

Decentralized Exchanges for Stablecoins*

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Abstract

We examine decentralized exchanges (DEXs) like Curve that specialize in stablecoin trading, which co-exist with centralized exchanges (CEXs) like Binance. We develop a simple model of stablecoin trading in which a DEX uses a low-convexity bonding curve to determine trading prices, liquidity traders choose between the DEX and CEX conditional on trade size, and an arbitrageur trades to profit from price staleness when the stablecoin experiences a de-peg shock. Using trade-level data of stablecoins, we empirically confirm the implications of the model's main economic mechanism—the price impact is lower on the DEX than on the CEX—for liquidity traders' venue choice, arbitrage trading volume, and deviations from the peg. Our analyses inform the market design of stablecoin trading with respect to maintaining its price peg.

Keywords: AMM, Blockchain, Cryptocurrency, Decentralized Exchanges, Smart Contract, Stablecoins

JEL Classification: G12, G23, O36

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1 Introduction

The market for stablecoins—crypto assets designed to maintain a stable value relative to a reference asset, such as the U.S. dollar (USD), on a one-to-one basis—has expanded substantially in recent years. For instance, the market capitalization of major USD-denominated stablecoins, including Tether (USDT), USD Coin (USDC), and Dai, increased from approximately \$5.6 billion at the beginning of 2020 to more than \$310 billion in 2025. Stablecoins serve a pivotal function within the decentralized finance (DeFi) ecosystem, for example by facilitating transactions involving other crypto assets such as Bitcoin.¹ Furthermore, they possess the potential to evolve into a general medium of exchange that could compete directly with fiat money and traditional bank deposits.

The price peg of stablecoins is central to their role in the crypto ecosystem and to their potential as widely adopted payment instruments. One mechanism that helps maintain the peg is issuer intervention, adjusting stablecoin supply much like the management of pegged fiat currencies (e.g., the Hong Kong dollar). Another mechanism, highlighted by [Lyons and Viswanath-Natraj \(2023\)](#), is arbitrage by private investors between primary and secondary markets. However, both mechanisms rely on access to primary issuance, which is limited for many stablecoins. For instance, the primary market of USDT, the largest stablecoin, is restricted to a small group of approved customers, features a minimum transaction size, and imposes a minimum redemption fee. Most stablecoin users, especially retail participants, can access stablecoins only through secondary markets.

Therefore, maintaining the peg in secondary-market trading—before arbitrage by the small group of primary-market participants can eventually take effect—is critically important. This is especially true when buyers and sellers have offsetting trading needs but require time to find and trade with each other. In such cases, the imbalance between stablecoin demand and supply is only temporary, and a well-functioning secondary market can help smooth out deviations from peg. But how is the secondary market of stablecoins organized? What trading mechanisms

¹See [Harvey et al. \(2021\)](#), [Aramonte et al. \(2021\)](#), and [Schär \(2021\)](#) for comprehensive overviews of DeFi.

are available, and how do various investors select among them? Is the market functioning effectively in addressing temporary demand and supply shocks, thereby smoothing deviations from the peg? Answering these questions not only helps understand and enhance the design of stablecoin trading but also helps set up on-chain trading of traditional assets with relatively stable values (e.g., Treasury Bills and bank deposits) to take advantage of great accessibility and efficiency of blockchain technology.²

A number of important studies have analyzed secondary-market trading of cryptocurrencies, offering insights on decentralized exchanges (DEXs) that have attracted substantial trading volumes and account for nearly half of DeFi's total market capitalization. These studies primarily focus on general DEXs like Uniswap that trade all types of crypto tokens, including both non-stablecoin cryptocurrencies like Bitcoin and Ethereum and stablecoins (see discussions later). In this paper, we provide the first, to the best of our knowledge, comprehensive analysis of DEXs like Curve that specialize in stablecoin trading.

In the first part of our study (Section 2), we document institutional details of the secondary market of stablecoins and highlight key features of stablecoin-specialized DEXs. In particular, trades of a stablecoin against another stablecoin can be executed both on centralized exchanges (CEXs) such as Binance that use a centralized limit order book (LOB) and on DEXs that use an automated market maker (AMM) mechanism.³ Different from a LOB on which liquidity providers post limit orders that consist of price-quantity pairs, an AMM hosts a liquidity pool that all liquidity providers contribute into by depositing their stablecoins and uses a pre-defined pricing function to determine the transaction price between investors and the liquidity pool.

The curvature of the pricing function determines the price impact of trade on DEXs: the higher the convexity of the pricing curve, the larger the price impact. For example, for a linear pricing curve, also known as *constant-sum* pricing curve, the convexity is zero and hence there is no price impact. Thus, the exchange rate between two stablecoins can remain constant at

²The tokenization of traditional financial assets like Treasury securities is a major DeFi application in recent years. The market has exploded from under \$100 million two years ago to over \$8 billion in October 2025. Black-Rock, Franklin Templeton, and Ondo Finance now manage billions in tokenized Treasury products.

³Trading of a stablecoin against fiat currency only occurs on CEXs.

1 for trade of any size. On the other hand, for a *constant-product* pricing curve that has been widely used (in Uniswap V1 and V2), the price impact is quite significant, making it unsuitable for trading stablecoins. Indeed, few transactions of stablecoins occurred on Uniswap in early years (while trading of non-stablecoin cryptocurrencies on Uniswap picked up substantially).

In January 2020, Curve launched a DEX with the objective to lower price impact for stablecoin trading. It does so by using a pricing curve that combines the constant-sum and constant-product pricing functions, which keeps prices of stablecoins close to the \$1 peg even for large trades. As a result, Curve immediately dominated Uniswap in the trading of stablecoins once introduced in 2020, and continued to be a major player till today.⁴ Overall, since 2020, two different types of trading platforms coexist for stablecoins: CEXs using LOBs and DEXs using AMMs with low-convexity pricing curves.

Note that low-convexity pricing curves are designed to reduce price impact and help maintain the peg when a stablecoin's fundamentals are sound. However, stablecoins are not immune to shocks to their fundamentals. For example, in March 2023, USDC sharply de-pegged after its issuer, Circle, disclosed difficulties in withdrawing reserves held at Silicon Valley Bank prior to regulatory intervention. In these situations when stablecoin values should deviate from the \$1 peg, low-convexity pricing curves that ordinarily stabilize prices expose liquidity providers to high losses from trading by arbitrageurs to exploit price staleness on DEXs. Anticipating such potential losses, liquidity providers would reduce ex-ante liquidity provision, shrinking the liquidity pool. This, in turn, influences stablecoin traders' strategies and behavior. As a result, the equilibrium outcome is theoretically unclear a priori.

Hence, in the second part of our study (Section 3), we develop a simple model that incorporates the key features of stablecoin-specialized DEXs and derive their key economic effects on the trading and pricing of stablecoins. Specifically, we consider a trading game in a three-period economy in which three types of agents—liquidity providers, liquidity traders, and an arbitrageur—trade a stablecoin (against a numeraire asset) on a CEX and a DEX. At time 0, liq-

⁴Uniswap V3, introduced in May 2021, allows liquidity providers to set a price range, which leads to lower price impact than Uniswap V1 and V2. In consequence, it attracts a notable fraction of stablecoin trading volume and stands as a competitor to Curve.

liquidity providers decide their liquidity provision. At time 1, a shock hits either the private value of trading, which leads to trading by liquidity traders, or the common value of the stablecoin, which leads to trading by the arbitrageur. At time 2, liquidity providers withdraw their liquidity and realize their payoffs at the common value of the stablecoin.

Liquidity providers on the CEX submit price-quantity pairs which liquidity traders and the arbitrageur trade against. Liquidity providers on the DEX lock their stablecoin (and numeraire asset) into the liquidity pool against which trades occur,⁵ with the trading price determined by a pricing curve. Moreover, traders need to pay a transaction fee to trade against the DEX liquidity pool, which is distributed to liquidity providers on a pro rata basis. Hence, the effective trading cost on the DEX is the sum of the price impact and transaction fee, while that on the CEX is just the price impact.

For simplicity, we consider the case in which liquidity traders and the arbitrageur sell the stablecoin.⁶ Importantly, we consider non-unit trading size of liquidity traders and allow them to choose CEX vs DEX conditional on trading size.⁷ Specifically, a liquidity trader would choose the trading venue with lower effective trading cost for her trading size. Moreover, upon a shock to the common value, the arbitrageur trades on both the CEX and DEX to profit from liquidity providers' latency,⁸ up to the point that the marginal prices equal the new common value. Liquidity providers determine optimal liquidity provision by trading off profits from liquidity trading against losses from arbitrage trading and the cost of liquidity provision.

The key equilibrium implications of the model concern the effects of the DEX's low-convexity pricing curve on liquidity trading, arbitrage trading, and liquidity provision. Regarding liquidity trading, because price impact on the DEX—due to its low-convexity pricing curve—is lower

⁵The price of the stablecoin at time 0 is normalized to 1; we therefore assume that liquidity providers deposit equal amounts of the stablecoin and the numeraire asset into the liquidity pool as a normalization.

⁶For the arbitrageur, this is the same as considering the case in which the shock to the common value of stablecoin is a de-pegging shock. Both the economic mechanisms and main findings remain the same in the case in which they buy stablecoins.

⁷As standard in studies of multiple trading platforms, we assume that a liquidity trader would trade either totally on the CEX or totally on the DEX.

⁸Such latency arises on the CEX because liquidity providers may not be able to update quotes, monitor inventory, and process trades in real time on the CEX, and arises on the DEX because liquidity providers can adjust positions only discretely, face confirmation delays and transaction costs in blockchain settlement.

(higher) than that on the CEX for large (small) trades, liquidity traders larger (smaller) than a threshold choose the DEX (CEX). However, the difference in deviation from the peg between the DEX and CEX in equilibrium depends on two opposite effects. On the one hand, because the DEX accommodates larger trades in equilibrium, price deviations from the peg on the DEX tend to be higher than those on the CEX. On the other hand, if the fixed per-unit fee on the DEX is sufficiently large, the contribution of price impact to total trading costs on the DEX becomes relatively small. This implies that a DEX does not necessarily exhibit higher secondary-market price volatility than a CEX.

Regarding arbitrage trading when a shock hits the stablecoin's common value, we show that arbitrage trading volume is higher on the DEX than on the CEX. This arises from the lower price impact on the DEX compared with the CEX for large trades.

Regarding liquidity provision, we derive the effects of lowering the convexity of the DEX pricing curve. First, it increases expected trading volume on the DEX, thereby incentivizing liquidity providers to deposit more stablecoins into the liquidity pool. However, lowering convexity also increases the expected losses of liquidity providers during depegging events (i.e., when a common value shock realizes). In liquidity pools with sufficiently low convexity, the second effect dominates.

In the third part of our study (Section 4), we use trade-level data to test the equilibrium implications above on stablecoin trading. For the DEX, we use data of transactions on the Curve, each record of which includes the block number, timestamp, amount of tokens provided (or exchanged), and transaction fee. For the CEX, we use data of transactions on Binance. Our sample is from January 2020 to March 30 2023 overall, covering the three largest stablecoins—USDT, USDC, and DAI.

First, we test the model implications on liquidity trading. Specifically, we find that the average trade size on DEX is significantly larger than that on Binance. In particular, over May 5, 2021 to March 30, 2023, the average trade size of USDC-USDT on Binance was about three thousand USD, while it is around 580 thousand USD on Curve. This finding remains true even after the launch of Uniswap V3, which is a competitor to Curve for stablecoin trading. More-

over, we compare the average stablecoin price deviations from the peg on Curve and Binance. Although Curve accommodates significantly larger trades, the difference in average price deviations across the two venues is negligible. For the USDC–USDT trading pair, the average price deviation across all trades is 4.73 basis points on Binance and 4.85 basis points on Curve. Similarly, for the DAI–USDT pair, the average deviations are 5.38 and 5.18 basis points on Binance and Curve, respectively.

