Trust in DeFi: An Empirical Study of the Decentralized Exchange

Jianlei Han, Shiyang Huang, and Zhuo Zhong*

November 2023

Abstract

We empirically study the role of the decentralized cryptocurrency exchange (DEX) in guiding cryptocurrency trading. Investors trust the DEX: DEX's userbase information affects investor trading on the centralized cryptocurrency exchange (CEX). This effect intensifies during instances of market manipulation—"wash trading"—on the CEX or when investors have more concerns about it. Conversely, CEX's userbase doesn't reciprocally impact CEX trading. Using the "yield-farming" program launch as quasi-exogenous shocks, we confirm DEX's causal impact on CEX trading. Our study highlights that the DEX can foster efficient, transparent trading structures where trustworthy centralized mechanisms are impractical or costly.

JEL Classification: G12; G14
Keywords: blockchain, cryptocurrency, DeFi, smart contracts, wash trading, fake volume

---

*We thank Maureen O'Hara, Vincent Gregoire, Sean Foley, Talis Putnins, Danqi Hu, Carole Comerton-Forde, Agostino Capponi, Andreas Park, Jiasun Li, as well as seminar participants at the PBC of Tsinghua, the University of Melbourne, Monash University, Macquarie University, the University of Sydney, the University of Technology Sydney, Deakin University, Victoria University of Wellington, 2022 FIRN Annual Conference, 2022 China International Conference in Finance, the Asia-Pacific Market Microstructure workshop of 2021, Annual Conference in Digital Economics 2022, the 2022 Hong Kong Conference for Fintech, AI, and Big Data in Business, and the 2023 Plato MI3 Academic Conference for helpful comments and suggestions. Jianlei Han (jianlei.han@mq.edu.au) is at the Department of Applied Finance, Macquarie University; Shiyang Huang (huangsy@hku.hk) is at the Faculty of Business and Economics, the University of Hong Kong; Zhuo Zhong (zhuo.zhong@unimelb.edu.au) is at the Department of Finance, the University of Melbourne.

Trust in DeFi: An Empirical Study of the Decentralized Exchange

November 2023

Abstract

We empirically study the role of the decentralized cryptocurrency exchange (DEX) in guiding cryptocurrency trading. Investors trust the DEX: DEX's userbase information affects investor trading on the centralized cryptocurrency exchange (CEX). This effect intensifies during instances of market manipulation—"wash trading"—on the CEX or when investors have more concerns about it. Conversely, CEX's userbase doesn't reciprocally impact CEX trading. Using the "yield-farming" program launch as quasi-exogenous shocks, we confirm DEX's causal impact on CEX trading. Our study highlights that the DEX can foster efficient, transparent trading structures where trustworthy centralized mechanisms are impractical or costly.

JEL Classification: G12; G14
Keywords: blockchain, cryptocurrency, DeFi, smart contracts, wash trading, fake volume

Decentralized finance, or DeFi, in cryptocurrency, powered by Ethereum and other smart contract platforms, has become an important disruptive innovation to traditional financial marketplaces. Proponents of DeFi argue that the decentralized nature of blockchain technology and the transparency brought by smart contracts could better organize trading (Harvey, Ramachandran, and Santoro, 2021). However, there has been no clear empirical evidence of such advantage of blockchain-based decentralization. One challenge is the lack of a comparable centralized versus decentralized infrastructure. Our study aims to fill this gap, and we overcome the challenge by empirically comparing the nascent decentralized exchange with the centralized exchange of cryptocurrencies.

Compared to centralized cryptocurrency exchanges (CEXs), decentralized cryptocurrency exchanges (DEXs) offer a distinct advantage for organizing trading by creating a transparent and trustworthy marketplace. This benefit arises from the openness in the design of DEXs that employ blockchain for settlement and smart contract for execution. Both technologies ensure accessibility for all market participants. In contrast, CEXs have been linked to issues with transparency and trustworthiness. Investors' concerns about CEXs are not unfounded, given the opacity in the operation of CEXs. Aside from the risk of being hacked or the custodian risk, [1] recent studies have shown that CEXs are susceptible to market manipulation, such as "wash trading" or faked transactions in cryptocurrency trading (Cong et al., 2021).[2] Wash trading or faked transactions inevitably diminishes investors' confidence or trust in the financial markets (e.g., Allen and Gale, 1992; Aggarwal and Wu, 2006), which can lead to market breakdown.

The openness in the design of DEXs enhances investors' confidence in the trustworthiness of the marketplace in two key ways. First, DEXs leverage smart contracts that are openly accessible to all market participants. This accessibility allows any participant to readily retrieve crucial transaction details, such as the blockchain addresses of involved parties and the transaction data like price and volume. Second, all transactions on DEXs are irreversibly settled on the blockchain, which is validated through independent authentication nodes by the proof-of-work (or proof-of-stake) mechanism. This ensures that transactions are resistant to tampering or falsification. Collectively, these features contribute to the elevated transparency that characterizes DEXs. Given these inherent safeguards, it comes as little

[1] The custodian risk and mismanagement of client funds became evident during the collapse of FTX.
[2] For instance, Cong et al. (2021) estimate that over 70% of the reported volume is fake transactions on 29 cryptocurrency exchanges. A report published on the Nasdaq website shows that 93% of the trading volume on OKEx, 81.2% on Huobi, and a similar level of trading volume on Binance are considered to be wash trading (see https://www.nasdaq.com/articles/how-and-why-crypto-exchanges-fake-trading-volumes-2021-08-24).

surprise that DEXs have higher operational integrity and are more resistant to market manipulation, e.g., wash trading and faked transactions.[3]

The ability to gain investors' trust is perhaps one of the reasons why DEXs have had a remarkable growth.[4] While practitioners discuss many aspects of cryptocurrency trust issues (e.g., the risk of being hacked, the custodian risk, and market manipulation), we are particularly interested in investors' trust in the integrity of market operations. Investors' trust in markets being manipulation-resistant can avoid market breakdown and is critical for the development of cryptocurrency markets. More importantly, with the manipulation-resistant feature, we argue that the price or trading on DEXs can reflect investors' valuation of cryptocurrencies in a transparent and trustworthy way, which can better guide investor trading.

Specifically, our argument is about what investors can learn when observing prices across different marketplaces when some are susceptible to manipulation or lack of transparency (CEXs) and some are less so (DEXs). In our context, we posit that the trading price, together with the number of investors trading at that particular price, deliver important information regarding cryptocurrency's future price dynamics (or valuation dynamics).[5] As investors' demand, driven by either fundamental or non-fundamental motives, ultimately determines the cryptocurrency price dynamics (or future values), inferring investors' demand can help predict the price dynamics. For example, an upswing in the number of users willing to trade at a specific price suggests a rise in demand associated with that price. When investors observe such an increasing demand, they anticipate the future price to increase and then buy the cryptocurrency. Compared to opaque CEXs, DEXs provide more reliable information for investors to understand both the userbase and the user's willingness to trade, i.e., the number of investors participating at a particular price.[6] In this sense, DEXs can better gain investor trust and guide investor trading.

[3] One may argue that wash trading or faked transactions could also exist on a DEX. For example, one can use multiple addresses and initiate large trades between them. However, unlike with a CEX, one cannot fake a transaction without incurring a significant transaction cost on a DEX. The "trade" on the blockchain must be broadcasted with transaction fees and gas fees equivalent to a normal transaction. In short, wash trades or fake transactions on a DEX are subject to significant costs compared to on the CEX. In addition, all participants can observe such wash trades or faked transactions in the public ledger.

[4] In Section 2.1, we show that trading volume and total liquidity available for the DEX representative of our study, Uniswap, have grown dramatically since 2020.

[5] Throughout our paper, we use the terms *price dynamics* and *valuation dynamics* interchangeably.

[6] Our argument is in the spirit of the rational expectations equilibrium literature (e.g., Grossman and Stiglitz, 1980; Hellwig, 1980) and particularly the recent work on investors' learning on future investor demand (Farboodi and Veldkamp, 2020). Farboodi and Veldkamp (2020) explicitly show that information about investor demand is important and drives current investor trading.

To test our hypothesis, we focus on the two largest centralized and decentralized exchanges, Binance and Uniswap.[7] We conduct a systematic study on how investors trade in response to prices on the exchanges. More specifically, investors in each exchange trade on the difference between their beliefs about the cryptocurrency's value (denoted as μ) and the corresponding price on the exchange ($P_{exchange}$ where *exchange* refers to Binance or Uniswap). As prices on Binance/Uniswap reflect and aggregate investors' valuation (or beliefs about the future price) of the cryptocurrency, investors learn from these prices and form their beliefs by considering the weighted average of prices on Binance and Uniswap: $\beta P_{Uniswap} + (1 - \beta) P_{Binance}$.

As the DEX (Uniswap) offers better transparency and is more manipulation-resistant, we hypothesize that investors trust the information on Uniswap, and thus, Uniswap's information regarding userbase can more significantly affect investor trading. For example, when there is an increase in user participation in Uniswap on one particular price level, investors believe that the demand of the cryptocurrency at the current Uniswap price is increasing, and the future price will tilt toward the current Uniswap price. Consequently, investors assign more weight to the price on Uniswap in forming their beliefs and then trade based on the updated beliefs. Thus, β is positively associated with the size of the Uniswap userbase. In contrast, the CEX (Binance) is relatively opaque, e.g., investors cannot directly observe real users' participation in Binance due to the contamination of wash trading or faked transactions. This means that the observed Binance userbase size, which fails to reflect the genuine userbase size accurately, is less effective in shaping investors' belief-updating process, particularly in relation to β. This differential effect underscores DEXs' ability to gain trust in its operational integrity.

Our empirical analysis focuses on the trading behavior of Binance investors but not that of Uniswap investors. We do so for two reasons. First, Uniswap investor trading is relatively sparse. For example, about one-half of the five-minute intervals exhibit no trading activity on Uniswap. Second, some confounding factors simultaneously drive both Uniswap's userbase and Uniswap investor trading. For instance, an increase in Uniswap's userbase can mechanically impact Uniswap order imbalances, which makes an empirical test on Uniswap investor trading less convincing than those on Binance investor trading.[8]

[7] For a comparison, there are 40 cryptocurrencies cross listed on Binance and Uniswap, but there are only four cryptocurrencies cross-listed on Uniswap and Coinbase (another centralized exchange).
[8] Nevertheless, we still examine Uniswap investor trading for completeness (see Online Appendix Table A3).

Zooming into Binance investor trading, as mentioned earlier, Binance investors should trade in response to the difference between their beliefs about the cryptocurrency's value μ and the price on Binance $P_{Binance}$.[9] Specifically, their trading (measured by order flows: total buy volume minus total sell volume, scaled by the total trading volume) is associated with $-\beta \times (P_{Binance} - P_{Uniswap}) = (\underbrace{\beta P_{Uniswap} + (1-\beta)P_{Binance}}_{\mu} - P_{Binance})$. In other words, Binance investor trading is negatively responding to the price difference between Binance and Uniswap ($P_{Binance} - P_{Uniswap}$), and such a response strengthens with the increase in the Uniswap userbase, which is positively associated with β.

To empirically examine our aforementioned argument, we investigate the cryptocurrencies dual-listed on Binance and Uniswap and utilize high-frequency (at the five-minute interval) order/trading data. We first measure the size of the Uniswap userbase by the size of the Uniswap liquidity pool. This measure of the userbase serves as an ideal metric for testing our argument. Users actively contribute to the Uniswap liquidity pool and can easily adjust their contributions if they perceive that the current price does not accurately reflect the value of the cryptocurrency. Hence, the aggregate user contribution, represented by the size of the liquidity pool, acts as a proxy for the Uniswap users' demand associated with the current price of the cryptocurrency.[10]

We indeed find evidence supporting our argument. Specifically, we first find that order imbalance on Binance negatively responds to the lagged price difference between Binance and Uniswap. More importantly, this response intensifies as the size of the Uniswap userbase increases. This result substantiates our argument that as the Uniswap userbase becomes larger, investors put more weight on the Uniswap price in updating their beliefs and trade accordingly.[11]

Additionally, we find that the observed Binance userbase (measured by liquidity provision on Binance) does not affect the response of Binance investor trading to the price difference between Binance and Uniswap. The contrasting results between Binance and Uniswap reflect the uniqueness of the DEX (i.e., Uniswap in our context) relative to the CEX

---

[9] Such a difference can also be interpreted as the "mispricing" in Binance investors' beliefs.

[10] Our results are robust to using the number of users to measure the size of the userbase.

[11] Our argument also applies to Uniswap investor trading. Uniswap investor trading (i.e., order flow) is positively associated with $(1-\beta)(P_{Binance} - P_{Uniswap}) = (\underbrace{\beta P_{Uniswap} + (1-\beta)P_{Binance}}_{\mu} - P_{Uniswap})$. Thus, if Uniswap investors update their beliefs about the cryptocurrency value based on the prices of Uniswap and Binance, then Uniswap investor trading is positively responding to the price difference between Binance and Uniswap, and such a response decreases with the Uniswap userbase size. Our empirical test results on Uniswap investor trading support our claim (see Online Appendix Table A3).

(i.e., Binance in our context) in influencing investors' belief-updating processes on the price dynamics. This is in line with the notion that the DEX garners investors' trust in its operational integrity and can better guide investor trading.

We conduct additional cross-sectional studies based on the user experience in Uniswap to corroborate the importance of user participation information in inferring investors' demand and the price dynamics. Not surprisingly, as an early-stage financial innovation, it is challenging to forecast the long-term demand for cryptocurrencies. We hypothesize that if users who participate in Uniswap are more experienced, they are more likely to stay in the market in the future and their demand matters more for future price dynamics. Hence, current investors are more inclined to put more weight on the Uniswap price associated with a userbase comprising more experienced users, when shaping their beliefs about future price dynamics. We indeed find strong supporting evidence for these hypotheses.

The aforementioned empirical findings provide support for our hypothesis that DEXs gain investor trust and guide investor trading, because they offer a transparent and trustworthy marketplace for trading. It is intuitive to expect that this trust effect should get more pronounced when the CEX experiences incidents of manipulation, such as wash trading and faked transactions. Such manipulation undermines investors' trust in the CEX but increases their confidence in the DEX, relatively speaking. To test this argument, we adopt the approach used by Amiram, Lyandres, and Rabetti (2021) to estimate fake volume (i.e., volume related to the potential wash trades and faked transactions) for each cryptocurrency on each date in Binance. Based on the estimated fake volume, we find that the impact of Uniswap's userbase size on Binance investor trading mostly comes from cryptocurrencies with high fake volume in Binance.

We also find evidence that the impact of Uniswap's userbase size becomes more pronounced when investors are more concerned about fake volume issues on Binance. Specifically, we focus on investors' discussions on Reddit and construct the daily intensity of investors' attention to fake volume on Binance. The attention measure is derived from all Reddit posts and replies that include the keywords "fake" (or its synonyms "wash," "faked," "manipulated," "fraud," "fraudulent"), "volume" (or "trade," "trading"), and "Binance." We find that the Uniswap userbase has a more significant impact on Binance investor trading on days when investors display heightened attention to fake volume on Binance.

Admittedly, investors' responses to prices on Binance and Uniswap could also arise from the cross-market arbitrage activity that exploits the price discrepancy between the two exchanges. However, we present two pieces of evidence demonstrating that investors' responses to prices are beyond cross-market arbitrage. First, suppose it is the cross-market arbitrage activity that purely explains investors' responses to prices; then we would expect to observe a correlation between Binance investors' and Uniswap investors' trading directions of -1 (or at least a negative correlation). However, we do not find such a negative correlation in our data but rather observe the opposite.[12] Second, based on the argument of cross-market arbitrage, we should observe that the response of Uniswap investor trading to the price difference is positively associated with Uniswap's userbase size, as a larger userbase improves the liquidity and should facilitate cross-market arbitrage. Contrary to this hypothesis, we find that the response of Uniswap investors to the price difference decreases with the size of the Uniswap userbase, contradicting the argument of cross-market arbitrage.

We further zoom into the launch events of the "yield-farming" reward program on Uniswap and establish the causal impact of the Uniswap userbase on Binance investor trading activities. We argue that the introduction of the yield-farming reward program serves as a quasi-exogenous shock that is unrelated to Binance investor trading. Still, it has a significant and large impact on the size of the Uniswap userbase. Applying a difference-in-differences analysis approach, we show that the yield-farming reward program has significantly increased the size of the Uniswap userbase. Subsequently, we use a two-stage least-square (2SLS) instrumental variable regression based on the yield-farming reward program to ascertain the causal impact of Uniswap userbase size on Binance investor trading. We find that an increase in the Uniswap userbase, induced by the yield-farming reward program, leads to a more pronounced reaction of Binance investor trading to the price difference between Binance and Uniswap.

