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Abstract

Despite blockchain based digital assets trading since 2009, there has been a functional gap between (1) on-chain transactions and (2) trust based centralized exchanges. This is now bridged with the success of Uniswap, a decentralized exchange. Uniswap's constant product automated market maker enables the trading of blockchain token without relying on market makers, bids or asks. This overturns centuries of practice in financial markets, and constitutes a building block of a new decentralized financial system. We apply ARDL and VAR methodologies to a dataset of 999 hours of Uniswap trading, and conclude that its simplicity enables liquidity providers and arbitrageurs to ensure the ratio of reserves match the trading pair price. We find that changes in Ether reserves Granger causes changes in USDT reserves.

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

Highlights

- Uniswap is a decentralized exchange based on user provided liquidity reserves.
- Ratio of liquidity reserves are cointegrated with the token price off Uniswap.
- During the sample period Ether reserves Granger causes changes in USDT reserves.
- Decentralized exchanges are a financial primitive that may enable novel use cases.

1. Introduction

On 1 September 2020, USD 953 million worth of digital tokens traded on the Uniswap decentralized exchange (DEX) in a single day. These trades utilized almost USD 2 billion of committed liquidity.[1]. In the

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[1] uniswap.info/home

prior week, the platform's volumes had already exceeded the volumes of the largest centralized cryptoasset exchange Coinbase.[2] Two weeks later, Uniswap would issue its own digital governance token and airdrop (i.e. give away for free) at least 15% of its ultimate value to its prior users. As of 2 November 2020 the fully diluted market cap of the Uniswap governance token was USD 484 million.[3]

Although the record keeping functionality of blockchains make them natural payment and token transfer mechanisms, significant blockchain token trading takes place on centralized exchanges. These venues offer consistent transaction costs, fast settlement and optimized user interfaces. The most visible negative of such venues are the regular hacks, and occasional exchange 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 reserves requirements. Lin (2019) enumerates the benefits of DEXs as (1) lower counterparty risk, (2) potentially lower fees, and (3) 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 markets continue to evolve at speed. Alexander and Heck (2020) observes the problems arising from inconsistent regulation of cryptoasset and derivative markets. DEXs will exacerbate these differences.

Traditional exchanges bring all parties to a single marketplace and depend on specialists to provide liquidity. Both they 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 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

[2] cryptobriefing.com/uniswaps-daily-volume-overtook-coinbase-more-80-million/
[3] coingecko.com/en/coins/uniswap

income statement variables impact time variation in liquidity - in other words spreads widen when specialist participants have large positions or lose money. Given sufficient transaction flow, market makers may not be required to provide liquidity to a market. However a more revolutionary alternative to a bid-ask based financial market is a disintermediated reserve based model that holds pools of assets that traders can access.

