# Trust in DeFi: An Empirical Study of the Decentralized Exchange

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## Abstract

We provide empirical evidence that the decentralized cryptocurrency exchange helps reveal the consensus on the value of the cryptocurrency. By examining how investors on Binance (the largest centralized cryptocurrency exchange) trade in response to prices on Binance and Uniswap (the largest decentralized cryptocurrency exchange), we find the increase in the Uniswap userbase induces Binance investor trading towards the Uniswap price. In particular, the effect gets more pronounced when Binance exhibits "wash trading" or when investors have more concerns about "wash trading." We do not find Binance userbase affecting Binance investor trading. Using the launch of the "yield-farming" program as a quasi-natural experiment, we establish the causal impact of Uniswap userbase on Binance investor trading. Our results suggest that Uniswap, a decentralized exchange built on blockchain and smart contracts, can gain investors' trust in its ability to aggregate the consensus of the cryptocurrency's value. Our findings shed light that the blockchain and smart contracts powered decentralized infrastructure has the potential to provide an alternative solution to organize trading, when the trading structure underwritten by a credible central party, e.g., a centralized exchange, is not feasible or too costly to obtain.



*JEL Classification*: G12; G14

*Keywords*: blockchain, cryptocurrency, DeFi, smart contracts, wash trading, fake volume


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We provide empirical evidence that the decentralized cryptocurrency exchange helps reveal the consensus on the value of the cryptocurrency. By examining how investors on Binance (the largest centralized cryptocurrency exchange) trade in response to prices on Binance and Uniswap (the largest decentralized cryptocurrency exchange), we find the increase in the Uniswap userbase induces Binance investor trading towards the Uniswap price. In particular, the effect gets more pronounced when Binance exhibits "wash trading" or when investors have more concerns about "wash trading." We do not find Binance userbase affecting Binance investor trading. Using the launch of the "yield-farming" program as a quasi-natural experiment, we establish the causal impact of Uniswap userbase on Binance investor trading. Our results suggest that Uniswap, a decentralized exchange built on blockchain and smart contracts, can gain investors' trust in its ability to aggregate the consensus of the cryptocurrency's value. Our findings shed light that the blockchain and smart contracts powered decentralized infrastructure has the potential to provide an alternative solution to organize trading, when the trading structure underwritten by a credible central party, e.g., a centralized exchange, is not feasible or too costly to obtain.



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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, 2020). However, there has been no clear empirical evidence of the 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 the centralized counterpart, the decentralized cryptocurrency exchange, with the design incorporating blockchain-based settlement and smart-contract-based executing, has a unique advantage in providing a transparent and trustworthy marketplace for organizing trading. The trust issue is a concern for centralized exchanges, given that centralized exchanges exhibit "wash trading" or faked transactions in cryptocurrency trading.[1] "Wash trading" distorts prices, reduces investors' confidence or trust in the price, and discourages investors' participation in financial markets (Aggarwal and Wu, 2006).

The decentralized exchange can improve investors' confidence in the trustworthiness of the marketplace in two aspects. First, transactions are organized through smart contracts open to all participants. Any market participant can easily access the transaction data, such as the transaction counterparty (i.e., the blockchain address involved in the transactions) and the transaction price/amount. Second, all transactions in the decentralized exchange are settled on the blockchain, which is validated through independent authorization nodes by proof-of-work (or proof-of-stake). Thus, all transactions cannot be easily falsified. Based on these features, we argue that the decentralized exchange can gain investors' trust by mitigating the "wash trading" issue and help reflect and aggregate the trustworthy decentralized consensus on the value of the cryptocurrency.[2]

To study the influence of the decentralized cryptocurrency exchange, we focus on the two largest centralized and decentralized exchanges, Binance and Uniswap. We conduct a

[1] 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 volumes on OKEx, 81.2% on Huobi, and a similar level of trading volumes on Binance are inferred to be "wash trading" (see https://www.nasdaq.com/articles/how-and-why-crypto-exchanges-fake-trading-volumes-2021-08-24).

[2] One may argue that "wash trading" could also exist in decentralized exchange. For example, one can use multiple addresses to initiate large trades between each other. However, unlike the centralized exchange, one cannot fake transactions without incurring a significant transaction cost on the decentralized exchanges. The "wash trades" on the blockchain must be broadcasted with transaction fees and gas fees equivalent to a normal transaction. In addition, all participants can observe such "wash trades" in a public ledger.

systematic study on how investors trade in response to the prices on Binance and Uniswap. Intuitively, investors in each exchange trade on the difference between their beliefs about the cryptocurrency's value ($\mu$) and the corresponding price on the exchange ($P_{exchange}$ where *exchange* = Binance or Uniswap). As prices on Binance/Uniswap reflect and aggregate investors' beliefs about the value of the cryptocurrency, investors will learn from these prices and form their beliefs based on the weighted average of the cryptocurrency prices on Binance and Uniswap: $\beta P_{Uniswap} + (1-\beta)P_{Binance}$. Since the decentralized exchange (Uniswap) offers better transparency and trustworthiness, we argue that when more users participate on Uniswap, investors believe that the cryptocurrency's price on Uniswap aggregates more investors' beliefs and will put more weight on its prices in updating their beliefs. Thus, $\beta$ is positively associated with the size of Uniswap userbase. In contrast, the centralized exchange Binance is relatively opaque, e.g., investors cannot directly observe users' participation in Binance because of "wash trading" contamination. Thus, the observed Binance userbase size, which cannot reflect the true userbase size, cannot affect investors' belief updating process (the $\beta$ to be specific) in a similar fashion to the Uniswap userbase size. It is worth noting that our argument follows the spirit of the rational expectations equilibrium literature (e.g., Grossman and Stiglitz, 1980; Hellwig, 1980), in which investors learn information about asset payoffs from prices.

Our empirical analysis focuses on Binance investors' trading behavior. We do so for two reasons. First, Uniswap investor trading is relatively sparse. For example, about one-half of the five-minute intervals have zero trading on Uniswap. Second, some confounding factors (e.g., investor preference) drive both Uniswap userbase and Uniswap investor trading, making the empirical test on Uniswap investor trading less convincing than those on Binance investor trading.[3]

Zooming into Binance investor trading, as discussed above, Binance investors should trade in response to the difference between their beliefs about the cryptocurrency's value $\mu$ and the price on Binance $P_{Binance}$.[4] Specifically, their trading (measured by order flows: total buy volume minus total sell volume, scaled by the total trading volume) is associated with $\beta \times (P_{Uniswap} - P_{Binance}) = (\underbrace{\beta P_{Uniswap} + (1-\beta)P_{Binance}}_{\mu} - P_{Binance})$. Binance investor trading is negatively responding to the price difference between Binance and Uniswap

[3] Nevertheless, we still examine Uniswap investor trading for completeness.
[4] Such a difference can also be interpreted as the "mispricing" in Binance investors' beliefs.

($P_{Binance} - P_{Uniswap}$), and such a response increases with the size of Uniswap userbase, which is positively associated with $\beta$.

