We examine whether neighbors with higher outdegree centrality—those who share information with a larger audience, such as users at the center of a star-shaped network—exert greater influence on the focal user.

To test this possibility, we construct the variable $NeighborOutDegree_{i,t}$,[3] defined as the average outdegree of focal user i's neighbors, and we interact it with our key independent variables of interest $AdoptBTCPositive_{i,t}$ and $NonAdoptBTCPositive_{i,t}$. The results in Table K.1 do not show statistically significant interaction effects. This finding suggests that users at the center of a star-shaped network do not systematically influence the extent to which the alignment between neighbors' opinions and actions affects the focal user's Bitcoin adoption decision.

[3] We log-transform the variable to account for the skewed distribution of outdegree.

Table K.1 The moderating effect of network centrality

	Adopt
$\widehat{NeighborAdopt}$	0.105***
	(0.040)
$Adopt\widehat{BTC}Positive$	0.828***
	(0.242)
× NeighborOutDegree	-0.039
	(0.078)
$NonAdopt\widehat{BTC}Positive$	-0.297***
	(0.074)
× NeighborOutDegree	0.011
	(0.082)
NeighborOutDegree	0.004***
	(0.001)
Post_N	-0.000
	(0.000)
AccTrade	-0.018***
	(0.001)
Tenure	-0.013***
	(0.001)
NTrade	0.012***
	(0.000)
Diversification	0.044***
	(0.002)
AccReturn	-0.000
	(0.000)
AccSD	-0.000***
	(0.000)
User-level FE	Yes
Week-level FE	Yes
Observations	1,600,598

Note: Standard errors (in parentheses) are clustered at the user level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix L Alternative mechanisms

This appendix investigates potential alternative mechanisms that may explain our main empirical observation that users adopt Bitcoin after they observe the actions and opinions of their neighbors.

L.1 Alternative mechanism: Awareness

It is possible that users may adopt Bitcoin not as a result of social learning from their neighbors but simply because they have only recently become aware of Bitcoin's existence. That is, some users may initially be unaware of Bitcoin, and their adoption could be triggered by this initial awareness rather than by learning from others. To disentangle these two mechanisms—simple awareness versus informational insight from neighbors—we estimate a variation of our model using a subsample of users who were already aware of Bitcoin beforehand.

Table L.1 Results of alternative mechanisms

	Awareness (1)	Profitability (2)
$\widehat{NeighborAdopt}$	0.373***	0.102**
	(0.074)	(0.044)
$\widehat{AdoptBTCPositive}$	0.717**	1.284***
	(0.359)	(0.260)
$\widehat{NonAdoptBTCPositive}$	-0.842***	-0.255***
	(0.238)	(0.071)
Post_N	0.000	-0.00001**
	(0.000)	(0.000)
AccTrade	-0.057***	-0.018***
	(0.006)	(0.001)
Tenure	-0.129***	-0.013***
	(0.008)	(0.001)
NTrade	0.020***	0.011***
	(0.001)	(0.000)
Diversification	-0.020*	0.044***
	(0.011)	(0.002)
AccReturn	-0.0003	-0.000
	(0.0003)	(0.000)
AccSD	-0.002***	-0.0004***
	(0.000)	(0.000)
NeighborBTCReturn		0.002***
		(0.000)
NeighborBTCSD		-0.010***
		(0.002)
NeighborNonBTCReturn		-0.00003
		(0.00002)
NeighborNonBTCSD		-0.00006**
		(0.00002)
User-level FE	Yes	Yes
Week-level FE	Yes	Yes
Observations	367,378	1,600,598

Note: Standard errors (in parentheses) are clustered at the user level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Specifically, we use users with prior Bitcoin trading or posting activity, as these users are clearly already aware of Bitcoin. The subsample accounts for approximately 23% of the full data sample.

Given that users were already aware of Bitcoin prior to the adoption decision, the decision to adopt can no longer be explained by awareness alone.