As userbase affects trading and trading ultimately underpins the equilibrium price dynamics, Uniswap's userbase size has important asset-pricing implications. For example, when Binance investors observe a higher price for a cryptocurrency on Uniswap compared to Binance, they believe that the future price will be higher, and thus, buy this cryptocurrency on Binance, leading to an increase in its price on Binance. Given the impact of Uniswap userbase size on Binance investor trading, we conjecture that as the Uniswap userbase expands, Binance

[12] Binance investor trading in our argument is conceptually different from cross-market arbitrage. Different from the cross-market arbitrage, Binance investor trading in our argument is directional trade and does not need to involve simultaneous trading on Uniswap. Specifically, $\underbrace{\beta P_{Uniswap} + (1-\beta) P_{Binance}}_{\mu} - P_{Binance}$ can be interpreted as "mispricing" in Binance investors' beliefs. When Binance investors trade in response to this mispricing, the prices on Binance lean toward the prices on Uniswap. In this sense, the Binance investor trading in our argument plays a similar role of cross-market arbitrage in inducing the prices on Binance and Uniswap to converge.

investors will engage in more aggressive trading aligned with the price on Uniswap. As a result, we anticipate that the Uniswap price will play a more important role in determining the equilibrium valuation of the cryptocurrency.

To test our conjecture, we apply the Gonzalo-Granger decomposition of the common trend, which enables us to estimate the respective contributions of Binance and Uniswap to the common price component. The Gonzalo-Granger component share measures the contribution of Binance and Uniswap to the common price trend and can ideally test the tug-of-war between Binance and Uniswap in determining cryptocurrency valuation. The empirical evidence based on a similar 2SLS instrumental variable regression supports our conjecture. That is, the Uniswap userbase size leads to an increase in Uniswap's share in determining the common trend of the cryptocurrency price dynamics.

In sum, our empirical findings provide compelling evidence supporting that a DEX such as Uniswap gains trust from investors in its operational integrity. The unique advantage of the DEX comes from its blockchain plus smart contracts design, providing a transparent and trustworthy marketplace to organize trading. The DEX presents a case where a decentralized infrastructure could overcome deficiencies in the current centralized infrastructure of cryptocurrencies, the CEX. The deficiency, in our context, is the lack of a manipulation-resistant trading environment or the lack of investors' confidence that the CEX provides a manipulation-resistant trading environment. Unlike its origin—the centralized security exchange—the centralized cryptocurrency exchange often operates with minimal regulation and high opacity, making it susceptible to manipulation.[13] While establishing a tightly regulated CEX with significant regulatory costs could resolve the deficiency, we show that a DeFi application like a DEX powered by blockchain and smart contracts could be a viable alternative solution. Our results show that in the ecosystem where a consensus underwritten by a credible central monopoly is not feasible or can be too costly to obtain, DeFi could be an effective complement.

Our study on decentralized cryptocurrency trading contributes to the research on DeFi and blockchain disruption. Cong and He (2019) examine the advantage of blockchain technology in reaching a decentralized consensus and its cost in producing welfare-destroying collusion. Yermack (2017) analyzes blockchain's impact on corporate governance. Harvey, Ramachandran, and Santoro (2021) provide a survey on DeFi applications on Ethereum, where

[13] For example, price manipulation (Gandal et al., 2018; Li, Shin, and Wang, 2020) and volume manipulation (Cong et al., 2021; Li and Aloosh, 2021).

the DEX is one of the most widely used applications. Several theoretical papers have discussed the equilibrium of liquidity provision under the DEX (Aoyagi, 2020; Aoyagi and Ito, 2021) and its conceptual deficiency in some designs (Park, 2021). Capponi and Jia (2021) provide a theoretical analysis of the interaction between liquidity provision by automated market makers and arbitrageurs in the DEX. Their model suggests that the convexity of the pricing function in the decentralized exchange is the key to determining investors' welfare. Aspris et al. (2021) study the liquidity effect when cryptocurrencies in the DEX were listed in a centralized venue.

We contribute to the growing literature on cryptocurrency. Most theoretical studies consider the fundamental value of cryptocurrencies arises from the adoption of crypto assets as a new technology for payments (see Athey et al., 2016; Buraschi and Pagnotta, 2018; Sockin and Xiong, 2021; Biais et al., 2020; Cong, Li, and Wang, 2020). The value appreciation of the cryptocurrency relies on its increasing userbase. The theoretical predictions have been largely confirmed empirically. Liu and Tsyvinski (2020) show that cryptocurrency returns are predicted by cryptocurrency network factors that capture the user adoption of cryptocurrencies. They also establish a set of asset-pricing factors for cryptocurrencies, which complements other empirical regularities found in the literature, e.g., the factor structure of cryptocurrency returns (Liu, Tsyvinski, and Wu, Forthcoming), the violation of the law of one price (Borri and Shakhnov, 2018; Makarov and Schoar, 2020), and market manipulation (Gandal et al., 2018; Li, Shin, and Wang, 2020; Griffin and Shams, 2020; Cong et al. 2021).

Last, our paper adds to the literature on market fragmentation. The market structure of cryptocurrency shares a similarly, if not more, fragmented feature as modern equity trading. While a liquid stock can be traded in more than 10 venues in the US, a popular cryptocurrency can be traded in more than 20 marketplaces globally. Market fragmentation naturally leads to concerns from financial economists and regulators on issues like the price formation process, i.e., where the price information and price discovery are produced (Hasbrouck, 1995; Harris, McInish, Shoesmith, and Wood, 1995); the cross-market arbitrage activities and related externalities (Biais, Foucault, and Moinas, 2015; Budish, Cramton, and Shim, 2015; Foucault, Kozhan, and Tham, 2017; Shkilko and Sokolov, 2020); the comparison between centralized and decentralized trading (Biais, 1993; Madhavan, 1995; Yin, 2005; Zhong, 2016); and ultimately the impact of fragmentation on market quality (O'Hara and Ye, 2011).

The rest of our paper is organized as follows: Section 1 develops hypotheses to guide our empirical analyses. Section 2 describes the institutional background of the decentralized exchange, the yield-farming reward program, and our data. Section 3 shows our main results.

Section 4 applies the instrumental variable analysis to establish the causal relationship. Section 5 discusses and tests the economic implications. Finally, we conclude in Section 6.

1. Hypotheses development

In this section, we develop hypotheses to guide our empirical analysis. Our first hypothesis pertains to the trading behavior of Binance investors in response to the prices on Binance and Uniswap. We focus on Binance investor trading because Uniswap's trading is relatively sparse at the five-minute intervals and the reliability of empirical tests on Uniswap investor trading could be compromised by factors affecting both Uniswap's userbase and its trading.

Binance investors trade on the difference between their beliefs about the value of the cryptocurrency (μ) and its price on Binance ($P_{Binance}$). As discussed earlier, Binance investors form their beliefs based on the weighted average of the prices on Binance and Uniswap, i.e., $\beta P_{Uniswap} + (1-\beta)P_{Binance}$ with β capturing the weight. Further, we argue that β is positively associated with Uniswap's userbase size. For example, when more users participate in Uniswap, investors become aware of the heightened demand of the cryptocurrency associated with its Uniswap price. As demand determines the cryptocurrency price dynamics (or future values), investors assign greater weight to the price on Uniswap when updating their beliefs. As a result, Binance investor trading (i.e., order flow) is associated with $\left(\underbrace{\beta P_{Uniswap} + (1-\beta)P_{Binance}}_{\mu} - P_{Binance}\right) = -\beta \times (P_{Binance} - P_{Uniswap})$, and β positively associates with the size of the Uniswap userbase. In other words, defining the price difference as $P_{Binance} - P_{Uniswap}$, Binance investor trading is negatively related to β times the price difference. Using the size of the Uniswap liquidity pool to measure the size of the Uniswap userbase, we formalize our first hypothesis as follows:[14]

[14] Nevertheless, our argument also applies to Uniswap investor trading. Uniswap investor trading (i.e., order flow) is positively associated with $(1-\beta)(P_{Binance} - P_{Uniswap}) = (\underbrace{\beta P_{Uniswap} + (1-\beta)P_{Binance}}_{\mu} - P_{Uniswap})$, and β is positively associated with the Uniswap userbase. Thus, if Uniswap investors update their beliefs about the cryptocurrency value based on the prices on Uniswap and Binance, then Uniswap investor trading is positively responding to the price difference between Binance and Uniswap, and such a response will decrease with the size of the Uniswap userbase. We indeed find evidence supporting this argument.

Hypothesis 1. *Suppose Binance investors update their beliefs about the cryptocurrency value based on the prices on Uniswap and Binance. In that case, Binance investor trading (i.e., order flow) should respond negatively to the price difference between Binance and Uniswap, and such a response will increase with the size of the Uniswap userbase.*

While **Hypothesis 1** could also apply to the size of the Binance userbase, it is important to note that Uniswap, being a DEX, possesses distinct characteristics of transparency and trustworthiness compared to its centralized counterparts. In contrast, a centralized exchange like Binance is known to have been associated with wash trading or faked transactions, a practice that artificially inflates trading volume and contaminates transaction data. Based on these features, we argue that while the decentralized exchange can guide investor trading, the centralized exchange does not have this advantage.[15] To highlight the contrast between the decentralized and centralized exchanges, we present our sub-hypothesis as follows:

Hypothesis 1.a. *While Binance investor trading responds to the price difference between Binance and Uniswap, such a response is insensitive to the observed size of the Binance userbase.*

Binance investors trade in response to the price difference between Binance and Uniswap. Their reactions vary across cryptocurrencies. As experienced users have long-term perspectives, they are more likely to stay in the markets in the future and thus their demand could have more influence on the price dynamics. In this sense, when a cryptocurrency's Uniswap pool consists of more experienced users, its Uniswap price should be more informative about its future value (partially determined by these long-term investors' demand). As a result, Binance investors put more weight on the Uniswap price in the belief updating (higher β) and trade more aggressively on the price difference between Binance and Uniswap. Based on this cross-sectional feature, we have the following sub-hypothesis:

Hypothesis 1.b. *The response of Binance investor trading to the price difference between Binance and Uniswap is more pronounced among cryptocurrencies whose Uniswap liquidity pool has more experienced users.*

---

[15] Our intuition is similar to the rational expectations equilibrium literature (e.g., Grossman and Stiglitz, 1980; Hellwig, 1980), in which investors only consider informative signals when updating their beliefs.

As we argue, the DEX has the advantage of gaining investors' trust compared to the CEX, as the latter often has fake volume related to wash trading or fake transactions. Unlike the CEX, transactions are settled on the blockchain for decentralized trading. The transparency of the blockchain makes it difficult or costly to falsify transactions and inflate volume on the DEX. Therefore, relatively speaking, the advantage of gaining investors' trust in the DEX should be more significant when the CEX exhibits higher fake volume. Based on this intuition, we hypothesize the following:

Hypothesis 2. *The response of Binance investor trading to the price difference between Binance and Uniswap is more pronounced among cryptocurrencies whose Binance trading has more fake volume.*

Meanwhile, as fake volume is not directly observable, its effect largely depends on investors' concern about fake volume in the CEX. Thus, we propose the following hypothesis:

Hypothesis 2.a. *The response of Binance investor trading to the price difference between Binance and Uniswap is more pronounced when investors pay more attention to the fake volume issue in Binance.*

Unsurprisingly, trading in Binance and Uniswap plays a crucial role in shaping the equilibrium price dynamics. As a result, the impact of Uniswap's userbase size on Binance investor trading has important asset-pricing implications. For example, if investors put more weight on the Uniswap price (i.e., the decentralized price) in belief updating/trading, Binance investors would lean toward the Uniswap price, making Uniswap's price account for a larger share in the common price component underlying the price dynamic on each exchange. Based on this rationale, we have the following hypothesis:

Hypothesis 3. *Suppose Binance investors update their beliefs about the cryptocurrency value based on the prices on Uniswap and Binance. In that case, the rise of the Uniswap userbase size leads to an increase in Uniswap's share in determining the common trend of the cryptocurrency price dynamics.*

2. Institutional background and data description

In this section, we discuss some institutional background on the DEX, focusing on the most popular automated market-making mechanism. We then outline our data collection process for cryptocurrencies in both the DEX (Uniswap V2) and the CEX (Binance). Specifically, Section 2.1 introduces the automated market making; Section 2.2 describes the yield-farming program, which encourages liquidity provision on the DEX; Section 2.3 illustrates how we compile the data on cryptocurrencies dual-listed on Uniswap and Binance and provides some descriptive statistics of our sample; Section 2.4 briefly describes how investors on Uniswap and Binance trade.

2.1. Automated market making on the decentralized exchange

Since 2020, a growing number of protocols on the Ethereum blockchain have emerged to provide decentralized exchange services for cryptocurrencies. Most DEXs organize liquidity provision and trading through the automated market-making mechanism.[16] Any individual cryptocurrency holder can provide liquidity on the DEX by depositing certain cryptocurrencies into a liquidity pool. Effectively, individual cryptocurrency holders become market makers or liquidity providers and receive trading fee rewards for providing liquidity. On the other side, liquidity demanders trade against the liquidity pool, exchanging one cryptocurrency for another.

More specifically, the DEX works in the following way. It first pours cryptocurrencies (from liquidity providers) into a liquidity pool. Then, the DEX creates liquidity provider (LP) tokens to track the proportionate share of the pool that each liquidity provider is entitled to. The LP token also represents the reward entitlement for the liquidity provider. The LP token is updated whenever there is a change in the pool value, from either trading or liquidity addition/deletion. In the event of withdrawal, the liquidity provider uses the LP token to redeem her cryptocurrencies.

Finally, the DEX utilizes pre-defined mathematical functions encoded into a smart contract to automate trading and establish the price scheme. The most popular function is the constant product function or the constant product market making (CPMM) rule, which is the one used by Uniswap. Under the CPMM rule, a liquidity provider should simultaneously deposit two cryptocurrencies with the same worth into the pool. The product of the quantity of these two crypto assets in the liquidity pool should be a constant number when swapping occurs.

[16] The decentralized exchanges we will talk about hereafter all refer to automated market makers.

To illustrate, let's think of a liquidity pool consisting of two cryptocurrencies, Ethereum (ETH) and Tether (USDT).[17] If there are x units of ETH and y units of USDT in the pool, then the CPMM rule is such that $x \times y = K$.[18] The CPMM rule yields the price scheme for the swap between ETH and USDT. If a trader wants to buy Δx of the ETH, then she needs to pay (deposit into the pool) $p \times \Delta x$ of the USDT such that $(x\text{-}\Delta x)(y\text{+}p\Delta x) = K = x\times y$. The price of ETH in terms of USDT is p, $p = \frac{y}{x-\Delta x}$. When Δx is very small relative to x, the execution price approaches the mid-price, defined as the ratio of y over x, i.e., y/x. Panel A of Figure 1 visualizes the inversed demand curve of ETH/USDT under the CPMM.

[Insert Figure 1 here]

Although the CPMM rule has desirable features, such as avoiding any trader depleting the liquidity pool (as the price will approach infinity), the rule has several severe shortcomings. For liquidity demanders, the CPMM rule is not friendly to large orders. The price impact is the difference between the traded price and the mid-price, $\frac{y}{x-\Delta x} - \frac{y}{x}$ increases with Δx.

For liquidity providers, while they obtain the reward from trading (0.3% on Uniswap V2 in general), they could face "impermanent loss" when the price or swap rate of the two tokens deviates from the initial rate at which the provider deposits. For example, at the initial stage, the liquidity provider deposits a pair of 10 ETH and 1,000 USDT (so the product is 10,000) into the pool, creating the price of one ETH as 100 USDT. Now, if the true price of ETH rises to 400 USDT, then the arbitrageur or informed trader will start to trade against the pool by swapping out ETH with USDT until the swap rate becomes 1:400. The total amount of ETH swapped out is 5 and USDT swapped in is 1,000, making the pool consist of 5 ETH and 2,000 USDT (the product of them is 10,000). If the provider withdraws her ETH and USDT, she has $5 \times 400 + 2000 + 1000 \times 0.3\% = 4{,}003$ USDT, which is smaller than the current market value of the provider's initial deposit of $10 \times 400 + 1000 = 5{,}000$ USDT. The provider loses 997 USDT to the informed trader. This loss is known as the impermanent loss. Panel B of Figure 1 provides a simulation of this impermanent loss regarding variation in the true price.

