Uniswap and the emergence of the decentralized exchange

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Abstract

Despite blockchain based cryptoassets trading since 2009, there has been a functional gap between on-chain transactions and trust based centralized exchanges. Uniswap, a decentralized exchange, bridges this gap. Uniswap's constant product automated market maker enables the trading of blockchain tokens without relying on market makers, bids or asks. This reimagines conventional financial market structure in ways that challenge regulation, and increases market completeness as any size of volume can be traded at any time in a predictable way. We apply ARDL and VAR methodologies to 154 days of Ether-Tether trading pair from the Uniswap V2 exchange. We find that liquidity providers and arbitrageurs ensure the ratio of reserves match the trading pair price, and therefore Uniswap can be an effective financial market.

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Keywords: Uniswap, Decentralized exchange, Blockchain, Ethereum, Tokenomics

Highlights

- Uniswap is a decentralized exchange based on liquidity reserves provided by users.
- Ratio of liquidity reserves (the Uniswap price) is cointegrated with the token price off Uniswap.
- Decentralized exchanges jeopardize regulatory strategies focused on institutions.

1. Introduction

This paper is focused on a rapidly growing application of blockchain - the decentralized exchange (DEX). On 17 May 2021, USD 1.7 billion worth of digital tokens traded on the Uniswap V2 DEX in a single

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day. These trades utilized almost USD 9 billion of committed liquidity.[1] In the prior year the platform's volumes had exceeded that of the largest centralized cryptoasset exchange Coinbase.[2] Despite this success, the majority of cryptoasset trading takes place on centralized exchanges. The irony of this is that the record keeping functionality of blockchain makes them natural payment and token transfer mechanisms. Blockchains such as Bitcoin are payment systems (Huberman et al., 2019). In comparison, centralized exchanges offer consistent transaction costs, fast settlement and optimized user interfaces. The negative of such venues are the regular hacks, and collapses, that jeopardize the assets they custody. Gandal et al. (2018) examines the fall of the Mt Gox exchange as well as the increasing price manipulation leading up to the actual event. Only recently have DEXs gained significant share of cryptoasset volumes relative to centralized exchanges. Lin (2019) identifies four dimensions across which exchanges can be decentralized, including (1) the blockchain platform, (2) the mechanism for discovering a counterparty, (3) the order matching algorithm and (4) transaction settlement. Choices regarding these functions impact an exchange's trade off between performance, privacy and capital intensity. Lin (2019) enumerates the benefits of DEXs as lower counterparty risk, potentially lower fees, and more trading pairs. Trends favoring a switch towards DEXs include (1) increasing quantity of distinct cryptoassets, (2) the regulatory risk of listing a cryptoasset on a centralized exchange, and (3) user preferences to avoid Know Your Customer and Anti Money Laundering (KYC/AML) regulations required by a centralized exchange. Centralized exchanges are a focus of regulatory actions, with the CFTC and SEC charging the derivatives platform Bitmex with providing US based customers access to unregulated financial derivatives, and not following AML requirements CFTC (2020). In the UK, FCA (2020) banned the sale of derivatives that reference cryptoassets to retail investors. Importantly, the FCA has not banned the trading of cryptoassets. Uniswap and other DEXs are not offering derivatives, but it is clear that both regulation and cryptoasset infrastructure continue to evolve at speed. Alexander and Heck (2020) details the problems arising from inconsistent regulation of cryptoasset markets. The increasing significance of DEXs will make financial regulation more difficult.

Research into DEXs connects to the literature on financial market infrastructure and microstructure. Lees (2012) provides an overview of conventional capital markets. All financial markets seek to optimize price or transactions by bringing multiple parties to a single exchange. That electronic exchanges can be distributed geographically is not new. Biais et al. (2005) reviews the microstructure literature including transaction costs and bid ask spreads. Both centralized exchanges and early DEXs utilize order books of bids and asks. The bid consists of prices and volumes participants are openly willing to buy at. The ask

[1] v2.info.uniswap.org/home
[2] cryptobriefing.com/uniswaps-daily-volume-overtook-coinbase-more-80-million/

consists of prices participants are willing to sell at. If the same party engages on the bid and the ask at the same time, they are a specialist or market maker, looking to profit on the spread. Comerton-Forde et al. (2010) find that market maker balance sheet and income statement variables impact time variation in liquidity - in other words spreads widen when specialist participants have large positions or lose money - and the benefits of market makers become negatives during times of stress. However an alternative to a bid-ask based financial market is a disintermediated reserve based model that holds pools of assets that traders can access. Uniswap V2 is such a model.