Second, we test the model implications on arbitrage trading when a de-pegging shock occurs. Specifically, we consider the SVB collapse in March 2023, which led to a significant price depeg of the USDC stablecoin after its issuer, Circle, announced that a portion of its reserves was held as deposits at SVB. We compare trading volume in the USDC–USDT and DAI–USDT trading pairs on Curve and Binance and find that trading volume on Curve significantly exceeded volume on Binance during this episode. Because venue-level volume is a reduced-form proxy for arbitrage intensity and may also reflect exchange-specific trading constraints, this evidence should be interpreted as consistent with the model’s stress-state mechanism rather than as a direct measurement of arbitrage quantities.

Third, we test the model implications on the effects of varying the DEX pricing curve on liquidity provision. We collect information on changes that altered either the trading fee or the curvature of the pricing function in the largest Curve pool ("DAI-USDT-USDC"). We find that, controlling for other relevant variables, changes in these parameters are strongly associated with the size of the liquidity pool on Curve. In particular, an increase in the fee is associated with higher liquidity provision in the DAI-USDT-USDC pool, while a decrease in the convexity of the pricing function is associated with a reduction in the size of the liquidity pool.

In sum, our analysis highlights a fundamental trade-off related to the curvature of the DEX pricing curve in the design of stablecoin markets. Specifically, a flatter pricing curve reduces price impact and helps maintain the price peg, but also increases losses for liquidity providers, thereby weakening liquidity provision. Our framework provides a foundation for further research on the optimal design of DEXs for stablecoins, emphasizing the importance of balancing price stability and liquidity provision.

Related literature. The literature on DeFi and cryptocurrencies has expanded rapidly over the past few years; see [Harvey et al. \(2021\)](#), [John et al. \(2023\)](#), and [Makarov and Schoar \(2022\)](#), among others, for recent surveys. Among these studies, our paper is closely related to work focusing on DEXs and stablecoins.

Most existing work on DEXs focuses on how bonding curves, pool fees, and gas fees affect trading costs and liquidity provision on DEXs ([Angeris et al., 2021, 2020](#); [Milionis et al., 2022a,b](#); [Heimbach et al., 2021](#); [Hasbrouck et al., 2022, 2025](#); [Capponi and Jia, 2025](#); [Capponi et al., 2025](#); [Lehar et al., 2024](#); [Park, 2021](#); [Cao et al., 2023](#); [Fang, 2024](#)). A smaller set of studies examines CEXs and DEXs jointly. For example, [Lehar and Parlour \(2025\)](#) model a DEX and a CEX separately and compare their liquidity provision and trading costs, while [Aoyagi and Ito \(2024\)](#) model the coexistence of a DEX and a CEX and study their interactions in equilibrium liquidity. Moreover, [Barbon and Ranaldo \(2024\)](#) compare transaction costs and price efficiency across DEXs and CEXs empirically, and [Han et al. \(2022\)](#) find that traders respond to activity on DEXs.

Our paper also considers DEXs and CEXs jointly but differs from existing studies in several important ways. First, while most existing studies focus on general-purpose DEXs such as Uniswap, which trade both stablecoins and non-stablecoin cryptocurrencies, we focus on DEXs such as Curve that specialize in stablecoin trading. Accordingly, we emphasize the price impact of trading, which is closely related to deviations of stablecoin prices from their peg in secondary markets. Hence, unlike [Aoyagi and Ito \(2024\)](#)—the only other study that models the coexistence of a DEX and a CEX—we not only allow trading sizes to exceed one unit but also allow traders to choose trading venues conditional on trading size in the model.⁹ More broadly, we treat deviations from the peg as a key metric of market quality and a central objective in market design, whereas existing studies primarily focus on trading costs and price discovery.

Among studies on stablecoins, our paper is most closely related to those that examine market mechanisms for maintaining the price peg. In particular, [Lyons and Viswanath-Natraj \(2023\)](#) and [Ma et al. \(2025\)](#) provide detailed analyses of how primary–secondary market arbitrage af-

⁹Several studies, such as [Hasbrouck et al. \(2022\)](#) and [Capponi and Jia \(2025\)](#), also allow trading sizes to exceed one unit. However, unlike our model, which considers the coexistence of DEXs and CEXs, these studies focus exclusively on DEXs and do not examine traders' venue choice between DEXs and CEXs.

fects stablecoins’ price stability around \$1 and their run risk. Moreover, [Gorton et al. \(2025\)](#) show that lending to leveraged traders can help sustain stablecoin price pegs even in the presence of high run risk.¹⁰ Our paper complements this literature by analyzing how the structure of secondary markets for stablecoins affects deviations from the peg.

The innovative design of liquidity provision on DEXs, together with their rapid growth in the DeFi ecosystem, has motivated interest in applying DEX mechanisms to the trading of traditional financial assets. For example, [Malinova and Park \(2024\)](#) show that well-designed DEXs can significantly lower transaction costs in equity markets due to the risk-sharing properties of liquidity pools. Moreover, [Foley et al. \(2024\)](#) demonstrate that DEXs can offer deep liquidity and reduce trading costs for high-volume, low-volatility assets across a range of asset classes. Our work complements these studies by analyzing how DEXs with particularly low-curvature pricing curves affect the prices of crypto tokens with stable values. Our results are hence especially relevant for the trading of tokenized assets with relatively safe and stable values, such as Treasury securities.¹¹

The rest of the paper is organized as follows: Section 2 provides details of stablecoins and their trading mechanisms in the secondary market. Section 3 develops the model and derives economic implications, while Section 4 conducts the empirical analysis. Section 5 concludes.

2 Institutional Details of Stablecoins and Their Trading

In this section, we begin with a brief introduction to stablecoins and the mechanisms used to maintain their price peg. We then turn to secondary-market trading, focusing on the platforms through which stablecoins are traded.

¹⁰A number of studies examine how the design and protocol—the collateralization, supply adjustment, issuance mechanism, and redemption rule— affect stablecoin stability, including [Gorton and Zhang \(2021\)](#), [Gorton et al. \(2022\)](#), [Ahmed et al. \(2025\)](#), [Li and Mayer \(2022\)](#), and [d’Avernas et al. \(2021\)](#). Moreover, [Uhlig \(2022\)](#), [Liu et al. \(2023\)](#), and [Kurovskiy and Rostova \(2023\)](#) provide detailed analyses of the run and collapse of the algorithmic stablecoin Terra in 2022. In addition, [Barthelemy et al. \(2023\)](#) study the connection of stablecoins to traditional financial assets. See [Catalini et al. \(2022\)](#) for a recent survey.

¹¹The market for tokenized Treasuries has expanded from under \$100 million in 2023 to around \$9 billion in 2025, with BlackRock, Franklin Templeton, and Ondo Finance managing billions of dollars in tokenized Treasury products. See <https://app.rwa.xyz/treasuries> for a summary of tokenized Treasury products.

2.1 Stablecoin and Price Peg

Stablecoins are crypto tokens designed to maintain a peg to fiat currencies, typically a national currency like the US dollar (USD), and therefore act as a safe asset that is not subject to the same volatility as many crypto tokens like Bitcoin. Because of their (relative) stability in value, stablecoins have become a crucial component of the crypto ecosystem. For example, they are often used as collateral locked in smart contracts or borrowed to build leveraged positions, thereby fueling the development of Decentralized Finance (DeFi). Moreover, they are used to settle a majority of crypto transactions ([Gensler, 2021](#)), hence serving as a medium of exchange in crypto markets.¹² Accordingly, the market capitalization of stablecoins has been growing rapidly over the last few years, from just below \$5 billion in early 2020 to over \$300 billion as of late 2025.

Stablecoins pegged to USD make up the lion's share of the market. The existing stablecoins can be grouped into three categories in general according to how they are collateralized: fiat-backed stablecoins like USDT backed with cash and cash-equivalent reserves such as bank deposit, Treasury bill, and commercial paper; crypto-collateralized stablecoins like DAI backed by a basket of crypto-assets such as other stablecoins, Ether, and other ERC-20 tokens; algorithmic stablecoins like Terra using smart contracts that respond to supply and demand imbalances by minting or burning tokens to maintain their peg. Among them, fiat-backed stablecoins account for the major fraction of market capitalization. Specifically, of the top six stablecoins, five are fiat backed, including USDT, USDC, BUSD, TUSD, and PAX, and one is crypto-collateralized, which is DAI backed by ETH.

The price peg of stablecoins is central to their role in the crypto ecosystem and to their potential as widely adopted payment instruments. One mechanism that helps maintain the peg is issuer intervention, adjusting stablecoin supply much like the management of pegged fiat currencies (e.g., the Hong Kong dollar). Another mechanism, highlighted by [Lyons and Viswanath-](#)

¹²They have also been used beyond crypto markets. For example, humanitarian organizations have used stablecoins to make cross-border remittance payments, circumventing banking fees and regulatory frictions. Moreover, in countries where inflation is high or trust in financial intermediaries is low, such as Lebanon and Argentina, individuals have begun storing value and transacting using stablecoins, and merchants like the Unicorn Coffee House have begun accepting USDT as a form of payment.

Natraj (2023), is arbitrage by private investors between primary and secondary markets. For example, when a stablecoin trades above its one-dollar peg, authorized private investors can purchase stablecoins from the issuer at par and sell them in the secondary market at the higher prevailing price, thereby increasing supply and pushing the price back toward the peg.

Both mechanisms rely on access to primary issuance, which is limited for many stablecoins. For instance, USDT's primary market is restricted to approved customers, features a minimum transaction size of \$100,000, and imposes a minimum redemption fee of \$1,000 or 0.1%. For USDC, while creation and redemption are fee-free, access is limited to Circle's direct clients—primarily crypto exchanges, fintech firms, and institutional traders. Most stablecoin users, especially retail participants, can access stablecoins only through secondary markets.

Therefore, maintaining the peg in secondary-market trading—before arbitrage by the small group of primary-market participants can eventually take effect—is critically important. This is especially true when buyers and sellers have offsetting trading needs but require time to find and trade with each other. In such cases, the imbalance between stablecoin demand and supply is only temporary, and a well-functioning secondary market with strong liquidity provision can help smooth out deviations from the peg.

2.2 Secondary-Market Trading of Stablecoins

CEXs. Secondary-market trading of stablecoins (for fiat currencies or other stablecoins) used to occur off-chain totally on crypto exchanges such as Binance, Coinbase, and Kraken. Similar to exchanges that trade traditional financial assets like stocks, crypto exchanges use a centralized limit order book (LOB) as the main trading mechanism, hence also known as centralized exchanges (CEXs). Specifically, a group of investors, often known as market makers, post limit orders that consist of price-quantity pairs for other investors to trade against.

DEXs. Over the last few years, a type of trading platforms built on smart contracts of blockchain—decentralized exchanges (DEXs) that use automated market makers (AMMs)—have attracted a large fraction of crypto trading, even surpassing CEXs in trading volume for exchange pairs

listed on both types of platforms since 2024.¹³ The key distinctive features of AMMs are liquidity pools that can be contributed by any investors and algorithmic pricing mechanisms that determine the trading price.

In particular, a liquidity pool on DEX usually supports the exchange of two (or more) tokens. Investors who hold both tokens can participate as liquidity providers by depositing an equivalent value of both tokens into the pool, receiving pool tokens (also known as liquidity tokens) in return that represent their proportional share of the pool.¹⁴ Investors who need to trade one token for the other would pay a fee proportional to trading size and transact with the liquidity pool as a whole instead of any particular liquidity provider in the pool. The trading fee is distributed to all liquidity providers in proportion to their respective share of the liquidity pool.