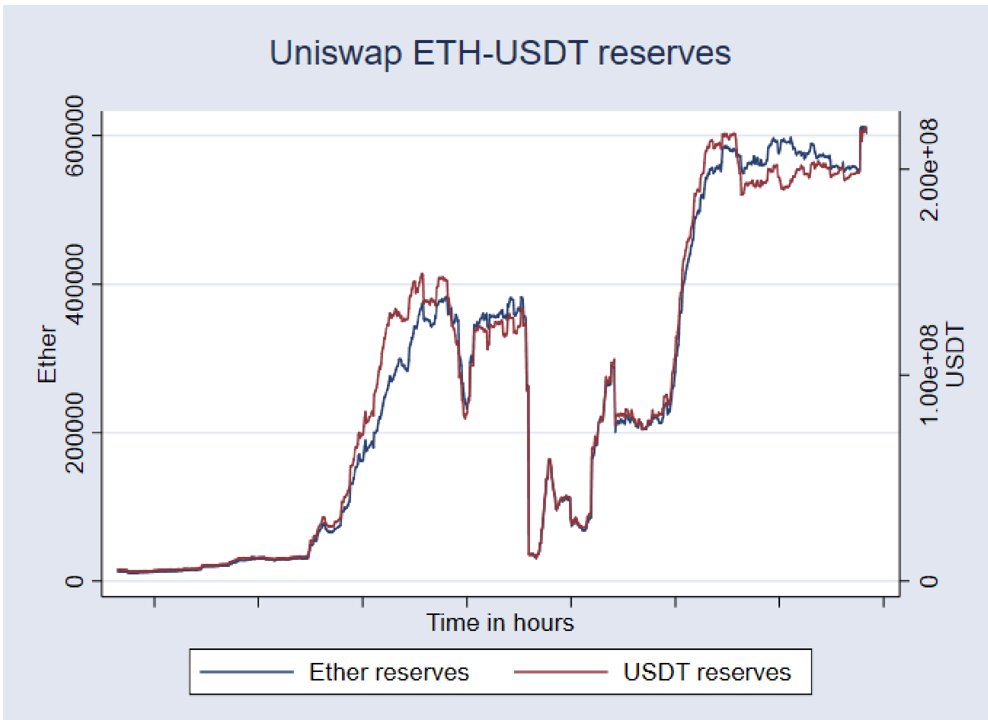

Figure 1: Ether and Tether reserves for the ETH-USDT pair on Uniswap

Uniswap is such a model. Liquidity providers (LPs) commit proportionate quantities of two cryptoassets to form the basis of a trading pair (Figure 1 shows the reserves for the ETH-USDT 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 a dataset of 999 hours of cryptoasset reserves for the ETH-USDT pair from Uniswap, and explore the research question: are DEXs, in particular Uniswap, an effective cryptoasset exchange? We examine this question with three testable hypotheses.

- H1: The price of the ETH-USDT 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 has discarded this strategy, 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 condition of the efficiency and effectiveness of Uniswap. It is where the pricing curve of Uniswap's constant product market maker equates to the price off platform. We formulate a series of equilibrium correction Auto Regressive Distributed Lag (ARDL) models in order to test this hypothesis.

- 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 provide evidence that the the Uniswap exchange is an effective cryptoasset exchange. We find a surprising relationship between the price of Bitcoin and underlying reserves. Our VAR analysis suggests that over the study period, changes in Ether reserves Granger causes changes in Tether reserves. The effectiveness of Uniswap has significant implications for the expansion of use cases for decentralized finance. Although blockchain promised the ability to digitally trade anything, in practice there has not necessarily been the liquidity for it. Reserve based markets imply that trades can now be carried out at any price and at any volume, enhancing the completeness of financial markets. Furthermore, decentralized marketplaces will challenge the objectives and enforcement capabilities of regulators. In particular, decentralizing the exchange 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 corollary of a record all agree with is that it is accepted as “true”, with a commensurate reduction in trust requirements. This may later enable decentralized organization and decision making. Secondly are the smart contracts coded on the blockchain, that are commonly used to issue and manipulate third party tokens, but may in future open up new types of automation and agent relationships. Shared code, that all agree to be “true”, can be thought of as shared rules. 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 the ease of deploying a payment system. There is circumscribed need for a new electronic currency that is a close substitute with bank deposits. However there is a large opportunity in a novel payments infrastructure. The United States and its allies control the SWIFT international payments system and the clearance of dollars - used to both 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 largely separate from the SWIFT international payments system. BOE (2020) discusses the potential 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, deposit accounts and its data to a single system owner.

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 transaction value.[4] Such stablecoins are unsuited to illicit activities as they are typically centralized and easily frozen by their issuers.[5]

Despite the growth of cryptoassets for payments, it is possible that the leading use case for digital tokens is speculation. Unfortunately this is difficult to address empirically. Lo (2017) argues 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. Tan et al. (2020) examine the Garman and Klass volatility of 102 cryptoassets. These papers reveal relatively little consistency and connection between any of these digital assets. 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. Lo and Medda (2020) examines a set of ICO tokens issued in 2017 categorized by token function, and 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 other cryptoassets have retained share of value of the space. This is not to deride the importance of speculation. Both venture capital and oil drilling (prior to the invention of seismic surveying) 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 Capital founder Kyle Samani defines DeFi as ”Enforcing financial contracts through code running on censorship resistant and permissionless public blockchains”.[6] Other large players in DeFi include Curve in the lending and borrowing of cryptoassets, and Synthetix in cryptoasset derivatives.[7] 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

[4]en.ethereumworldnews.com/tethers-usdt-daily-trade-vol-eclipses-btcs-marketcap-hits-13b/
[5]trustnodes.com/2020/09/26/tether-freezes-30-million-usdt-after-kucoin-hack
[6]twitter.com/KyleSamani/status/1308280047984242688
[7]curve.fi/ and synthetix.io/

handed out by the venture for platform scaling. Yearn.finance[8] is an example of how primitives are building blocks. Deposits on its platform are moved around cryptoasset pools such as Curve's, trading on Uniswap as necessary, in order 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.