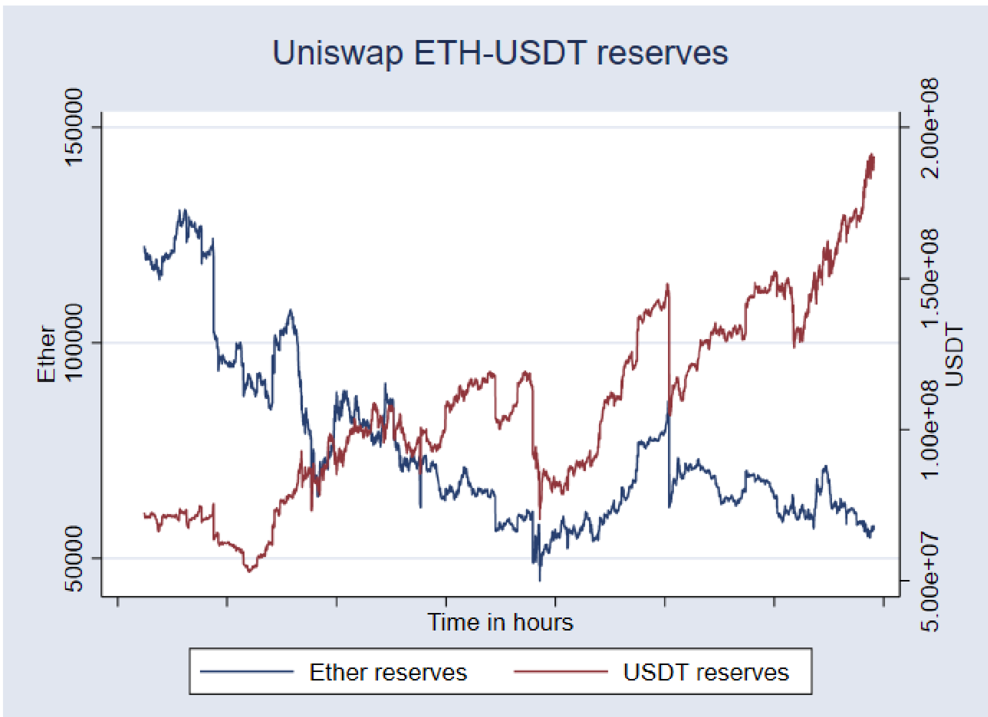

Figure 1: Ether and Tether reserves for the ETHUSDT pair on Uniswap

Liquidity providers (LPs) commit proportionate quantities of two cryptoassets to form the basis of a trading pair (Figure 1 shows the reserves for the ETHUSDT pair). In return LPs receive 0.3% of the value of trades. Angeris and Chitra (2020) notes how Uniswap applies a constant product rule to these reserves to map them to a marginal price. Further detail on these mechanics are provided in subsection 2.2. We utilize an hourly dataset of 154 days of cryptoasset reserves for the ETHUSDT pair from Uniswap, and explore the research question: are DEXs, in particular Uniswap, an effective cryptoasset exchange? If that is the case, then they improve market completeness in two ways. As DEXs replace non-linear liquidity providing agents with linear pricing curves (1) prices are available at any volume, and (2) are less influenced by agent profit and loss. We examine this question with three testable hypotheses.

- H1: The price of the ETHUSDT Uniswap pair matches its exchange rate off Uniswap.

In a centralized exchange, market makers and participants ensure varying degrees of the Efficient Market Hypothesis (Fama, 1970). Uniswap uses passive liquidity pools instead of active market makers, and therefore it is logical to test the connection between prices on and off Uniswap. Cointegration of the ratio of reserves and non-Uniswap pricing is a necessary, though not sufficient, condition of the effectiveness of Uniswap. It is where the pricing curve of Uniswap's constant product market maker equates to the price off platform. A series of equilibrium correction Auto Regressive Distributed Lag (ARDL) models are formulated to test this hypothesis. We use a Vector Error Correction Model (VECM) as a robustness test.

- H2: The price of Ether, Bitcoin and the volume of transactions provide information that help predict changes in Uniswap reserves.

Here we examine which independent variables assist in predicting changes in reserve balances. Additionally, ARDL requires that there is at most one cointegrating relationship with the dependent variable.

- H3: Changes in one reserve balance, of a pair, cause changes in the other reserve balance.

ARDL does not prove causality. Therefore we apply a VAR model, and its test of Granger causality, to see if changes in one reserve balance, of a pair, influences the other reserve balance.

Our results contribute empirical evidence that the Uniswap exchange can be an effective cryptoasset exchange. It complements Angeris et al. (2020) that analyses the mathematical implications of different constant function market maker curves. We find a surprising relationship between the price of Bitcoin and underlying reserves. Our VAR analysis suggests that over the study period, changes in Tether reserves Granger causes changes in Ether reserves. The effectiveness of DEXs impacts both market completeness and cryptoasset regulation. Although blockchain promised the ability to digitally trade anything, in practice the liquidity may not have existed. Reserve based markets imply that trades can now be carried out at any volume, enhancing the completeness of financial markets. Furthermore, decentralized marketplaces will challenge the objectives and enforcement capabilities of regulators. In particular, as highlighted by Zetzsche et al. (2020), decentralizing the institution eliminates the venture's need for a registered address and permanently located infrastructure, and therefore reduces the surface it exposes to the authorities. The next section provides background to decentralized finance and Uniswap's pricing mechanism. Following that are sections on Data, Methodology, Results and Discussion. The research closes with a short Conclusion.

2. Background

2.1. Blockchain, speculation and decentralized finance

Blockchain has become synonymous with digital tokens like those traded on Uniswap. However there is more to the technology than this. We highlight five threads. The first is as a mechanism to enable decentralized record keeping - and exemplified by Maersk and IBM's TradeLens project that records the movement of 60% of the world's shipping containers (Jensen et al., 2019). A record agreed by all is by definition accepted as "true". This reduces the need for trust, and at a minimum accelerates dispute resolution. In the future this may enable decentralized decision making. Secondly are the smart contracts coded on the blockchain, that are commonly used to issue and manipulate third party tokens. Shared code, that all agree to be "true", can be thought of as shared rules. This may later open up new types of automation and agent relationships. Cong and He (2019) provides a formal proof of how a blockchain based consensus, using smart contract based prices contingent on delivery, can support new entrants. In their paper, new entrants signal quality by trustlessly guaranteeing buyers compensation if the product fails, explicitly increasing the completeness of the contract space. The shared computer code referred to as smart contracts do not come with guarantees. Rather any consequences are public prior to interaction. The third thread are digital tokens. It is noted that both record keeping and tokens can be separately used to enable payments and the transfer of value. However it is with tokens that we enter the field of tokenomics, and their ability to reduce project networking costs. Catalini and Gans (2016) implicitly divide these cost reductions into venture bootstrapping, where tokens are sold to investors or incentivize employees; and platform scaling where tokens are offered to miners to process transactions, or to evangelize users.

The fourth thread is distributed ledger as a payment infrastructure. There is limited need for a new electronic currency to substitute for bank deposits. However there is demand for a novel payments infrastructure. Internationally, the USA are a pivotal part of the SWIFT payments system used to cut off Iran and sanction multinational companies (Majd, 2018). Critically, a blockchain based Chinese Central Bank Digital Currency (CBDC) would bootstrap a new payments system that can operate separately from existing infrastructures. Furthermore, BOE (2020) discusses the domestic resiliency benefit of a core payment network that sits outside the commercial banking system. But it only touches on why this facilitates features such as negative interest rates: a blockchain based CBDC hands the payment system, user balances and its data to a single system owner. Kahn et al. (2020) argues that distributed ledgers do not change the tradeoffs of retail central bank accounts, but they do change the tradeoffs of offering a token based system.