[17] To use DeFi applications on Ethereum, ETH and BTC are always wrapped to their ERC20 format WETH and WBTC. For convenience, we will keep the notations ETH and BTC for any of their formats hereafter.

[18] K varies when the size of the pool changes. That is, suppose a liquidity provider adds x_+ and y_+ units into a pool with existing units of x and y; then the total quantity in the pool becomes $x + x_+$ *and* $y + y_+$, and the product becomes $(x + x_+) \times (y + y_+)$. A notable feature in adding liquidity is that y_+ / x_+ should equal y/x, so that the mid-price for the pool remains the same. When the liquidity provider disagrees with the existing mid-price, she should first swap out the overpriced lag to adjust the mid-price to her believed value, then add in liquidity.

The figure shows a region where the liquidity provider earns a profit. This corresponds to the case of little or no price deviation, which occurs when providing liquidity to uninformed traders. When trading against uninformed traders, liquidity providers collect the reward without incurring the impermanent loss.

With the pre-set CPMM rule governing the price scheme, trading can occur if individuals deposit cryptocurrencies into the liquidity pool. Through the hard-coded CPMM rule and the liquidity pool, the DEX can democratize market-making and organize trading in a decentralized fashion. An essential aspect is that all activities are executed under blockchain authentication. By the nature of the open source, traders can access and review the contract code, and the blockchain ensures that they maintain ownership of their redeemable cryptocurrencies. Unlike the CEX, where the exchange acts as the custodian of traders' tokens, in the DEX tokens are under the custody of the trader. Activities on the DEX are organized through smart contracts providing maximum transparency.

In summary, there are benefits to and costs of the DEX. On the benefit side, trading does not rely on a central party to organize, so it is less affected by problems like exchange outages, hacking, or malpractice. The openness of organizing transactions through smart contracts and the hard-to-hack blockchain authentication makes the DEX transparent, which helps to build trust for its operation. On the cost side, the blockchain settlement, which broadcasts transactions to the miners' pool for authentication purposes, leaves room for attackers to front-run large orders (see Park, 2021, for details regarding the front-running issue). Despite this disadvantage, trading volume and total liquidity available for DEXs, such as Uniswap, have grown dramatically since 2020 (see Figure 2).

[Insert Figure 2 here]

2.2. Yield-farming for liquidity provision

A key ingredient to the success of the DEX (e.g., Uniswap) is that cryptocurrency holders provide liquidity to others who demand liquidity. That means liquidity providers are willing to lock up their cryptocurrencies (in the previous example, ETH and USDT) for others to swap one against another. As liquidity is vital for a pair of cryptocurrencies to be tradable on the DEX, some cryptocurrency projects initiate additional rewards to encourage liquidity provision. The reward comes in the form of yield-farming. That is, liquidity providers can stake their LP tokens into a smart contract and collect a reward token from the cryptocurrency issuer. The longer the LP token is staked, the more the liquidity provider can collect reward tokens. The yield-farming program provides additional incentive for liquidity providers to lock their cryptocurrencies on the DEX.

Six cryptocurrencies initiated the yield-farming reward program for the corresponding Uniswap liquidity provision during our sample periods. These six pairs of cryptocurrencies are "ADXETH," "BNTETH," "EASYETH," "ETHBTC," "ETHUSDT," and "LRCETH."

2.3. Data description

This section describes how we compile the sample of cryptocurrencies in our study. We focus on the largest DEX on the Ethereum network, Uniswap, and manually collect trading cryptocurrencies dual-listed in Uniswap V2 and Binance from January 2020 to January 2021. Our final sample consists of 40 cryptocurrencies. As shown in Appendix Table A1, all cryptocurrencies except ETH are denominated by ETH, and ETH has a denominator of USDT.

Uniswap V2 data

We obtain the Uniswap data from parsing records in the Ethereum blockchain via the Etherscan API node. Etherscan provides an indexed data service for the Ethereum network.[19] Specifically, we obtain and construct three categories of data: (a) trading data, including price and volume information, (b) userbase data, and (c) liquidity providers data. The detailed description of the data is as follows.

(a) Trading data

On Uniswap V2, a cryptocurrency has one denominator: another cryptocurrency. Once a trading pair (a cryptocurrency and its denominator, e.g., ETH-USDT) is created, one smart contract address (LP address hereafter) is generated as the token address for the trading pair's liquidity pool. In this LP address, a standard Uniswap router program is deployed, which has functions of swapping, adding liquidity, and removing liquidity. The LP address also stores the cryptocurrency pair as the liquidity pool. When a user initiates a trade, the swapping function is called, and a transaction will be broadcasted. In each transaction, we observe two transfer events: the sold cryptocurrency will be transferred to the LP address, and the bought one will be transferred from the LP address. The ratio of the quantities of these two cryptocurrencies is used as the price. Each transaction is timestamped. Further, we apply the following filters to identify valid transactions: (1) there are only two transfer events in the transaction and (2) the transfer directions of the two events are opposite. By exploring all transfer events that interacted with the LP address, we can calculate the price and volume of each transaction.

[19] The API document is available at https://etherscan.io/apis.

(b) Userbase data

The key variable in our study is Uniswap's userbase size. To measure the userbase size, we calculate the balance of the two cryptocurrencies of a pair in the liquidity pool contract at each block. Specifically, we first download all transfer events interacting with each pair's LP address via the Etherscan API node. Then starting from the LP address creation block, we aggregate the quantities transferred of the two cryptocurrencies to track their balance in each subsequent block. Each block is timestamped. Throughout the process, we obtain the balance of the two cryptocurrencies of a trading pair stored in the userbase at each block time.

(c) Liquidity provider data

To corroborate with the measure of userbase size in (b), we also collect detailed information about users (individual liquidity providers) for each cryptocurrency pair. Such detailed information is available on the blockchain. When a user adds liquidity to a cryptocurrency pair, she will initiate a transaction including three events: two transferring events into the LP address of the cryptocurrency pair and one minting event of the LP token to the user. The LP token is the receipt denoting her share of the liquidity pool. Therefore, we can construct the balance for each LP token holder and measure the liquidity provision associated with each liquidity provider. The detailed process of collecting liquidity provisions of individual liquidity providers is as follows.

First, we download all transfer events of each LP token via the Etherscan API node. Like constructing the liquidity pool balance, we aggregate the quantities of the LP token for each user address block-by-block. Note that we filter out all smart contract addresses, as some are used for staking purposes. Finally, we get all user addresses that provide liquidity in each block and the quantity of the LP token they hold.

Binance and Coinbase data

As for the CEX, we focus on Binance, which has the largest trading volume among all centralized exchanges. We obtain tick-by-tick trade and order book data of Binance from Kaiko for our sample of the 40 cryptocurrencies from January 2020 to January 2021. We also collect tick-by-tick trade and order book data from Coinbase during the same sample period. However, there are only four pairs of cryptocurrencies traded on both Uniswap and Coinbase during our sample period.

Summary statistics

Table 1 reports the summary statistics of our sample. As shown in Table 1, the average market capitalization of our sample cryptocurrencies is about 16 billion USD (measured at the price level of January 2021), with an average daily turnover (Binance plus Uniswap) of 104.1%. The average daily price difference between Binance and Uniswap, measured by the difference of the natural logarithmic of the volume-weighted average trading prices between Binance and Uniswap, is about 7.8%.

Our study also considers two intraday variables: (1) *Variance Ratio*; (2) Binance's or Uniswap's long-run impact on the common price component. The detailed construction of these variables is as follows.

First, for each cryptocurrency, we calculate the daily *Variance Ratio* as the absolute value of the difference between the ratio of the 300-second return variance and the 60-second return variance and one, i.e., $Variance\ Ratio\ = \left|\frac{Return\ Variance_{300s}}{5 \times Return\ Variance_{60s}} - 1\right|$.

The second variable of interest is to measure Binance's or Uniswap's long-run impact on the common price component. To this end, we apply the Gonzalo-Granger decomposition of the common trend (Gonzalo and Granger, 1995) to back out Binance's and Uniswap's contributions to the common price component, respectively. Specifically, we apply the 2-by-1 Binance and Uniswap price vector-error-correction model with five lags to model the joint price dynamics on the two exchanges. Then, we estimate the accumulated impulse response on Binance and Uniswap over 100 periods of one unit shock in the price series. The Gonzalo-Granger component share is calculated as the impulse response of each venue normalized by their sum. As de Jong (2002) pointed out, the Gonzalo-Granger component share is closely related to the Hasbrouck information share measure. The Gonzalo-Granger component share is more useful if one's interest is in modelling the common trend as a weighted average between multiple cointegrated time series.

As shown in Table 1, the average *Variance Ratio* is 0.193 in our sample. Meanwhile, the *Component share (Binance) average* is 81.2%, suggesting that the price of Binance has a larger impact than Uniswap on the common price component. This is not surprising as Binance—the largest centralized exchange—has dominated the trading of cryptocurrencies for a long time.

[Insert Table 1 here]

2.4. Lagged price differences and trading activity on Binance and Uniswap

We aim to understand the uniqueness of the DEX relative to the CEX. The answer to this fundamental question lies in studying whether and how investors respond differently to the prices of the same cryptocurrency on the two exchanges. The action of trading reveals how investors update their beliefs.

To study how Binance or Uniswap investors respond to prices on Binance and Uniswap, we first look at the correlation between the lagged price difference between Binance and Uniswap and order imbalance on Binance or Uniswap. We denote the two correlations as *Corr(Lag Price Diff, Order Imbalance Binance)* and *Corr(Lag Price Diff, Order Imbalance Uniswap)* respectively. We take the following steps to calculate these two correlations. For each cryptocurrency on each day, we first split the trading hours into five-minute intervals and estimate *Corr(Lag Price Diff, Order Imbalance Binance)* as the correlation between the price difference on Binance and Uniswap in one particular five-minute interval and order imbalance on Binance in the next five-minute interval. The price difference is between the natural logarithm of the volume-weighted average price on Binance and Uniswap. The order imbalance is defined as $\frac{Buy\ volume - Sell\ volume}{Buy\ volume + Sell\ volume}$ at each five-minute interval.[20] We calculate *Corr(Lag Price Diff, Order Imbalance Uniswap)* similarly.

Intuitively, suppose investors on Binance observe the price difference between Binance and Uniswap but update their beliefs through the price on Uniswap. In that case, they will buy (sell) the cryptocurrency on Binance when the price on Binance is lower (higher) than that on Uniswap, and thus we expect *Corr(Lag Price Diff, Order Imbalance Binance)* to be negative. Following a similar intuition, if investors on Uniswap observe the price difference but update their beliefs through the price on Binance, they will buy (sell) the cryptocurrency on Uniswap when the price on Uniswap is lower (higher) than that on Binance. Thus, we expect *Corr(Lag Price Diff, Order Imbalance Uniswap)* to be positive.

We examine the cross-sectional average and the time-series average of the sample mean on *Corr(Lag Price Diff, Order Imbalance Binance)* and *Corr(Lag Price Diff, Order Imbalance Uniswap)* in Figure 3. Panels A and C illustrate the average for each cryptocurrency on Binance and Uniswap. Panels B and D show the time series of the daily sample mean. From Panels A and B, we find that the *Corr(Lag Price Diff, Order Imbalance Binance)* is negative for most days and most cryptocurrencies. Meanwhile, as shown in Panels C and D, *Corr(Lag Price Diff, Order Imbalance Uniswap)* is positive for almost all days and most cryptocurrencies. As we calculate, both the cross-sectional average and the time-series average of the sample mean of the *Corr(Lag Price Diff, Order Imbalance Binance)* are negative (-0.06 and -0.03, respectively).

[20] Our tick-by-tick data flags out the side of the trade initiator for both the Uniswap and Binance transactions, which enables us to perfectly constructure the order imbalance measure.

In contrast, the *Corr(Lag Price Diff, Order Imbalance Uniswap)* are positive (0.28 and 0.29, respectively).

[Insert Figure 3 here]

[Insert Figure 4 here]

The negative *Corr(Lag Price Diff, Order Imbalance Binance)* and positive *Corr(Lag Price Diff, Order Imbalance Uniswap)* suggest that investors on Binance track the Uniswap price and update their beliefs from the Uniswap price, and investors on Uniswap do the opposite. Admittedly, these patterns could also arise from the cross-market arbitrage activity that exploits the price discrepancy between Binance and Uniswap. We will leave the discussion of this alternative mechanism until Section 3.3.

In Figure 4, we show the daily average of the probability of Binance and Uniswap investors trading for each cryptocurrency in the five-minute interval conditional on observing past (previous) five-minute price differences. Clearly, Uniswap investor trading is relatively sparse, i.e., about one-half of the five-minute intervals have zero trading on Uniswap. This is one of the reasons that our empirical analysis focuses on Binance investors' trading behavior.

3. The impact of the decentralized exchange

In this section, we empirically test **Hypotheses 1** and **2**. Section 3.1 examines the impact of the Uniswap userbase size (measured by the liquidity pool size) on how Binance investors respond to prices on these two exchanges (**Hypotheses 1** and **1.a**). Section 3.2 conducts cross-sectional tests and examines the roles of the experience of Uniswap users (**Hypotheses 1.b**). Section 3.3 examines the Uniswap userbase's impact on Binance investor trading when Binance exhibits wash trading (**Hypotheses 2** and **2.a**). Section 3.4 rules out the alternative explanation for our findings, e.g., cross-market arbitrage.

3.1. Binance investor trading and Uniswap userbase size

We examine how Uniswap userbase size affects Binance investors' responses to the price difference between Binance and Uniswap. As we discussed in **Hypotheses 1**, Binance investors form a belief (μ) based on the weighted average of the prices on Binance and Uniswap: $\mu = \beta P_{Uniswap} + (1-\beta) P_{Binance}$. Binance investors trade on the difference between their beliefs about the value of cryptocurrency and the observed price on Binance, i.e., $(\underbrace{\beta P_{Uniswap} + (1-\beta) P_{Binance}}_{\mu} - P_{Binance})$. With a simple operation, we can see that Binance investor trading (i.e., order flow) is negatively associated with $\beta(P_{Binance} - P_{Uniswap})$. More importantly, as more users trade on Uniswap (i.e., the userbase size gets larger on Uniswap), investors interpret that both the userbase and the users' willingness to trade the cryptocurrency at the current price increase. In this regard, Uniswap prices play a more important role in shaping investors' beliefs.

To test our hypothesis, we run the following regression model,

$$\begin{aligned}
&\textit{Order imbalance on Binance}_{i,t,k} \\
&\quad = \beta_1 \times \textit{Price Diff}_{i,t,k-1} \times \textit{Lag Uniswap Userbase Size}_{i,t} \\
&\quad + \beta_2 \times \textit{Lag Uniswap Userbase Size}_{i,t} \\
&\quad + \beta_3 \times \textit{Price Diff}_{i,t,k-1} + \textit{Controls} + \textit{Fixed Effects} + \epsilon_{i,t,k},
\end{aligned} \tag{1}$$

where *Order imbalance on Binance*$_{i,t,k}$ is cryptocurrency *i's* order imbalance at the *k*th five-minute interval on day *t*. Order imbalance is calculated as buy volume minus sell volume, scaled by the sum of buy and sell volumes on Binance within each five-minute interval. Independent variables include *Lag Uniswap Userbase Size*$_{i,t}$, *Price Diff*$_{i,t,k-1}$, and their interaction term. *Price Diff*$_{i,t,k-1}$ is the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap for cryptocurrency *i* at the *k*-1th five-minute interval on day *t*. *Lag Uniswap Userbase Size*$_{i,t}$ is the daily Uniswap userbase size at day *t-1*. Uniswap userbase size is calculated as 100 times the time-weighted average pool size on Uniswap scaled by the total issuance of the cryptocurrency. We control the lagged *Log Variance Ratio,* the natural logarithm of one plus the variance ratio. The variance ratio is the absolute value of the difference between the 300-/60-second variance ratio and one. As for fixed effects, we consider two specifications: one with the date fixed effect and the other with both date and cryptocurrency fixed effects. Standard errors are clustered by cryptocurrencies. We report the results in Table 2.