To empirically test our argument, we focus on 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 Uniswap userbase by the size of the Uniswap liquidity pool. This measure of userbase is ideal for testing our argument. Users contribute to the Uniswap liquidity pool, and users can easily change their contribution to the pool if they do not believe that the current price reflects the value of the cryptocurrency. As our argument is based on the premise that the prices on the exchange can reflect investors' beliefs, the size of the liquidity pool captures the weighted average of Uniswap users' beliefs.[5]

We indeed find evidence supporting our argument. Specifically, we find that order imbalance on Binance negatively responds to the lagged price difference between Binance and Uniswap. More importantly, such a response increases with Uniswap userbase size. This result supports our argument that as Uniswap userbase becomes larger, investors are more confident in the Uniswap price. Thus, the Uniswap price is more important in determining investors' beliefs.[6]

Interestingly, 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 decentralized exchange (i.e., Uniswap in our context) relative to the centralized exchange (i.e., Binance in our context) in gaining investors' trust in updating their beliefs over the value of the cryptocurrency.

We conduct additional cross-sectional studies based on the Uniswap liquidity pool user experience to corroborate our main findings. Not surprisingly, as an early-stage financial innovation, cryptocurrencies have considerable valuation uncertainty. Investors are more likely to form their beliefs based on the consensus from the majority—the wisdom of the crowd—when users who provide liquidity on Uniswap are more experienced. We indeed find strong supporting evidence for these hypotheses.

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

[6] 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. We indeed find supporting evidence.

The aforementioned findings support our hypothesis that investors trust the decentralized exchange as it can provide a transparent and trustworthy marketplace for organizing trading. Intuitively, the trust effect should get more pronounced when the centralized exchange exhibits manipulation incidents such as the "wash trading" event. "Wash trading" undermines investors' trust in the centralized exchange but increases their confidence in the decentralized one. To test this argument, we first follow Amiram, Lyandres, and Rabetti (2021) and estimate fake volume (volume related to the potential "wash trades") for each cryptocurrency on each date in Binance. Based on the estimated fake volume, we find that the impact of Uniswap 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 userbase size is larger when investors pay more attention to fake volume issues in Binance. Specifically, we focus on investors' discussions on Reddit and construct the daily intensity of investors' attention on fake volume in Binance. The attention measure is based on all Reddit posts and replies, which include the keywords "fake" (or its synonym "wash," "faked," "manipulated," "fraud," "fraudulent"), "volume" (or "trade," "trading"), and "Binance." We find that Uniswap userbase has a more significant impact on Binance investor trading on days when investors pay more attention to fake volume in 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. But we have two pieces of evidence to show that investors' responses to prices reflect information beyond cross-market arbitrage. First, suppose it is the cross-market arbitrage activity that purely explains investors' responses to prices, we would expect the correlation between Binance investors' and Uniswap investors' trading directions to be −1 (or at least negative). However, we do not find such a negative correlation in our data but observe the opposite.[7] Second, with 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 userbase size, as larger userbase should facilitate cross-market

[7] 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 the "mispricing" in Binance investors' beliefs. When Binance investors trade in response to this "mispricing", the prices on Binance lean toward to 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.

arbitrage. However, we find that the response of Uniswap investor trading to the price difference decreases with the size of Uniswap userbase, going against the argument of cross-market arbitrage.

We further zoom into the "yield-farming" program launch events on Uniswap and establish the causal impact of Uniswap userbase on Binance investor trading activities. We argue that the "yield-farming" reward program is a quasi-exogenous shock that has no direct relation to Binance investor trading. Still, it has a significant and large impact on Uniswap userbase. Applying a difference-in-differences analysis approach, we show that the "yield-farming" reward program has significantly increased the size of Uniswap userbase. After that, we use a two-stage least-square (2SLS) instrumental variable regression based on the "yield-farming" reward program to pin down the causal impact of Uniswap userbase size on Binance investor trading. An increase in Uniswap userbase caused by the "yield-farming" reward program induces Binance investor trading to react more strongly to the price difference between Binance and Uniswap.

The impact of Uniswap userbase size on trading has important asset pricing implications, as trading ultimately underpins the equilibrium price dynamics. For example, for a particular cryptocurrency, when Binance investors observe a higher price of this cryptocurrency on Uniswap relative to Binance, they believe that the consensus price should be higher, and thus, buy this cryptocurrency on Binance, increasing its price on Binance. Given the impact of Uniswap userbase size on Binance investor trading, we conjecture that when Uniswap userbase size gets larger, Binance investors trade more aggressively towards the price on Uniswap. As a result, we expect the Uniswap price to play a more important role in determining the equilibrium cryptocurrency valuation.

To test our conjecture, we apply the Gonzalo-Granger decomposition of the common trend to estimate Binance and Uniswap's contribution to the common price component, respectively. 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. We find supporting evidence for our conjecture by applying a similar 2SLS instrumental variable regression. That is, the Uniswap userbase size leads to an increase in the Uniswap's share in determining the common trend of the cryptocurrency price dynamics.

In sum, we provide empirical evidence that the decentralized cryptocurrency exchange such as Uniswap gains trust from investors. The unique advantage of the decentralized exchange comes from its blockchain plus smart contracts design, providing a transparent and trustworthy marketplace to aggregate price opinions. The decentralized cryptocurrency exchange presents a case where a decentralized infrastructure could overcome deficiencies in the current centralized infrastructure of cryptocurrencies. The deficiency, in this case, is the lack of a manipulation-proof trading environment from the centralized infrastructure or the lack of investors' confidence that the centralized cryptocurrency exchange provides the manipulation-proof trading environment. Unlike its origin—the centralized security exchange—the centralized cryptocurrency exchange is often associated with a lack of regulation and operational opacity, which makes it a breeding ground for manipulation.[8] While having a tightly regulated centralized cryptocurrency exchange with significant regulatory costs could resolve the deficiency, we show that a DeFi application like the decentralized exchange powered by blockchain and smart contracts could be an alternative solution. Our results can 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 the blockchain's impact on corporate governance. Harvey, Ramachandran, and Santoro (2021) provide a survey on DeFi applications on Ethereum, where the decentralized exchange is one of the most widely used applications. Several theoretical papers have discussed the equilibrium of liquidity provision under the decentralized exchange (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 decentralized exchange. 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 decentralized exchange got 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

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

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 the 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).

Lastly, our paper adds to the literature on market fragmentation. The market structure of cryptocurrency shares a similar, if not more, fragmented feature as modern equity trading. While a liquid stock can be traded in more than ten 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, and 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. The first hypothesis is regarding how Binance investors trade in response to the prices on Binance and Uniswap. We focus on Binance investor trading for two reasons. First, Uniswap investor trading is relatively sparse. About one-half of five-minute intervals have zero trading on Uniswap.

Second, some confounding factors (e.g., investor preference) drive both Uniswap userbase size and Uniswap investor trading, making the empirical tests on Uniswap investor trading less convincing than those on Binance investor trading.

Binance investors trade on the difference between their beliefs about the value of the cryptocurrency ($\mu$) and its price on Binance ($P_{Binance}$). As the prices on Binance/Uniswap reflect and aggregate investors' beliefs about the value of cryptocurrency value, we argue that investors form their beliefs based on the weighted average of the cryptocurrency prices on Binance and Uniswap, i.e., $\beta P_{Uniswap} + (1-\beta)P_{Binance}$ with $\beta$ capturing the weight. Our argument is in a similar spirit to the rational expectations equilibrium literature (e.g., Grossman and Stiglitz, 1980; Hellwig, 1980), in which investors learn information about asset payoffs from prices.