2.2. Uniswap's constant product automated market maker

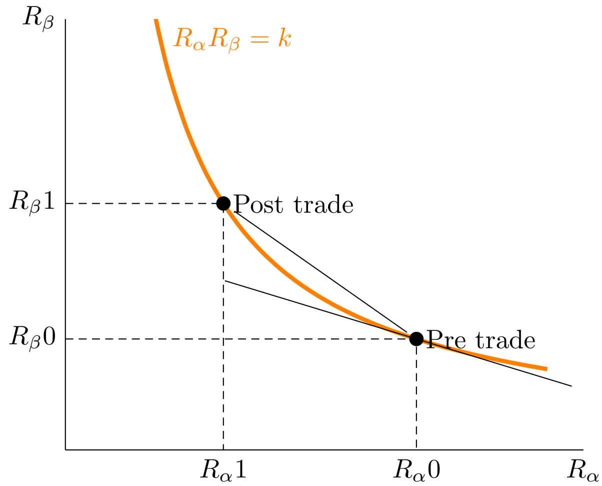

Figure 2: Uniswap constant product automated market maker

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

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

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.

[8]yearn.finance/dashboard

Angeris and Chitra (2020) generalizes the mathematics of constant product market makers, and argues that they work because they provide a tractable optimization problem for arbitrageurs to synchronize on and off chain price data for a pair of cryptoassets. It should be clear that on a traditional exchange, the price of an asset lies between the bid and the ask, but that this does not apply on DEXs such as Uniswap. Market makers are price setters based on their interpretation of supply and demand, but liquidity providers are price takers. LPs have no price protection other than the constant product function, and this 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 (Angeris and Chitra, 2020). This is deceptively referred to as impermanent loss. 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. In particular, large trades on Uniswap are vulnerable to front running, where bots watch the mempool of Ethereum's unprocessed trades, and look to buy before and sell after a market moving trade.[10]

3. Data

The study is based on closing hourly Uniswap data for the period midnight 18 August 2020 to 2pm 28 September 2020, via a 1000 hour query of the Uniswap V2 subgraph.[11] Subgraphs are a way of storing public data, and accessible via Graph Query Language (GQL). As the final hour is incomplete, 999 hours are retained. The Uniswap subgraph does not contain hourly price data, only daily price data. Therefore we acquire via API the matching 999 hours of closing ETH-USDT price from the Cryptocompare.com data aggregator. We do not know the relationship between Cryptocompare's benchmark exchange rate (a composite of unknown weights) and the third party pricing oracle utilized by Uniswap. 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. The large drop in reserves and volumes in the middle of the chart relates to a copy cat exchange SushiSwap, that offered token incentives to LPs willing to switch to their platform. Competitor moves such as these are sometimes referred to as vampire attacks.[12]

[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
[12] finematics.com/vampire-attack-sushiswap-explained/

	N	Mean	St dev	Min	p50	Max
Ether reserves, tokens	999	254,727	208,648	11,195	219,063	611,322
USDT reserves, tokens	999	93,533,764	73,919,675	4,704,488	81,763,952	220,368,144
Total reserves, USD mil	999	186	147	9.43	163	439
Ether transaction volume, ETH/hr	999	6,462	5,850	559	4,932	58,799
USDT transaction volume, USDT/hr	999	2,421,322	2,122,218	226,818	1,846,440	20,523,222
ETH reserves * USDT reserves	999	3.91e+13	4.46e+13	5.31e+10	1.81e+13	1.34e+14
Ratio of reserves USDT to ETH	999	381	31.8	319	381	483
ETHUSDT close price, USD	999	381	31.7	319	381	483
BTCUSDT close price, USD	999	10,977	596	9,946	10,883	12,352
Diff in log Ether reserves	998	.00383	.0746	-1.97	.00168	.668
Diff in log USDT reserves	998	.00366	.0749	-1.97	.00152	.67