Moreover, the transaction price between investors and the liquidity pool is determined by a pre-defined pricing function (often known as bonding curve) with the state of pools as an input. To illustrate, consider a trade between two tokens x and y , with the current liquidity pool consisting of d_x units of token x and d_y units of token y . Suppose a trader attempts to buy Δ_x units of token x by paying Δ_y units of token y , implying that the average price of token x in units of token y for this trade is equal to

$$P = \frac{\Delta_y}{\Delta_x}. \quad (1)$$

After this trade, the liquidity pool would consist of $d_x + \Delta_x$ units of token x and $d_y - \Delta_y$ units of token y . DEX uses an invariance constraint on the pricing function F

$$F(d_x + \Delta_x, d_y - \Delta_y) = F(d_x, d_y). \quad (2)$$

to determine the relationship between Δ_x and Δ_y .

¹³DEXs that do not use AMMs exist, but account for a much lower fraction of total DEX trading volumes. Throughout our paper, DEXs refer to those based on AMMs.

¹⁴For example, suppose a liquidity pool initially contains 1 unit of token A and 1 unit of token B. If an LP contributes an additional 1 unit of token A and of token B, the pool now contains 2 units of each token, and the LP owns 50% of the pool. The value of the LP's stake depends on the pool's composition at the time of withdrawal. If, at withdrawal, the pool contains 4 units of token A and 1 unit of token B, the LP would receive 2 units of token A and 0.5 units of token B, assuming no other deposits or withdrawals occurred in the interim.

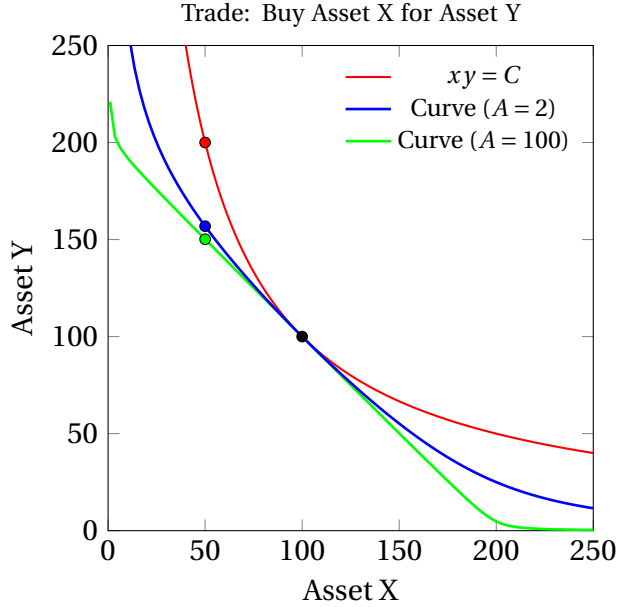


Figure 1. This figure compares the price impact of a trade of a given size in the constant-product Automated Market Maker (AMM) ($xy = C$ in red) with that in the Curve AMM ($A = 2$ in blue and $A = 100$ in green). Parameter A defines the curvature of the pricing function. A higher A results in a flatter pricing curve and lower price impact. The black dot indicates the state of the liquidity pool before the trade; the red, blue, and green dots – after the trade. For a more detailed description, see the Curve White Paper (Egorov (2019)).

Price impact and market developments of DEXs for stablecoin trading. Denote the relationship between the amounts of tokens A and B exchanged, which can be solved implicitly from Eq. (2), as $\Delta_y = g(\Delta_x)$. Taking the negative of the derivative, $-g'(\Delta_x)$, we obtain the marginal exchange rate at which token x is exchanged for token y . The price impact of the trade that exchanges Δ_x units of token x for token y can be captured by the change in $g'(\Delta_x)$, i.e., the curvature of the pricing curve. In particular, a higher convexity leads to a larger price impact for a given trade size.

For a linear pricing curve with $F(x, y) = x + y$, also known as constant-sum pricing curve, the convexity is zero and hence there is no price impact. In fact, the marginal exchange rate remains constant at 1. However, the most popular pricing function used in early AMMs, like Uniswap V2, is a constant-product function $F(x, y) = xy$ that has significant price impact, as illustrated in Figure 1. This makes it unsuitable for trading stablecoins. Indeed, few transactions of stablecoins occurred on Uniswap in early years, even when trading of non-stablecoin cryptocurrencies on Uniswap picked up substantially.

In January 2020, a DEX named Curve was launched with the intention of solving the issue of large price impact for stablecoin trades. They created the AMM with a modified pricing function, essentially making it "flatter" when a liquidity pool is balanced. This was achieved by combining the constant-product pricing curve and the constant-sum pricing curve. Specifically, the pricing function for exchanging two tokens is, as defined in the Curve White Paper (Egorov, 2019),¹⁵:

$$4A(x + y) + C = 4AC + \frac{C^3}{4(x * y)} \quad (3)$$

where x and y are quantities of the two assets in the liquidity pool, A is the parameter of the pricing curvature, and C is the constant defined by the initial composition of the pool. The parameter A controls the relative weight of the constant-product and constant-sum components and hence the price impact. The higher the A , the lower the price impact. For example, when $A = 0$, the curvature is of the constant-product type. As A increases, the weight of the constant-sum component is larger.

Figure 1 demonstrates the price impact of the same trade using the Curve pricing function, for different values of the parameter A . We observe that increasing A indeed decreases the price impact. This design keeps stablecoin prices close to their \$1 peg even for large trades. As a result, Curve immediately dominated Uniswap in the trading of stablecoins once introduced in 2020, and continued to be a major player till today.

Overall, since 2020, two different types of trading platforms coexist for stablecoins: CEXs using LOBs and DEXs using AMMs with low-convexity pricing curves. Next, we build a theoretical model to investigate the economic effects of the DEXs like Curve on stablecoins' trading and price peg in the secondary market.

¹⁵Note that compared to other exchanges, Curve also allows for pools consisting of three and more stablecoins. In such cases, the pricing curvature has a more general form: $An^n \sum_i x_i + C = ACn^n + \frac{C^{n+1}}{n^n \prod_i x_i}$, where n - the number of tokens in the pool and x_i is the quantity of asset i .

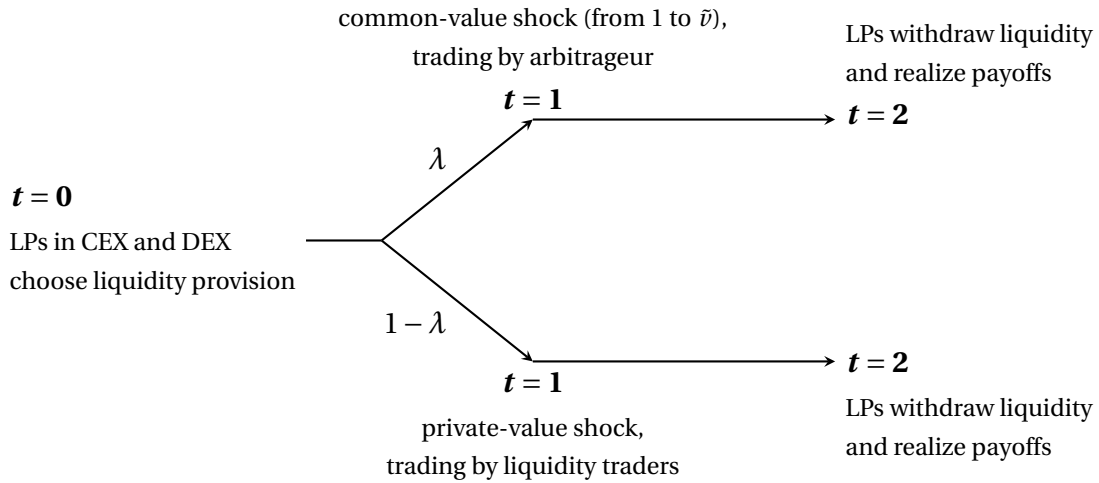


Figure 2. Timeline of the model

3 Model

In this section, we present our simple model. We first describe the model setup. We then characterize the equilibrium and develop the economic implications.

3.1 Setup

We consider a trading game in a three-period economy ($t = 0, 1, 2$) in which three types of agents—liquidity providers, liquidity traders, and an arbitrageur—trade a stablecoin on two platforms: a centralized exchange (CEX) and a decentralized exchange (DEX). The initial common value of the stablecoin is assumed, without loss of generality, to be equal to the value of a numeraire asset (US dollar or another stablecoin), which is normalized to be 1.¹⁶ Figure 2 demonstrates the timeline of the trading game.

The model delivers two sets of implications that map directly to the empirical section: (i) in normal times (no common-value shock), how liquidity traders’ endogenous venue choice shapes trade sizes and peg deviations across venues; and (ii) in market-stress times (common-value shock), how arbitrage trading against stale liquidity affects trading volume and liquidity provision.

¹⁶In practice, DEXs trade a stablecoin against another stablecoin, while CEXs deal with both—trades between a stablecoin and a fiat currency, and trades between one stablecoin and another.

The key variables are:

- $Q \sim U[0, \bar{Q}]$: liquidity-trader order size realized at $t = 1$ in the no-shock state.
- \tilde{v} : post-shock common value realized at $t = 1$ in the shock state; $\bar{v} := \mathbb{E}_0[\tilde{v}]$ is its ex-ante mean.
- X_D : total DEX pool size chosen by LPs at $t = 0$; $X_C(\cdot)$: CEX supply schedule chosen by LPs at $t = 0$.
- (A, f) : DEX pricing-curve curvature and fee; ρ : LP inventory/capital cost; λ : shock probability.

The timing is: LPs commit to X_D and $X_C(\cdot)$ at $t = 0$; at $t = 1$ either liquidity trading occurs (no shock) or the arbitrageur trades against stale liquidity (shock); payoffs realize at $t = 2$.

Events. At time $t = 0$, liquidity providers decide their liquidity provision for the subsequent rounds. At $t = 1$, a shock hits either the common value of the asset (with probability λ), which leads to trading by arbitrageur, or the private value of trading (with probability $1 - \lambda$), which leads to trading by liquidity traders. The common value of the stablecoin changes from 1 to \tilde{v} in the former case and remains unchanged in the latter case. At $t = 2$, liquidity providers withdraw their liquidity and realize their payoffs at the common value of the stablecoin. We assume that liquidity providers cannot update their CEX supply schedules or DEX pool deposits at $t = 1$, which creates stale quotes/inventories that an arbitrageur can trade against following a shock.

We assume that agents know λ and the distribution of \tilde{v} at $t = 0$, but not its realization. If the common-value shock occurs at $t = 1$, the arbitrageur observes \tilde{v} before trading. For notational convenience, we denote $\bar{v} := \mathbb{E}_0[\tilde{v}]$.

CEX and DEX. We model the centralized limit order book on CEX by a price-quantity schedule

$$X_C(P_C), \tag{4}$$

where P_C is the average price for trading $X_C(P_C)$ units of stablecoins. The DEX, as discussed in Section 2.2, runs a liquidity pool. In particular, liquidity providers lock their stablecoin and

numeraire asset in the liquidity pool against which liquidity takers trade by paying a transaction fee. This fee is charged in terms of the stablecoin and accumulated in a separate account (Lehar and Parlour, 2025). At $t = 2$, transaction fees are distributed to liquidity providers who supplied liquidity to the DEX on a pro rata basis.