The fifth thread is conversely the ability of using decentralization to break rules. The rise of blockchain tokens have facilitated online crime and money laundering. Foley et al. (2019) use a variety of network analyses, such as transactions with known dark web wallets, to estimate that one quarter of Bitcoin users were involved with illegal activities, equating to USD 76 billion in transactions. "Cryptocurrencies are transforming...black markets by enabling black e-commerce", Foley et al. (2019, Page 1798). However, the evolution and use of digital tokens suggest that illicit activities are not the primary use case of digital tokens. Firstly, Brainard (2020) observes that the money-like use cases of (1) means of exchange, (2) store of value and (3) unit of account, (which Dwyer (2015) argues were never well addressed by Bitcoin) have increasingly been taken over by stablecoins. BOE (2020) defines cryptoassets as "a type of private asset that depends primarily on cryptography and distributed ledger or similar technology as part of their perceived or inherent value", and stablecoins as a type of cryptoasset "whose value is linked to another asset", i.e. the US dollar. The most popular stablecoin is the Tether digital token (USDT). It is 5% of the value of all cryptoassets, compared to 60% for Bitcoin, but manages double the daily transaction value.[3] Such stablecoins are unsuited to illicit activities as they are typically centralized and easily frozen by their issuers.[4]

Despite the growth of cryptoassets for payments, arguably the leading use case for digital tokens is speculation. This is difficult to address empirically. Lo (2017) provides evidence that the price action of Bitcoin is consistent with it being traded as a proxy for the prototyping phase of a new technology. Ciaian et al. (2017) use an ARDL methodology to find a variety of relationships between Bitcoin, altcoins and a set of macroeconomic variables. These intriguing papers however reveal relatively little consistency or connection between any of these digital assets. Lo and Medda (2020) categorizes and tests a set of ICO tokens, issued prior to 2017, by token function. It highlights the large quantity of funds directed to a set of ventures that consisted of little more than a white paper and a website. Although a number of these projects are still in operation, none have a noteworthy number of users. Other than Bitcoin, Ether and stablecoins, few cryptoassets have retained share of value of the space. Cumulatively, all this speaks to the speculative context of trading such vehicles. Arthur et al. (2016) review the differences between gambling, speculation and investing. The key distinctions are expected value (EV) and variability of returns. Speculation involves a higher EV than gambling (where negative EV is the norm), and higher variability than investing. This is not to deride the importance of speculation. Both venture capital and oil drilling (especially prior to seismic surveys and shale drilling) observe a high number of project failures. In particular in the crypto space, these flows of funds have been critical to the creation of decentralized building blocks, known as primitives.

Uniswap is one of the primitives of the wider space known as Decentralized Finance (DeFi). Multicoin

[3] en.ethereumworldnews.com/tethers-usdt-daily-trade-vol-eclipses-btcs-marketcap-hits-13b/
[4] trustnodes.com/2020/09/26/tether-freezes-30-million-usdt-after-kucoin-hack

Capital founder Kyle Samani defines DeFi as “Enforcing financial contracts through code running on censorship resistant and permissionless public blockchain”.[5] Other large players in DeFi include Compound in the lending and borrowing of cryptoassets, and Synthetix in cryptoasset derivatives.[6] The DeFi space has become popular for liquidity mining or yield farming, where ether, stablecoins and other assets are committed and rewarded. Part of these rewards are payments such as Uniswap’s 0.3% fee for liquidity providers, but the majority are tokens handed out by the venture for platform scaling. Yearn.finance[7] is an example of how primitives are building blocks. Smart contracts manage deposits on its platform, minting assets on Synthetix and trading on DEXs as required, to maximize potential rewards. The emergence of DeFi has exacerbated congestion and operation costs (i.e. gas fees) on the Ethereum network, similar to the situation on the Bitcoin network in 2018. Proof of work blockchain networks are capacity constrained by design (Lo and Medda, 2018). It is how Nakamoto consensus blockchains, such as Bitcoin, enable decentralization and censorship resistance. DeFi primitives are expanding the scope of both these functions.

2.2. Uniswap’s constant product automated market maker

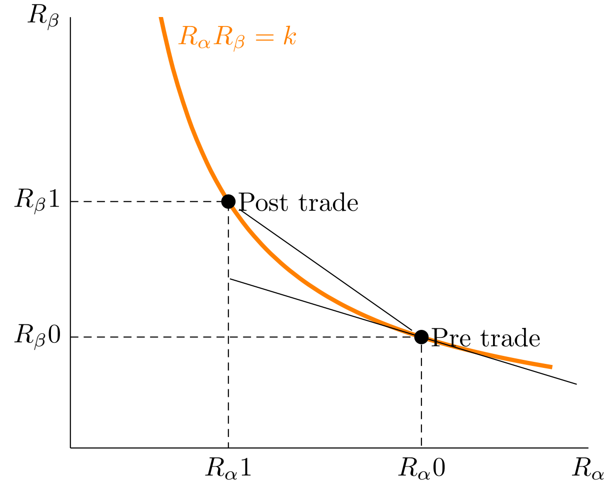

Figure 2: Uniswap constant product automated market maker

A constant product automated market maker (AMM) ensures that the reserves before and after the trade (assuming no fees) adhere to the function:

$$R_\alpha R_\beta = k \tag{1}$$

[5]twitter.com/KyleSamani/status/1308280047984242688
[6]compound.finance and synthetix.io
[7]yearn.finance/dashboard

R_α is the quantity of reserves of asset α; R_β is the quantity of reserves of asset β; and k is a constant. Equation 1 is plotted in Figure 2. Where trades do not change the ratio of reserves (i.e. small) price $p_{\alpha\beta} = R_\beta/R_\alpha$. This is the slope of the tangent where the current mix of reserves intersect the curve. Reserves following a purchase of α adhere to $(R_\alpha - \Delta R_\alpha)(R_\beta + \Delta R_\beta) = k$. The marginal price of a new transaction is trivially the relative change in quantity of the two reserves $p_{\alpha\beta} = \Delta R_\beta/\Delta R_\alpha$. This is the slope of the line joining the before and after points on the curve. The slippage (realized price less than market price) of a trade is positively correlated with trade size and inversely correlated to the size of reserves.

Angeris and Chitra (2020) generalizes the mathematics of constant product market makers, and argues that they provide a tractable optimization problem for arbitrageurs to synchronize on and off chain prices. On a traditional exchange, the price of an asset lies between the bid and the ask, but this does not apply on DEXs. Market makers contribute to price discovery, but liquidity providers are price takers. LPs have no price protection other than the constant product function, which treats price as an output. Because arbitragers capture some of the value of price changes, the assets of an LP excluding fees will underperform a fixed portfolio of the original assets, unless price reverts. This is deceptively referred to as impermanent loss - yet even if price reverts, LPs underperform a portfolio that actively rebalances.[8] The CEO of Uniswap Hayden Adams has referred to LPs as "Long fees/volatility and short volatility/fees"[9] In other words LPs benefit from fees which are a function of volatility, but suffer from price change volatility. Separately, traders can specify a maximum deviation relative to an external price oracle, to protect themselves from short term reserve fluctuations. Notably, large trades on Uniswap are vulnerable to front running, where bots watch Ethereum's mempool of unprocessed trades, and buy and sell around market moving transactions.[10]