We argue that $\beta$ is positively associated with Uniswap userbase size. Our argument lies in the intuition of the wisdom of crowds. As the cryptocurrency price on Uniswap is traded by investors, the price aggregates investors' opinions, and it can represent the wisdom of crowds. As more investors trade and provide liquidity with current prices on Uniswap (i.e., Uniswap userbase size increases), which are far easier to observe than that in Binance, investors believe that the cryptocurrency price on Uniswap is more informative about crypto valuations or at least investors' crypto valuations (e.g., due to the law of large numbers theorem). Thus, the cryptocurrency price on Uniswap will play a more important role in shaping investors' beliefs.[9] In this sense, Binance investor trading (i.e., order flow) is associated with $\beta \times (P_{Uniswap} - P_{Binance}) = (\underbrace{\beta P_{Uniswap} + (1-\beta)P_{Binance}}_{\mu} - P_{Binance})$, and $\beta$ positively associates with the size of Uniswap userbase. In other words, defining the price difference as $P_{Binance} - P_{Uniswap}$, Binance investor trading is negatively related to $\beta$ times the price difference. Using the size of the Uniswap liquidity pool to measure the size of Uniswap userbase, we formalize our first hypothesis as follows:[10]

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[9] Our intuition is similar to the rational expectations equilibrium literature (e.g., Grossman and Stiglitz, 1980; Hellwig, 1980), in which investors will put more weights on more informative signals when updating their beliefs.

[10] 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 $\beta$ is positively associated with the Uniswap user base. 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 is decreasing 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 increases with the size of Uniswap userbase.*

While **Hypothesis 1** could also apply to the size of Binance userbase, Uniswap as a decentralized exchange has unique features of transparency and trustworthiness relative to its centralized counterparts, i.e., Binance in our context. First, transactions are organized through smart contracts open to all participants. Any market participant can easily access the transaction data, such as the transaction counterparty (i.e., the blockchain address involved in the transactions) and the transaction price/amount. Second, all transactions in the decentralized cryptocurrency exchange are settled on the blockchain, which is validated through independent authorization nodes by proof-of-work (or proof-of-stake). Thus, market participants cannot easily falsify transactions. In contrast, a centralized exchange like Binance is known to exhibit "wash trading," which inflates trading volume and contaminates transaction data. Based on these features, we argue that while the decentralized cryptocurrency exchange can help reflect the trustworthy decentralized consensus on the value of the cryptocurrency, the centralized cryptocurrency exchange does not have this advantage. To highlight the contrast between the decentralized and centralized exchanges, we formalize 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 Binance userbase.*

Binance investors trade in response to the price difference between Binance and Uniswap. Their reactions vary across cryptocurrencies due to cryptocurrency characteristics. Intuitively, as experienced users are more sophisticated, when a particular cryptocurrency's Uniswap liquidity pool consists of more experienced users, its Uniswap price should be more informative about its value. As a result, Binance investors put more weight on the Uniswap price in the belief updating (higher $\beta$) 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.*

As we argue, the decentralized exchange has the advantage of trust compared to the centralized exchange as the latter often has fake volume, volume related to "wash trading." Unlike the centralized exchange, 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 decentralized exchange. Hence, the decentralized exchange's advantage of being trustworthy should be more pronounced when the centralized one exhibit fake volume. Based on this intuition, we hypothesize that:

**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 public information, investor trading largely depends on investors' concern about fake volume in the centralized exchange. Thus, we have a hypothesis that:

**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 ultimately underpins the equilibrium price dynamics. As a result, the impact of Uniswap userbase size on Binance investor trading has important asset pricing implications. For example, if investors are more confident in the Uniswap price (i.e., the decentralized price consensus), Binance investors would lean towards the Uniswap price, making Uniswap's price accounts for a larger share in the common price component underlying the price dynamic on each exchange. Based on this intuition, 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 size of Uniswap userbase leads to an increase in the 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 decentralized exchange focusing on the most popular automated market-making mechanism. We then describe how we collect cryptocurrency data in the (de)centralized exchange, i.e., Uniswap V2 and Binance. Specifically, Section 2.1 introduces the automated market making; Section 2.2 describes the "yield-farming" program, which encourages liquidity provision on the decentralized exchange; 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 decentralized exchanges organize liquidity and trading through the automated market-making mechanism.[11] Any individual cryptocurrency holder can provide liquidity on the decentralized exchange 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 decentralized exchange works in the following way. The decentralized exchange first pours cryptocurrencies (from liquidity providers) into a liquidity pool. The decentralized exchange then creates liquidity provider (LP) tokens to track the share of the pool that each liquidity provider is entitled to. The LP token also tracks the reward to the liquidity provider. The LP token is updated whenever there is a change in the pool value, either from trading or liquidity addition/deletion. In the event of withdrawal, the liquidity provider uses the LP token to redeem her cryptocurrencies.

[11] The decentralized exchanges we talk about thereafter all refer to automated market makers.

Finally, to automate trading, which requires the price scheme, the decentralized exchange adopts certain pre-defined mathematical functions codified into a smart contract to generate prices from parameters such as the size of the liquidity pool. 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 deposit two cryptocurrencies with the same worthy amount as a trading pair. The product of the quantity of these two assets in the liquidity pool should be a constant number when swapping occurs. For illustrative purposes, let's think of a liquidity pool consisting of two cryptocurrencies, Ethereum (ETH[12]) and Tether (USDT). If there are $x$ units of ETH and $y$ units of USDT in the pool, then the CPMM rule is such that $x \times y = K$.[13] The CPMM rule yields the price scheme for the swap between ETH and USDT. If a trader wants to buy $\Delta x$ 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 the ETH in terms of USDT is $p$, $p = \frac{y}{x-\Delta x}$. The price of the ETH increases when $\Delta x$ increases reflecting the law of demand. When $\Delta x$ 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 demand curve of the ETH/USDT under the CPMM.

[Insert Figure 1 here]

Although the CPMM rule has desirable features, such as following the law of demand and 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 $\Delta x$.

For liquidity providers, while they obtain the reward from trading (0.3% on Uniswap V2), 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,

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[12] To use DeFi applications on Ethereum, ETH and BTC are always wrapped to their ERC20 format WETH and WBTC. To be convenient, we keep the notation ETH and BTC for any of their formats thereafter.

[13] $K$ varies when the size of the pool changes. That is, suppose a liquidity provider add $x_+$ 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 liquidity provider deposits a pair of 10 ETH and 1000 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 1000, making the pool consist of 5 ETH and 2000 USDT (the product of them is 10,000). If the provider withdrawals her ETH and USDT, she has $5 \times 400 + 2000 + 1000 \times 0.3\% = 4003$ USDT, which is smaller than the current market value of the provider's initial deposit of $10 \times 400 + 1000 = 5000$ USDT. The provider loses 997 USDT to the informed trader. The 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. 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 providing 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 decentralized exchange can democratize market-making and organize trading in a decentralized fashion. Most importantly, all activities are run under blockchain authentication. By the nature of the open source, traders can read the contract code, and the blockchain ensures that they maintain ownership of their redeemable cryptocurrencies. Unlike the centralized exchange, where the exchange acts as the custodian of traders' tokens, tokens are under the custody of the trader in the decentralized exchange. Activities on the decentralized exchange are organized through smart contracts providing maximum transparency.

In summary, there are benefits and costs of the decentralized exchange. On the benefit side, trading does not rely on a central party to organize, so it is less affected by problems like exchange outages, or hacking, or malpractices. The openness of organizing transactions through smart contracts and the hard-to-hack blockchain authentication help build trust for the 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 the disadvantage, trading volume and total liquidity available for decentralized exchanges, such as Uniswap, have grown dramatically since 2020 (see Figure 2).

[Insert Figures 2 here]

### 2.2. "Yield-farming" for liquidity provision

A key ingredient to the success of the decentralized exchanges (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 above 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 decentralized exchange, 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 for liquidity provision on the decentralized exchange provides additional incentive for liquidity providers to lock their cryptocurrencies in the pool.