We summarize the estimation results in Column (1) of Table L.1. We find a significantly positive coefficient of $NeighborAdopt$, highlighting that the importance of social learning in the adoption of Bitcoin trading goes beyond awareness. We also find that adopters who post positively about Bitcoin significantly increase the likelihood of adoption by the focal user, whereas nonadopters who post positively about Bitcoin significantly decrease the likelihood of adoption by the focal user. These results are consistent with our main estimation results.

L.2 Alternative mechanism: Profitability of neighbors

Another explanation for our main finding could be that the focal user's decisions are influenced by her neighbors' profitability rather than the sentiments expressed in Bitcoin-related posts. Thus, users could be driven by a fear of missing out and trying to keep up with the Joneses (see, e.g., Klocke et al. 2025, among others) rather than obtaining informative insights from their neighbors. To address this concern, we control for the portfolio performance of neighbors by including the return and risk of both Bitcoin-related and non-Bitcoin-related trades ($NeighborBTCReturn_{i,t}$, $NeighborBTCSD_{i,t}$, $NeighborNonBTCReturn_{i,t}$, and $NeighborNonBTCSD_{i,t}$). The idea is to differentiate the effects of sentiments expressed in posts from the financial performance of neighbors, especially their Bitcoin-related performance. We re-estimate our model and summarize the estimation results in Column (2) of Table L.1. We find that our main results remain qualitatively the same. Neighbors' Bitcoin returns have a positive effect on the focal user's Bitcoin adoption, whereas the returns on neighbors' non-Bitcoin assets do not influence the focal user's Bitcoin adoption.

L.3 Alternative mechanism: Strategic referral

The literature shows that online customer reviews are frequently manipulated through fake or incentivized postings that mislead consumers, undermine review credibility, and influence purchase decisions (Narciso 2022, Wu et al. 2020, Zhuang et al. 2018). In line with this literature, one may suspect potential strategic behavior among leaders and copiers, with leaders offering copiers monetary incentives to copy their trading strategies. Leaders have incentives to recruit copiers through offline referrals to the platform to increase their commission fees.

While leaders have incentives to recruit copiers, copiers have to invest real money in their accounts to automatically replicate leaders' trading strategies. Therefore, strategic behavior in our setting fundamentally differs from low-cost actions such as following an account or writing a customer review on other social media platforms. Because copiers bear financial risk, they are unlikely to participate in any coordinated or manipulative referral scheme unless leaders offer substantial monetary incentives or there is a strong pre-existing trust relationship (e.g., offline friendships). Considering that leaders' commission fees amount to a small percentage of assets under management and performance-related payments, sharing these commission fees does not provide incentives to copiers that are large enough to bear financial risk, assuming standard risk preferences and risk-averse behavior. Thus, strategic behavior between leaders and copiers through offline agreements is unlikely.

Moreover, our study examines how neighbors' actions and opinions influence a focal user's decision to adopt cryptocurrency. Even if such strategic referral behavior exists, strategic referrals would need to be used in systematically different ways by Bitcoin adopters and nonadopters—as well as along their posting activities—to explain our results. Therefore, the strategic referral mechanism is unlikely to be a concern in our setting.

Appendix M Using a large language model to classify posts

This appendix summarizes prompts from our large language model (LLM) usage to classify posts. We use an LLM to quantify the textual features of posts on the social trading platform. We use the “o4-mini” model to systematically label various aspects of each post, including sentiment, emotional arousal, textual quality, and whether the post contains a forward-looking statement. Listing M.1 presents the prompt that we use to generate the labels.

```
prompt = f"""
    Post: "{row_text}"

    This post is from a social trading platform. Please label below textual features
        of this post:

    1. Sentiment (1 = Negative, 2 = Neutral, 3 = Positive)
    2. Emotional arousal level (1 = Calm, 5 = Highly aroused)
    3. Text quality (1 = Lowest, 5 = Highest), considering:
    * Informativeness (e.g., useful and more information)
    * Credibility (e.g., backed by URLs or evidence)
    * Readability (e.g., clear and well-structured)
    4. Forward-looking statement? (Yes/No)
    * e.g., projection of the future return of a financial asset.

    Return in JSON:
    Return your answers in JSON format:
    {{
    "sentiment": int,
    "arousal": int,
    "quality": int,
    "forward_looking": "Yes" or "No"
    }}
    """
```