The trading price on the DEX is determined by a pre-defined pricing curve. Specifically, we assume the following form of the pricing curve:

$$[(1 - A)x + AC] \times [(1 - A)y + AC] = C^2 \quad (5)$$

where $A \in (0, 1)$ determines the curvature, C is the constant defined by the initial composition of the pool, and x and y are the quantities of the stablecoin and the numeraire asset, respectively.¹⁷

Note that since the price of the stablecoin at $t = 0$ is normalized to 1, we assume that liquidity providers deposit equal amounts of the stablecoin and numeraire asset, which we denote by X_D . This normalization is without loss of generality, as the model's economic implications depend on relative trading costs and price impacts rather than on the absolute price level. In this case, we have $C = X_D$, which is obtained by setting $x = y = X_D$ in Eq. (5). Therefore, if a trader sells q units of stablecoins to this liquidity pool, the average trading price of the stablecoin (in units of numeraire assets) $P_D(q; X_D)$ can be obtained by the following equation

$$[(1 - A)(X_D + q) + AX_D] \times [(1 - A)(X_D - P_D q) + AX_D] = X_D^2, \quad (6)$$

as

$$P_D(q; X_D) = \frac{X_D}{(1 - A)q + X_D}. \quad (7)$$

Liquidity traders. As mentioned above, a private-value shock triggers their exogenous trading needs (e.g., hedging motives). For simplicity, we assume that the private benefit of trading is sufficiently large so that they participate in the market upon being hit by the shock. Importantly,

¹⁷Fig. A.1 in the Appendix compares the pricing curve in Eq. (5) with that in Egorov (2019). In the model, we assume that parameter A varies from 0 to 1, while in Egorov (2019) $A \in (0, \infty)$.

unlike most existing studies in the literature that assume the trading size of liquidity traders to be one unit, we consider the case in which the trading size to be Q units. Furthermore, we allow liquidity traders to decide on their trading venues conditional on the trading size Q . In addition, as standard in studies of multiple trading platforms, we assume that the liquidity trader would trade all Q units either on the CEX or on the DEX.

The arbitrageur. If a common-value shock hits the stablecoin at $t = 1$, the arbitrageur immediately observes the realized value of the shock and trades the stablecoin for profits. We allow the arbitrageur to trade on both the CEX and DEX. Note that the arbitrageur's profit arises from liquidity providers' latency costs. On CEXs, these costs arise from updating quotes, monitoring inventory, and processing trades in real time. On DEXs, these costs arise because LPs can adjust positions only discretely, face confirmation delays and transaction costs in blockchain settlement.

Liquidity providers. At $t = 0$, each of N_C CEX liquidity providers determines her liquidity supply schedule $x_C(P_C)$, where P_C is the average price at which she will be willing to trade $x_C(P_C)$ units of stablecoin. Hence,

$$X_C(P_C) = \sum_{N_C} x_C(P_C). \quad (8)$$

Each of N_D DEX liquidity providers, instead, only determines the quantity x_D she is willing to contribute into the liquidity pool. Therefore, we have

$$X_D = \sum_{N_D} x_D. \quad (9)$$

We consider the simple case in which all liquidity providers are homogeneous in their liquidity-provision costs. Specifically, for providing x_k ($k = C$ or D) units of liquidity, all liquidity providers incur a cost equal to $\frac{\rho}{2} x_k^2$, where ρ determines the marginal liquidity-provision cost.

At $t = 0$, liquidity providers do not know whether the time-1 shock would hit the common

value of the stablecoin or the private value of trading. Moreover, they only know the distribution (but not the value) of the size Q of a time-1 liquidity trade, which we assume follows a uniform distribution over $[0, \bar{Q}]$.

3.2 Equilibrium

In this section, we first examine the behavior and choice of different traders and then provide the equilibrium characterization.

Liquidity traders' behavior and choice. We start by analyzing liquidity traders' behavior and choice at $t = 1$. Because they always trade upon being hit by the shock, as discussed above in Section 3.1, liquidity traders simply choose the trading venue with a lower trading cost.

The average trading cost in the CEX for trading Q units of stablecoins is equal to

$$1 - P_C(Q), \text{ where } P_C(\cdot) = X_C^{-1}(\cdot). \quad (10)$$

The average trading cost on the DEX is

$$f + 1 - P_D(Q; X_D), \quad (11)$$

where $P_D(Q; X_D)$ is the average price in selling Q units of stablecoins to the DEX liquidity pool based on Eq. (6) and f is the per-unit pool fee.¹⁸ Intuitively, $1 - P_C(Q)$ and $1 - P_D(Q; X_D)$ capture the price impacts of a trade of size Q on CEX and DEX, respectively.

The liquidity trader of size Q chooses the CEX if and only if:

$$1 - P_C(Q) < f + 1 - P_D(Q; X_D). \quad (12)$$

We note that trading size affects the average price impact but not the average liquidity fee. Thus,

¹⁸On DEX, $1 - P_D(Q; X_D)$ is known as “slippage” while the liquidity fee f is known as “pool fee.” Another trading cost is “gas fee”—a fixed cost for trade execution in blockchain—that we leave out for simplicity but does not affect our economic analysis.

the effect of trade size on liquidity traders' venue choice depends entirely on the venues' differences in price impact. We can define the set of trades that occur on CEX and DEX as

$$\Omega_C = \{Q : Q \text{ satisfies Eq. (12)}\}, \Omega_D = \{Q : Q \text{ violates Eq. (12)}\}$$

The arbitrageur's behavior and choice. If the shock to the common value of the stablecoin occurs in $t = 1$, the informed trader trades on both the CEX and DEX, with the amounts that bring the marginal price to \tilde{v} as discussed above in Section 3.1.¹⁹

Specifically, on the CEX, the volume q_C of her trades that will bring the marginal price to \tilde{v} is determined by

$$\frac{d(q_C P_C(q_C))}{dq_C} = \tilde{v}, \quad (13)$$

where $P_C(\cdot)$ is defined as in Eq. (10).

On the DEX, which consists of X_D units of the stablecoin and X_D units of the numeraire asset initially, the informed trading volume q_D (stablecoins sold into the liquidity pool) and z (numeraire assets taken out of the liquidity pool) satisfy the following relationship

$$[(1 - A)(X_D + q_D) + AX_D] \times [(1 - A)(X_D - z) + AX_D] = X_D^2. \quad (14)$$

Further, define $f(x, y) = [(1 - A)x + AX_D] \times [(1 - A)y + AX_D] - X_D^2$. Then the marginal price of the stablecoin is after the informed trading is

$$\frac{f'_X}{f'_Y} \Big|_{x=X_D+q_D, y=X_D-z} = \frac{(1 - A)(X_D - z) + AX_D}{(1 - A)(X_D + q_D) + AX_D} = \tilde{v}. \quad (15)$$

Combining Eqs. (14) and (15), the informed trading amounts q_D and z that will bring the marginal

¹⁹In the presence of transaction costs and price impact, the equilibrium price should generally differ from \tilde{v} , leading to small discrepancies between CEX and DEX stablecoin prices. Modeling this distinction would complicate the derivations but does not affect the qualitative predictions of the model.

price to \tilde{v} on DEX as

$$q_D = \frac{X_D}{1-A} \left(\frac{1}{\sqrt{\tilde{v}}} - 1 \right), \quad z = \frac{X_D}{1-A} \left(1 - \sqrt{\tilde{v}} \right), \quad (16)$$

which imply that

$$P_D(q_D; X_D) = \frac{z}{q_D} = \sqrt{\tilde{v}}.$$

Liquidity providers' behavior and choice. We first consider the CEX liquidity providers. Each CEX liquidity provider takes the price P_C as given and chooses the liquidity supply x_C to maximize his expected profit π_C :

$$\pi_C = (1-\lambda) \underbrace{x_C(1-P_C)}_{\text{gain from liquidity trading}} + \lambda \underbrace{x_C(\tilde{v}-P_C)}_{\text{loss to informed trading}} - \underbrace{\frac{\rho}{2} x_C^2}_{\text{liquidity provision cost}},$$

where P_C is the trading price of the stablecoin on the CEX. Under our information assumption, CEX liquidity providers integrate over the shock distribution at $t = 0$; for tractability, the common-value shock enters through its mean \tilde{v} . At $t = 0$, liquidity providers do not know whether the time-1 shock will hit the common value or the private value, so they maximize the expected profit. The first order condition with respect to x_C yields

$$x_C(P_C) = \frac{1 - P_C - \lambda(1 - \tilde{v})}{\rho}. \quad (17)$$

Then, we consider the DEX liquidity providers. Each DEX liquidity provider takes the total liquidity pool size X_D as given and chooses to deposit x_D units of stablecoin into the pool to maximize her expected profit

$$\pi_D = (1-\lambda) \underbrace{\pi_D^{Liquidity}}_{\text{gain from liquidity trading}} + \lambda \underbrace{\mathbb{E}_0 \left[\pi_D^{Informed}(\tilde{v}) \mid \text{shock} \right]}_{\text{loss to informed trading}} - \underbrace{\frac{\rho}{2} x_D^2}_{\text{liquidity provision cost}}, \quad (18)$$

In contrast to the CEX case, the DEX LP's loss from informed trading is nonlinear in \tilde{v} through

$q_D(\tilde{v})$ and the AMM pricing function, so we keep the expectation explicitly, where

$$\begin{aligned}\pi_D^{Liquidity} &= \frac{x_D}{X_D} E_0 [Q(f + 1 - P_D(Q; X_D)) | \Omega_D], \\ \pi_D^{Informed}(\tilde{v}) &= \frac{x_D}{X_D} q_D(\tilde{v}) (f + \tilde{v} - P_D(q_D(\tilde{v}); X_D)),\end{aligned}$$

and $P_D(Q; X_D)$ and $P_D(q_D; X_D)$ are the average prices for selling Q and q_D units of stablecoins to the DEX liquidity pool. The first order condition is

$$(1 - \lambda) \partial \pi_D^{Liquidity} / \partial x_D + \lambda \partial E_0 [\pi_D^{Informed}(\tilde{v}) | \text{shock}] / \partial x_D - \rho x_D = 0 \quad (19)$$

Equilibrium definition. Based on the analyses of the behavior and choice of traders above, we can now define the equilibrium.

Definition 1. The equilibrium is a collection of strategies and prices

$$\{x_C(\cdot), x_D, \Omega_C, \Omega_D, q_C, q_D, P_C(\cdot), P_D(\cdot; X_D)\}$$

such that

1. **(LPs' profit maximization):** $x_C(\cdot)$ satisfies Eq. (17), while x_D satisfies Eq. (19).
2. **(Liquidity traders' venue choice):** $Q \in \Omega_C$ or $Q \in \Omega_D$ according to Eq. (12).
3. **(Informed trader's trading volume):** q_C satisfies Eq. (13), while q_D satisfies Eq. (16).
4. **(Trading prices):** For any trade size q , the price on the CEX satisfies

$$X_C(P_C(q)) = q$$

with X_C defined in Eq. (8), and the price on the DEX $P_D(q; X_D)$ is determined by Eq. (6) with X_D as in Eq. (9).

Solving the equilibrium. We now solve for the equilibrium. For tractability, we only consider symmetric and competitive strategies and rational expectation equilibrium. Moreover, we consider the non-degenerate equilibrium in which both DEX and CEX are viable. This is ensured by the following assumption (Appendix A.2 provides details):

Assumption 1. The parameters satisfy

$$\lambda(1 - \bar{v}) < f \quad \text{and} \quad N_C(1 + f - \lambda(1 - \bar{v})) < \rho \bar{Q}.$$

Given the conditions in Assumption 1, we now solve for the equilibrium. First of all, based on Eqs. (8) and (17), we have

$$X_C(P_C) = N_C \frac{1 - P_C - \lambda(1 - \bar{v})}{\rho},$$

which implies that for any level of trade size q , the average trading price on the CEX is:

$$P_C(q) = 1 - \frac{\rho q}{N_C} - \lambda(1 - \bar{v}). \quad (20)$$

Thus, from (13), trading volume by arbitrageurs q_C is

$$q_C = \frac{N_C}{2\rho} \left(1 - \lambda(1 - \bar{v}) - \bar{v} \right). \quad (21)$$

That is, although the CEX pricing schedule is set *ex ante* at $t = 0$ based on \bar{v} , the arbitrageur's realized trading volume depends on the realized shock \bar{v} at $t = 1$. Using (7), in the equilibrium, a liquidity trader of size Q chooses the CEX if and only if:

$$\frac{\rho Q}{N_C} + \lambda(1 - \bar{v}) < \frac{(1 - A)Q}{(1 - A)Q + X_D} + f. \quad (22)$$

We observe that $1 - P_D(Q; X_D)$ is concave in Q because $\partial^2 s_D / \partial Q^2 < 0$.