Six cryptocurrencies initiate 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 decentralized exchange 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 A.1, 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 indexed data service for the Ethereum network.[14] Specifically, we obtain and construct three categories of data: a). trading data, including price and volume information, and b). userbase data, and c). liquidity providers data. The detailed description of the data is as follows.

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

*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 thereafter) is generated as the token address for the trading pair's liquidity provision. 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 would be transferred to the LP address, and the bought one would 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; 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.

*b). userbase data*

The key variable in our study is Uniswap userbase size. To measure the userbase size, we aggregate all historical quantities of the two cryptocurrencies transferred in to or out from the LP address 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.

Firstly, we download all transfer events of each LP token via the Etherscan API node. Like constructing liquidity provision 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 data***

As for the centralized exchange, 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.

***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 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 in our 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 and Uniswap's contribution to the common price component, respectively. Specifically, we apply the 2-by-1 Binance and Uniswap price Vector-Error-Correction-Model (VECM) 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 modeling 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 been dominating 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 decentralized exchange relative to the centralized exchange. 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.

The (at least partial) market segmentation between different exchanges (centralized vs. decentralized ones) provides an ideal empirical setting to explore the uniqueness and potential advantage of the decentralized exchange in anchoring investors' price beliefs. There are two different groups of investors. One trades cryptocurrencies on Binance (the centralized exchange in our context) and the other trades on Uniswap (the decentralized exchange in our context). Although different investors trade on different exchanges (e.g., probably due to historical reasons or habits), all investors always observe the prices of the same cryptocurrency on both exchanges and update their beliefs about the future cryptocurrency value through these prices. This belief updating process ultimately will affect investor trading.

To study how the Binance or Uniswap investors respond to prices on Binance and Uniswap, we have a first glance at the correlation between the lagged price difference between Binance and Uniswap, and order imbalance on Binance or Uniswap. The correlation between the lagged price difference between Binance and Uniswap, and order imbalance on Binance is measured as *Corr(Lag Price Diff, Order Imbalance Binance)*. The correlation between the lagged price difference between Binance and Uniswap and order imbalance on Uniswap is measured as *Corr(Lag Price Diff, Order Imbalance Uniswap)*. We take the following steps to calculate these two correlations. For each cryptocurrency on each day, we first split the trading hours into 5-min intervals and estimate *Corr(Lag Price Diff, Order*

*Imbalance Binance)* as the correlation between the price difference on Binance and Uniswap in one particular 5-min interval and order imbalance on Binance in the next 5-min 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 5-min interval.[15] 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 that *Corr(Lag Price Diff, Order Imbalance Binance)* to be negative. Following a similar intuition, if investors on Uniswap observe the price difference between Binance and Uniswap 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 Panel 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 for *Corr(Lag Price Diff, Order Imbalance Uniswap)*, the correlation between the lagged price difference and order imbalance on 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). 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]

[15] 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.

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 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 leave the discussion of this alternative mechanism to Section 3.3.

In Figure 4, we show the daily average of the probability of Binance and Uniswap trading for each cryptocurrency in the 5-minute interval conditional on observing past (previous 5-min) 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**, **1.a**, **1.b,** and **2**. Section 3.1 examines the impact of 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 or liquidity providers (**Hypotheses 1.b**). Section 3.3 examines 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 have discussed in **Hypotheses 1**, when the prices on Binance/Uniswap reflect and aggregate investors' beliefs about the cryptocurrency value, Binance investors form a belief ($\mu$) 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), the cryptocurrency price on Uniswap aggregates more investors' beliefs. Thus, the Uniswap price will play a more important role in shaping investors' beliefs.

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

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

where $\textit{Order imbalance on Binance}_{i,t,k}$ is cryptocurrency *i's* order imbalance at the *k*th five-minute interval in day *t*. Order imbalance is calculated as buy volume minus sell volume scaled by the sum of buy and sell volume on Binance within each five-minute interval. Independent variables include $\textit{Lag Uniswap Userbase Size}_{i,t-1}$, $\textit{Price Diff}_{i,t,k-1}$, and their interaction term. $\textit{Price Diff}_{i,t,k-1}$ 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 in day *t*. $\textit{Lag Uniswap Userbase Size}_{i,t-1}$ is the daily Uniswap userbase size at day *t-1*. Uniswap userbase size is calculated as 100 times the time-weighted average market depth 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 $\textit{Lag Uniswap Userbase Size}_{i,t-1}$ and $\textit{Price Diff}_{i,t,k-1}$ is negative and statistically significant, suggesting that an increase in Uniswap userbase enlarges Binance investors' responses to the price difference, which is consistent with **Hypothesis 1**. Second, to test **Hypothesis 1.a**, we replace *Lag Uniswap Userbase Size*$_{i,t-1}$ with the lagged size of Binance userbase in columns [3] and [4], and we find that 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 *Lag Uniswap Userbase Size*$_{i,t-1}$. To be consistent with the construction of Uniswap userbase size, we measure Binance userbase size with the (100 times) time-weighted depth of the top 10 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 find similar results (Online Appendix Table A2). Second, in Online Appendix Table A3, we examine the impact of Uniswap 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 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 ($\mu$) 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 $\beta$ 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 Uniswap userbase. We indeed find evidence supporting this hypothesis.

In summary, the results in this section support our argument that Binance investors update their beliefs about cryptocurrency value based on the prices on both Binance and Uniswap, and then trade on the difference between their beliefs and the cryptocurrency price on Binance. More importantly, as the size of Uniswap userbase becomes larger, the Uniswap price plays a larger role in determining Binance investors' beliefs. The contrasting results between columns [1]-[2] and columns [3]-[4] of Table 2 highlight the uniqueness of the decentralized exchange (i.e., Uniswap in our context) relative to the centralized exchange (i.e., Binance in our context) —— the decentralized exchange gains investors' trust on its price being informative about the consensus of the value of the cryptocurrency.

### 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 of a cryptocurrency. In this sense, investors are more likely to form their belief on the consensus from Uniswap——"trusting the wisdom of the crowd"——when liquidity providers on Uniswap are more experienced. To strengthen our argument, we conduct a cross-sectional test based on Uniswap liquidity providers' experience.

In the following steps, we conduct the cross-sectional test based on Uniswap liquidity providers' experience. First, among liquidity providers on Uniswap, we define 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 userbase size on Binance investor trading mostly comes from cryptocurrencies with Uniswap liquidity pools consisting of more experienced users. Specifically, 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 the increase in Uniswap userbase size plays a more 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 that the decentralized exchange can gain trust compared to the centralized exchange is due to the "wash trading" phenomenon of the latter. The lack of regulation on the centralized exchange gives rise to potential market manipulation such as "wash trading," also known as fake volume, which is well-documented by Cong et al. (2021) and Amiram, Lyandres, and Rabetti (2021). Fake volume inflates the quantity of value-relevant transactions creating a false impression of the popularity of crypto trading in the centralized exchange. This is likely to reduce investors' confidence in the price from centralized trading as a valid consensus aggregator.

On the other hand, transactions are settled on the blockchain for decentralized trading. All transactions are recorded in a public ledger. The transparency of the blockchain makes it difficult or costly to falsify transactions and inflate volume. Hence, we argue that the advantage of the decentralized exchange over its centralized counterpart should be more pronounced when the centralized exchange exhibits high fake volume or when investors' attention to fake volume is high (Hypothesis 2 and 2.a). In this section, we directly test these hypotheses using *MAD* to measure 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 compute *MAD* to measure the likelihood that Binance trading exhibits fake volume. *MAD* stands for the mean absolute deviation. 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.[16]

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]

[16] The 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 the Benford's Law to detect fake volume.