3. Data

This study is based on closing hourly Uniswap data for the period 2 December 2020 to 5 May 2021, via multiple queries of the Uniswap V2 subgraph.[11] Subgraphs are a way of storing public data, and accessible via Graph Query Language (GQL). The 3,705 hours captured equates to 154 days. We note that on 5 May Uniswap V3 launched with its concentrated liquidity product, so later data is not comparable. We acquire via API the closing ETHUSDT and BTCUSDT price from the Cryptocompare.com data aggregator, used by firms including Refinitiv and Quandl. The integration of the two datasets is based on the hourly unix

[8] medium.com/coinmonks/uniswap-a-graphical-exposition-part-ii-ba440b3fc522
[9] twitter.com/haydenzadams/status/1309176877869826048?s=20
[10] medium.com/token-flow-insights/how-to-munch-on-pickles-from-a-whale-dinner-edb5628cc769
[11] thegraph.com/explorer/subgraph/uniswap/uniswap-v2

	N	Mean	St dev	Min	p50	Max
Ether reserves, tokens	3,705	75,754	19,562	44,800	69,271	130,929
USDT reserves, tokens	3,705	107,042,548	30,741,537	52,994,920	103,405,152	191,274,496
Total reserves, USD mil	3,705	214	61.5	106	207	383
Ether transaction volume, ETH/hr	3,705	2,630	3,824	573	2,010	194,929
USDT transaction volume, USDT/hr	3,705	3,840,317	3,285,136	405,076	3,116,107	50,567,096
ETH reserves * USDT reserves	3,705	7.76e+12	1.74e+12	3.16e+12	7.89e+12	1.26e+13
Ratio of reserves USDT to ETH	3,705	1,542	631	538	1,629	3,473
ETHUSDT close price, USD	3,705	1,542	632	539	1,627	3,484
BTCUSDT close price, USD	3,705	43,210	13,800	17,649	47,455	64,568
Diff in log Ether reserves	3,704	-.000207	.0131	-.319	-.000137	.14
Diff in log USDT reserves	3,704	.00026	.0127	-.311	.000495	.142

Table 1: Descriptive statistics - 154 day snapshot of Uniswap ETH-USDT pair

timestamps native to both. We do not know the exchange weights or methodology used by Cryptocompare's benchmark exchange ETHUSDT rate. Descriptive statistics for a selection of dataset variables are shown in Table 1. Total reserves for the pair in USD are charted against trading volumes in Figure 3.

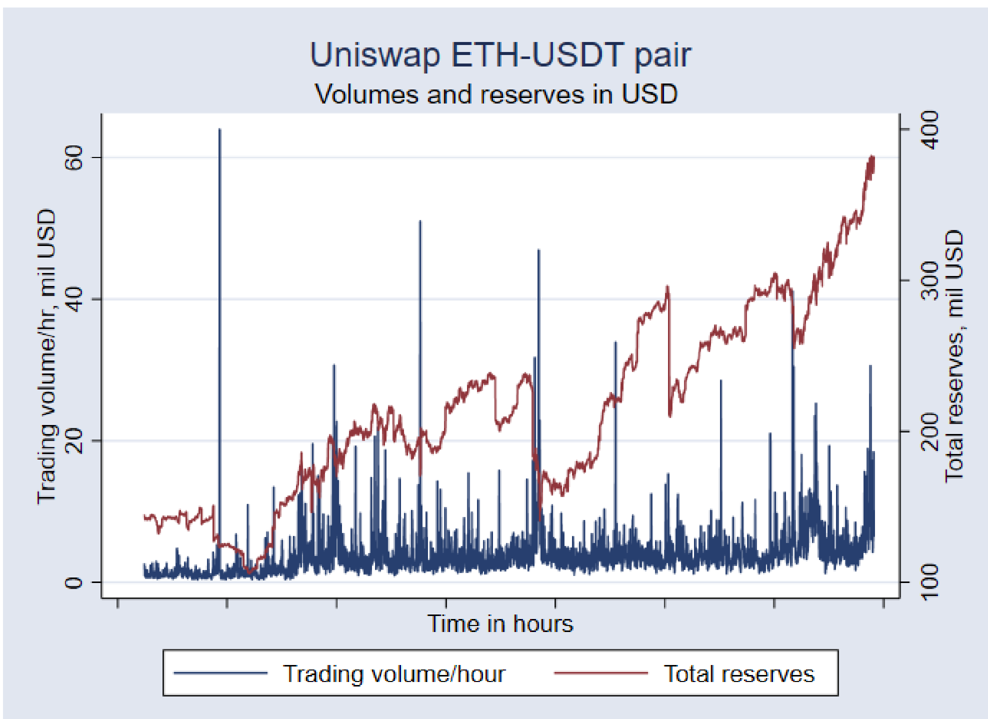

Figure 3: Total reserves and trading volumes for the ETHUSDT pair on Uniswap

4. Methodology

Hypothesis H1 requires us to test for cointegration between price and the ratio of reserves. This cointegration is central to the effective trading of cryptoassets on Uniswap, and can be thought of as a common stochastic trend. Within equilibrium correction ARDL, the test of cointegration is referred to as the Bounds test. We proceed there via (1) categorizing the variables by their order of integration; (2) discussing the framework of the ARDL model; and (3) laying out the equilibrium correction ARDL to which the Bounds test is applied. Although Pesaran et al. (2001) commented that ascertaining the order of integration was unnecessary prior to testing for cointegration under ARDL, this was asserted in a bounded fashion: the framework does not extend directly to variables that are integrated of order two I(2). Therefore we test for unit roots using Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Dickey-Fuller GLS (DFGLS) tests. We use the Akaike Information Criteria (AIC) to determine the appropriate number of lags.

	ADF		PP		DF-GLS	
	level	1st diff.	level	1st diff.	level	1st diff.
Ether reserves	NS	S	NS	S	NS	S
USDT reserves	NS	S	NS	S	NS	S
Ether volumes	S	S	S	S	S	S @ <18 lags
USDT volumes	S	S	S	S	S	S @ <21 lags
ETHUSDT price	NS	S	NS	S	NS	S
BTCUSDT price	NS	S	NS	S	NS	S
Ratio of reserves	NS	S	NS	S	NS	S

3 tests of stationarity applied to 7 time series, on levels and first differences.

NS = non-stationary, S = stationary, at the 5% statistical significance level.