Table 1: Descriptive statistics - 999 hour snapshot of Uniswap ETH-USDT pair

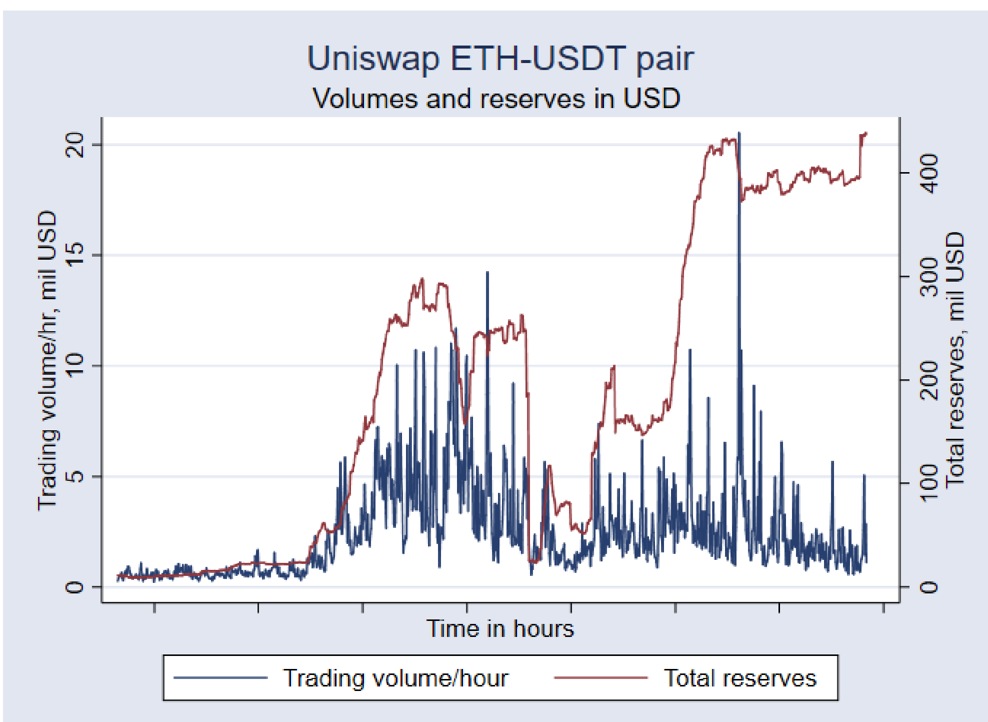

Figure 3: Total reserves and trading volumes for the ETH-USDT pair on Uniswap

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. 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-Peron (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	level	1st diff.
Statistical significance	5%	5%	5%	5%	5%	10%	5%
Ether reserves	NS	S	NS	S	NS	NS	S
USDT reserves	NS	S	NS	S	NS	NS	S
Ether volumes	S	S	S	S	NS	S @ 19 lags	S
USDT volumes	S	S	S	S	NS	S @ 18 lags	S
ETHUSDT price	NS	S	NS	S	NS	NS	S
BTCUSDT price	NS	S	NS	S	NS	NS	S
Ratio of reserves	NS	S	NS	S	NS	NS	S

3 tests of stationarity applied to 7 time series, on levels and first differences. NS = non-stationary. S = stationary.

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 such 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:

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

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 large 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.

$$\begin{aligned}\Delta R_t =& c_0 + c_1 t + \alpha(R_{t-1} - \theta_1 ETH_{t-1} - \theta_2 BTC_{t-1}) + \sum_{i=1}^{p-1} \varphi_{Ri} \Delta R_{t-i} + \omega_1 \Delta ETH_t + \omega_2 \Delta BTC_t \\ &+ \sum_{i=1}^{q-1} \varphi_{ETHi} \Delta ETH_{t-i} + \sum_{i=1}^{r-1} \varphi_{BTCi} \Delta BTC_{t-i} + u_t\end{aligned} \tag{3}$$

α is the adjustment coefficient.

θ are the long run coefficients on first lags of ETH_t and BTC_t.

ω are the short run coefficients on the first differences of ETH_t and BTC_t.

φ are the short run coefficients on the lagged differences of R_t, ETH_t and BTC_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). 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 ETH-USDT. Hypothesis H2 utilizes the same methodology and searches for the presence of cointegrating and auto regressive relationships between reserves, transactions and price. These models are subjected to two parts of the ARDL Bounds test.

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. The coefficients need to be stable over time. 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.