[Insert Table 2 here]

In Table 2, we have several observations. First, as shown in columns [1] and [2], the coefficient of $\textit{Price Diff}_{i,t,k-1}$ is negative and statistically significant, suggesting that Binance investors are indeed trading in response to the price difference between Binance and Uniswap. More importantly, the coefficient of the interaction term between $\textit{Lag Uniswap Userbase Size}_{i,t}$ and $\textit{Price Diff}_{i,t,k-1}$ is negative and statistically significant, suggesting that an increase in the Uniswap userbase enlarges Binance investors' responses to the price difference, which is consistent with **Hypothesis 1**. Second, to test **Hypothesis 1.a**, we replace $\textit{Lag Uniswap Userbase Size}_{i,t}$ with the lagged size of the Binance userbase in columns [3] and [4], and we find that the Binance userbase does not affect the response of Binance investor trading to the price difference between Binance and Uniswap. Third, controlling Binance userbase size barely changes the impacts of $\textit{Lag Uniswap Userbase Size}_{i,t}$. To be consistent with the construction of the Uniswap userbase size, we measure Binance's userbase size with the (100 times) time-weighted depth of the top ten price levels on Binance scaled by the total issuance of the cryptocurrency.

We conduct additional robustness tests and find consistent results. First, we use several alternative measures for *Order imbalance on Binance*, including the buy dollar volume minus sell dollar volume scaled by the sum of buy and sell dollar volume on Binance at five-minute intervals and order imbalance measured at ten-minute intervals, and find similar results (see Online Appendix Table A2). Second, in Online Appendix Table A3, we examine the impact of Uniswap's userbase size on how Uniswap investors respond to prices on these two exchanges. Third, in Online Appendix Table A4, we use the number of users in the Uniswap liquidity pool to measure the size of the userbase and find that our main results in Table 2 are qualitatively unchanged.

Although the study of Uniswap investor trading has some caveats (e.g., sparse trading and confounding factors underlying Uniswap userbase size and trading on Uniswap), we still find Uniswap investor trading is consistent with the implication of **Hypothesis 1**. Like Binance investors, Uniswap investors trade on the difference between their beliefs about the cryptocurrency value (μ) and its price on Uniswap ($P_{Uniswap}$). That is, Uniswap investor trading is positively associated with $(1-\beta)(P_{Binance} - P_{Uniswap}) = (\underbrace{\beta P_{Uniswap} + (1-\beta)P_{Binance}}_{\mu} - P_{Uniswap})$, and β is positively associated with the Uniswap userbase. Thus, Uniswap investor trading (i.e., order flow from directional traders on Uniswap) positively responds to the price difference between Binance and Uniswap, and such a response decreases with the size of the

Uniswap userbase. We indeed find evidence supporting this hypothesis as shown in Online Appendix Table A3.

In summary, the results in this section support our argument that Binance investors infer information about cryptocurrency price dynamics through the price on Uniswap together with the number of investors trading at that particular price, and then trade on the difference between their inferred beliefs and the price on Binance. More importantly, as the size of the Uniswap userbase becomes larger, the Uniswap price plays a larger role in determining Binance investors' beliefs. The upswing in the number of users willing to trade at a specific price suggests a rise in demand associated with that price.

More importantly, the contrasting results between columns [1]-[2] and columns [3]-[4] of Table 2 highlight the uniqueness of the DEX (i.e., Uniswap in our context) relative to the CEX (i.e., Binance in our context). Specifically, the transparent DEX instills confidence in investors regarding its operational integrity. This confidence, in turn, positions DEX to provide valuable information that can effectively steer investor trading decisions.

3.2. Cross-sectional results on the impact of Uniswap userbase size

Cryptocurrencies are not like conventional financial assets (e.g., stocks or bonds) and do not have a well-defined future income stream. The lack of an income stream naturally generates a high degree of uncertainty regarding the value and the long-term demand for the cryptocurrency. We hypothesize that more experienced users are more likely to stay in the market in the long term and their demand matters more for future price dynamics. Thus, current investors put more weight on the Uniswap price when forming their beliefs on the price dynamics, if the participating users are more experienced. To examine our argument, we conduct a cross-sectional test based on Uniswap liquidity providers' experience.

Specifically, we conduct the cross-sectional test based on Uniswap liquidity providers' experience in the following steps. First, among liquidity providers on Uniswap, we measure one liquidity provider's experience as her age since her first transaction on the chain. For each Uniswap liquidity pool on each day, we calculate the value-weighted average of all liquidity providers' experience in that pool. Each day, we split our sample equally into the old Uniswap userbase and the young Uniswap userbase based on the pool's average experience. Finally, we repeat the analyses in columns [1] and [2] of Table 2 for old and young Uniswap liquidity groups separately. We report the regression results in Table 3. From Table 3, we find that the impact of Uniswap's userbase size on Binance investor trading mostly comes from cryptocurrencies with Uniswap liquidity pools consisting of more experienced users. The interaction term coefficient in the old Uniswap userbase group is more than five times that of the young Uniswap userbase group.

[Insert Table 3 here]

The results from the cross-sectional test in Table 3 strengthen our argument that information on the Uniswap userbase plays an important role in determining Binance investors' beliefs and trading.

3.3. Binance investor trading and Uniswap userbase size under wash trading

One of the reasons why DEX instills trust in users compared to CEX is its resistance to manipulation, a feature notably absent in the latter. The lack of regulation and transparency on the CEX gives rise to potential market manipulation such as wash trading, also known as fake transactions (or fake volume), which is well-documented by Cong et al. (2021) and Amiram, Lyandres, and Rabetti (2021). Fake transactions inflate the quantity of value-relevant transactions, creating a false impression of the popularity of crypto trading in the CEX. This is likely to reduce investors' confidence in the reliability of information from the CEX relative to the DEX, where trading is organized in a more transparent fashion. Hence, we argue that the advantage of the DEX over its centralized counterpart should be more pronounced when the CEX exhibits high fake volume or when investors' attention to fake volume is high (Hypotheses 2 and 2.a).

In this section, we directly test these hypotheses using fake volume (following Amiram, Lyandres, and Rabetti, 2021) and the number of posts on Reddit discussing fake volume to capture investors' attention. For each cryptocurrency on each day, we follow Amiram, Lyandres, and Rabetti (2021) and construct a measure called *MAD* that is the likelihood that Binance trading exhibits fake volume. *MAD* stands for the mean absolute deviation. Specifically, the deviation is the difference between the benchmark, the Benford's Law-based distribution of the first significant digit of a series of data, and the empirical distribution of the first significant digit on Binance trading volume.[21]

[21] Benford's Law states that the probability of $N \in \{1,2,3,4,5,6,7,8,9\}$ being the first significant digit follows the formula of $\Pr(N \text{ is the first significant digit}) = \log_{10}(1 + N^{-1})$. Cong et al. (2021) also applies Benford's Law to detect fake volume.

After obtaining *MAD*, we sort our sample into two groups based on the median *MAD* of all cryptocurrencies on the previous day. The *High MAD* group consists of cryptocurrencies that exhibit a larger likelihood of fake volume than those in the *Low MAD* group. We repeat the analyses in columns [1] and [2] of Table 2 for each group, i.e., run the regression model as in Equation (1) on the *High* and *Low MAD* groups, respectively. Regression results are reported in Table 4.

[Insert Table 4 here]

We find that the impact of Uniswap's userbase size on Binance investor trading mostly comes from cryptocurrencies in the *High MAD* group. The coefficient of the interaction term *Lag Uniswap Userbase Size* × *Price Diff* is statistically significant at the 1% level for the *High MAD* group (columns [1] and [2]), but only marginally significant for the *Low MAD* group (columns [3] and [4]). The empirical findings support our Hypothesis 2.

In addition to *MAD*, we use Reddit to construct the daily intensity of investors' attention on fake volume in Binance. Specifically, we manually collect all Reddit posts and replies that include the keywords "fake" (or its synonyms "wash," "faked," "manipulated," "fraud," "fraudulent"), "volume" (or "trade," "trading"), and "Binance" during our sample period. Then we count the number of posts and replies on each day as the attention measure—*Reddit discussion*. Based on the median value of *Reddit discussion*, we split our sample into *High* and *Low Reddit discussion* days. For each group, we repeat the tests in columns [1] and [2] of Table 2. Regression results are presented in Table 5.

[Insert Table 5 here]

Although the interaction term *Lag Uniswap Userbase Size* × *Price Diff* is significant on both *High* and *Low Reddit discussion* days, we find that the coefficient on *High Reddit discussion* days is almost twice the one on *Low Reddit discussion* days. Our results suggest that the impact of Uniswap's userbase size on Binance investor trading is more pronounced when investors' attention to fake volume is high.

We demonstrate that Uniswap holds a more significant advantage over Binance, particularly when Binance exhibits wash trading or when there is heightened attention on the issue of wash trading. This finding further bolsters our argument that DEXs have the unique advantage over CEXs in gaining investors' trust, especially when the latter is opaque and faces regulatory deficiencies or ineffective regulation.

One caveat on the advantage of a DEX, like Uniswap, over a CEX is that it could be diminished when the CEX is adequately regulated. The challenge to explore this possibility lies in data limitation, as regulated centralized exchanges are very rare. During our sample period, Coinbase is the only centralized exchange that is known to be tightly regulated.[22] However, there are only four pairs of cryptocurrencies traded on both Uniswap and Coinbase, making the statistical exercises less convincing. Nevertheless, we still carry out a similar empirical analysis to examine how investor trading on Coinbase reacts to its own userbase size and Uniswap's. We find that the size of Coinbase's userbase has a positive significant impact on Coinbase investors' response to the price difference. Though we still observe the consistent pattern of the size of Uniswap's userbase affecting Coinbase investors' response to the price difference, the effect is less pronounced and only statistically significant at the 10% level (see Online Appendix Table A5).

3.4. Discussion of alternative explanations

Thus far, we have shown that Binance investors trade in response to the price difference between Binance and Uniswap. Such a response increases with the size of Uniswap's userbase but has no association with Binance's userbase size (captured by depth on Binance). These empirical findings are consistent with our argument that a DEX like Uniswap has unique advantages in transparency and trustworthiness. Uniswap's userbase is vital in determining investors' beliefs and trading. However, there are potential alternative explanations for our empirical findings.

First, the positive impact of Uniswap's userbase size on the response of Binance investor trading, when there is a price difference between Binance and Uniswap, could be driven by cross-market arbitrage activity. Increasing Uniswap's userbase size could facilitate cross-market arbitrage. Admittedly, this explanation is plausible but cannot explain the insignificant impact of Binance's userbase size on Binance investor trading, as the increase in Binance's userbase size should also facilitate cross-market arbitrage if the liquidity is the main driving force. Also, in Table A3, we find that the response of Uniswap investor trading to the

[22] Coinbase has established itself as one of the most regulated and compliant cryptocurrency exchanges. It operates in compliance with various regulations, including Know Your Customer and Anti-Money Laundering laws. Coinbase was among the first entities to obtain the BitLicense from the New York Department of Financial Services in 2017. Most importantly, Cong et al. (2021) show that regulated exchanges like Coinbase exhibit little fake volume issue, which fits well with our context.

price difference decreases with the size of Uniswap's userbase, which goes against the argument of cross-market arbitrage.

Nevertheless, we conduct a formal test to rule out the alternative explanation based on cross-market arbitrage. We examine the contemporary relationship of investor trading between Binance and Uniswap. We measure investor trading on Binance by *Corr(Lag Price Diff, Order Imbalance Binance)* and on Uniswap by *Corr(Lag Price Diff, Order Imbalance Uniswap)*. These two daily measures capture how investors on Binance or Uniswap respond to the price difference between Binance and Uniswap.[23] Suppose the cross-market arbitrage activity mainly drives the negative *Corr(Lag Price Diff, Order Imbalance Binance)* and positive *Corr(Lag Price Diff, Order Imbalance Uniswap)*. In that case, we should expect the correlation between *Corr(Lag Price Diff, Order Imbalance Binance)* and *Corr(Lag Price Diff, Order Imbalance Uniswap)* to be −1 (or at least negative). That is, investors' trading direction should be negatively correlated in the two markets for cross-market arbitrage. However, this is not the case in our data, and we observe the opposite. As shown in Table 6, the association between *Corr(Lag Price Diff, Order Imbalance Binance)* and *Corr(Lag Price Diff, Order Imbalance Uniswap)* is positive, and such an association does not depend on Uniswap's userbase size.

[Insert Table 6 here]

While the sharp contrasting result of the impact of Uniswap's userbase size and Binance's userbase size on Binance investor trading is consistent with our argument regarding the unique features of Uniswap, some may have concern that the contrasting result could be due to heterogeneities of investors across these two exchanges.[24] To rule out this possibility, we manually collect Uniswap users' information and focus on those who have participated in both Binance and Uniswap. Specifically, we identify users whose addresses have interacted with Binance hot wallets and Uniswap smart contracts as they participate in both. Based on Uniswap users (liquidity providers in particular) who use both Binance and Uniswap, we recalculate Uniswap's userbase size and repeat the empirical tests in columns [1] and [2] of Table 2. As shown in Online Appendix Table A6, when we focus on a userbase consisting of

[23] Even for cross-market arbitrage, there is a potential time mismatch of trading between Binance and Uniswap, and hence, we focus on daily-level measures of investor trading. When we examine the relation between high-frequency (i.e., at the five-minute interval) trading on Binance and Uniswap, we find similar results as in Table 6.
[24] Another possible explanation for our results is related to the impact of liquidity. We argue that this is unlikely. First, there is not a clear theory on why investors put more weight on the prices when liquidity is better. Meanwhile, if our results are driven by liquidity, we should also observe that Binance's userbase has a similar impact on investor trading as Uniswap's userbase, but this is not what we observe in Table 2.

investors participating in both Binance and Uniswap, we still find that Uniswap's userbase size significantly and positively affects the response of Binance investor trading to the price difference between Binance and Uniswap.

Overall, the results in Table 6 and Online Appendix Table A6 reassure us that our results are driven by neither cross-market arbitrage nor investor heterogeneities between Binance and Uniswap.

4. Establish the causal relationship with the launch of the yield-farming program

So far, the results in Tables 2–6 are consistent with our argument that Binance investors update their beliefs based on prices on both Binance and Uniswap. More importantly, Uniswap, rather than Binance's userbase size, affects Binance investors' trading decisions in response to the price difference between Binance and Uniswap, highlighting the uniqueness of the userbase size of Uniswap. However, one can still argue that our results are driven by unobservable characteristics affecting Uniswap's userbase size and Binance investor trading. In this section, we exploit one quasi-natural experiment—the launch of the yield-farming program—as an exogenous shock to the size of Uniswap's userbase to pin down the causal impact of the Uniswap userbase size on Binance investors' trading activities. In Section 4.1, we apply a difference-in-differences analysis and show that the launch of the yield-farming program has significantly increased the size of Uniswap's userbase. In Section 4.2, we apply a 2SLS instrumental variable regression based on the yield-farming reward program to study the causal impact of Uniswap's userbase size on Binance investor trading.

4.1. The yield-farming reward program for Uniswap userbase size

As described in the institutional background in Section 2.2, some cryptocurrency issuers use a yield-farming reward program to attract liquidity provisions on Uniswap. During our sample period, there are six cryptocurrencies (i.e., "ADXETH," "BNTETH," "EASYETH," "ETHBTC," "ETHUSDT," and "LRCETH") that launched the yield-farming reward program on different dates. We argue that the yield-farming reward program is a quasi-exogenous shock with no direct relation to Binance investor trading but that significantly impacts the size of Uniswap's userbase.

To show that the yield-farming reward program significantly impacts the size of the Uniswap userbase, we apply a difference-in-differences analysis to study the yield-farming reward program's impact on the Uniswap userbase size. We focus on the 5 (or 10, or 20, or 30) trading days before and after the launch event day for each program launch. We assign the cryptocurrencies that launch the program as the treatment group and all the rest as the control group. Meanwhile, we define a dummy variable, *Post*, that equals one if the trading day is after the program launch event and zero otherwise. After that, we track the change in the size of the Uniswap userbase, the natural logarithmic of the Uniswap liquidity pool size (dubbed as *Log Uniswap Userbase*), for the treatment and control groups, respectively.[25] To facilitate the cross-event comparison, we normalize *Log Uniswap Userbase* by its level at each cryptocurrency's starting day of the event window. Specifically, we take the difference between *Log Uniswap Userbase* and its level at the start of the event period. We plot the *Normalized Log Uniswap Userbase* throughout the event period of -10 and +10 days of the launch date in Figure 5.