We find that the impact of Uniswap 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 search for all Reddit posts and replies, which include the keywords "fake" (or its synonym "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 userbase size on Binance investor trading is more pronounced when investors' attention to fake volume is high.

### 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 userbase but has no association with Binance userbase size (captured by depth on Binance). These empirical findings are consistent with our argument that Uniswap, as a decentralized exchange, 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 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 userbase size could facilitate cross-market arbitrage. Admittedly, this explanation is plausible but cannot explain the insignificant impact of Binance userbase size on Binance investor trading, as the increase in Binance userbase size should also facilitate cross-market arbitrage. Also, in Table A3, we find that the response of Uniswap investor trading to the price difference decreases with the size of Uniswap 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.[17] Suppose the cross-market arbitrage activity purely 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, and we observe the opposite in our data. 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 userbase size.

[Insert Table 6 here]

While the sharp contrasting result of the impact of Uniswap userbase size and Binance userbase size on Binance investor trading is consistent with our argument regarding the unique feature of Uniswap, some may have the concern that the contrasting result could be due to heterogeneities of investors across these two exchanges.[18] To rule out this possibility, we manually collect Uniswap liquidity providers' information and focus on those

[17] 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.

[18] 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 weights on the prices when liquidity is better. Meanwhile, if our results are driven by liquidity, we should also observe that Binance userbase has a similar impact on investor trading as Uniswap userbase, but this is not what we observe in Table 2.

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 userbase size and repeat the empirical tests in columns [1] and [2] of Table 2. As shown in Online Appendix Table A5, when we focus on userbase consisting of investors participating in both Binance and Uniswap, we still find that Uniswap 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 A5 comfort us that our results are neither driven by 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 2-5 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 userbase size, impacts Binance investors' trading decisions in response to the price difference between Binance and Uniswap, highlighting the uniqueness of the decentralized exchange. However, one can still argue that our results are driven by unobservable characteristics affecting Uniswap 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 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 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 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 the "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") 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 significantly impacts the size of Uniswap userbase.

To show that the "yield-farming" reward program significantly impacts the sizes of Uniswap userbase, we apply a difference-in-differences analysis to study the "yield-farming" reward program's impact on 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 Uniswap userbase, the natural logarithmic of Uniswap liquidity pool size (dubbed as *Log Uniswap Userbase*), for the treatment and control group, respectively.[19] To facilitate the cross-event comparison, we normalized *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 has changed for the control group around the launch date.

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

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

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

where the coefficient of the interaction term *Treatment*×*Post* captures the differences in userbase size between the treatment and control group before and after the launch date. We use the *Normalized Log Uniswap Userbase* to measure the size of Uniswap userbase to be 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 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).[20]

One potential concern about the results in Figure 5 and Table 7 is that Uniswap userbase size in cryptocurrencies 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:

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

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

[20] In Online Appendix Table A6, 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 6.

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]

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 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 have demonstrated that the launch of the "yield-farming" program has significantly increased Uniswap 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 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 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 to conclude that there is a causal impact of Uniswap 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 uncover several intriguing and novel findings. First, we find that cryptocurrency investors trade in response to prices on Binance and Uniswap, suggesting that investors observe/learn information from prices across the decentralized and the centralized exchanges and use those prices to update their beliefs about cryptocurrency valuation. Second, we find that the size of Uniswap rather than Binance userbase significantly affects investors' response to the price difference between Binance and Uniswap. The sharp contrast between Uniswap and Binance highlights the uniqueness of the decentralized exchange in influencing investor trading. That is, cryptocurrency investors adopt the wisdom of the crowd mindset (i.e., using prices on Binance and Uniswap) to update their belief on cryptocurrency valuation, and the decentralized exchange (i.e., Uniswap) can reflect investors' consensus or confidence in cryptocurrency valuations in a transparent and trustworthy way. When decentralized exchange userbase gets larger, the decentralized exchange reinforces cryptocurrency investors' confidence in the decentralized exchange's price. Consequently, investors put more weight on the price of the decentralized exchange to update their beliefs about the value of the cryptocurrency.

The impact of Uniswap userbase size on investor trading has important economic implications as trading ultimately underpins the equilibrium price dynamics. In this section, we examine the economic implication of Uniswap userbase size. To study the implication, we focus on examining how Uniswap userbase size affects the dynamic of cryptocurrency valuation. This empirical exercise provides further support to our argument that the decentralized exchange plays a unique role in determining the belief updating process and sheds light on cryptocurrency valuation. The latter is always a challenging topic.

Based on our findings in Sections 3 and 4, we conjecture that when Uniswap userbase size gets larger, Binance investors trade cryptocurrency prices more aggressively towards the price on Uniswap. As a result, we expect the Uniswap price to play a more important role in determining the equilibrium cryptocurrency valuation. That is, when Binance investors observe a higher price of this cryptocurrency on Uniswap relative to that on Binance, they believe that the value of the cryptocurrency should be higher (than its price on Binance). Thus, buying this cryptocurrency on Binance increases the price of this cryptocurrency on Binance, which leads to an increasing co-movement between the price of Binance and Uniswap. In other words, the increase in Uniswap userbase leads to Uniswap contributing more towards 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 and Uniswap's contribution to the common price component, respectively. Specifically, we apply the 2-by-1 Binance and Uniswap price Vector-Error-Correction-Model (VECM) 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) pointed 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 modeling the common trend as a weighted average 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 cryptocurrency valuation.

[Insert Table 10 here]

To address the endogeneity issue, we follow the methodology used in Table 9 and apply a 2SLS instrumental variable regression approach to study how Uniswap 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 Uniswap userbase becomes larger, the Uniswap price undertakes a more significant weight in determining the equilibrium cryptocurrency valuation than the Binance price.

## 6. Conclusion

Backed by smart contracts and blockchain authentication, the decentralized cryptocurrency exchange is featured with 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 the decentralized exchange has the unique advantage of aggregating investors' beliefs over the value of the cryptocurrency. Most importantly, investors trust this aggregation perceiving the price on the decentralized exchange as an informative signal of the decentralized consensus.

Our study focuses on the two largest centralized and decentralized cryptocurrency exchanges, Binance and Uniswap. We study how 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) is negatively responding to the price difference between Binance and Uniswap, and such a response increases with the size of Uniswap userbase (measured by the size of the Uniswap liquidity pool). In contrast, Binance userbase (measured by depth in the Binance limit order book) does not have such an impact. The contrasting results between the size of Binance and Uniswap userbase reflect the uniqueness of the decentralized exchange (i.e., Uniswap in our context) relative to the centralized exchange (i.e., Binance in our context). The decentralized exchange featuring transparency and trustworthiness gains investors' trust in its price by being informative about the consensus of the value of the cryptocurrency. Further, we conduct cross-sectional studies to corroborate our evidence. We find that the impact of the Uniswap userbase size is more pronounced when cryptocurrencies' liquidity providers on Uniswap are more experienced, the likelihood of Binance exhibiting "wash trading" is higher, and investors care more about "wash trading."

We are aware of the 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. When Uniswap userbase becomes larger, more investors are confident in, or investors are more confident in, the price on the decentralized exchange, Uniswap. Thus, investors put more weight on the Uniswap price in updating their beliefs regarding the value of the cryptocurrency. All our results are consistent with the hypothesis that the decentralized exchange as a transparent and trustworthy marketplace has advantages in reflecting the decentralized consensus on the cryptocurrency's value.