Listing M.1: LLM prompt to quantify textual features

We provide the summary statistics of the text measures for Bitcoin-related posts and positive Bitcoin-related posts in Table M.1 separately for adopters and nonadopters.

For Bitcoin-related posts in general, we observe that adopters post with significantly higher arousal levels. They also include forward-looking statements (FLSs) more frequently. We do not find significant differences in the quality of posts. Turning to positive Bitcoin-related posts, we observe higher quality and arousal for adopters than for nonadopters. Again, we find a greater tendency for FLSs than for nonadopters. These patterns suggest that adopters’ (positive) Bitcoin posts are characterized by greater emotional intensity, more future-oriented projections, and higher informational quality (for positive posts).

Table M.1 Text characteristics of Bitcoin posts, split by adoption status

Characteristic	Nonadopters	Adopters	% Diff	*t*-stat	*p*-value
All Bitcoin-related posts					
Quality	1.696	1.737	+2.4%	-1.539	0.124
Arousal	2.166	2.576	+18.9%	-9.190	0.000
Forward-looking	0.285	0.536	+88.1%	-14.238	0.000
Positive Bitcoin-related posts					
Quality	2.002	2.137	+6.7%	-3.038	0.002
Arousal	2.344	2.881	+22.9%	-7.293	0.000
Forward-looking	0.293	0.674	+129.7%	-10.389	0.000

Note: Arousal and quality are scaled from 1 to 5. Forward-looking is a dummy variable that takes a value of 1 if the post contains forward-looking statements (FLS), and 0 otherwise. % Diff is calculated as the difference between nonadopters and adopters, divided by the adopters' value.

Appendix N Full estimation results

Due to space limitations in the main paper, we omitted the estimation results for the control variables. In this appendix, we provide the full estimation results.

Table N.1 Full results of Table 4: Text characteristics of Bitcoin posts and adoption decisions

	Adopt (1)
$\widehat{NeighborAdopt}$	0.190*** (0.046)
$\widehat{AdoptPositiveBTCQuality}$	42.413*** (4.928)
$\widehat{NonAdoptPositiveBTCQuality}$	13.408*** (2.228)
$\widehat{AdoptPositiveBTCArousal}$	-12.375** (5.605)
$\widehat{NonAdoptPositiveBTCArousal}$	-14.058*** (2.162)
$\widehat{AdoptPositiveBTCFLS}$	-27.334*** (3.384)
$\widehat{NonAdoptPositiveBTCFLS}$	2.467*** (0.607)
Post_N	-0.0001*** (0.00002)
AccTrade	-0.022*** (0.001)
Tenure	-0.004*** (0.001)
NTrade	0.010*** (0.000)
Diversification	0.051*** (0.002)
AccReturn	0.0002*** (0.00005)
AccSD	-0.0001 (0.00006)
User-level FE	Yes
Week-level FE	Yes
Observations	1,600,598

Note: Standard errors (in parentheses) are clustered at the user level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table N.2 Full results of Table 5: Uncertainty, returns, and demographic characteristics implications