The subsets of trade sizes Q for which a liquidity trader chooses to trade on the CEX or on

the DEX—denoted by Ω_C and Ω_D , respectively—are determined by the indifference condition

$$\frac{\rho \hat{Q}}{N_C} + \lambda(1 - \bar{v}) = \frac{(1 - A)\hat{Q}}{(1 - A)\hat{Q} + X_D} + f, \quad (23)$$

where \hat{Q} denotes the trade size at which the liquidity trader is indifferent between executing the trade on the CEX and on the DEX.

Finally, the equilibrium pool size \hat{X}_D is determined by combining the first order condition for DEX liquidity providers (18) (taking the pool size X_D as given) with $X_D = x_D N_D$:

$$(1 - \lambda)E_0 \left[Q \left(f + 1 - \frac{\hat{X}_D}{(1 - A)Q + \hat{X}_D} \right) \middle| \Omega_D \right] + \lambda E_0 \left[q_D(\bar{v}) \left(f + \bar{v} - \sqrt{\bar{v}} \right) \middle| \text{shock} \right] = \rho \frac{\hat{X}_D^2}{N_D} \quad (24)$$

3.3 Economic Implications

Based on the equilibrium solved, we now derive the main economic implications. The resulting testable predictions are summarized in Section 4 and listed explicitly in Propositions 1 to 4.

3.3.1 Trade Size and Price Deviation from Peg of Liquidity Trading

In this section, we derive economic implications on liquidity trading when the common value shock does not occur. Specifically, we shall compare the trade size and price deviation from the peg on the CEX and DEX. In this “liquidity” state, there is no common-value shock, and all differences across venues are driven by the interaction of (i) the venues’ pricing rules (LOB versus AMM), (ii) the fee wedge on the DEX, and (iii) the endogeneity of venue choice in trade size.

First, the choice of the liquidity trader given by Eq. (22) is as follows

$$\frac{\rho Q}{N_C} + \lambda(1 - \bar{v}) \begin{cases} < f + \frac{(1 - A)Q}{(1 - A)Q + X_D} & \text{for } Q \in \Omega_C, \\ \geq f + \frac{(1 - A)Q}{(1 - A)Q + X_D} & \text{for } Q \in \Omega_D, \end{cases} \quad (25)$$

To understand this condition, Fig. 3 demonstrates the average trading cost on the CEX versus

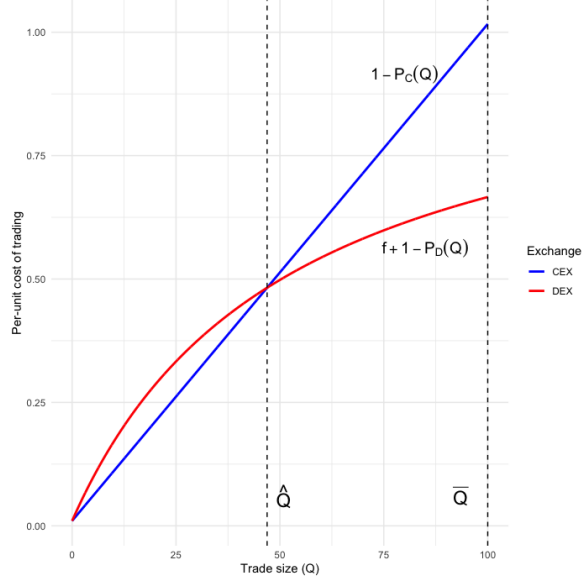


Figure 3. Per-unit cost of trading on the CEX (in blue) and the DEX (in red) as a function of trade size Q . Parameters are fixed at: $\lambda = 0.05$, $\bar{v} = 0.8$, $\rho = 0.151$, $N_C = 15$, $N_D = 3$, $A = 0.6$, $f = 1\%$, and $\bar{Q} = 100$.

the DEX, as a function of trade size Q . We observe that while the CEX trading cost is linear in Q , the DEX cost increases non-linearly with Q . As a result, there exists a threshold \hat{Q} such that liquidity traders choose to trade on the DEX when their trade size $Q > \hat{Q}$ and trade on the CEX for $Q < \hat{Q}$. We hence have the following implication:

Proposition 1. (Size of Liquidity Trading on the CEX and DEX). *For any set of parameters under which the DEX is viable, the average trade size on the CEX is smaller than that on the DEX.*

Next, we look into the price deviation from peg. Specifically, using Eq. (20) and the uniform distribution of Q , we derive the expected price deviation induced by liquidity trades on the CEX:

$$\mathbb{E}[1 - P_C(Q) \mid Q \leq \hat{Q}] = \frac{1}{\hat{Q}} \int_0^{\hat{Q}} \left(\frac{\rho Q}{N_C} + \lambda(1 - \bar{v}) \right) dQ.$$

Similarly, from Eq. (7), the expected price deviation on the DEX is:

$$\mathbb{E}[1 - P_D(Q) \mid Q \geq \hat{Q}] = \frac{1}{\bar{Q} - \hat{Q}} \int_{\hat{Q}}^{\bar{Q}} \frac{(1 - A)Q}{(1 - A)Q + X_D} dQ.$$

These measures correspond to the average deviation of the stablecoin price from the peg of \$1 examined by empirical studies (Lyons and Viswanath-Natraj, 2023).

The comparison of the price deviation from peg on the CEX and DEX, based on these two measures, is stated in the following

Proposition 2. (*Price Deviation from Peg of Liquidity Trading on the CEX and DEX*). Under parameter sets for which the DEX and the CEX coexist in equilibrium, the average price deviation from peg on the DEX is lower than that on the CEX when the DEX trading fee f and the curvature parameter A are sufficiently high, but higher otherwise.

That is, on the one hand, the DEX attracts larger trades, which tend to induce greater price deviations. On the other hand, the lower convexity of the pricing curve works to reduce price deviations. Depending on the relative strength of these two effects, price deviations on the DEX may be either higher or lower than those on the CEX. Overall, however, the introduction of a DEX reduces the price deviation of stablecoin prices.

3.3.2 Arbitrage Trading Volume

In this section, we derive economic implications on arbitrage trading when the common value shock occurs. Specifically, we compare the arbitrage trading volumes on the CEX and DEX (q_C and q_D).

Trading volumes of informed arbitrageurs on the CEX and DEX depend on \tilde{v} , as well as other parameters such as A , N_C , and ρ . In particular, based on Eqs. (16) and (21), we have

Proposition 3. (*Arbitrage Trading Volume on the CEX and DEX*). The arbitrage trading volume in the DEX is larger than in the CEX if and only if

$$\frac{X_D}{1-A} \left(\frac{1}{\sqrt{\tilde{v}}} - 1 \right) > \frac{N_C}{2\rho} \left(1 - \lambda(1 - \tilde{v}) - \tilde{v} \right) \quad (26)$$

In Fig. 4, we plot the trading volumes of arbitrageurs on the CEX and the DEX (q_C and q_D , respectively) as functions of \tilde{v} , holding all other parameters fixed. In particular, we set A to a relatively high value of 0.85, which corresponds to the practice used by Curve for stablecoins. We observe that arbitrage trading volume on the DEX exceeds that on the CEX, and that the difference increases with the size of the shock $1 - \tilde{v}$.

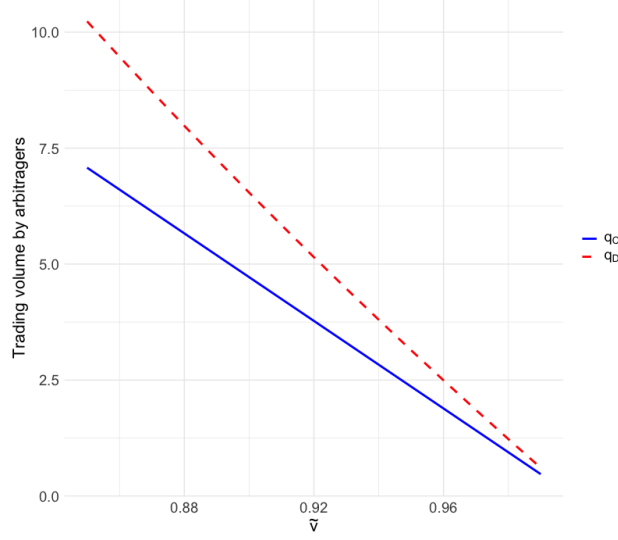


Figure 4. Trading volumes of arbitrageurs on CEXs and DEXs (q_C and q_D) during market stress for different values of the shock size \tilde{v} . Parameters are fixed at $A = 0.85$, $\lambda = 0.05$, $\rho = 0.151$, $N_C = 15$, $N_D = 3$, $f = 0.05\%$, and $\bar{Q} = 100$. Market stress is defined as the realization of a negative shock to the fundamental value of the stablecoin.

3.3.3 Liquidity Pool Size

In this section, we examine how changes in the curvature of the DEX pricing curve affect the equilibrium liquidity pool size \hat{X}_D .

Using the indifference condition for trading venue choice Eq. (23) and the FOC for the DEX liquidity providers' maximization problem Eq. (24), we obtain the following

Proposition 4. (*Effects of the Curvature of the DEX Pricing Curve on Liquidity Pool Size*) *When both CEX and DEX are viable, there exists $A^* \in [0, 1)$ such that*

$$\frac{\partial \hat{X}_D}{\partial A} > 0 \quad \text{for } A < A^*, \quad \frac{\partial \hat{X}_D}{\partial A} < 0 \quad \text{for } A > A^*,$$

where \hat{X}_D is the equilibrium DEX liquidity pool size.

Fig. 5 demonstrates the effect of A on the DEX liquidity pool size. We observe that when the convexity of the pricing curve is high (i.e., lower A), the DEX trading cost is high compared to the CEX. As a result, the expected trading volume on the DEX is low, and DEX liquidity providers commit less capital. As A increases, the expected profits of DEX liquidity providers rise, and

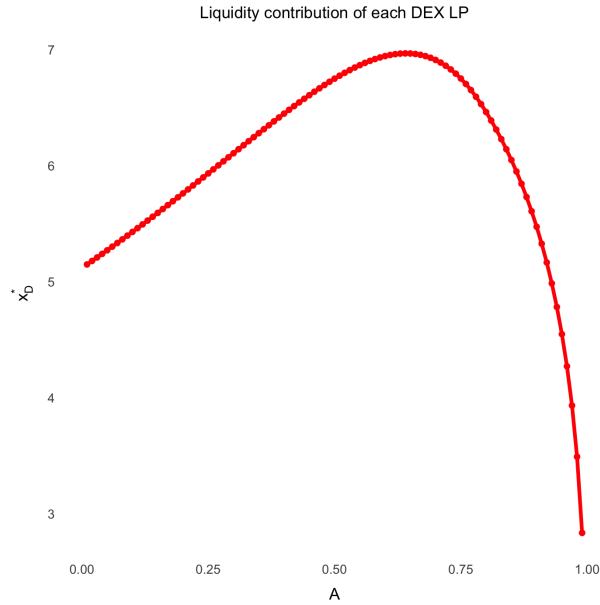


Figure 5. This figure reports the liquidity contribution of each liquidity provider in the DEX (x_D) as a function of the curvature of the pricing function (A). Parameters: $f = 0.5\%$, $\rho = 0.151$, $N_C = 15$, $N_D = 3$, $\bar{Q} = 100$, $\nu = 0.95$, $\lambda = 0.05$.

the pool size expands. On the other hand, the expected impermanent loss increases with A . Therefore, as this second effect begins to dominate at higher values of A , the optimal size of the liquidity pool decreases.