Last, we extend our study to examine the asset pricing implication of Uniswap userbase size. We study the contribution of each exchange (Binance or Uniswap) to the equilibrium price dynamics. We find that when Uniswap 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 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 study compares the decentralized and centralized cryptocurrency exchanges to study the uniqueness of the decentralized infrastructure. The decentralized exchange 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-proof trading environment from the centralized exchange or the lack of investors' confidence in the ability of the centralized exchange to provide such an environment. The lack of credibility of the centralized exchange arises from many aspects, including operational opacity, insufficient regulation, being the prime target by hackers, scandals, etc. While better self or third-party regulation could help the credibility concern and resolve the deficiency, it always involves considerable regulatory costs. Our study shows that a DeFi application, like the decentralized exchange powered by blockchain and smart contracts, could be an alternative solution. Our results suggest that in the 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.

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## Table 1: Summary statistics

This table reports the summary statistics of our sample that includes 40 cryptocurrencies (see Appendix Table A.1 for the detailed list) from 1st January 2020 to 31st January 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 capitalization 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 the natural logarithm of the volume-weighted average trading price in Uniswap. *Component share (Binance)* is the Gonzalo-Granger common factor weight for Binance, which is estimated by the 2-by-1 VECM 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. | 5% | 25% | 50% | 75% | 95% |
|---|---|---|---|---|---|---|---|
| *Mktcap (in millions of USD)* | 16127.108 | 87898.278 | 1.200 | 19.459 | 58.442 | 188.218 | 8582.737 |
| *Turnover (%)* | 104.127 | 638.935 | 0.097 | 0.190 | 0.541 | 1.225 | 26.756 |
| *Price Diff (%)* | 7.830 | 49.546 | -2.301 | -0.389 | 0.055 | 0.522 | 2.377 |
| *Component share (Binance)* | 0.812 | 0.207 | 0.427 | 0.749 | 0.860 | 0.942 | 1.031 |
| *Variance Ratio* | 0.193 | 0.055 | 0.142 | 0.152 | 0.180 | 0.215 | 0.297 |

## 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 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 volume 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 regression, 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 10 price levels) on Binance scaled by the total issuance of the cryptocurrency. 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| *DepVar:* | *Order imbalance on Binance* | | | | |
|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] |
| *Lag Uniswap Userbase Size × Price Diff* | -0.0560*** | -0.0609*** | - | - | -0.0650*** |
| | (-3.0165) | (-2.7142) | - | - | (-2.7529) |
| *Lag Uniswap Userbase Size* | -0.0009*** | 0.0018 | - | - | 0.0018 |
| | (-5.3182) | (1.4074) | - | - | (1.4031) |
| *Price Diff* | -1.5726*** | -1.5382** | -1.8700*** | -1.8752*** | -1.5750** |
| | (-2.7555) | (-2.6246) | (-3.1488) | (-3.0455) | (-2.6104) |
| *Lag Log Variance Ratio* | 0.1941** | 0.0859*** | 0.1966** | 0.0850*** | 0.0861*** |
| | (2.2476) | (3.0880) | (2.2710) | (3.0169) | (3.1092) |
| *Lag Binance Userbase Size × Price Diff* | - | - | -0.1582 | -0.1080 | 0.1276 |
| | - | - | (-0.6379) | (-0.4608) | (1.1355) |
| *Lag Binance Userbase Size* | - | - | -0.0145 | 0.0030 | 0.0054 |
| | - | - | (-1.1925) | (0.4335) | (0.8822) |
| *Fixed.Effects* | Date | Crypto, Date | Date | Crypto, Date | Crypto, Date |
| *Adj. $R^2$* | 0.0087 | 0.0164 | 0.0084 | 0.0168 | 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 two 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 userbase 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 volume 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 regression, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. *Lag Log Variance Ratio* is 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level 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 two 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 volume 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 regression, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. *Lag Log Variance Ratio* is 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level 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 two 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 volume 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 regression, the order imbalance measure leads the price difference measure, *Price Diff*, by five minutes. *Lag Log Variance Ratio* is 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level 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 volume 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 volume 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| *DepVar:* | *Corr(Price Diff, Order imbalance on Binance)* | | | |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| *Corr(Price Diff, Order imbalance on Uniswap)* | 0.0559** | 0.0668*** | 0.0541** | 0.0653*** |
| | (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 Uniswap)× Lag Uniswap Userbase Size* | - | - | 0.0018 | 0.0019 |
| | - | - | (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 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 trading days are after the program launch day and equals zero otherwise. After that, we run panel regressions of Uniswap userbase size on *Treatment*, *Post*, and their interaction term. In the regression, we use the *Normalized Log Uniswap Userbase* to measure the size of 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level 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* | 2267 | 4317 | 8005 | 11739 |

## 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 6. 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 trading days are 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 userbase size on *Treatment*, *Post*, *Treatment*×*Post,* and *Treatment*×*Post(-$T_n$)*. In the regression, we use the *Normalized Log Uniswap Userbase* to measure the size of 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 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level 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* | 11739 | 11739 | 11739 | 11739 |

## Table 9: IV results for trading and Uniswap userbase size

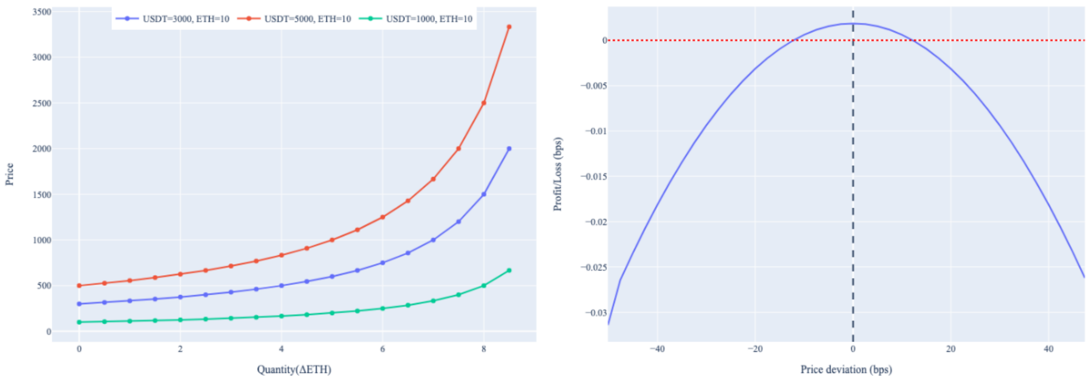
This table reports the second-stage results of the 2SLS instrumental variable regression based on the "yield-farming" reward program. We argue that the "yield-farming" reward program is a quasi-exogenous shock unrelated to order imbalance on Binance but significantly impacts the size of Uniswap userbase. In this table, we run 2SLS instrumental variable regressions based on the "yield-farming" reward program to pin down the causal effect of Uniswap 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 6, and *Lag Uniswap Userbase Size* are defined as in Table 2. The second stage of the regression examines the association between the lagged 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| *DepVar:* | *Order imbalance on Binance* | | | |
|---|---|---|---|---|
| | ± 5 days | ± 10 days | ± 20 days | ± 30 days |
| | [1] | [2] | [3] | [4] |
| *Lag Uniswap $\widehat{\text{Userbase}}$ Size* | -0.1342*** | -0.1360*** | -0.1206** | -0.1005** |
| × *Price Diff* | (-2.8758) | (-2.8252) | (-2.0778) | (-2.3995) |
| *Lag Uniswap $\widehat{\text{Userbase}}$ 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 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 6, and *Lag Uniswap Userbase Size* is defined in Table 2. The second stage of the regression examines the association between the lagged predicted value of *Lag Uniswap Userbase Size* and the difference between the component share of Binance and Uniswap. The component share captures Binance 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 VECM 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level 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 |