	Volatility (1)	Return (2)	Age (3)	Risk (4)	Experience (5)	Income (6)
$\widehat{NeighborAdopt}$	0.182***	0.159***	0.105**	0.110**	0.107**	0.107**
	(0.036)	(0.041)	(0.043)	(0.042)	(0.042)	(0.043)
$\widehat{AdoptBTCPositive}$	0.589***	0.665***	2.072***	0.477*	0.535**	0.663***
	(0.190)	(0.224)	(0.430)	(0.245)	(0.241)	(0.240)
× Volatility_High	0.371**	–	–	–	–	–
	(0.169)					
× Return_Large_Positive	–	0.526***	–	–	–	–
		(0.133)				
× Age_Young	–	–	–1.296***	–	–	–
			(0.338)			
× Risk_High	–	–	–	0.969***	-	–
				(0.180)	-	
× Experience_Long	–	–	–	–	0.808***	-
					(0.188)	-
× Income_High	–	–	–	-	–	1.374***
				-		(0.248)
$\widehat{NonAdoptBTCPositive}$	-0.747***	-0.485**	-0.326**	-0.102	-0.096	-0.291***
	(0.180)	(0.199)	(0.149)	(0.102)	(0.094)	(0.085)
× Volatility_High	0.658***	–	–	–	–	–
	(0.157)					
× Return_Large_Positive	–	0.357**	–	–	–	–
		(0.178)				
× Age_Young	–	–	0.088	–	–	–
			(0.172)			
× Risk_High	–	–	–	–0.310**	-	–
				(0.132)	-	
× Experience_Long	–	–	–	–	–0.338**	-
					(0.143)	-
× Income_High	–	–	–	-	–	0.074
						(0.145)
Post_N	0.000	–0.000**	–0.000	–0.000	–0.000*	–0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AccTrade	–0.017***	–0.018***	–0.018***	–0.018***	–0.018***	–0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	–0.014***	–0.013***	–0.013***	–0.013***	–0.013***	–0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NTrade	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diversification	0.043***	0.043***	0.044***	0.044***	0.044***	0.044***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AccReturn	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AccSD	–0.000***	–0.000***	–0.000***	–0.000***	–0.000***	–0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
User-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-level FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,600,598	1,600,598	1,600,598	1,600,598	1,600,598	1,600,598

Note: The dependent variable is $Adopt_{i,t}$. Age_Young is a dummy variable that takes a value of 1 if a user's age is less than 45 years old, and 0 otherwise; $Income\_High$ is a dummy variable that takes a value of 1 if a user's annual income is greater than 50,000 U.S. dollars, and 0 otherwise; $Risk\_High$ is a dummy variable that takes a value of 1 if a user's risk preference is above medium, and 0 otherwise; $Experience\_Long$ is a dummy variable that takes a value of 1, if a user's trading experience is more than 1 year, and 0 otherwise. Standard errors (in parentheses) are clustered at the user level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix O Supplementary analysis: Do investors trade in line with their posts?

In addition to the visualizations in Figure 3 in the main paper, we estimate a linear regression model on the holding period of users' Bitcoin positions with user-level and week-level fixed effects. The explanatory variables are whether the user makes a Bitcoin-related post while holding a position ($NoPost$, which takes a value of 1 if the user does not make a Bitcoin-related post while holding a Bitcoin position and 0 otherwise), the sentiment of a Bitcoin-related post ($Sentiment$, which takes a value of 1 if the sentiment is positive and 0 otherwise), and the profit of the trade ($Profit$). We summarize the estimation results in Table O.1. In line with the visualization evidence, the results indicate that users who make Bitcoin-related posts hold their Bitcoin positions longer than do users who do not post about Bitcoin. Similarly, users who post positive sentiments hold their positions longer than do users who post neutrally or negatively about Bitcoin. Again, these results indicate that users on the platform, on average, post in line with their trading activities.

Table O.1 Holding periods and posting behaviors

Dependent variable	Holding period (1)
NoPost	-1.453***
	(0.056)
Positive	0.556***
	(0.096)
Profit	0.001***
	(0.000)
Intercept	4.952***
	(0.056)
User-level FE	Yes
Week-level FE	Yes
Observations	105,417

Note. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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