[Insert Figure 5 here]

In Figure 5, we see a clear spike in the size of the Uniswap userbase right after the reward program is launched. For the treatment group, Uniswap userbase size increases almost twice after the reward program initiation. In comparison, little changes for the control group around the launch date.

To formally establish the impact of the reward program on the size of the Uniswap userbase, we run the following panel regression of Uniswap userbase size on *Treatment*, *Post*, and their interaction term:

$$\begin{aligned} &\textit{Normalized Log Uniswap Userbase}_{i,t} \\ &\qquad = \beta_1 \times \textit{Treatment} \times \textit{Post} + \beta_2 \times \textit{Treatment} + \beta_3 \times \textit{Post} \\ &\qquad + \textit{Fixed Effects} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where the coefficient of the interaction term *Treatment* × *Post* captures the differences in userbase size between the treatment and control groups before and after the launch date. We use the *Normalized Log Uniswap Userbase* to measure the size of Uniswap's userbase to be

[25] We apply the log transformation to facilitate the interpretation of the economic magnitude of the quasi-exogenous shock.

comparable to Figure 5. We control for the cryptocurrency and event fixed effects. Standard errors are clustered by cryptocurrencies. Table 7 reports the results.

[Insert Table 7 here]

Table 7 confirms the pattern in Figure 5 and clearly shows that the yield-farming reward program has significantly increased Uniswap's userbase size of the cryptocurrency. The increased Uniswap userbase size due to the yield-farming reward program is statistically significant for various event windows ranging from short (± 5 days) to long (± 30 days).[26]

One potential concern about the results in Figure 5 and Table 7 is that Uniswap userbase size is increasing before the yield-farming reward program, and the cryptocurrency issuers observe the increasing trend and strategically choose to launch the yield-farming reward program. This concern is related to the parallel trend assumption in the difference-in-differences analysis. We formally address this concern by running the following regression:

$$\begin{aligned} &\textit{Normalized Log Uniswap Userbase}_{i,t} \\ &= \sum_{n=1}^{4} \beta_n \times \textit{Treatment} \times \textit{Post}(-T_n) + \beta_5 \times \textit{Treatment} \times \textit{Post} \\ &+ \beta_6 \times \textit{Treatment} + \textit{Fixed Effects} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where *Post(-T_n)* is the pre-period indicator for the T_n period before the event date. We consider two groups of pre-period indicators: one is a daily dummy for the previous four days {*Post(-4), Post(-3), Post(-2), Post(-1)*}; the other one is a weekly dummy for the previous four weeks {*Post[-29,-21], Post[-20,-14], Post[-13,-7], Post[-6,-1]*}. The coefficients of the interaction terms between *Treatment* and pre-period indicators *Post(-T_n)* can clearly tell whether Uniswap userbase size has been increasing before the yield-farming reward program. We report the test results in Table 8.

[Insert Table 8 here]

[26] In Online Appendix Table A7, we manually collect the number of liquidity providers for each cryptocurrency in Uniswap and find that the yield-farming reward program also has significantly increased the number of liquidity providers on cryptocurrencies. This result is consistent with that in Table 7.

As shown in Table 8, the coefficients of the interaction terms between *Treatment* and all pre-period indicators *Post(-T_n)* are statistically insignificant, confirming that there is no clear increasing trend in Uniswap's userbase size before the launch of the yield-farming reward program.

4.2. Instrumental variable analysis on the impact of Uniswap userbase size

In Section 4.1, we demonstrated that the launch of the yield-farming program has significantly increased Uniswap's userbase size. We argue that the yield-farming reward program is unrelated to Binance investor trading as the launching decision was determined by the cryptocurrency issuer rather than Binance investors. Based on this argument, we apply a 2SLS instrumental variable regression using the yield-farming reward program to investigate the causal impact of Uniswap's userbase size on Binance investor trading.

In the first stage of the 2SLS instrumental variable regression, we focus on trading days in the window of ± 5 (or ± 10, or ± 20, or ± 30) days around the yield-farming reward program event. We use *Treatment* × *Post* as the instrument variable to predict Uniswap userbase size, where *Treatment* and *Post* are defined as in Table 7, and Uniswap userbase size is calculated as 100 times the time-weighted average market depth on Uniswap scaled by the total issuance of the cryptocurrency (as defined in Equation 1). The second-stage regression examines how the predicted value of Uniswap userbase size affects Binance investors' responses to the price difference between Binance and Uniswap. In other words, our second-stage regression follows the regression model in Equation (1), except we replace Uniswap userbase size with the predicted value of Uniswap userbase size from the first-stage regression. We control for the cryptocurrency and event fixed effects. Standard errors are clustered by cryptocurrencies. Table 9 reports the results of the 2SLS instrumental variable regression.

[Insert Table 9 here]

As shown in Table 9, 2SLS instrumental variable regression results are consistent with our previous findings on the impact of Uniswap userbase size. Specifically, we find that the yield-farming program-induced increase in the Uniswap userbase leads to a stronger negative association between *Order imbalance on Binance* and the price difference between Binance and Uniswap. Using the yield-farming program as a quasi-natural experiment, we are confident in our conclusion that there is a causal impact of Uniswap's userbase size on the response of Binance investor trading to the price difference between Binance and Uniswap.

5. Asset-pricing implications

In previous sections, we showed that the size of Uniswap's rather than Binance's userbase significantly affects investors' trading decisions in response to the price difference between Binance and Uniswap. In words, we observe when Binance investors see a higher price for a cryptocurrency on Uniswap compared to Binance, they believe that the future price will be higher, and thus, buy this cryptocurrency on Binance. And when the Uniswap userbase expands, Binance investors engage in more aggressive trading. Trading ultimately underpins the equilibrium price dynamics. The impact of Uniswap's userbase size on investor trading could have important economic implications for the equilibrium price dynamics. In this section, we examine the asset-pricing implication of Uniswap's userbase size.

Based on our findings in Sections 3 and 4, we conjecture that when Uniswap's userbase size gets larger, the Uniswap price plays a more important role in determining the equilibrium cryptocurrency price dynamics, as Binance investors trade more aggressively toward the price on Uniswap. Thus, the increase in Uniswap's userbase leads to Uniswap contributing more toward the common price trend between the two exchanges.

To test our conjecture, we apply the Gonzalo-Granger decomposition of the common trend to estimate Binance's and Uniswap's contributions to the common price component, respectively. Specifically, we apply the 2-by-1 Binance and Uniswap price vector-error-correction model with five lags to model the joint price dynamics on the two exchanges. We then estimate the accumulated impulse response on Binance and Uniswap over 100 periods of one unit shock in the price series. The Gonzalo-Granger component share is calculated as the impulse response of each exchange normalized by their sum. As de Jong (2002) points out, the Gonzalo-Granger component share is closely related to the Hasbrouck information share measure. Meanwhile, the Gonzalo-Granger component share is particularly useful if one's interest is to model the common trend between multiple cointegrated time series. In this sense, the Gonzalo-Granger component share measure can ideally test the tug-of-war between Binance and Uniswap prices in determining the equilibrium price dynamics of the cryptocurrency.

[Insert Table 10 here]

To address the endogeneity concern, we follow the methodology used in Table 9 and apply a 2SLS instrumental variable regression approach to study how Uniswap's userbase size affects the difference in the component share between Binance and Uniswap (Binance minus Uniswap). Table 10 reports the second-stage results of the 2SLS instrumental variable regression. As shown in Table 10, the results are consistent with our conjecture. As the Uniswap userbase becomes larger, the Uniswap price takes on a more significant weight in determining the equilibrium price dynamics than the Binance price.

6. Conclusion

Backed by smart contracts and blockchain authentication, DEXs have transparency and trustworthiness in trading (e.g., investors can easily access the transaction data, and the data cannot be easily falsified). Based on these features, we argue that DEXs have a unique advantage in gaining investors' trust in the integrity of market operations. As a result, the price or trading on DEXs can reflect investors' valuation of cryptocurrencies in a transparent and trustworthy way, which can better guide investor trading.

Our study focuses on the two largest centralized and decentralized cryptocurrency exchanges, Binance and Uniswap. We study how the Uniswap userbase affects the response of investor trading to the prices on these two exchanges. We have several novel and intriguing empirical findings. First, we find that Binance investor trading (i.e., order flow) negatively responds to the price difference between Binance and Uniswap, and such a response increases with the size of the Uniswap userbase (measured by the size of the Uniswap liquidity pool). In contrast, the Binance userbase (measured by depth in the Binance limit order book) does not have such impact. The contrasting results between the sizes of Binance's and Uniswap's userbases reflect the uniqueness of the DEX (i.e., Uniswap in our context) relative to the CEX (i.e., Binance in our context). Further, we conduct cross-sectional studies to corroborate our evidence. We find that the impact of the Uniswap userbase size is more pronounced when liquidity providers on Uniswap are more experienced, the likelihood of Binance exhibiting wash trading is higher, and investors care more about wash trading in Binance.

We are aware of potential endogenous issues. Hence, we use the launch event of the yield-farming program as a quasi-natural experiment to pin down the causal relation between

Uniswap userbase size and Binance investor trading. Our 2SLS instrumental variable regression yields consistent results and can help address the endogenous concerns.

Last, we extend our study to examine the asset pricing implication of Uniswap's userbase size. We study the contribution of each exchange (Binance or Uniswap) to the equilibrium price dynamics. We find that when Uniswap's userbase size increases, Uniswap plays a more important role in determining the common price trend between Binance and Uniswap. This implication echoes our findings on investor trading: when Uniswap's userbase increases, investors trade cryptocurrencies more responsively to the price on Uniswap, which leads to a larger contribution of Uniswap to the equilibrium price dynamics.

To sum up, our work presents a case where a decentralized infrastructure could overcome deficiencies in the centralized infrastructure. In our context, the deficiency is the lack of a manipulation-resistant trading environment from the CEX or the lack of investors' confidence in the ability of the CEX to provide such an environment. The lack of credibility of the CEX arises from many aspects, including operational opacity, insufficient regulation, being the prime target of hackers, scandals, etc. While better self or third-party regulation could help credibility concerns and resolve the deficiency, it always involves considerable regulatory costs. Our study shows that a DeFi application, like the DEX powered by blockchain and smart contracts, could be an alternative solution. Our results suggest that in an ecosystem where a consensus underwritten by a central monopoly is not feasible or can be too costly to obtain, DeFi could be an effective complement.

References

Aggarwal, Rajesh K., and Guojun Wu, 2006, Stock market manipulations. *Journal of Business*, 79 (4), 1915-1953.

Aloosh, Arash, and Jiasun Li, 2021, Direct evidence of bitcoin wash trading, *Working Paper*.

Aspris, Angelo, Sean Foley, Jiri Svec, and Leqi Wang, 2021, Decentralized exchanges: The "wild west" of cryptocurrency trading, *International Review of Financial Analysis*, 101845.

Aoyagi, Jun, 2020, Liquidity provision by automated market makers, *Working paper*.

Aoyagi, Jun, and Yuki Ito, 2021, Liquidity implications of constant product market makers, *Working paper*.

Athey, Susan, Ivo Parashkevov, Vishnu Sarukkai, and Jing Xia, 2016, Bitcoin pricing, adoption, and usage: Theory and evidence, *Working Paper*.

Biais, Bruno, 1993, Price formation and equilibrium liquidity in fragmented and centralized markets, *Journal of Finance* 48, 157–185.

Biais, Bruno, Christophe Bisière, Matthieu Bouvard, Catherine Casamatta, and Albert Menkveld, 2020, Equilibrium bitcoin pricing, *Working Paper*.

Biais, Bruno, Thierry Foucault, and Sophie Moinas, 2015, Equilibrium fast trading, *Journal of Financial Economics* 116, 292–313.

Budish, Eric, Peter Cramton, and John Shim, 2015, The high-frequency trading arms race: Frequent batch auctions as a market design response, *Quarterly Journal of Economics* 130, 1547–1621.

Buraschi, Andrea, and Emiliano S. Pagnotta, 2018, An equilibrium valuation of bitcoin and decentralized network assets, *Working Paper*.

Borri, Nicola, and Kirill Shakhnov, 2018, Cryptomarket discounts, *Working Paper*.

Capponi, Agostino, and Ruizhe Jia, 2021, The adoption of blockchain-based decentralized exchanges, *Working Paper*.

Cong, Lin William, and Zhiguo He, 2019, Blockchain disruption and smart contracts, *Review of Financial Studies* 32, 1754–1797.

Cong, Lin William, Ye Li, and Neng Wang, 2020, Tokenomics: Dynamic adoption and valuation, *Review of Financial Studies* 34, 1105–1155.

Cong, Lin William, Xi Li, Ke Tang, and Yang Yang, 2021, Crypto wash trading, *Working Paper*.

Easley, David, Nicholas M. Kiefer, Maureen O'Hara, and Joseph B. Paperman, 1996, Liquidity, information, and infrequently traded stocks, *Journal of Finance* 51, 1405–1436.

Easley, David, Marcos M. Lopez de Prado, and Maureen O'Hara, 2012, Flow toxicity and liquidity in a high-frequency world, *Review of Financial Studies* 25, 1457–1493.

Foucault, Thierry, Roman Kozhan, and Wing Wah Tham, 2017, Toxic arbitrage, *Review of Financial Studies* 30, 1053–1094.

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

Gonzalo, Jesus, and Clive Granger, 1995, Estimation of common long-memory components in cointegrated systems, *Journal of Business and Economic Statistics* 13, 27–35.

Griffin, John M., and Amin Shams, 2020, Is Bitcoin really un-Tethered?, *Journal of Finance* 75, 1913-1964.

Grossman, Sanford J., and Stiglitz, Joseph E., 1980, On the impossibility of informationally efficient markets. *American Economic Review* **70**, 393–408.

Harris, Frederick H. deB., Thomas H. McInish, Gary L. Shoesmith, and Robert A. Wood, 1995, Cointegration, error correction, and price discovery on informationally linked security markets, *Journal of Financial and Quantitative Analysis* 30, 563–579.

Harvey, Campell R., Ashwin Ramachandran, and Joey Santoro, 2021, Defi and the future of finance. Working paper.

Hasbrouck, Joel, 1995, One security, many markets: Determining the contributions to price Discovery, *Journal of Finance* 50, 1175–1199.

Hasbrouck, Joel, 2007, *Empirical Market Microstructure*. Oxford University Press.

Hellwig, Martin F., 1980, On the aggregation of information in competitive markets. *Journal of Economic Theory* 22, 477–498.

de Jong, Frank, 2002, Measures of contributions to price discovery: a comparison, Journal of Financial Markets 5, 323-327.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1335.

Li, Tao, Donghwa Shin, and Baolian Wang, 2020, Cryptocurrency pump-and-dump schemes, *Working Paper*.

Liu, Yukun, and Aleh Tsyvinski, 2020, Risks and returns of cryptocurrency, *Review of Financial Studies* 34, 2689–2727.

Liu, Yukun, Aleh Tsyvinski, and Xi Wu, forthcoming, Common risk factors in cryptocurrency, *Journal of Finance*.

Madhavan, Ananth, 1995, Consolidation, fragmentation, and the disclosure of trading information, *Review of Financial Studies* 8, 579–603.

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

O'Hara, Maureen, and Mao Ye, 2011, Is market fragmentation harming market quality?, *Journal of Financial Economics* 100, 459–474.

Park, Andreas, 2021, The conceptual flaws of constant product automated market making, *Working Paper*.

Shkilko, Andriy, and Konstantin Sokolov, 2020, Every cloud has a silver lining: Fast trading, microwave connectivity, and trading costs, *Journal of Finance*.

Sockin, Michael, and Wei Xiong, 2021, A model of cryptocurrencies, *Working Paper*.

Yermack, David, 2017, Corporate governance and blockchains, *Review of Finance* 21, 7–31.

Yin, Xiangkang, 2005, A comparison of centralized and fragmented markets with costly search, *Journal of Finance* 60, 1567–1590.

Zhong, Zhuo, 2016, Reducing opacity in over-the-counter markets, *Journal of Financial Markets* 27, 1–27.

Table 1: Summary statistics

This table reports the summary statistics of our sample that includes 40 cryptocurrencies (see Appendix Table A1 for the detailed list) from January 1, 2020 to January 31, 2021. *Mktcap* is the market capitalization of each cryptocurrency in millions of USD measured at the end of January 2021. Note that the denominators of all cryptocurrencies (except ETH itself) are ETH, and we transform the market capitalizations in ETH into those in USD. *Turnover* is the cryptocurrency's daily trading volume on Binance and Uniswap divided by the number of shares outstanding. For each cryptocurrency on each day, *Price Diff* is the difference between the natural logarithm of the volume-weighted average trading price in Binance and that in Uniswap. *Component share (Binance)* is the Gonzalo-Granger common factor weight for Binance, which is estimated by the 2-by-1 vector-error-correction model with five lags. For each cryptocurrency on each day, *Variance Ratio* is the absolute value of the difference between the 300-/60-second variance ratio and one.