4 Empirical Analysis

In this section, we present our empirical analysis based on the economic implications derived from the model above. Our model implications distinguish between (i) normal periods in which trading is predominantly driven by liquidity-trading needs and (ii) market-stress periods following common-value shocks in which arbitrage activity is elevated. Accordingly, we focus on samples that exclude major depegging episodes when testing implications for liquidity trading. For testing implications on arbitrage trading, we focus on the SVB episode in March 2023, during which depeg-related trading is concentrated. We start by introducing the data.

4.1 Data

Our primary data source is Etherscan. Using the Etherscan API, we collect transactions from the three major DEXs: Curve, Uniswap V2, and Uniswap V3. Transactions on decentralized exchanges are categorized into two types: liquidity provision/withdrawals (LP) and liquidity trading (LT), which we refer to as “swaps”. Each transaction record includes parameters such as block number, timestamp, amount of tokens provided (or exchanged), and fees. On Uniswap V3, liquidity providers also have the option to specify a price range.

The second data source is Binance, the largest cryptocurrency CEX. Given our paper’s focus on assets with stable value, we exclude other centralized exchanges like Kraken and Coinbase, as they do not feature trading pairs consisting of two stablecoins, or the trading volumes for such pairs are negligible. Binance offers a comprehensive history of transaction-level data for all traded cryptocurrency pairs. Each trade recorded on Binance includes the timestamp, quantity, and an identifier indicating whether the transaction was initiated by the seller or the buyer.

Tables 1 provides an overview of the data from decentralized exchanges and Binance. Our time period starts on January 1, 2021, and ends on March 30, 2023, where available. Uniswap V3 and some trading pairs on Curve were introduced in May 2022 or later, as indicated in Table 1. The tables indicate that the number of trades on Binance significantly surpasses the number of trades on decentralized exchanges.

In addition, we use the website CurveMonitor.com, which collects all governance proposals voted on by the Curve DAO. This information allows us to track changes in the parameters of liquidity pools, such as trading fees and the curvature of the pricing function.

4.2 Liquidity Trade Size and Peg Deviation

In this section, we empirically examine the trade size and price deviation from peg of liquidity trading based on the model implications stated in Propositions 1 and 2. While the model is stated at the transaction level (one trade per round), we work with daily aggregates (average trade size and average absolute peg deviations); under standard stationarity and law-of-large-

Exchange	Pair	Exchange Fee	Other Fees	Start Date	# obs. Swap	# obs. LP	Pool Contract Address
Uniswap V3	USDC - USDT	0.05%	gas	May 4, 2021	232,408	11,719	0x7858e59e0c01ea06df3af3d20ac7b0003275d4bf
Uniswap V3	USDC - USDT	0.01%	gas	Nov 14, 2021	484,427	11,412	0x3416cf6c708Da44DB2624D63ea0AAef7113527C6
Uniswap V3	DAI - USDC	0.3%	gas	May 23, 2021	321	171	0xa63b490aa077f541c9d64bfc1cc0db2a752157b5
Uniswap V3	DAI - USDC	0.05%	gas	May 4, 2021	107,254	8,357	0x6c6bc977e13df9b0de53b251522280bb72383700
Uniswap V3	DAI - USDC	0.01%	gas	Nov 13, 2021	200,777	5,879	0x5777d92f208679db4b9778590fa3cab3ac9e2168
Uniswap V3	DAI - USDT	0.01%	gas	July 15, 2021	26,972	452	0x48da0965ab2d2cbf1c17c09cfb5cbe67ad5b1406
Uniswap V3	DAI - USDT	0.05%	gas	May 5, 2021	79,222	1,907	0x6f48eca74b38d2936b02ab603f4e36a6c0e3a77
Uniswap V2	USDC - USDT	0.3%	gas	Jan 1, 2021	313,870	23,986	0x3041cbd36888bec7bbcbcc0045e3b1f144466f5f
Curve	USDC - USDT	0.01%	gas, DAO (0.005%)	Jan 1, 2020	119,191	406,180	0xbebc44782c7db0a1a60cb6fe97d0b483032ff1c7
Curve	USDT - DAI	0.01%	gas, DAO (0.005%)	Jan 1, 2020	45,363	-	0xbebc44782c7db0a1a60cb6fe97d0b483032ff1c7
Curve	USDC - DAI	0.01%	gas, DAO (0.005%)	Jan 1, 2020	49,404	-	0xbebc44782c7db0a1a60cb6fe97d0b483032ff1c7
Binance	DAI - USDT	0.01%	no	Jan 01, 2020	6,754,342	-	-
Binance	USDC - USDT	0.01%	no	Jan 01, 2020	44,683,708	-	-

Table 1. Stablecoin Pairs on Major Exchanges. This Table reports the description of selected stablecoin pairs on major exchanges: decentralized – Uniswap V3, Uniswap V2, and Curve, and centralized – Binance. Data starts on January 1st, 2021 (where available) and ends on March 30, 2023.

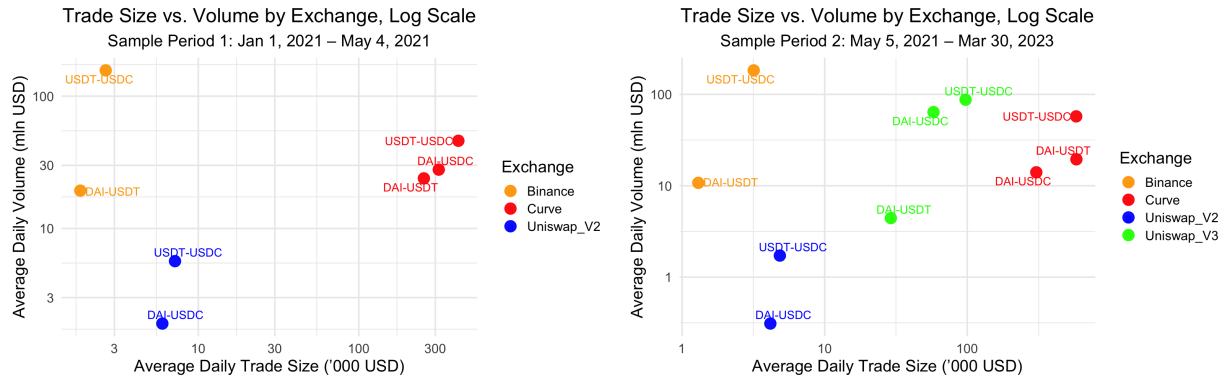


Figure 6. Both figures illustrate the average trade size (in thousand USD) and trading volume (in million USD) on daily data, comparing centralized exchange Binance (depicted in orange) with decentralized exchanges (Curve in red, Uniswap V2 in blue, and Uniswap V3 in green). Data is presented in a log scale for clarity, given the wide range of values. The left-hand panel covers the period from January 1, 2021, to May 4, 2021. This timeframe precedes the launch of Uniswap V3, and therefore, includes data for Binance, Curve, and Uniswap V2 only. The right-hand panel spans from May 5, 2021, to March 30, 2023 and includes data on Uniswap V3.

numbers arguments, cross-venue comparisons in the data map to the corresponding conditional moments implied by the model.

To align the empirical tests with the model’s liquidity-trading state, we exclude major depegging windows (in particular, the SVB episode in March 2023 and the Terra–Luna collapse in May 2022) whenever the corresponding measures are meant to capture typical, non-stress trading.

Figure 6 presents the average trade size and trading volume (in log scale) across exchanges. The left-hand panel shows the period from January 1, 2021, to May 4, 2021 (before the launch of Uniswap V3). The right-hand panel shows the period from May 5, 2021, to March 30, 2023 (following the launch of Uniswap V3). Both figures show statistics on stablecoin-stablecoin trading pairs (USDT-USDC, DAI-USDC, and DAI-USDT).

The results are consistent with the model implication in Proposition 1: The centralized exchange Binance shows the lowest average trade size. In contrast, Curve, a platform specifically designed for stablecoin trading, attracts the largest stablecoin traders. The trade size on Curve varies from 143.6k USD to 588.58k USD, while that of Binance is only between 1.23k and 3.18k USD. In addition, Uniswap V2 and Uniswap V3 are positioned between Binance and Curve. The average daily trade size on Uniswap V3 reaches 98k USD for the USDC-USDT trading pair.

Table 2. Average daily trade size across exchanges

	log(Trade Size)
Curve	5.015*** (0.043)
Uniswap v2	-0.318*** (0.052)
Uniswap v3	3.111*** (0.035)
Curve × Gas	0.001* (0.0004)
Uniswap v2 × Gas	0.010*** (0.001)
Uniswap v3 × Gas	0.002*** (0.0004)
Observations	8,580
Pair × Day FE	Yes
Adjusted R^2	0.885

The table presents the results of the regression in Equation 27. The dependent variable is the logarithm of average daily trade size. Daily trade size is measured in thousands of USD, gas is measured in gwei. Standard errors clustered at the pair-by-day level are reported in parentheses. The sample excludes May 7–13, 2022 and March 11–23, 2023. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

One potential concern is that the observed differences in trade sizes between DEXs and Binance may be driven by gas fees on the Ethereum network. During the period considered, gas fees were non-negligible and could have affected trading behavior on DEXs, while they are irrelevant for centralized exchanges such as Binance.

To address this concern, we explicitly control for gas prices. We collect a time series of Ethereum gas prices from Etherscan and estimate the following regression:

$$\log(\text{TradeSize}_{i,p,t}) = \alpha + \sum_{k \in \{U2, U3, Crv\}} \beta_k \cdot \mathbb{1}_{\{i=k\}} + \sum_{k \in \{U2, U3, Crv\}} \theta_k \cdot \mathbb{1}_{\{i=k\}} \times \text{Gas}_t + \gamma_{p,t} + \varepsilon_{i,p,t}, \quad (27)$$

where $\text{TradeSize}_{i,p,t}$ denotes the average trade size on exchange i (Uniswap V2, Uniswap V3, Curve, Binance) for trading pair p (USDT-USDC, DAI-USDT, DAI-USDC) at time t . The indicator $\mathbb{1}_{\{i=k\}}$ captures exchange-specific effects relative to Binance, Gas_t is the average daily gas price on the Ethereum blockchain, and $\gamma_{p,t}$ denotes pair-day fixed effects.

The results are presented in Table 2. They show that, while higher gas prices are associated

Table 3. Average stablecoin price deviations from the peg

Trading Pair	Binance $ 1 - p $	Curve $ 1 - p $	Difference (DEX–CEX)	p-value
USDC–USDT	4.73	4.85	0.124	0.132
DAI–USDT	5.38	5.18	-0.198	0.023
Pooled	5.09	5.03	-0.054	0.371

This Table reports the mean absolute price deviation from the \$1 peg for two stablecoin trading pairs—USDC–USDT and DAI–USDT—on Binance and Curve, and p-values for t-tests of the differences. Values are expressed in basis points (bps). The figures are based on trade-level data. The sample period is January 1, 2021 to April 28, 2023. Two major depegging events—the collapse of Luna from May 7–13, 2022, and the collapse of Silicon Valley Bank (SVB) from March 11–23, 2023—are excluded from the sample.

with higher trade sizes on DEXs, our main finding remains unchanged: even after accounting for gas fees, average trade sizes on Curve are significantly larger than those on Binance.