Table 2: Stationarity test results

The results shown in Table 2 indicate that our sample contains a mix of integration orders. Reserves, ratio of reserves and prices are stationary in the first differences I(1), while volumes are likely to be stationary in levels I(0). The DF-GLS test applies a generalized least squares (GLS) detrending on the series prior to running an ADF test, which can improve the power of the test (Elliott et al., 1996). Although both OLS and GLS based tests see declining power in the presence of level or trend breaks, the risk is in misidentifying a stationary time series with a structural break as non-stationary i.e. that the order of integration is over estimated (Cook and Manning, 2004). Therefore ARDL is appropriate and can be represented thus:

$$y_t = c_0 + c_1 t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=0}^{q} \beta_j x_{t-j} + u_t \tag{2}$$

y_t is the dependent variable at time t, with up to p lags included in the model.

x_t is the k x 1 vector of independent variables. For simplicity we display here lag order q as the same for all the independent variables - this does not have to be the case.

u_t is a random error term.

c_0 and c_1 are deterministic intercept and time trend coefficients.

An extension of the model in Equation 2 estimates the long run relationships as an equilibrium correction process (Pesaran et al., 2001). It frames the independent variables as long run forcing of the dependent variable (Kripfganz and Schneider, 2020). This assumes the independent variables are weakly exogenous, and models should consider the directionality of effects during formulation e.g. it may be plausible for transactions to drive changes in reserves, but it is less likely that reserves force transactions. With respect to hypothesis H1, y_t becomes the ratio of reserves R_t; while x_t are the exchange rates of ETH_t and BTC_t with Tether. This is shown in Equation 3.

$$\begin{aligned}\Delta R_t =& c_0 + c_1 t + \alpha(R_{t-1} - \theta_1 ETHUSDT_{t-1} - \theta_2 BTCUSDT_{t-1}) + \sum_{i=1}^{p-1} \varphi_{Ri} \Delta R_{t-i} + \omega_1 \Delta ETHUSDT_t + \\ & \omega_2 \Delta BTCUSDT_t + \sum_{j=1}^{q-1} \varphi_{ETHj} \Delta ETHUSDT_{t-j} + \sum_{k=1}^{r-1} \varphi_{BTCk} \Delta BTCUSDT_{t-k} + u_t\end{aligned} \tag{3}$$

α is the adjustment coefficient.

θ are the long run coefficients on first lags of $ETHUSDT_t$ and $BTCUSDT_t$.

ω are the short run coefficients on the first differences of $ETHUSDT_t$ and $BTCUSDT_t$.

φ are the short run coefficients on the lagged differences of R_t, $ETHUSDT_t$ and $BTCUSDT_t$.

This choice of methodology benefits from its ability to estimate both short run and long run parameters at the same time. Furthermore, Pesaran and Shin (1999) observes that an appropriate estimation of the orders of the extended ARDL(p,m) model is sufficient to both correct for the residual serial correlation, and the problem of endogenous regressors. The ARDL models and coefficients are estimated in Stata utilizing the ARDL package, which is based on Kripfganz and Schneider (2020). These models are subjected to two parts of the ARDL Bounds test. Note that if there is no cointegration, then the ARDL model in Equation 2 is used to estimate relationships between variables and their lags. Hypothesis H1 is investigated via a variety of specifications that look for cointegration between the ratio of Ether and USDT reserves and the exchange rate of ETHUSDT. Hypothesis H2 utilizes the same methodology and searches for the presence of cointegrating and auto regressive relationships between reserves, transactions and price.

Cointegration implies that there are stationary equilibrium relationships between separate non-stationary variables. A corollary of this is that when these variables diverge, at least one of the cointegrated variables converges back to return the system to a long run equilibrium. In Equation 3 the rate of this is estimated by the coefficient α. The Bounds test begins with a Wald test (F-statistic) of the joint hypothesis H_0^F that $\alpha = 0$ and $\sum_{i=0}^{q} \varphi_{xi} = 0$, versus the alternative hypothesis H_1^F that $\alpha \neq 0$ and $\sum_{i=0}^{q} \varphi_{xi} \neq 0$. If the null hypothesis is rejected, then the t-statistic is used to test the second H_0^t of $\alpha = 0$ versus H_1^t of $\alpha \neq 0$. The distributions of these test statistics are nonstandard and depend on the integration order of the independent variables. Kripfganz and Schneider (2020) extend the set of available critical values for the bounds test via estimating response surface models, with each significance level showing four critical values based on I(0) and I(1) for the F-test and t-tests. There can be at most one cointegrating relationship between the independent variables and the dependent variable (although there may be additional cointegrating relationships between the independent variables). The validity of the Bounds test depends on normally distributed error terms that are homoskedastic and serially uncorrelated. For the equilibrium correction ARDL model for the ratio of ETH/USDT reserves to ETHUSDT price, we carry out the Breusch-Godfrey LM test for autocorrelation, and the Breusch-Pagan test for heteroskedasticity. Kripfganz and Schneider (2020) notes that Bounds testing with higher lag order can be useful for addressing remaining serial error correlation, with a more parsimonious model applied after testing for forecasting purposes. Across our analysis AIC, which indicates the optimality of a model, is used to select the set of variables and the number of lags. AIC is less parsimonious than Schwarz's Bayesian Information Criteria (BIC), but in ARDL lowers the risk of serial correlation.

Our study uses a Vector Error Correction Model (VECM) as a robustness check of our hypothesis H1. VECM models are an extension of Vector Auto Regressive (VAR) model we use to test for Granger causality as part of hypothesis H3. We explain how VAR models explain directional changes in cryptoasset reserves before moving on to discussing VECM. VAR modeling specifies as many models as dependent variables (Enders, 1995). We use first difference of logs, to ensure the linearity of changes in the two rapidly increasing reserve balances. In a basic form of two variables with a single lag, VAR modeling would define two equations thus.

$$\Delta(lnETH_t) = \alpha_u + \beta_{u1}\Delta(lnUSDT_{t-1}) + \epsilon_u \tag{4}$$

$$\Delta(lnUSDT_t) = \alpha_e + \beta_{e1}\Delta(lnETH_{t-1}) + \epsilon_e \tag{5}$$

Variables are considered endogenous. Although it is possible to use lags selectively, typically each model repeats the same lagged explanatory variables symmetrically. The Granger causality tests within the VAR model examine if prior period first difference of log of one cryptoasset reserve provides information about the value of current period first difference of log of the other cryptoasset reserve. Tests of Granger causality exploits the directionality of time to imply the directionality of the relationship. Changes in reserve balances are a corollary of trades on the Uniswap platform, and following such trades, the mechanism by which arbitrageurs cointegrate the reserve ratio and price.