Variable:	Mean	Std.	10%	25%	50%	75%	90%
Mktcap (in millions of USD)	16127.11	87898.28	9.93	19.46	58.44	188.22	669.98
Turnover (%)	104.13	638.94	0.12	0.19	0.54	1.23	8.43
Price Diff (%)	7.83	49.55	-1.34	-0.39	0.05	0.52	0.74
Component share (Binance)	0.81	0.21	0.53	0.75	0.86	0.94	1.00
Variance Ratio	0.19	0.06	0.14	0.15	0.18	0.22	0.28

Table 2: Trading and Uniswap userbase size

This table reports the results of panel regressions of Binance order imbalance on the price difference between Binance and Uniswap and the size of Uniswap's userbase (measured by the liquidity pool size). The dependent variable is *Order imbalance on Binance* at each five-minute interval, which is calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Binance every five minutes. Independent variables include *Lag Uniswap Userbase Size*, *Price Diff*, and their interaction term *Lag Uniswap Userbase Size* × *Price Diff*. *Lag Uniswap Userbase Size* is calculated as 100 times the time-weighted average market depth on Uniswap (scaled by the total issuance of the cryptocurrency) on the previous day. *Price Diff* is the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap computed every five minutes. In the regressions, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. To mitigate influences of infrequent trading and outliers, we drop cryptocurrency-date pairs if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. We control the lagged *Log Variance Ratio* that is the natural logarithm of one plus the *Variance Ratio*, the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. We also include the interaction term between *Price Diff* and *Lag Binance Userbase Size*, which is 100 times the time-weighted depth (of the top ten price levels scaled by the total issuance of the cryptocurrency) on Binance. Date fixed effects are controlled for columns [1] and [3]. Date and cryptocurrency fixed effects are controlled for columns [2], [4], and [5]. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Binance*				
	[1]	[2]	[3]	[4]	[5]
Lag Uniswap Userbase	-0.0560***	-0.0609***	-	-	-0.0603***
Size × Price Diff	(-3.0165)	(-2.7142)	-	-	(-2.5817)
Lag Uniswap Userbase	-0.0009***	0.0018	-	-	0.0019
Size	(-5.3182)	(1.4074)	-	-	(1.4802)
Price Diff	-1.5726***	-1.5382**	-3.2359***	-2.8395**	-1.6293
	(-2.7555)	(-2.6246)	(-2.6325)	(-2.4218)	(-1.5434)
Lag Log Variance Ratio	0.1941**	0.0859***	0.0917	0.0839***	0.0853***
	(2.2476)	(3.0880)	(1.4596)	(2.9458)	(3.0547)
Lag Binance Userbase	-	-	0.1417	0.0900	0.0085
Size × Price Diff	-	-	(1.5133)	(1.0036)	(0.1174)
Lag Binance Userbase	-	-	0.0064***	0.0016	0.0018
Size	-	-	(2.6155)	(0.5636)	(0.6603)
Fixed.Effects	Date	Crypto, Date	Date	Crypto, Date	Crypto, Date
Adj. R^2	0.0087	0.0164	0.0097	0.0160	0.0164
N. of Obs	320,220	320,220	320,220	320,220	320,220

Table 3: Trading and Uniswap userbase size conditional on provider experience

This table reports the results of the subsample analysis of Table 2 based on Uniswap liquidity provider experience. On each day, we split our sample into halves based on the liquidity provider's experience on the previous day with the following steps. First, we define one liquidity provider's experience as her age since the first transaction on the chain. For each Uniswap liquidity pool on each day, we calculate the value-weighted average of all liquidity providers' experience in that pool. Each day, we split our sample equally into old and young Uniswap userbases based on the liquidity pool's average experience. The sample in columns [1] and [2] consists of cryptocurrencies in the old userbase group, and the sample in columns [3] and [4] consists of those in the young userbase group. *Order imbalance on Binance* is at the five-minute interval, calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Binance every five minutes. *Lag Uniswap Userbase Size* is calculated as 100 times the time-weighted average market depth on Uniswap scaled by the total issuance of the cryptocurrency. *Price Diff* is the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap computed every five minutes. In the regressions, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. *Lag Log Variance Ratio* is the lagged value of the natural logarithm of one plus the *Variance Ratio*, which is the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. To mitigate influences of infrequent trading and outliers, we drop the cryptocurrency-date pair if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. In columns [1] and [3] we control for the date fixed effects. In columns [2] and [4] we control for the cryptocurrency and date fixed effects. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Binance*			
	Old Uniswap userbase		Young Uniswap userbase	
	[1]	[2]	[3]	[4]
Lag Uniswap Userbase Size × Price Diff	-0.2072*	-0.2829**	-0.0422***	-0.0417***
	(-1.7182)	(-2.7125)	(-6.6003)	(-6.4289)
Lag Uniswap Userbase Size	-0.0022	-0.0024	-0.0009***	-0.0028***
	(-0.6621)	(-1.2557)	(-10.9913)	(-2.6667)
Price Diff	-0.8615	-0.7317	-1.7132***	-1.5453**
	(-0.9567)	(-0.8142)	(-3.0134)	(-2.6667)
Lag Log Variance Ratio	0.1755**	0.2009***	0.1627**	0.0566
	(2.2979)	(4.5762)	(2.4665)	(1.3092)
Fixed.Effects	Date	Crypto, Date	Date	Crypto, Date
Adj. R^2	0.0125	0.0208	0.0101	0.0149
N. of Obs	152,125	152,125	168,095	168,095

Table 4: Trading and Uniswap userbase size conditional on fake volume

This table reports the results of the subsample analysis of Table 2 based on fake volume. On each day, we split our sample into halves based on the median value of the fake volume measure *MAD* of all cryptocurrencies in the previous day. The sample in columns [1] and [2] consists of cryptocurrencies in the high fake volume group, and the sample in columns [3] and [4] consists of cryptocurrencies in the low fake volume group. *Order imbalance on Binance* is at the five-minute interval, calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Binance every five minutes. *Lag Uniswap Userbase Size* is calculated as 100 times the time-weighted average market depth on Uniswap scaled by the total issuance of the cryptocurrency every five minutes. *Price Diff* is the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap computed every five minutes. In the regressions, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. *Lag Log Variance Ratio* is the lagged value of the natural logarithm of one plus the *Variance Ratio*, which is the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. To mitigate influences of infrequent trading and outliers, we drop cryptocurrency-date pairs if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. In columns [1] and [3] we control for the date fixed effects. In columns [2] and [4] we control for the cryptocurrency and date fixed effects. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Binance*			
	High MAD		Low MAD	
	[1]	[2]	[3]	[4]
Lag Uniswap Userbase Size × Price Diff	-0.0667***	-0.0688**	-0.0205*	-0.0346*
	(-3.1501)	(-2.8912)	(-1.7715)	(-1.8164)
Lag Uniswap Userbase Size	-0.0011***	0.0006	-0.0003	0.0062*
	(-5.3932)	(0.5356)	(-0.4066)	(1.7995)
Price Diff	-1.5485*	-1.6278*	-1.7049***	-1.5965***
	(-1.8980)	(-1.9829)	(-3.2937)	(-3.1108)
Lag Log Variance Ratio	0.2663***	0.1669***	0.0369	0.0305
	(3.2690)	(4.8868)	(0.6281)	(0.8374)
Fixed.Effects	Date	Crypto, Date	Date	Crypto, Date
Adj. R^2	0.0141	0.0027	0.0054	0.0115
N. of Obs	152,741	152,741	128,130	128,130

Table 5: Trading and Uniswap userbase size conditional on Reddit discussion

This table reports the results of the subsample analysis of Table 2 based on Reddit discussion of fake volume. We split our sample into halves based on the median value of the frequency of discussion of fake volume on Reddit. The sample in columns [1] and [2] consists of days in the high frequency of discussion of fake volume on Reddit group, and the sample in columns [3] and [4] consists of days in the low frequency of discussion of fake volume on Reddit group. *Order imbalance on Binance* is at the five-minute interval, calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Binance every five minutes. *Lag Uniswap Userbase Size* is calculated as 100 times the time-weighted average market depth on Uniswap scaled by the total issuance of the cryptocurrency every five minutes. *Price Diff* is the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap computed every five minutes. In the regressions, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. *Lag Log Variance Ratio* is the lagged value of the natural logarithm of one plus the *Variance Ratio*, which is the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. To mitigate influences of infrequent trading and outliers, we drop cryptocurrency-date pairs if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. In columns [1] and [3] we control for the date fixed effects. In columns [2] and [4] we control for the cryptocurrency and date fixed effects. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Binance*			
	High Reddit discuss		Low Reddit discuss	
	[1]	[2]	[3]	[4]
Lag Uniswap Userbase Size × *Price Diff*	-0.0720***	-0.0753***	-0.0447***	-0.0473**
	(-3.0743)	(-2.9368)	(-2.8483)	(-2.2601)
Lag Uniswap Userbase Size	-0.0005**	0.0004	-0.0013***	0.0057***
	(-2.3583)	(0.2616)	(-5.5319)	(4.0213)
Price Diff	-1.7010***	-1.5311**	-1.4042***	-1.7104***
	(-2.5819)	(-2.2452)	(-2.8273)	(-3.4772)
Lag Log Variance Ratio	0.1710***	0.0553	0.2310*	0.1513***
	(2.8276)	(1.6394)	(1.7500)	(4.0223)
Fixed.Effects	Date	Crypto, Date	Date	Crypto, Date
Adj. R^2	0.0101	0.0155	0.0070	0.0194
N. of Obs	180,158	180,158	140,062	140,062

Table 6: The relation between trading on Binance and Uniswap

This table reports the result of the relationship between trading on Binance and Uniswap. The dependent variable is *Corr(Price Diff, Order imbalance on Binance)*, the correlation between the price difference of cryptocurrencies on Binance and Uniswap and *Order imbalance on Binance*. *Order imbalance on Binance* is calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Binance every five minutes. The independent variable, *Corr(Price Diff, Order imbalance on Uniswap)*, is the correlation between the price difference of cryptocurrencies on Binance and Uniswap and *Order imbalance on Uniswap*. *Order imbalance on Uniswap* is calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Uniswap every five minutes. *Lag Uniswap Userbase Size* is calculated as 100 times the time-weighted average market depth on Uniswap scaled by the total issuance of the cryptocurrency. In columns [1] and [3] we control for the date fixed effects. In columns [2] and [4] we control for the cryptocurrency and date fixed effects. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Corr(Price Diff, Order imbalance on Binance)*			
	[1]	[2]	[3]	[4]
Corr(Price Diff, Order imbalance on	0.0559**	0.0668***	0.0541**	0.0653***
Uniswap)	(2.2285)	(3.3175)	(2.1345)	(3.2016)
Lag Uniswap Userbase Size	-	-	0.0003	0.0005
	-	-	(0.5902)	(0.8706)
Corr(Price Diff, Order imbalance on	-	-	0.0018	0.0019
Uniswap)× Lag Uniswap Userbase Size	-	-	(1.0925)	(1.2251)
Fixed.Effects	Date	Date, Crypto	Date	Date, Crypto
Adj. R^2	0.0644	0.1101	0.0944	0.1416
N. of Obs	12,415	12,415	12,415	12,415

Table 7: The yield-farming reward program and Uniswap userbase size

This table reports the results of the difference-in-differences analysis of the yield-farming reward program's impact on the size of the Uniswap userbase. For each program launch event, we focus on 5 (or 10, or 20, or 30) days before and after the launch event day. We assign the cryptocurrency that launches the program as the treatment group and all the rest as the control group. Meanwhile, we define a dummy variable, *Post*, that equals one if the date is after the program launch day and equals zero otherwise. After that, we run panel regressions of Uniswap's userbase size on *Treatment*, *Post*, and their interaction term. In the regressions, we use the *Normalized Log Uniswap Userbase* to measure the size of the Uniswap userbase, where *Normalized Log Uniswap Userbase* is the difference between the natural logarithm of quoted liquidity of each cryptocurrency and its level at the start of the event period. We control for the cryptocurrency and event fixed effects. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Normalized Log Uniswap Userbase*			
	± 5 days	± 10 days	± 20 days	± 30 days
	[1]	[2]	[3]	[4]
Treatment×Post	1.3001*	1.3711*	1.6388**	1.8578**
	(1.9031)	(1.8277)	(2.0396)	(2.2425)
Treatment	0.2295***	0.2743	0.4857***	0.5341***
	(3.3552)	(1.2136)	(4.6663)	(3.2585)
Post	-0.0196	0.0072	0.0839**	0.1475***
	(-0.5791)	(0.2130)	(2.0985)	(2.8598)
Fixed.Effects	Crypto, Event			
Adj. R^2	0.2379	0.2763	0.2484	0.3376
N. of Obs	2,267	4,317	8,005	11,739

Table 8: Parallel trend tests

This table reports the results of analyses that examine the parallel-trend assumption in the difference-in-differences analysis of Table 7. For each program launch event, we focus on the trading days 30 days before and after the launch event day. We assign the cryptocurrency that launches the program as the treatment group and all the rest as the control group. Meanwhile, we define a dummy variable, *Post*, that equals one if the date is after the program launch day and equals zero otherwise. Moreover, we consider two groups of pre-period indicators *Post(-T_n)*: one is a daily dummy for the previous four days {*Post(-4), Post(-3), Post(-2), Post(-1)*}; the other one is a weekly dummy for the previous four weeks {*Post[-29,-21], Post[-20,-14], Post[-13,-7], Post[-6,-1]*}. After that, we run panel regressions of Uniswap's userbase size on *Treatment*, *Post*, *Treatment*×*Post,* and *Treatment*×*Post(-T_n)*. In the regressions, we use the *Normalized Log Uniswap Userbase* to measure the size of Uniswap's userbase, where *Normalized Log Uniswap Userbase* is the difference between the natural logarithm of quoted liquidity of each cryptocurrency and its level at the start of the event period. We control for the event and event-date fixed effects in columns [1] and [3] and we control for cryptocurrency, event, and event-date fixed effects in columns [2] and [4]. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Normalized Log Uniswap Userbase*			
	[1]	[2]	[3]	[4]
Treatment×*Post(-4)*	0.4276	0.4117		
	(1.2534)	(1.2088)		
Treatment×*Post(-3)*	0.4192	0.4033		
	(1.2812)	(1.2348)		
Treatment×*Post(-2)*	0.3119	0.2960		
	(1.3909)	(1.3225)		
Treatment×*Post(-1)*	0.5188	0.5029		
	(1.4760)	(1.4333)		
Treatment×*Post[-29,-21]*			0.0053	0.0047
			(0.0543)	(0.0481)
Treatment×*Post[-20,-14]*			0.3834	0.3857
			(0.9412)	(0.9481)
Treatment×*Post[-13,-7]*			0.5124	0.4950
			(1.2046)	(1.1650)
Treatment×*Post[-6,-1]*			0.6548	0.6327
			(1.3421)	(1.2979)

Table 8 continued

Treatment×Post	1.9204**	1.9061**	2.2061**	2.1858**
	(2.2574)	(2.2489)	(2.3230)	(2.3277)
Treatment	0.2563	0.4829***	-0.0294	0.2032
	(1.3785)	(2.8225)	(-0.1879)	(0.7959)
Fixed.Effects	Event, Event Date	Crypto, Event, Event Date	Event, Event Date	Crypto, Event, Event Date
Adj. R^2	0.1884	0.3383	0.1890	0.3388
N. of Obs	11,739	11,739	11,739	11,739