Next, in Table 3, we examine the average stablecoin price deviations from the peg on Curve and Binance for two trading pairs: USDC–USDT and DAI–USDT. As our interest is to compare the average price deviations in "normal market times," i.e., when stablecoin prices are driven by private-value shocks rather than common-value shocks, we exclude two major depegging events: the collapse of the Terra–Luna stablecoin in May 2022 and the collapse of Silicon Valley Bank in March 2023.

We find that although Curve accommodates significantly larger trades, the difference in average price deviations across the two venues is negligible. For the USDC–USDT trading pair, the average price deviation across all trades is 4.73 basis points on Binance and 4.85 basis points on Curve. Similarly, for the DAI–USDT pair, the average deviations are 5.38 and 5.18 basis points on Binance and Curve, respectively. The overall difference in price deviations between the two exchanges is -0.05 basis points and is statistically insignificant, consistent with our model predictions.

4.3 Arbitrage Trading Volume

In this section, we empirically examine the arbitrage trading volume based on the model implications stated in Proposition 3. Towards this direction, we consider the market episode of the collapse of Silicon Valley Bank (SVB) in March 2023. Specifically, on March 11, 2023, the issuer

of USDC, Circle, announced its exposure to the failing bank. This announcement was followed by heightened activity in cryptocurrency markets and a substantial depeg of USDC.

We measure arbitrage activity using daily trading volume on each venue during this stress window. While total volume includes liquidity trading as well as arbitrage trades, depeg-related arbitrage demand is a first-order driver of trading volume during the event, so the venue comparison provides a reduced-form test of the model's prediction. One important practical caveat is that exchange-specific trading constraints (e.g., temporary delistings or trading halts) can affect observed venue volumes during stress and are not modeled; the evidence should therefore be interpreted as comparing realized venue activity given institutional frictions.

In Figure 7, we report daily trading volume for two stablecoin pairs—USDC–USDT and DAI–USDT—on Binance (CEX) and Curve (DEX). Daily trading volume increased dramatically on both venues. However, the spike in trading volume on Curve was significantly larger than on Binance, despite Binance typically exhibiting substantially higher liquidity and trading volume under normal market conditions.

For the USDC–USDT trading pair, trading volume on Curve exceeded 2.81bn USD on March 11, whereas on Binance it reached a maximum of 1.33bn USD. This observation is consistent with the model prediction that during periods of market stress, stablecoin trading volume in liquidity pools with a high parameter A exceeds that on the CEX.

4.4 DEX Liquidity Pool Size

In this section, we study the effects of varying the design parameters of the DEX on the size of the liquidity pool based on the model implications stated in Proposition 4.

We focus on the largest liquidity pool on Curve that consists of the three largest stablecoins USDT, USDC, and DAI (named "3pool"). We note that the market design of liquidity pools on Curve DEX has evolved over time through a voting procedure of Curve token holders. We gather information on those governance proposals that altered either the trading fee (f in our model) or the curvature of the pricing function (parameter A) in the "3pool". In Table 4 we provide

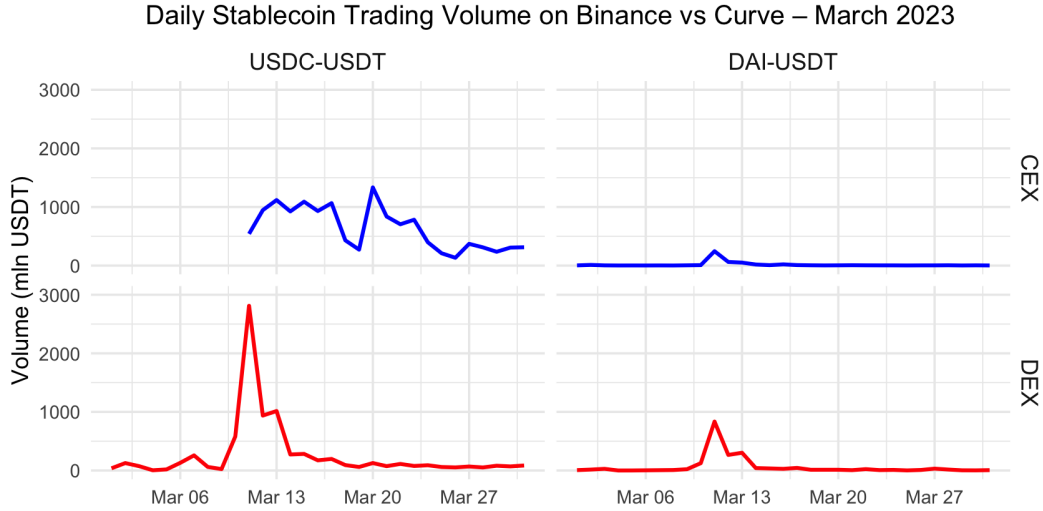


Figure 7. This figure plots daily stablecoin trading volume (in mln USDT) on Binance and Curve for two trading pairs, USDC–USDT and DAI–USDT, during March 2023. The period of market stress between March 10 and 15, 2023 corresponds to the collapse of Silicon Valley Bank (SVB). Note that Binance did not trade USDC between March 1 and March 10, 2023.

Proposal	Date Implemented
Decrease A from 5000 to 2000	26/05/2022
Reduce fee to 0.01%	10/05/2022
Increase from 2000 to 5000 for 3pool	23/02/2022
Reduce the 3pool trade fee (from 0.04%) to 0.03%	02/07/2021
Increase A to 2000	06/05/2021
Increase A parameter to 600	18/02/2021
Increase A (from 100) to 200	16/10/2020

Table 4. This Table provides the list of relevant implemented governance proposals on Curve Exchange that altered either the smooth parameter of the pricing function (parameter A) or the pool fee (f). Source: The information about proposals is collected from the Curve Finance website, Curve Monitor, and Etherscan (contract $0x6e8f6D1DA6232d5E40b0B8758A0145D6C5123eB7$).

the list of relevant proposals. In total, there are 7 proposals, five of them changed the pricing curvature, and the remaining two altered the pool fee paid by traders.

We estimate the following regression:

$$Y_{it} = \alpha + \beta A_t + \gamma f_t + controls_t + \varepsilon_{it} \quad (28)$$

where Y_{it} is the total number of stablecoins deposited in the 3pool (referred to as the pool balance) for stablecoin i at time t , A_t is the parameter governing the curvature of the pricing func-

	balance
A	-0.045*** (0.007)
f	560.60*** (8.11)
Std Bitcoin Return	82.93*** (14.70)
USDC Dummy	-3.681 (17.31)
USDT Dummy	-153.00*** (17.31)
Intercept	-218.80*** (25.12)
R^2	0.78
N. obs	1613
Period	01/20-04/23

Table 5. This Table presents regressions of the pool balance in the 3crv pool (DAI-USDC-USDT) on the parameter of the curvature of the pricing function, pool fee, the intra-day standard deviation of Bitcoin returns, and token fixed effects. Pool Balance is measured in mln of tokens. The standard deviation of Bitcoin returns is computed based on the second-level data on Binance (BTC-USDT trading pair). Standard errors in parentheses. Fees and standard deviation are measured in basis points.

tion, and f_t is the pool fee at time t . We control for the intra-day standard deviation of Bitcoin returns, gas price, and token fixed effects.

Table 5 displays the results. We find that changes in A and f significantly affect the amount of liquidity provided in the 3pool (i.e., the pool balance). In particular, an increase in the pool fee f leads to an increase in liquidity provided, while a decrease in the curvature of the pricing function (i.e., a flatter pricing function induced by a higher A) is associated with a reduction in liquidity provided. This is consistent with the model prediction that, in liquidity pools with high A , a further increase in A leads to a reduction in the pool balance, as a higher A is associated with larger expected losses for DEX liquidity providers to informed arbitrageurs during depeg events.

5 Conclusion

Benefiting from their price peg, stablecoins play a central role in the DeFi ecosystem and hold promise as a general medium of exchange. Unlike mechanisms that maintain stablecoin pegs through the primary market—access to which is often limited to a small group of large investors—we examine stablecoin trading and deviations from the peg in the secondary market, which is accessible to all investors, including retail traders.

We focus on decentralized exchanges (DEXs) such as Curve that specialize in stablecoin trading and coexist with centralized exchanges (CEXs) such as Binance. We develop a simple model of stablecoin trading in which a DEX employs a low-convexity bonding curve to set prices, liquidity traders choose between the DEX and the CEX conditional on trade size, and an arbitrageur exploits price staleness following de-peg shocks. Using trade-level stablecoin data, we empirically confirm the model’s implications of the key economic mechanism— price impact is lower on DEXs than on CEXs—for traders’ venue choices, arbitrage activity, and deviations from the peg. Our findings not only contribute to the understanding of stablecoin market design but also have broader implications for on-chain trading of traditional assets with relatively stable values, such as Treasury bills and bank deposits.

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Appendices

In this appendix, we provide details of data and measures, and also conduct robustness checks and further analyses.

A.1 The Pricing Curve in the Model

In this section, we present a comparison of the bonding curve used in the model and that of the Curve.

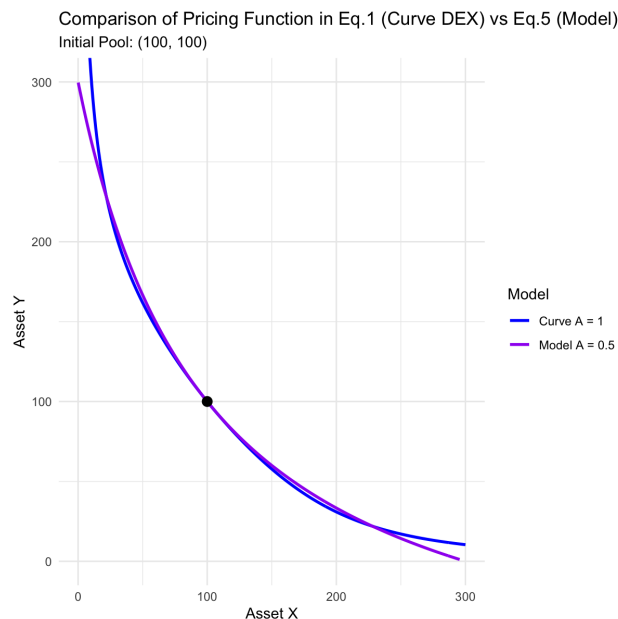


Figure A.1. AMM Pricing Function: Curve vs Model

A.2 Conditions for the Non-Degenerate Equilibrium

In this section, we provide details of how Assumption 1 ensures the non-degenerate equilibrium.

Proposition A.1. *Under Assumption 1, the CEX and the DEX are both viable in equilibrium.*

Proof. **Proposition A.1.**

Since $0 < s_D < 1$, we have

$$\frac{N_C(f - \lambda(1 - \bar{v}))}{\rho} < \hat{Q} < \frac{N_C(1 + f - \lambda(1 - \bar{v}))}{\rho}.$$

Therefore, whenever

$$N_C(1 + f - \lambda(1 - \bar{v})) < \rho \bar{Q},$$

we obtain $\hat{Q} < \bar{Q}$, which ensures that the DEX is viable.

In addition, the condition $\lambda(1 - \bar{v}) < f$ is sufficient to ensure positive trading volume on the CEX. From (22), for Q close to zero, the liquidity traders' choice of trading venue depends on the comparison between $\lambda(1 - \bar{v})$ and f . If $\lambda(1 - \bar{v}) < f$, then for sufficiently small Q liquidity traders strictly prefer the CEX, which guarantees that the CEX attracts positive trading volume in equilibrium. \square

A.3 Proofs

In this section, we provide proofs of the key results in the paper. First of all, we discuss the degenerate equilibrium in which either DEX or CEX is not viable.