VAR models require stationary time series. Earlier, we used first difference of logs of the original I(1) time series to ensure this. VECM models add back some of the information of the undifferenced time series. First it estimates the long-run equilibrium using ordinary least squares. Note that the VAR model is applied to changes in reserves, but hypothesis H1 and this VECM is on the ratio of reserves and the ETHUSDT price. If they are cointegrated, residuals are stationary and estimators super consistent (Enders, 1995).

$$R_t = \alpha + \beta' ETHUSDT_t + \epsilon \tag{6}$$

The differences between actual observations and modeled observations are then included in the VECM. These residuals are the deviation from the long run equilibrium. One form of this is shown below, with one lag and no deterministic trend.

$$\Delta R_t = \alpha + \lambda(R_{t-1} - \beta^{'} ETHUSDT_{t-1}) + \beta_1 \Delta ETHUSDT_{t-1} + \epsilon_1 \tag{7}$$

Note that in multivariate notation typically a cointegration matrix $\prod$ is used to represent the potentially complex nature of the cointegrating relationship, whereas here it is written out explicitly. λ is the error correction term, which estimates how changes in R_t varies when one of the variables deviates from the common stochastic trend. As with VAR modeling, VECM is symmetric and $\Delta ETHUSDT_t$ is also estimated as a function of R_t. In the next section we examine the results.

5. Results and discussion

The results of applying ARDL to our dependent variable, the ratio of Ether to USDT reserves, with the exchange rate of Ether and the exchange rate of Bitcoin (both priced in USDT) are shown in Table 3. As

	[A]	[B]
Adjustment factor		
L. (Diff from equilibrium)	-0.900***	-0.904***
Long run effects		
L. (ETHUSDT price)	1.000***	1.000***
L. (BTCUSDT price)		0.000
Short run effects		
LD. (Ratio of reserves)	-0.063***	-0.063***
D. (ETHUSDT price)	0.951***	0.937***
LD. (ETHUSDT price)	0.069***	0.063***
D. (BTCUSDT price)		0.001***
LD. (BTCUSDT price)		0.000
aic	20387.975	20376.652
bic	20425.273	20432.599
N	3701	3701
Bounds test results		
F-statistic	798.271	536.459
t-statistic	-39.956	-40.116
F-test p-value I(1)	0.000	0.000
t-test p-value I(1)	0.000	0.000

Bounds test rejects H0 no level relationship at 5% significance level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: ARDL - Ratio of reserves and ETHUSDT price

all three variables in this model are I(1), the bounds test statistics are compared to the I(1) critical values. The F-statistic and the t-statistic are more extreme than the related critical values (p-value = 0.000), which rejects the null hypothesis of no level relationship. This provides evidence in favor of the first of our testable hypothesis.

- H1: The price of the ETHUSDT Uniswap pair matches its exchange rate off Uniswap.

This result confirms empirically the effectiveness of Uniswap's reserve balance based Ether and USDT exchange pair on an hourly time frame. These results are supported graphically in Figure 4. The lower part of this figure indicates that some of the arbitrage opportunity is visible in the data, but over the sample period exceeds 1% only 5 times. We note that because of fees, arbitrage is unlikely to take place when the difference between on and off Uniswap prices are less than 0.3%.

Returning to Table 3, during the study time period, the adjustment factor α is 0.9. This suggests that

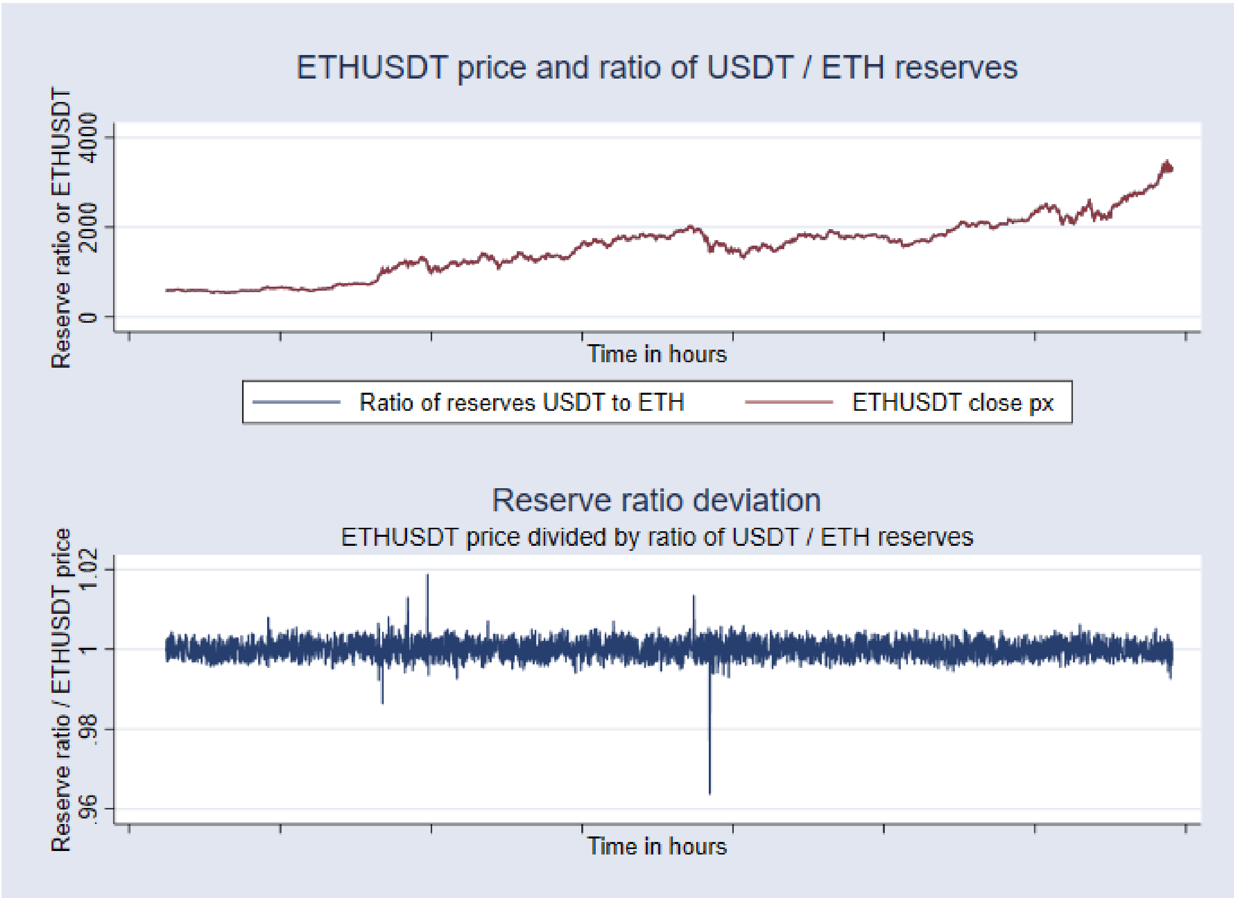

Figure 4: The ratio of Ether and Tether reserves (on the ETHUSDT pair on Uniswap) versus the ETHUSDT price