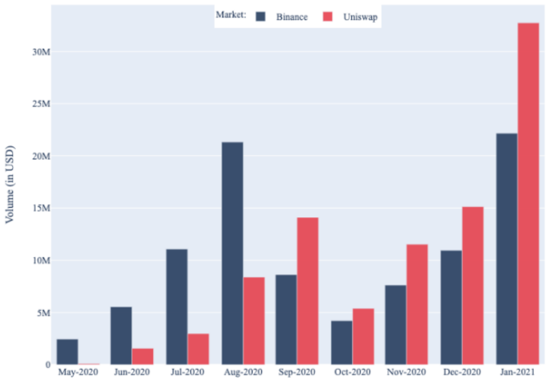



Panel A: Demand curve

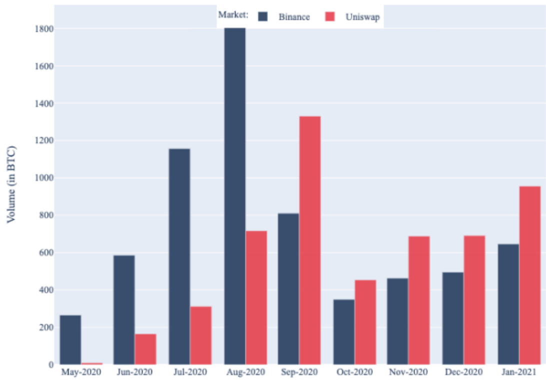
Panel B: Impermanent loss

**Figure 1: Demand curve and "impermanent loss" under the CPMM rule**

This figure illustrates the demand curve 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 $y$=1000. Then we consider the mid-price varies 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 $y$=1000 position.



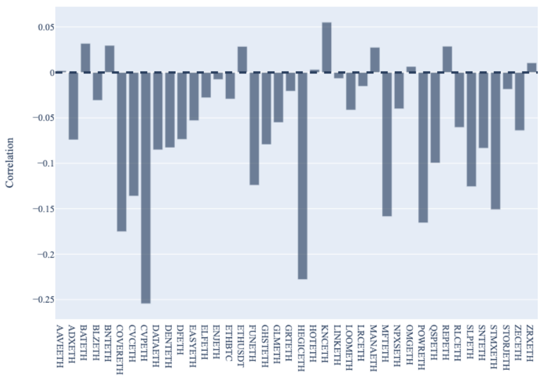

Panel A: Volume in USD



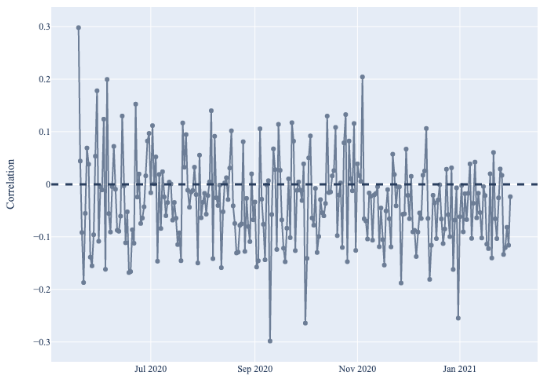

Panel B: Volume in Bitcoin

**Figure 2: Trading volume on Binance and Uniswap**

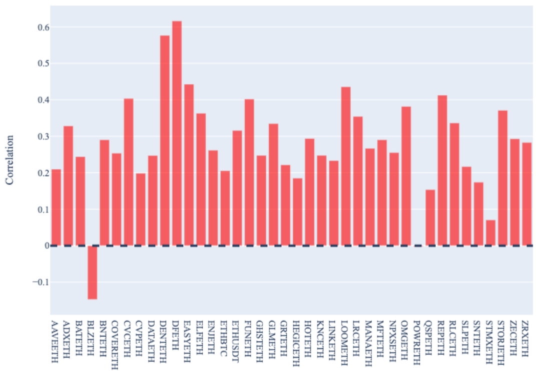
This figure shows the monthly average trading volume on Binance and Uniswap for our sample cryptocurrencies (excluding the "ETHUSDT" and "ETHBTC" pairs). Panel A is volume denominated in USD, and Panel B is in Bitcoin.



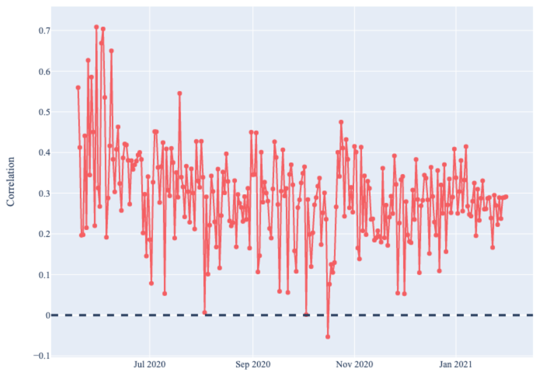

Panel A: Correlation on Binance across cryptocurrencies




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 (5-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 5-min intervals, and *Corr(Lag Prc.Df, OI Binance)* is the correlation between the price difference on Binance and Uniswap in one particular 5-min interval and order imbalance on Binance in the next 5 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 $\frac{\textit{Buy volume} - \textit{Sell volume}}{\textit{Buy volume} + \textit{Sell volume}}$ in each 5-min interval. Similarly, for each cryptocurrency on each day, we first split the trading hours into 5-min intervals, and *Corr(Lag Prc.Df, OI Uniswap)* is the correlation between the price difference on Binance and Uniswap in one particular 5-min interval and order imbalance on Uniswap in the next 5 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.