Table 9: IV results for trading and Uniswap userbase size

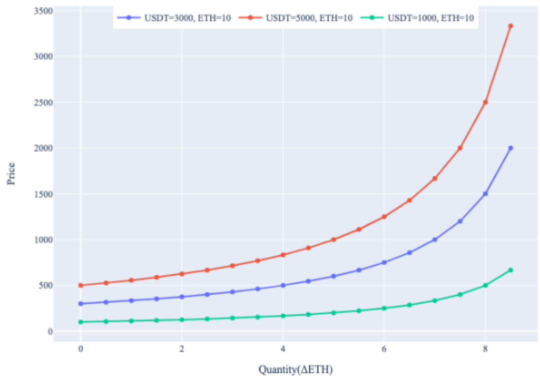
This table reports the second-stage results of the 2SLS instrumental variable regression based on the yield-farming reward program. We argue that the yield-farming reward program is a quasi-exogenous shock unrelated to order imbalance on Binance but significantly impacts the size of the Uniswap userbase. In this table, we run 2SLS instrumental variable regressions based on the yield-farming reward program to pin down the causal effect of Uniswap's userbase size on order imbalance on Binance. In the first stage, focusing on trading days in the window of ± 5 (or ± 10, or ± 20, or ± 30) days around the yield-farming reward program event, we use *Treatment*×*Post* as an instrumental variable to predict *Lag Uniswap Userbase Size*, where *Treatment* and *Post* are defined in Table 7, and *Lag Uniswap Userbase Size* are defined in Table 2. The second stage of the regression examines the association between the predicted value of *Lag Uniswap Userbase Size* and *Order imbalance on Binance*. *Order imbalance* and *Price Diff* are calculated at the five-minute interval, and the order imbalance measure leads the price difference measure by five minutes in the regression. To reduce influences of infrequent trading and outliers, we drop the cryptocurrency-date pair if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. Across all regressions, we control for the cryptocurrency and event fixed effects. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Binance*			
	± 5 days	± 10 days	± 20 days	± 30 days
	[1]	[2]	[3]	[4]
Lag $\widehat{\textit{Uniswap Userbase}}$ *Size*	-0.1342***	-0.1360***	-0.1206**	-0.1005**
× *Price Diff*	(-2.8758)	(-2.8252)	(-2.0778)	(-2.3995)
Lag $\widehat{\textit{Uniswap Userbase}}$ *Size*	-0.0123*	-0.0106*	-0.0016	-0.0045
	(-1.8906)	(-1.9246)	(-0.3649)	(-1.5379)
Price Diff	-0.4353	-0.7336	-1.0622	-1.1906
	(-0.5737)	(-0.9550)	(-1.2783)	(-1.4242)
Instruments	Treatment × Post			
Fixed.Effects	Crypto, Event			
Adj. R^2	0.0056	0.0059	0.0083	0.0089
N. of Obs	78,628	148,933	265,308	382,215

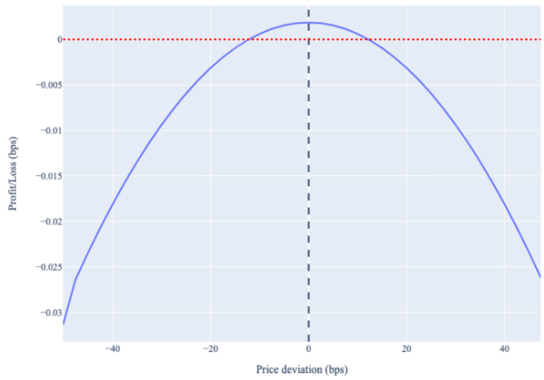
Table 10: Binance and Uniswap in price determination

This table reports the second-stage results of a 2SLS instrumental variable regression on the difference in the component share of Binance and Uniswap using the inception of the yield-farming reward program as the instrumental variable. We argue that the yield-farming reward program is a quasi-exogenous shock unrelated to order imbalance on Binance but has significant impacts on the size of Uniswap's userbase. In this table, we run 2SLS instrumental variable regressions based on the yield-farming reward program to pin down the causal effect of the Uniswap userbase size on Binance and Uniswap's contribution to the common price component. In the first stage, focusing on trading days in the window of ± 5 (or ± 10, or ± 20, or ± 30) days around the yield-farming reward program event, we use *Treatment*×*Post* as an instrumental variable to predict *Lag Uniswap Userbase Size*, where *Treatment* and *Post* are defined in Table 7, and *Lag Uniswap Userbase Size* is defined in Table 2. The second stage of the regression examines the association between the predicted value of *Lag Uniswap Userbase Size* and the difference between the component share of Binance and Uniswap. The component share captures Binance's or Uniswap's contribution to the common price component. It is estimated from the cumulated impulse responses of the 2-by-1 Binance and Uniswap price vector-error-correction model with five lags accumulating over 100 periods. The difference in the component share is calculated as the Binance component share minus the Uniswap component share. Across all regressions, we control for the cryptocurrency and event fixed effects. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	Differences in component share between Binance and Uniswap			
	± 5 days	± 10 days	± 20 days	± 30 days
	[1]	[2]	[3]	[4]
Lag $\widehat{\textit{Uniswap Userbase}}$ *Size*	-0.0891	-0.1089*	-0.1191**	-0.1308*
	(-1.3840)	(-1.9559)	(-2.3917)	(-1.8491)
Instruments	Treatment×Post			
Fixed.Effects	Crypto, Event			
Adj. R^2	0.2312	0.2206	0.2163	0.2248
N. of Obs	2,195	4,202	7,747	11,355



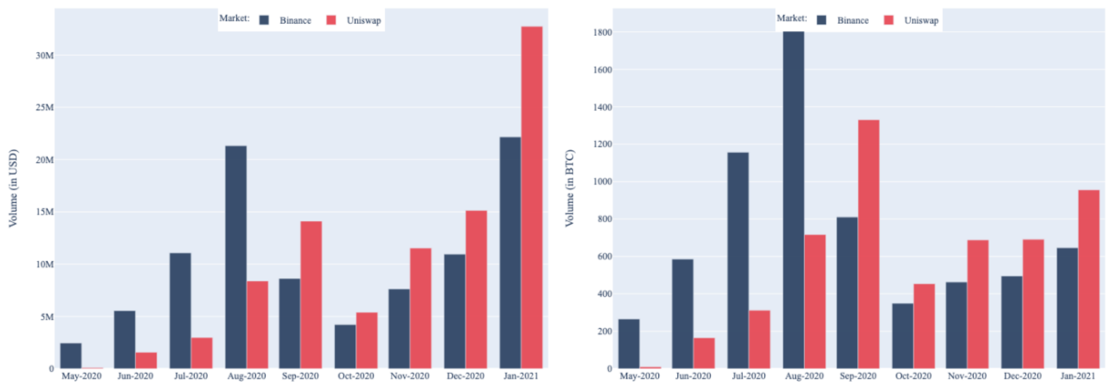
Panel A: Inverse demand function



Panel B: Impermanent loss

Figure 1: Inverse demand function and impermanent loss under CPMM

This figure illustrates the inverse demand function and impermanent loss under the CPMM rule. Panel A illustrates the demand curve with $y \in \{1000, 3000, 5000\}$, $x = 10$, and $\Delta x \in \{0, 1, 2, 3, \ldots, 9\}$. Panel B simulates the impermanent loss faced by the liquidity provider. In the simulation, we use $k = 10{,}000$ with the initial $x = 10$ and $y = 1{,}000$. Then we consider the mid-price between 99.5 and 100.5. The x-axis is the price deviation compared to the initial mid-price of 100, and the y-axis is the profit/loss for the liquidity provider, comparing her redeemed value and the value if she simply holds the initial $x = 10$ and $y = 1{,}000$ position.

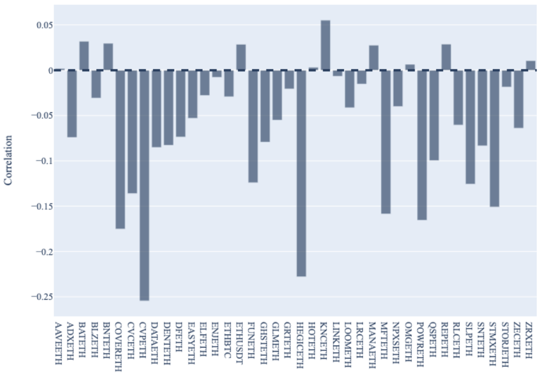


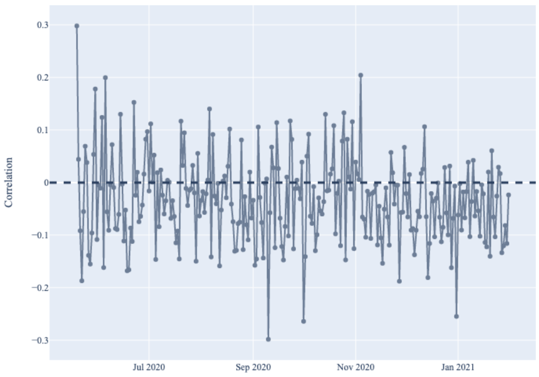
Panel A: Volume in USD

Panel B: Volume in Bitcoin

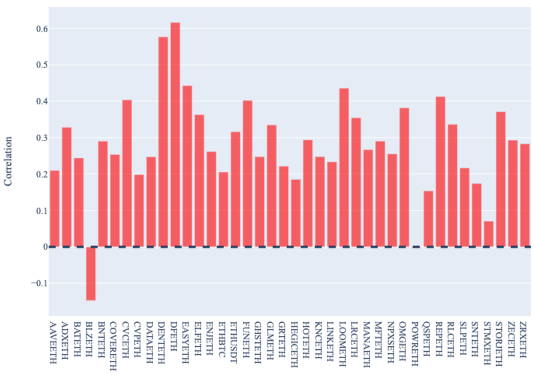
Figure 2: Trading volume on Binance and Uniswap

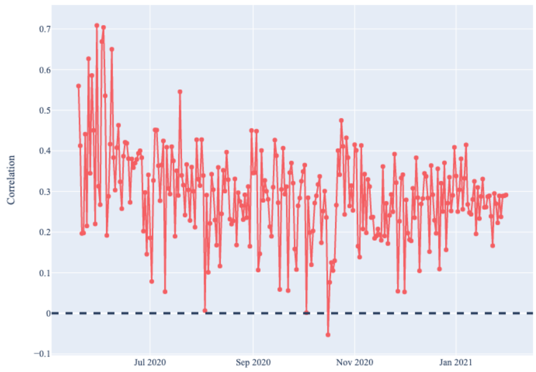
This figure shows the monthly average trading volumes on Binance and Uniswap for our sample cryptocurrencies (excluding the “ETHUSDT” and “ETHBTC” pairs). Panel A is volume denominated in USD, and Panel B is in Bitcoin.





Panel A: Correlation on Binance across cryptocurrencies   Panel B: Correlation on Binance over time





Panel C: Correlation on Uniswap across cryptocurrencies   Panel B: Correlation on Uniswap over time

Figure 3: Price differences and trading activity on Binance and Uniswap

This figure shows the intraday (five-minute interval) correlation between the lagged price difference and order imbalance on Binance and Uniswap, respectively. For each cryptocurrency on each day, we first split the trading hours into five-minute intervals, and *Corr(Lag Prc.Df, OI Binance)* is the correlation between the price difference on Binance and Uniswap in one particular five-minute interval and order imbalance on Binance in the next five minutes, where the price difference is the difference between the natural logarithm of the volume-weighted average trading price in Binance and the natural logarithm of the volume-weighted average trading price in Uniswap and order imbalance is defined as $\frac{Buy\ volume - Sell\ volume}{Buy\ volume + Sell\ volume}$ in each five-minute interval. Similarly, for each cryptocurrency on each day, we first split the trading hours into five-minute intervals, and *Corr(Lag Prc.Df, OI Uniswap)* is the correlation between the price difference on Binance and Uniswap in one particular five-minute interval and order imbalance on Uniswap in the next five minutes. Panels A and C illustrate the cross-section of the time series average for each cryptocurrency. Panels B and D show the daily average in the whole sample.

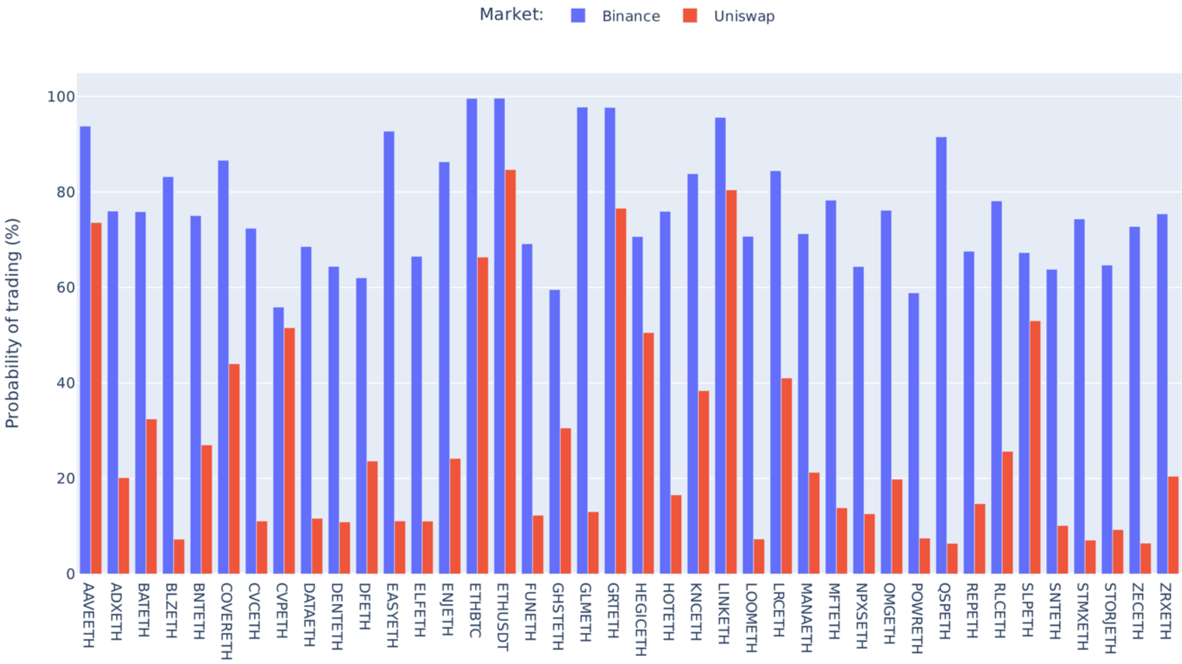


Figure 4: The daily average of the probability of Binance and Uniswap trading in the five-minute interval

In this figure, we show the daily average of the probability of Binance and Uniswap trading for each cryptocurrency in the five-minute interval conditional on observing past (previous five-minute) price differences.

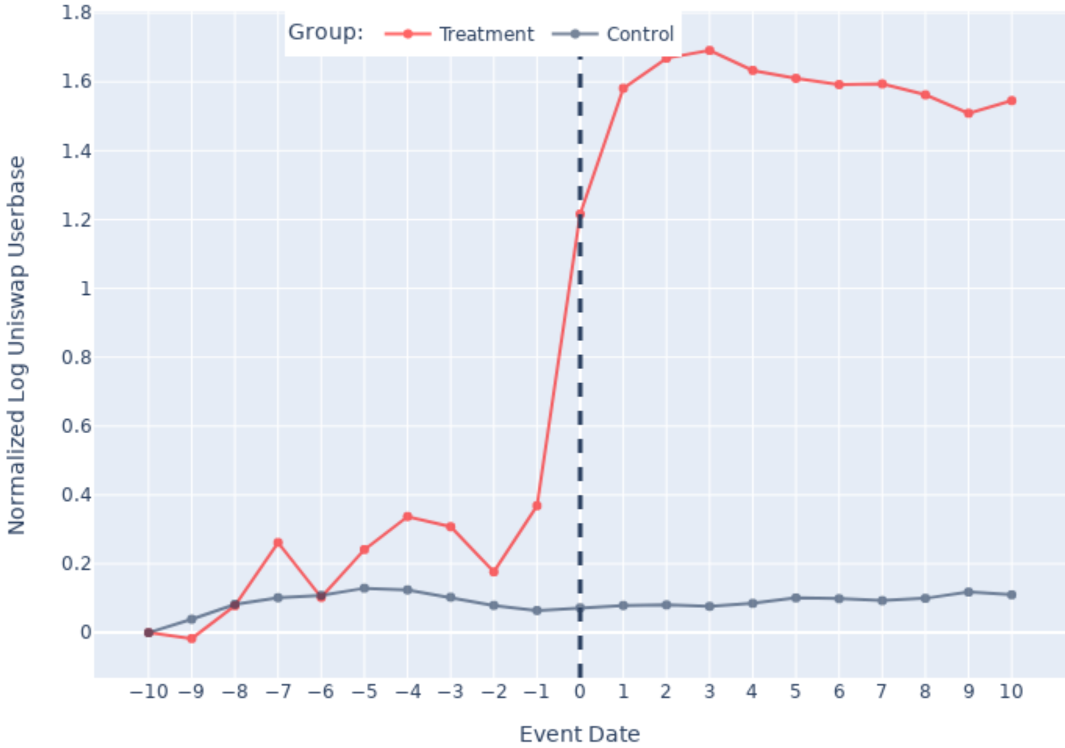


Figure 5: The launch of the yield-farming reward program

This figure shows the dynamic change of Uniswap's userbase size, *Normalized Log Uniswap Userbase*, around the yield-farming reward program inception for the cryptocurrencies in the treatment and control groups, respectively. The horizontal x-axis represents the event date from -10 to +10 days related to the program launch date. For each program event, we assign the cryptocurrency that launches the program as the treatment group and all the rest as the control group. The vertical y-axis is the *Normalized Log Uniswap Userbase*, which is the difference between the natural logarithm of the quoted liquidity of each cryptocurrency and its level at the start of the event period.