90% of the difference between the ratio of reserves and the ETHUSDT price is adjusted back to long run equilibrium over the course of the subsequent hour. The long run effects are the coefficients θ on the lagged exchange rates of ETHUSDT and BTCUSDT. In both specifications, the coefficient on the lagged ETHUSDT price is 1. Of the long run coefficients, only ETHUSDT is statistically significant. The short run effects are φ and ω from equation 3, which are the coefficients on the first and lagged differences of our variables. All of the short run effects are statistically significant except for the lagged difference of BTCUSDT. The lower AIC value and the statistical significance of the first difference of BTCUSDT suggests the Bitcoin price does contain information in predicting changes in the ratio of reserves. This may be because of Bitcoin's importance in the cryptoasset space; its impact on trader wealth; or some residual use as a unit of account. We run a Breusch-Godfrey LM test for autocorrelation, which does not reject the null of no serial correlation for 1 to 10 lags at the 5% significance level. The Breusch-Pagan test for heteroskedasticity has a χ^2 test statistic of 0.24 and a p-value of 0.6269. Therefore we do not reject the null of constant variance at the 5% significance levels.

	[C]	[D]
D. (Ratio of reserves)		
L. (Error correction coefficient)	-0.893***	-0.853***
LD. (Ratio of reserves)		-0.023
LD. (ETHUSDT price)		0.038
D. (ETHUSDT price)		
L. (Error correction coefficient)	0.079	0.049
LD. (Ratio of reserves)		0.043
LD. (ETHUSDT price)		-0.033
aic	52822.888	52798.676
bic	52847.757	52848.411
N	3704	3703

Models ordered by AIC descending

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Robustness check - Vector error correction model

As a robustness check, we execute a VECM model to complement our ARDL model. It is an alternative way to examine our two time series, the ratio of reserves between Ether and USDT, and the ETHUSDT price. As required, both are integrated of order 1. The first differences are taken and regressed on zero or one lagged difference, as suggested by selection order information criteria. The error correction coefficient is the critical output - and indicates whether and how the two time series converge. The results in Table 4 indicate that the reserve ratio moves towards the model equilibrium, in both specifications, at the 99.9% statistical significance level. We do not find evidence that the ETHUSDT price moves towards the ratio of reserves. This supports the case that the two time series are cointegrated using a second methodology - and offers evidence that Uniswap pricing moves to match the benchmark.

We note that a finding of cointegration is a necessary, but not sufficient, condition for the effectiveness of Uniswap and its automated market maker. If they are not cointegrated then one of these prices is wrong for a prolonged period, and an arbitrage opportunity for risk free profits would be sustained. Drilling further into the efficiency of the ETHUSDT pair is a vector for future research as more data becomes available. Additionally, analyzing the effectiveness and efficiency of other markets on Uniswap is a different open problem. The issue of the 0.3% trading fee is universal. But the long tailed nature of many of the token pairs on Uniswap results in variations in data available. This paper has focused on a token pair where off

DEX pricing is liquid and high frequency. Yet for many token pairs this is not the case and we highlight the difficulty in empirical analysis of illiquid markets that may exist solely because of a LP based platform such as Uniswap e.g. where there is no off Uniswap benchmark price. However we observe that this is a opportunity as well as a constraint. Anecdotally, it is now possible to observe changes in liquidity as prices changes, which opens up a largely unexplored space for empirical researchers.

- H2: The price of Ether, Bitcoin and the volume of transactions provide information that help predict changes in Uniswap reserves.

	[E]	[F]	[G]
L. (ETH reserves)	0.903***	0.903***	0.899***
L2. (ETH reserves)	0.095***	0.095***	0.099***
(USDT reserves)	0.001***	0.001***	0.001***
L. (USDT reserves)	-0.001***	-0.001***	-0.001***
L2. (USDT reserves)	-0.000***	-0.000***	-0.000***
L3. (USDT reserves)	0.000*	0.000*	0.000*
(ETH price)	-38.534***	-38.519***	-35.147***
L. (ETH price)	32.288***	32.243***	28.683***
L2. (ETH price)	6.746***	6.663***	6.420***
L3. (ETH price)	-1.266*	-1.208*	
L4. (ETH price)	0.731	0.790	
(ETH volume)		-0.001	-0.000
(USDT volume)		0.000	0.000
L. (USDT volume)		-0.000*	-0.000*
(BTCUSDT price)			-0.203***
L. (BTCUSDT price)			0.201***
aic	56105.509	56106.529	56058.911
bic	56180.105	56199.775	56152.157
N	3701	3701	3701

Models ordered by AIC descending

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Short run ARDL model of Ether reserves within ETHUSDT Uniswap pair

In order to explore our second hypothesis H2, we put the ratio of reserves to one side, and run ARDL models with Ether reserves and USDT reserves as our dependent variables. The Bounds tests on these equilibrium correction models (not shown) do not reject the null hypothesis of no level relationship - we find no evidence of cointegration. Because of this, the equilibrium correction models are not appropriate, and

	[H]	[I]	[J]
L. (USDT reserves)	0.862***	0.865***	0.862***
L2. (USDT reserves)	0.160***	0.161***	0.163***
L3. (USDT reserves)	-0.025**	-0.029***	-0.029***
(ETH reserves)	1138.738***	1135.284***	1140.416***
L. (ETH reserves)	-983.720***	-982.353***	-984.978***
L2. (ETH reserves)	-153.029***	-150.898***	-152.422***
(ETH price)	52473.761***	52261.263***	48944.982***
L. (ETH price)	-4.27e+04***	-4.26e+04***	-3.91e+04***
L2. (ETH price)	-9620.627***	-9504.396***	-9637.803***
(ETH volume)		0.947	0.899
(USDT volume)		-0.011*	-0.010*
L. (USDT volume)		0.016***	0.016***
L2. (USDT volume)		-0.004	-0.003
L3. (USDT volume)		0.008	0.008
L4. (USDT volume)		-0.009*	-0.009*
(BTCUSDT price)			208.153***
L.(BTCUSDT price)			-206.205***
aic	1.09e+05	1.09e+05	1.09e+05
bic	1.10e+05	1.10e+05	1.10e+05
N	3701	3701	3701