Moving on, hypothesis H3 requires an alternative methodology to test for Granger causality. We implement a Vector Auto Regressive (VAR) model to analyze directional changes in cryptoasset reserves. 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 selectively use lags, typically each model repeats the same lagged explanatory variables symmetrically. This way it can be argued that VAR modeling is theory-free with no preconceptions. 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. In the next section we examine the results.

5. Results and discussion

	[A]	[B]
Adjustment factor		
L. (Ratio of reserves)	-0.611***	-0.613***
Long run effects		
L. (ETHUSDT price)	1.002***	1.007***
L. (BTCUSDT price)		-0.000
Short run effects		
LD. (Ratio of reserves)	-0.191***	-0.185***
L2D. (Ratio of reserves)	-0.093**	-0.089**
D. (ETHUSDT price)	0.905***	0.858***
LD. (ETHUSDT price)	0.205***	0.200***
L2D. (ETHUSDT price)	0.116***	0.112***
L3D. (ETHUSDT price)	0.022	0.021
D. (BTCUSDT price)		0.004**
aic	3450.675	3443.950
bic	3494.800	3497.880
Adj R^2	0.855	0.857
N	995	995
Bounds test results		
F-statistic	92.700	61.081
t-statistic	-13.611	-13.526
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

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

Table 3: ARDL - Ratio of reserves and ETHUSDT price

The results of applying ARDL to our dependent variable, the ratio of Ether to USDT reserves, with the price of Ether and the price of Bitcoin (both relative to USDT) are shown in Table 3. As 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 ETH-USDT Uniswap pair matches its exchange rate off Uniswap.