Table A1: The list of trading pairs

This table lists all cryptocurrencies and their denominators used in our sample. For each cryptocurrency, we report its average daily trading volume of January 2021 in Binance and Uniswap, respectively. Volume is in thousand US dollars.

Cryptocurrency-Denominator	Trading Volume in Binance (thousands USD)	Trading Volume in Uniswap (thousands USD)
AAVE-ETH	87,543.81	255,000.64
ADX-ETH	5,770.39	6,023.36
BAT-ETH	9,697.66	16,995.68
BLZ-ETH	6,053.98	63.61
BNT-ETH	3,521.84	2,862.22
BTC- ETH	15,361,612.15	1,129,695.70
COVER-ETH	7,427.14	42.79
CVC-ETH	10,909.79	286.34
CVP-ETH	3,580.52	33,913.35
DATA-ETH	3,428.16	892.84
DENT-ETH	10,392.78	83.84
DFE-ETH	1,774.83	3,147.49
EASY-ETH	23,311.79	996.62
ELF-ETH	2,647.34	107.76
ENJ-ETH	63,509.65	17,256.01
ETH-USDT	66,126,276.87	2,888,784.54
FUN-ETH	26,992.77	7,551.04
GHST-ETH	4,636.92	7,723.59
GLM-ETH	6,556.67	2,446.81
GRT-ETH	65,721.99	66,689.32
HEGIC-ETH	10,590.74	23,224.06
HOT-ETH	22,139.51	1,713.08
KNC-ETH	16,186.24	15,179.85
LINK-ETH	229,439.42	494,033.85
LOOM-ETH	13,797.55	499.10
LRC-ETH	56,010.64	222,608.20
MANA-ETH	10,703.72	8,625.14
MFT-ETH	21,545.59	5,305.08
NPXS-ETH	27,134.98	5,260.63
OMG-ETH	17,933.30	22,561.96
POWR-ETH	3,197.90	193.68
QSP-ETH	4,764.59	357.93
REP-ETH	4,096.80	586.21
RLC-ETH	6,919.54	6,380.69

SLP-ETH	5,790.77	2,674.01
SNT-ETH	11,896.18	2,745.27
STMX-ETH	6,455.90	309.05
STORJ-ETH	447.46	85.75
ZEC-ETH	22,749.62	2,976.79
ZRX-ETH	8,809.24	6,315.13

Table A2: Robustness check on trading and Uniswap userbase size

This table reports the results of the robustness checks in Table 2. We consider several alternative measures for *Order imbalance on Binance*, including the buy dollar volume minus sell dollar volume scaled by the sum of buy and sell dollar volume on Binance every five minutes and order imbalance measured every ten minutes. Independent variables include *Lag Uniswap Userbase Size*, the lagged daily Uniswap liquidity pool size that is calculated as 100 times the time-weighted average market depth on Uniswap scaled by the total issuance of the cryptocurrency; and *Price Diff*, the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap computed every five (or ten) minutes; and the interaction term *Lag Uniswap Userbase Size* × *Price Diff*. In the regressions, the order imbalance measure leads the price difference measure by five (or ten) minutes. To mitigate influences of infrequent trading and outliers, we drop the cryptocurrency-date pair if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. We control the lagged *Log Variance Ratio* that is the natural logarithm of one plus the *Variance Ratio*, the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. We also include the interaction term of *Lag Binance Userbase Size*, which is 100 times the time-weighted depth (of the top ten price levels) on Binance scaled by the total issuance of the cryptocurrency, and *Price Diff*. Date fixed effects are controlled for columns [1] and [3]. Date and cryptocurrency fixed effects are controlled for the remaining columns. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Binance*					
	Order imbalance based on dollar volume			*Order imbalance by 10 mins*		
	[1]	[2]	[3]	[4]	[5]	[6]
Lag Uniswap Userbase Size × Price Diff	-0.0560***	-0.0609***	-0.0650***	-0.0621**	-0.0690**	-0.0759**
	(-3.0165)	(-2.7142)	(-2.7530)	(-2.1956)	(-2.0978)	(-2.1388)
Lag Uniswap Userbase Size	-0.0009***	0.0018	0.0018	-0.0009**	0.0006	0.0005
	(-5.3182)	(1.4074)	(1.4034)	(-3.4013)	(0.5859)	(0.4838)
Price Diff	-1.5726***	-1.5382**	-1.5751**	-1.1368**	-1.2332**	-1.2876**
	(-2.7555)	(-2.6246)	(-2.6105)	(-2.1617)	(-2.2064)	(-2.2248)
Lag Log Variance Ratio	0.1941**	0.0859***	0.0861***	0.1270**	0.0521**	0.0516**
	(2.2476)	(3.0880)	(3.1092)	(2.2473)	(2.1945)	(2.1687)
Lag Binance Userbase Size × Price Diff	-	-	0.1278	-	-	0.2073
	-	-	(1.1377)	-	-	(1.4689)
Lag Binance Userbase Size	-	-	0.0054	-	-	-0.0024
	-	-	(0.8881)	-	-	(-0.8221)
Fixed.Effects	Date	Crypto, Date	Crypto, Date	Date	Crypto, Date	Crypto, Date
Adj. R^2	0.0087	0.0164	0.0164	0.0082	0.0141	0.0142
N. of Obs	320,220	320,220	320,220	235,076	235,076	235,076

Table A3: Uniswap trading and Uniswap userbase size

This table reports the results of panel regressions of Uniswap order imbalance on the size of Uniswap's userbase. The dependent variable is *Order imbalance on Uniswap* at the five-minute interval, and it is calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Uniswap every five minutes. Independent variables include *Lag Uniswap Userbase Size*, the lagged daily Uniswap liquidity pool size that is calculated as 100 times the time-weighted average market depth on Uniswap scaled by the total issuance of the cryptocurrency; and *Price Diff*, the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap computed every five minutes; and the interaction term *Lag Uniswap Userbase Size* × *Price Diff*. In the regressions, the order imbalance measure leads the price difference measure by five minutes. To mitigate influences of infrequent trading and outliers, we drop the cryptocurrency-date pair if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. We control the lagged *Log Variance Ratio* that is the natural logarithm of one plus the *Variance Ratio*, the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. Date fixed effects are controlled for columns [1] and [3]. Date and cryptocurrency fixed effects are controlled for the remaining columns. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Uniswap*	
	[1]	[2]
Lag Uniswap Userbase Size ×	-0.0853*	-0.1007*
Price Diff	(-1.6624)	(-1.7311)
Lag Uniswap Userbase Size	0.0003	0.0017
	(1.1160)	(0.4469)
Price Diff	12.1849***	12.9436***
	(5.6270)	(5.4856)
Lag Log Variance Ratio	0.0339	-0.0417
	(0.3797)	(-1.1860)
Fixed.Effects	Date	Crypto, Date
Adj. R^2	0.0279	0.0358
N. of Obs	238,597	238,597

Table A4: Trading and Uniswap userbase size by number of liquidity providers

This table reports the results of panel regressions of Binance order imbalance on the price difference between Binance's and Uniswap's userbase size measured by the number of Uniswap liquidity providers. The dependent variable is *Order imbalance on Binance* at each five-minute interval, which is calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Binance every five minutes. Independent variables include *Lag Uniswap Userbase Size_Num* at each five-minute interval, *Price Diff*, and their interaction term *Lag Uniswap Userbase Size_Num × Price Diff*. The lagged daily Uniswap userbase size by number of liquidity providers, *Lag Uniswap Userbase Size_Num*, is calculated as the number of participants providing liquidity for a cryptocurrency on Uniswap scaled by the total issuance of the cryptocurrency on the previous day. *Price Diff* is the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap computed every five minutes. In the regressions, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. To mitigate influences of infrequent trading and outliers, we drop cryptocurrency-date pairs if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. We control the lagged *Log Variance Ratio* that is the natural logarithm of one plus the *Variance Ratio*, the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. We also include the interaction term between *Price Diff* and *Lag Binance Userbase Size*, which is 100 times the time-weighted depth (of the top ten price levels) on Binance scaled by the total issuance of the cryptocurrency every five minutes. Date fixed effects are controlled for columns [1] and [3]. Date and cryptocurrency fixed effects are controlled for columns [2], [4], and [5]. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Binance*				
	[1]	[2]	[3]	[4]	[5]
Lag Uniswap Userbase Size_Num × Price Diff	-0.1134***	-0.1463***	-	-	-0.1491***
	(-2.7640)	(-2.9623)	-	-	(-3.5602)
Lag Uniswap Userbase Size_Num	-0.0074***	0.0151***	-	-	0.0149***
	(-5.8149)	(3.8037)	-	-	(3.7498)
Price Diff	-1.6174***	-1.4179**	-3.2359***	-2.8395**	-2.4177**
	(-2.5050)	(-2.1892)	(-2.6325)	(-2.4218)	(-2.3686)
Lag Log Variance Ratio	0.1954**	0.0881***	0.0917	0.0839***	0.0874***
	(2.1830)	(3.0890)	(1.4596)	(2.9458)	(3.0504)
Lag Binance Userbase Size × Price Diff	-	-	0.1417	0.0900	0.0998
	-	-	(1.5133)	(1.0036)	(1.6248)
Lag Binance Userbase Size	-	-	0.0064***	0.0016	0.0016
	-	-	(2.6155)	(0.5636)	(0.5655)
Fixed.Effects	Date	Crypto, Date	Date	Crypto, Date	Crypto, Date
Adj. R^2	0.0096	0.0164	0.0097	0.0160	0.0164
N. of Obs	320,220	320,220	320,220	320,220	320,220

Table A5: Trading on Coinbase and userbase size

This table reports the results of panel regressions of Coinbase order imbalance on the price difference between Coinbase and Uniswap and the size of Uniswap's userbase (measured by the liquidity pool size). The dependent variable is *Order imbalance on Coinbase* at each five-minute interval, which is calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Coinbase every five minutes. Independent variables include *Lag Uniswap Userbase Size*, *Price Diff*, and their interaction term *Lag Uniswap Userbase Size* × *Price Diff*. *Lag Uniswap Userbase Size* is calculated as 100 times the time-weighted average market depth on Uniswap scaled by the total issuance of the cryptocurrency on the previous day. *Price Diff* is the natural logarithm difference of the volume-weighted average trading price between Coinbase and Uniswap computed every five minutes. In the regressions, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. To mitigate influences of infrequent trading and outliers, we drop cryptocurrency-date pairs if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. We control the lagged *Log Variance Ratio* that is the natural logarithm of one plus the *Variance Ratio*, the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. We also include the interaction term between *Price Diff* and *Lag Coinbase Userbase Size*, which is 100 times the time-weighted depth (of the top ten price levels) on Coinbase scaled by the total issuance of the cryptocurrency. Date fixed effects are controlled for column [1]. Date and cryptocurrency fixed effects are controlled for columns [2] and [3]. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Coinbase*		
	[1]	[2]	[3]
Lag Coinbase Userbase Size	0.2368***	0.2253**	0.2479**
× *Price Diff*	(5.0039)	(4.8734)	(5.0377)
Lag Coinbase Userbase Size	-0.0002	0.0035	0.0027
	(-0.5121)	(2.0897)	(1.0812)
Price Diff	-2.0881**	-1.9686	-2.0424*
	(-2.2776)	(-2.3018)	(-2.3701)
Lag Log Variance Ratio	0.0389	0.0342	0.0436
	(0.9252)	(1.3480)	(1.3140)
Lag Uniswap Userbase Size ×	-	-	-0.0238*
Price Diff	-	-	(-2.5577)
Lag Uniswap Userbase Size	-	-	-0.0004
	-	-	(-2.5577)
Fixed.Effects	Date	Crypto, Date	Crypto, Date
Adj. R^2	0.0025	0.0028	0.0029
N. of Obs	168,209	168,209	168,209

Table A6: Trading and Uniswap userbase size from overlapped users

This table reports the results of panel regressions of Binance order imbalance on Uniswap userbase size from liquidity providers who use both Binance and Uniswap. The dependent variable is *Order imbalance on Binance*, which is calculated as the buy volume minus sell volume scaled by the sum of buy and sell volumes on Binance every five minutes. Independent variables include *Lag Uniswap Userbase Size*, the lagged daily Uniswap userbase size that is calculated as 100 times the time-weighted average market depth on Uniswap provided by users who use both Binance and Uniswap, scaled by the total issuance of the cryptocurrency; and *Price Diff*, the natural logarithm difference of the volume-weighted average trading price between Binance and Uniswap computed every five minutes; and the interaction term *Lag Uniswap Userbase Size* × *Price Diff*. In the regressions, the order imbalance measure leads the price difference measure by five minutes. To mitigate influences of infrequent trading and outliers, we drop the cryptocurrency-date pair if the cryptocurrency has less than 30 non-missing intraday *Price Diff* observations on the date, and we winsorize *Price Diff* at the 0.5% and 99.5% levels. We control the lagged *Log Variance Ratio* that is the natural logarithm of one plus the *Variance Ratio*, the absolute value of the difference between the 300-/60-second variance ratio and one, for each cryptocurrency on each day. Date fixed effects are controlled for columns [1] and [3]. Date and cryptocurrency fixed effects are controlled for the remaining columns. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Order imbalance on Binance*	
	[1]	[2]
Lag Uniswap Userbase Size ×	-0.0607***	-0.0655**
Price Diff	(-2.9576)	(-2.6393)
Lag Uniswap Userbase Size	-0.0010***	0.0008
	(-5.6414)	(0.3845)
Price Diff	-1.5867***	-1.5623**
	(-2.8056)	(-2.6722)
Lag Log Variance Ratio	0.1933**	0.0854***
	(2.2406)	(3.0342)
Fixed.Effects	Date	Crypto, Date
Adj. R^2	0.0087	0.0163
N. of Obs	320,220	320,220

Table A7: The yield-farming reward program and Uniswap userbase size

This table reports the results of the difference-in-differences analysis of the impact of the yield-farming reward program on the Uniswap userbase size measured by the number of Uniswap liquidity providers. For each program launch event, we focus on 5 (or 10, or 20, or 30) days before and after the launch event day. We assign the cryptocurrency that launches the program as the treatment group and all the rest as the control group. Meanwhile, we define a dummy variable, *Post*, that equals one if the date is after the program launch event and equals zero otherwise. After that, we run panel regressions of the Uniswap userbase size by number of liquidity providers on *Treatment*, *Post*, and the interaction term. In the regression, *Normalized Log Uniswap Userbase Size_(the number of liquidity providers)* is the difference between the natural logarithm of the number of liquidity providers on Uniswap of each cryptocurrency and its level at the start of the event period. We control for the cryptocurrency and event fixed effects. Standard errors are clustered by cryptocurrency. We report *t*-statistics in the parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

DepVar:	*Normalized Log Uniswap Userbase Size (the number of liquidity providers)*			
	± 5 days	± 10 days	± 20 days	± 30 days
	[1]	[2]	[3]	[4]
Treatment × *Post*	0.7233***	0.8381***	1.0351***	1.1842***
	(2.8724)	(2.8237)	(3.1699)	(3.5260)
Treatment	0.0769	0.0734**	0.1036	0.0660
	(0.9306)	(2.1707)	(0.9532)	(0.4428)
Post	0.0056	0.0076	0.1855***	0.2349***
	(0.2909)	(0.3356)	(5.2129)	(6.0762)
Fixed.Effects	Crypto, Event			
Adj. R^2	0.2598	0.0585	0.0902	0.1039
N. of Obs	2,267	4,317	8,005	11,739