Models ordered by AIC descending

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Short run ARDL model of USDT reserves within ETHUSDT Uniswap pair

the results of the standard ARDL model are presented in Table 5 and 6. For both dependent variables, we execute 3 models with different independent variables, from specific to general. The lower the AIC the more appropriately specified the model. For both Ether reserves and USDT reserves the most general models with the most variables appear to be preferred in predicting changes in the dependent variables. That the price of Ether impacts reserves makes sense as reserves are a function of (1) liquidity provision in a ratio set by price and (2) trades that exchange one reserve for another at a price dependent on impact. The statistical significance on volumes is somewhat weaker. Notably, the statistical significance of Bitcoin is a surprise. Together these results find in favor of our hypothesis H2. We test the other variables to ensure no additional cointegrating relationships that may impact our earlier analysis. Mostly there is no logic for such directionality, and we do not find such evidence. Over the study time period we also do not find cointegration between the price of Ether and the price of Bitcoin (not shown). The result of this may be different over longer time periods.

Our third hypothesis examines how the Uniswap ETHUSDT reserves returns to equilibrium.

- H3: Changes in one reserve balance, of a pair, cause changes in the other reserve balance.

	[K]	[L]
First difference of log Ether reserves		
LD. (log ETH reserves)	-0.008	-0.013
L2D. (log ETH reserves)	-0.018	
L3D. (log ETH reserves)	0.033	
L4D. (log ETH reserves)	-0.079***	
LD. (log USDT reserves)	-0.045*	-0.047*
L2D. (log USDT reserves)	0.066**	
L3D. (log USDT reserves)	-0.077***	
L4D. (log USDT reserves)	0.019	
First difference of log USDT reserves		
LD. (log ETH reserves)	-0.026	-0.030
L2D. (log ETH reserves)	-0.004	
L3D. (log ETH reserves)	0.043*	
L4D. (log ETH reserves)	-0.002	
LD. (log USDT reserves)	-0.023	-0.022
L2D. (log USDT reserves)	0.044*	
L3D. (log USDT reserves)	-0.090***	
L4D. (log USDT reserves)	-0.045*	
aic	-4.50e+04	-4.50e+04
bic	-4.49e+04	-4.49e+04
N	3700	3703

Models ordered by AIC descending

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: VAR model of Ether and USDT reserves

We investigate this with a VAR model. We begin by reviewing the order selection statistics for our two variables. The lag order selection information criteria suggest 1 and 4 lags. We run two models, one with 4 lags and the second with 1 lag. The results of this are shown in Table 7. Tests of model stability suggest that the Eigenvalues are appropriately within the unit circle.

When the dependent variable is the first difference in log of Ether reserves, the lagged first difference in log of USDT reserves are statistically significant under both specifications. Although the 4 lag model identifies a number of other statistically significant autoregressive relationships, the AIC and BIC are very slightly higher, so do not appear to boost predictiveness.

At the 5% statistical significance level, we reject the null that the first differences of the log of USDT reserves does not Granger-cause changes in the first differences in the log of Ether reserves. For 1 lag the χ^2 test statistic is 5.14 with a p-value of 0.023. For 4 lags the χ^2 test statistic is 29.24 with a p-value of 0.00. However we do not reject the null that the first differences of the log of Ether reserves does not Granger-cause changes in the first differences in the log of USDT reserves (p=0.125 and p=0.154 for 1 and 4 lags respectively). Overall we find evidence in favor of H3 that changes in one reserve balance (USDT), of a pair, Granger causes changes in the other reserve balance (Ether). It is hard to state definitely why this would be the case. However, we can make inferences because on Uniswap every trade has a price impact. Ceteris paribus, arbitrage trades following off Uniswap price changes should not have next period impacts. Only arbitrage trades following trading induced reserve changes should link two time periods. Arguably arbitrage should lead to bidirectional Granger causality. As this is not the case, it may simply be that non-arbitrage trades are tending to be purchases of Ether. Because of the nature of the automated market maker, that is when the USDT balance changes by more. In other words, our Granger causality results are consistent with a reserve ratio at equilibrium impacted by a first trade of buying Ether that pushes USDT reserves out of balance. Afterwards, an arbitrage trade sells Ether (buys USDT) to bring the reserve ratio back into equilibrium with benchmark pricing. This sequence sees a change in USDT reserves leading a change in Ether reserves.

Bringing together the various findings, the error correction ARDL and VECM results support the case that ETHUSDT prices on and off Uniswap V2 are cointegrated. The VECM results suggest that the on Uniswap reserve ratio and price move towards the off Uniswap price, hinting that price discovery for ETHUSDT occurs on centralized exchanges. Hasbrouck (1995)'s Information Share would be a suitable method for analyzing this further. The VAR results delve further into the equilibrium process, finding that changes in the USDT reserves Granger causes changes in the Ether reserve balances.

6. Conclusion

This research provides empirical evidence regarding the effectiveness of reserve based asset exchanges. We find that for the sample period, the ratio of Ether and USDT reserves on the ETHUSDT pair is cointegrated with a third party ETHUSDT exchange rate benchmark. For a constant product automated market maker, this cointegration is a necessary condition of the exchange rate on platform approximating the exchange rate off platform. The success of Uniswap is a rare example of a financial market operating without the classic features of bids and asks, market makers or auctioneers. It is a clarion call to regulators, governments and financial market participants that the innovation and decentralization promised by blockchain based systems is starting to gain traction. It is easy to discount the long term impact of new highly speculative trading instruments, but less easy to deride new financial infrastructure that improves market completeness. DEX structures may be able to complement traditional bid ask based capital markets. An argument made by Lo and Medda (2020) is that blockchain does not build strictly superior systems, but alternative systems that are attractive along uncommon dimensions, e.g. no single point of control (political decentralization) and censorship resistance. Yet improved market completeness would constitute a quantitative benefit of blockchain. Further, DEXs have important implications for regulation, as decentralized exchanges do not require a legal form or fixed geographical infrastructure. This begs the question of how should regulators and governments respond to a marketplace that does not need a registered address and geographically fixed physical infrastructure? To date, rule makers have focused on regulating the institutions of the emerging cryptoasset space (Blandin et al., 2019). This may no longer be possible.

Directions for future research include the potential to add an uncorrelated LP asset to investor portfolios; whether decentralized exchanges are more or less risky than centralized exchanges; and if decentralized exchanges can exist without centralized exchanges providing price discovery.

7. Declaration of interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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