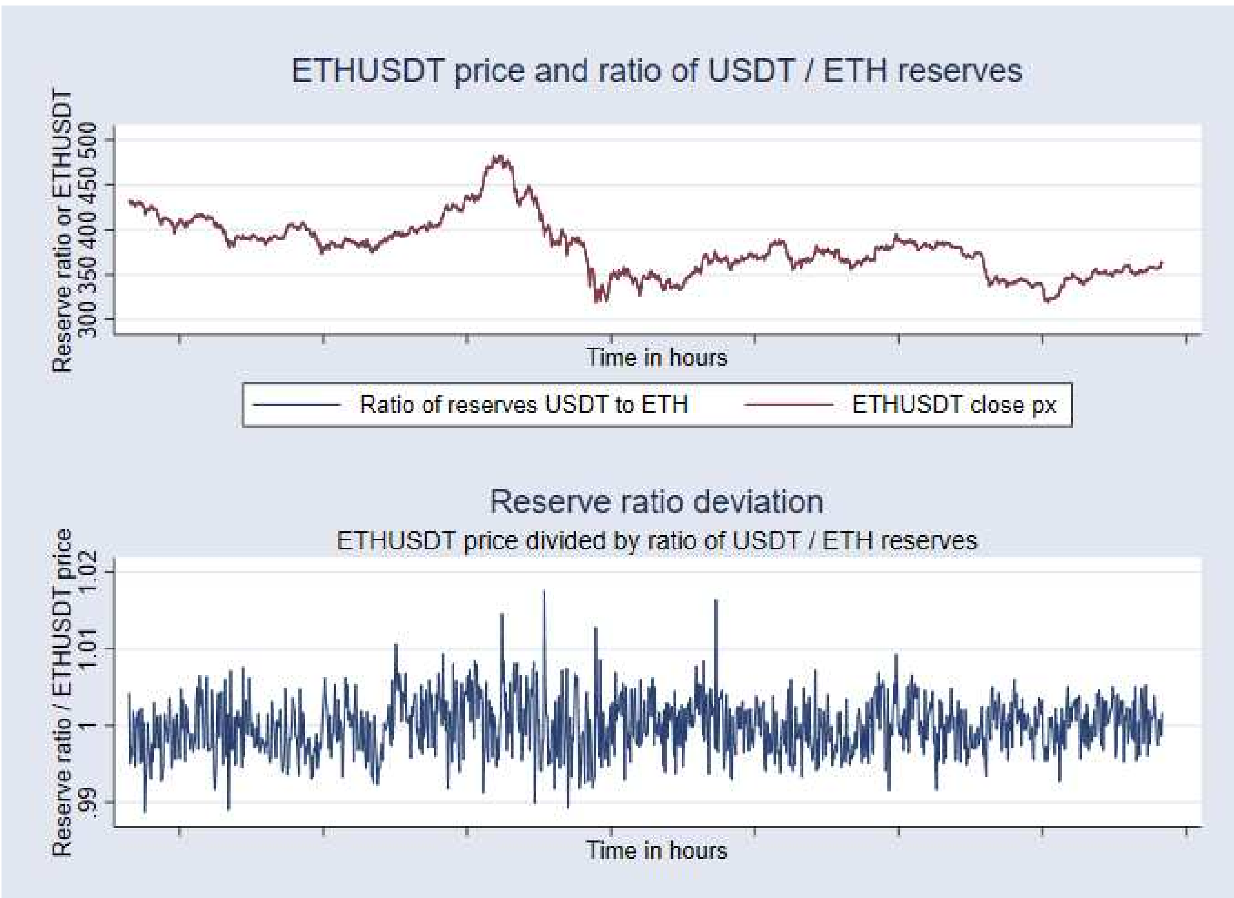

Figure 4: The ratio of Ether and Tether reserves (on the ETH-USDT pair on Uniswap) versus the ETHUSDT price

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 largely stays under 1%. 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, the short run effects are φ and ω from equation 3, which are the coefficients on the first and lagged differences of our variables. The majority of these coefficients are statistically significant. The long run effects are the coefficients θ on the, off platform, lagged exchange rates of ETHUSDT and BTCUSDT. In both specifications, the coefficient on the lagged ETHUSDT price is approximately 1. Of the long run coefficients, only the one on ETHUSDT is statistically significant. During the study time period, the adjustment factor α is 0.61. This suggests that 61% 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. There is no specific theoretical reason why the ratio of reserves should be impacted by the price of Bitcoin BTCUSDT, however the lower AIC value and the statistical significance of the first difference coefficient 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 lag and 5 lags at the 5% significance level, but does reject the null for 2-4. We force higher lags on the dependent variable and rerun the bounds test and observe similar results (not shown). The Breusch-Pagan test for heteroskedasticity has a χ^2 test statistic of 2.6 and a p-value of 0.1069. Therefore we do not reject the null of constant variance at the 5% and 10% significance levels.

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

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 the results of the standard ARDL model are presented in Table 4 and 5. For both dependent variables, we execute 3 models with different independent variables, and rank them by AIC. 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. 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. Therefore the presence of statistically significant relationships between these variables are within expectations. The statistical significance of Bitcoin is a surprise, while the statistical significance on volumes is somewhat weaker. Together these results find in favor of our hypothesis H2. The BIC would rank the models for both dependent variables differently, but would also increase risks of serial correlation in the residuals. 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. The result of this may be different over longer time periods.

	[B]	[D]	[E]
L. (ETH reserves)	0.883***	0.861***	0.861***
L2. (ETH reserves)	0.102**	0.122***	0.117***
(USDT reserves)	0.003***	0.003***	0.003***
L. (USDT reserves)	-0.002***	-0.002***	-0.002***
L2. (USDT reserves)	-0.000***	-0.000***	-0.000***
(ETHUSDT price)	-637.565***	-619.692***	-518.689***
L. (ETHUSDT price)	498.591***	487.398***	374.865***
L2. (ETHUSDT price)	96.852**	94.694**	118.811***
L3. (ETHUSDT price)	28.018	24.263	
(ETH volume)		0.483**	0.540**
L. (ETH volume)		-0.346	-0.458*
L2. (ETH volume)		-0.012	-0.009
L3. (ETH volume)		0.020	0.017
L4. (ETH volume)		-0.049**	-0.039*
(USDT volume)		-0.001*	-0.001**
L. (USDT volume)		0.001	0.001*
(BTCUSDT price)			-8.585***
L. (BTCUSDT price)			9.367***
L2. (BTCUSDT price)			-2.946
L3. (BTCUSDT price)			2.571*
aic	17839.896	17815.129	17796.283
bic	17888.923	17898.476	17894.338
N	995	995	995