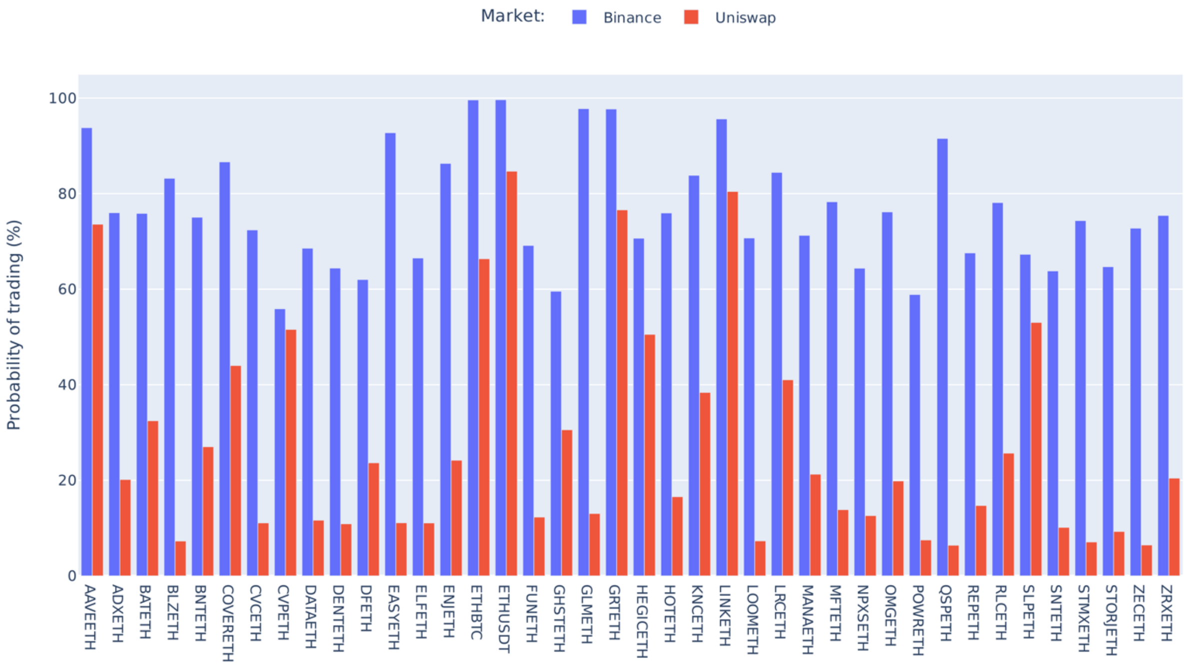



**Figure 4: The daily average of the probability of Binance and Uniswap trading in the 5-minute interval**

In this figure, we show the daily average of the probability of Binance and Uniswap trading for each cryptocurrency in the 5-minute interval conditional on observing past (previous 5-min) price differences.

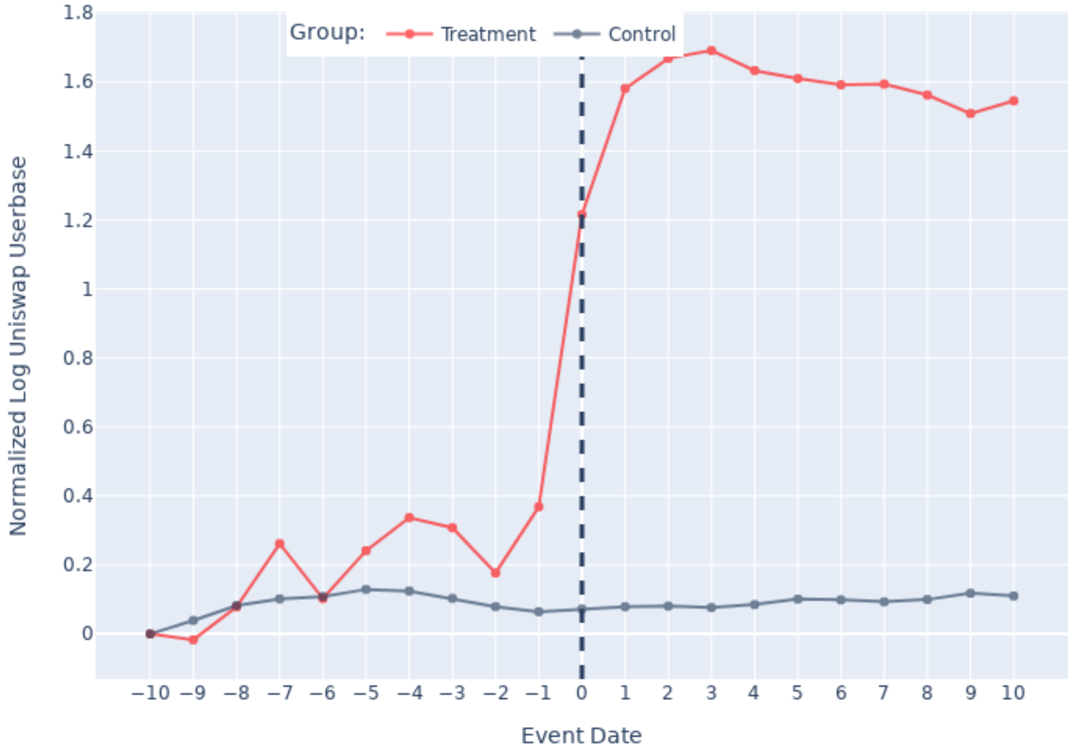



**Figure 5: The launch of the "yield-farming" reward program**

This figure shows the dynamic change of Uniswap userbase size, *Normalized Log Uniswap Userbase*, around the "yield-farming" reward program inception for the cryptocurrencies in the treatment and control group, 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 Jan 2021 in Binance and Uniswap, respectively. Volume is at 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 |
| 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 |
| BTC- ETH | 15,361,612.15 | 1,129,695.70 |
| 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 regression, 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 10 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level 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 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 volume 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 regression, 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| *DepVar:* | *Order imbalance on Uniswap* | |
|---|---|---|
| | [1] | [2] |
| *Lag Uniswap Userbase Size* × *Price Diff* | -0.0853* | -0.1007* |
| | (-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 number of Uniswap liquidity providers

This table reports the results of panel regressions of Binance order imbalance on the price difference between Binance and Uniswap and 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 volume on Binance every five minutes. Independent variables include *Lag Uniswap Providers* at each five-minute interval, *Price Diff*, and their interaction term *Lag Uniswap Providers* × *Price Diff*. The lagged daily number of Uniswap liquidity providers, *Lag Uniswap Providers*, 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 regression, 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 10 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| *DepVar:* | *Order imbalance on Binance* | | | | |
|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] |
| *Lag Uniswap Providers × Price Diff* | -0.1134*** | -0.1463*** | - | - | -0.1546*** |
| | (-2.7640) | (-2.9623) | - | - | (-3.0986) |
| *Lag Uniswap Providers* | -0.0074*** | 0.0151*** | - | - | 0.0149*** |
| | (-5.8149) | (3.8037) | - | - | (3.6871) |
| *Price Diff* | -1.6174*** | -1.4179** | -1.8700*** | -1.8752*** | -1.4406** |
| | (-2.5050) | (-2.1892) | (-3.1488) | (-3.0455) | (-2.1930) |
| *Lag Log Variance Ratio* | 0.1954** | 0.0881*** | 0.1966** | 0.0850*** | 0.0883*** |
| | (2.1830) | (3.0890) | (2.2710) | (3.0169) | (3.1026) |
| *Lag Binance Userbase Size × Price Diff* | - | - | -0.1582 | -0.1080 | 0.1107* |
| | - | - | (-0.6379) | (-0.4608) | (1.7721) |
| *Lag Binance Userbase Size* | - | - | -0.0145 | 0.0030 | 0.0040 |
| | - | - | (-1.1925) | (0.4335) | (0.7721) |
| *Fixed.Effects* | Date | Crypto, Date | Date | Crypto, Date | Crypto, Date |
| *Adj. $R^2$* | 0.0096 | 0.0164 | 0.0084 | 0.0168 | 0.0164 |
| *N. of Obs* | 320,220 | 320,220 | 320,220 | 320,220 | 320,220 |

## Table A5: 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 both use 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 volume 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 both use 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 regression, 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level 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 A6: The "yield-farming" reward program and Uniswap liquidity providers

This table reports the results of the difference-in-differences analysis of the impact of the "yield-farming" reward program on the number of liquidity providers on Uniswap. 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 trading days are after the program launch event and equals zero otherwise. After that, we run panel regressions of the number of Uniswap liquidity providers on *Treatment*, *Post*, and the interaction term. In the regression, we use the *Normalized Log Number of Uniswap Liquidity Providers* to measure the number of liquidity providers on Uniswap, where *Normalized Log Number of Uniswap 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 parenthesis. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| *DepVar:* | *Normalized Log Number of Uniswap 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* | 2267 | 4317 | 8005 | 11739 |