Proof. **Proposition 1.** Under the assumption that $f > \lambda(1 - \bar{v})$, the average trading cost on the DEX is higher than on the CEX for sufficiently small Q . Moreover, from Eq. (7), the average trading cost on the DEX is concave in Q , since

$$\frac{\partial^2(1 - P_D)}{\partial Q^2} = -2 \frac{(1 - A)^2 X_D}{((1 - A)Q + X_D)^3} < 0.$$

By contrast, the average trading cost on the CEX is linear in Q . Hence, there exists a unique $\hat{Q} > 0$ that solves the indifference condition in equation (23).

For parameter values under which the DEX is viable, this threshold satisfies $0 < \hat{Q} < \bar{Q}$.

Therefore, the venue choice rule in (25) can be rewritten as

$$\frac{\rho Q}{N_C} + \lambda(1 - \nu) \begin{cases} < f + \frac{(1 - A)Q}{(1 - A)Q + X_D} & \text{for } 0 \leq Q \leq \hat{Q}, \\ \geq f + \frac{(1 - A)Q}{(1 - A)Q + X_D} & \text{for } \hat{Q} \leq Q \leq \bar{Q}, \end{cases} \quad (\text{A.1})$$

so that liquidity traders with $Q \in [0, \hat{Q}]$ optimally trade on the CEX, while those with $Q \in [\hat{Q}, \bar{Q}]$ trade on the DEX. With trade sizes uniformly distributed on $[0, \bar{Q}]$, the average trade size in each venue is:

$$\mathbb{E}[Q | \text{CEX}] = \frac{\hat{Q}}{2} \quad \text{and} \quad \mathbb{E}[Q | \text{DEX}] = \frac{\hat{Q} + \bar{Q}}{2}.$$

It then follows that

$$\mathbb{E}[Q | \Omega_{\text{CEX}}] < \mathbb{E}[Q | \Omega_{\text{DEX}}].$$

□

Proof. Proposition 2. We use the modification of Figure 3, which reports $1 - P_C(Q)$ and $f + 1 - P_D(Q)$ as a function of trade size Q . In equilibrium, traders with $Q \leq \hat{Q}$ execute trades on the CEX, while traders with $Q \geq \hat{Q}$ —on the DEX.

The realized stablecoin price deviation induced by a trade of size Q equals $1 - P_C(Q)$ if the trade is executed on the CEX and $1 - P_D(Q)$ if the trade is executed on the DEX. Let Q_0 denote the intersection of $1 - P_C(Q)$ and $1 - P_D(Q)$, i.e. $1 - P_C(Q_0) = 1 - P_D(Q_0)$ (Figure A.2).

In the left panel of Figure A.2, the parameters are fixed at $f = 0.5\%$, $\rho = 0.151$, $N_C = 15$, $N_D = 3$, $\bar{Q} = 100$, $\nu = 0.95$, $A = 0.7$, and $\lambda = 0.05$. As Q is uniformly distributed over $[0, \bar{Q}]$, the mean value of $1 - P_D(Q)$ over $Q \in [\hat{Q}, \bar{Q}]$ is strictly larger than the mean value of $1 - P_C(Q)$ over $Q \in [0, Q_0]$. For values of $Q \in (Q_0, \hat{Q})$, we have $1 - P_C(Q) > 1 - P_D(Q)$. However, when f is sufficiently small, \hat{Q} lies arbitrarily close to Q_0 , so that the interval (Q_0, \hat{Q}) has negligible measure. Therefore, the average realized price impact (and hence stablecoin price volatility) is higher on the DEX than on the CEX.

In the right panel, the parameters are fixed at $f = 25\%$, $\rho = 0.13$, $N_C = 1$, $N_D = 3$, $\bar{Q} = 10$,

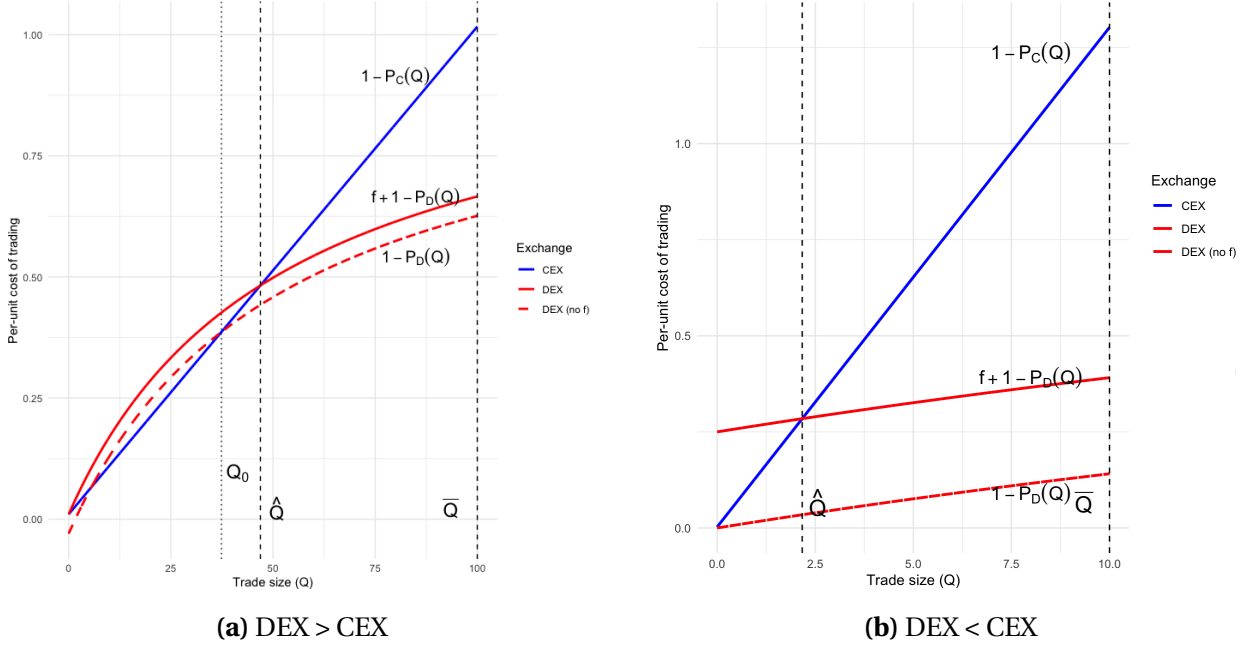


Figure A.2. Stablecoin price deviations from the peg of \$1 in CEX ($1 - P_C(Q)$) vs. DEX ($1 - P_D(Q)$) as a function of trade size Q for two different set of parameters. In (a), the equilibrium average price deviation on the DEX is larger than that on the CEX. In (b), the opposite holds.

$\nu = 0.95$, $A = 0.9$, and $\lambda = 0.05$. In this case, when both f and A are high, in equilibrium the average price deviation on the CEX ($E[1 - P_C(Q) | Q < \bar{Q}]$) is larger than that on the DEX. \square

Proof. **Proposition 3.**

Combining Eq. (16) and Eq. (21), it follows that $q_D > q_C$ if and only if

$$\frac{X_D}{1 - A} \left(\frac{1}{\sqrt{\bar{\nu}}} - 1 \right) > \frac{N_C}{2\rho} \left(1 - \lambda(1 - \bar{\nu}) - \bar{\nu} \right) \quad (\text{A.2})$$

\square

Proof. **Proposition 4.**

From Eq. (23), \hat{X}_D can be expressed as:

$$X_D = (1 - A)\hat{Q} \left(\frac{1}{\frac{\rho\hat{Q}}{N_C} + \lambda(1 - \bar{\nu}) - f} - 1 \right).$$

Since $\hat{Q} \in [0, \bar{Q}]$ is bounded and the term in parentheses is bounded, it follows that X_D is

proportional to $(1 - A)$. Hence,

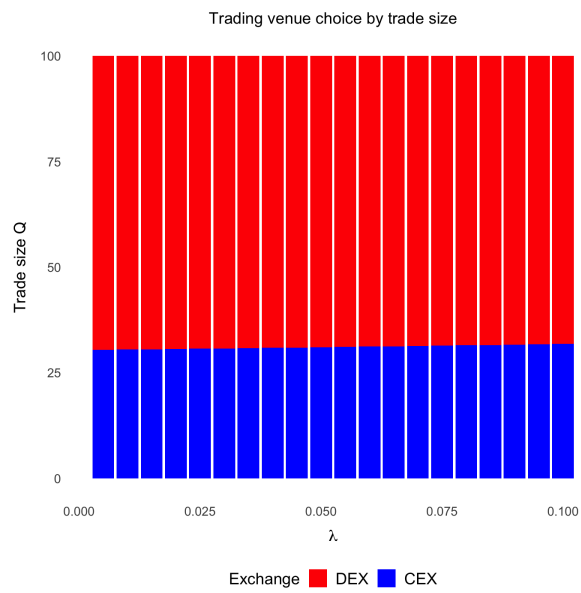
$$\lim_{A \rightarrow 1} X_D = 0.$$

This implies that \hat{X}_D is decreasing for A sufficiently close to 1. Therefore, there exists $A^* \in [0, 1)$ such that \hat{X}_D decreases for all $A > A^*$.

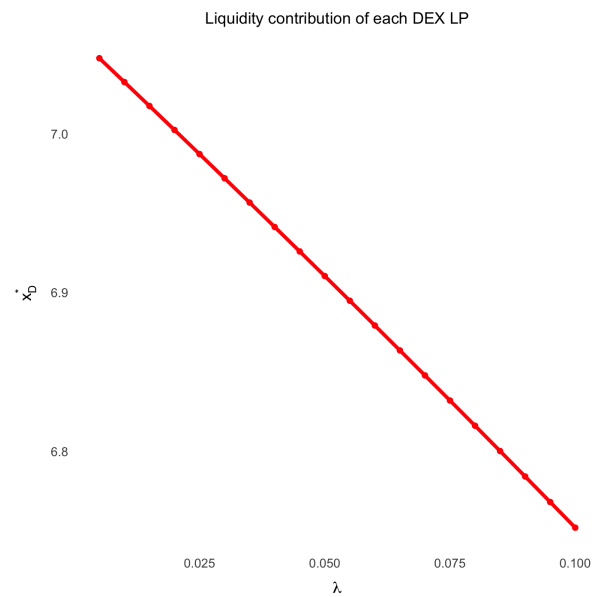
□

A.4 Effects of the Probability of De-peg Shock

An increase in the probability of the common-value shock has two effects in the model. First, a higher λ increases the expected impermanent loss of liquidity providers in the DEX, which in turn leads to a decrease in the amount of liquidity committed to the liquidity pool in the DEX. Second, however, a higher λ also increases the cost of trading in the DEX for all trade sizes. As a result, as λ increases, \hat{Q} also increases. However, as shown in Figure 5, the second effect is small and, as a result, the first effect on X_D dominates, so the liquidity pool size decreases with the probability of a de-peg event.



(a) Trader choice between CEX and DEX



(b) Liquidity contribution in the DEX

Figure A.3. This figure reports comparative statics with respect to the probability of the common-value shock (λ). The left plot shows the liquidity trader's choice between the CEX (blue) and the DEX (red) as a function of trade size Q . The right plot shows the liquidity contribution of each liquidity provider in the DEX (x_D). Parameters: $f = 0.5\%$, $\rho = 0.151$, $N_C = 15$, $N_D = 3$, $\bar{Q} = 100$, $v = 0.95$, $A = 0.7$.