Models ordered by AIC descending

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

Table 4: Short run ARDL model of Ether reserves within ETH-USDT Uniswap pair

	[F]	[G]	[H]
L. (USDT reserves)	0.880***	0.857***	0.858***
L2. (USDT reserves)	0.106***	0.126***	0.120***
(ETH reserves)	359.660***	359.814***	359.155***
L. (ETH reserves)	-316.353***	-307.481***	-307.090***
L2. (ETH reserves)	-37.979**	-46.147***	-43.853***
(ETHUSDT price)	2.36e+05***	2.30e+05***	1.88e+05***
L. (ETHUSDT price)	-1.87e+05***	-1.82e+05***	-1.37e+05***
L2. (ETHUSDT price)	-3.35e+04**	-3.30e+04**	-4.21e+04***
L3. (ETHUSDT price)	-1.10e+04	-9394.944	
(ETH volume)		-182.284**	-205.483**
L. (ETH volume)		115.697	159.812*
L2. (ETH volume)		7.660	6.336
L3. (ETH volume)		-8.740	-7.309
L4. (ETH volume)		17.894**	13.854*
(USDT volume)		0.430*	0.494**
L. (USDT volume)		-0.287	-0.409*
(BTCUSDT price)			3453.907***
L. (BTCUSDT price)			-3744.165***
L2. (BTCUSDT price)			1078.459
L3. (BTCUSDT price)			-944.970*
aic	29585.068	29560.327	29537.154
bic	29634.096	29643.674	29635.209
N	995	995	995

Models ordered by AIC descending

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

Table 5: Short run ARDL model of USDT reserves within ETH-USDT Uniswap pair

Our third hypothesis examines how the Uniswap ETH-USDT pair returns to equilibrium.

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

We investigate this with a VAR model. We begin by reviewing the order selection statistics for our two variables. The BIC recommends zero lags but the AIC opts for 3 lags. We run two models, one with 3 lags and the second with 1 lag. The results of this are shown in Table 6. Tests of model stability suggest that the Eigenvalues are appropriately within the unit circle. We find a single statistically significant coefficient on the first difference in log of Ether reserves, when the dependent variable is the first difference in log of USDT reserves. A test of Granger causality under model [J] finds that the first differences in the log of Ether

	[I]	[J]
DLRETH		
L.DLRETH	0.451	0.476
L2.DLRETH	-0.069	
L3.DLRETH	0.027	
L.DLRUSD	-0.402	-0.419
L2.DLRUSD	0.105	
L3.DLRUSD	0.115	
DLRUSD		
L.DLRETH	0.490*	0.516*
L2.DLRETH	-0.051	
L3.DLRETH	-0.022	
L.DLRUSD	-0.439	-0.457
L2.DLRUSD	0.086	
L3.DLRUSD	0.164	
aic	-8775.818	-8787.288
bic	-8707.179	-8757.860
N	995	997

Models ordered by AIC descending

DLRETH is first difference of log Ether reserves

DLUSDT is first difference of log USDT reserves

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

Table 6: VAR model of Ether and USDT reserves

reserves Granger causes changes in the first difference in the log of USDT reserves at the 5% statistical significance level (p=0.038). Over this time period we reject the null that first differences in the log of USDT reserves Granger causes changes in the first differences in the log of Ether at the same significance level (p=0.089). It is hard to state definitely why this would be the case. However, we can make inferences from the fact that on Uniswap, no trade is neutral, every trade has a price impact, whether large or small. 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 this arbitrage should lead to bidirectional Granger causality. As this is not the case, one possibility is that arbitrageurs have a slight preference to buy Ether when it is cheap over selling Ether when it is expensive. The logic for this is that, following a trading induced reserve imbalance, if the next trade impacts USDT more than Ether, this is by definition of a purchase of Ether along a constant product curve (1 quantum decline in Ether reserve balance, $1 + x$ quantum proportionate rise in USDT reserve balance).

6. Conclusion

This research provides empirical evidence regarding the effectiveness of reserve based asset exchanges. We find that for a 999 hour period of Uniswap's existence, including the majority of its reserve build, the ratio of Ether and USDT reserves on the ETH-USDT 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 - with significant implications for financial trading, stability and regulation. An argument made by Lo and Medda (2020) is that blockchain does not build strictly superior systems, but alternative systems that are attractive along less common dimensions, e.g. decentralization and censorship resistance. The question now becomes how should regulators and governments respond to a marketplace that does not need a registered address and geographically fixed physical infrastructure? Historically, 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 asset to investor portfolios; the optimal fee to maximize LP wealth, and whether or not decentralized exchanges are more or less risky than centralized exchanges.

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