Impermanent Loss and Price Discovery: Are Automated Market Makers a Sustainable Exchange Model?

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Certificate of Original Authorship

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Abstract

Automated market markers (AMMs) are a new decentralised exchange model that has grown to a multi-billion-dollar market; yet, it is unclear whether they are an economically robust and sustainable market type. Accounting for microstructure noise, I find that AMMs are the first to reflect new information in prices 62% of the time compared to their centralised counterparts. I also conclude that the QuickSwap exchange is the price leader within AMMs 72% of the time. Moreover, I demonstrate that profitability of liquidity provision within AMMs is primarily dependent on the asset's price dynamics and that trade fees and impermanent loss have a measurable impact on AMM informational efficiency. My findings provide evidence that AMMs are a sustainable model for facilitating digital-asset trading, which benefits liquidity providers and protocol developers.

Keywords: crypto-assets, automated market making, price discovery, liquidity provision.

JEL classifications: C33, G14, O30

1. Introduction

The emergence of Bitcoin in 2009 has seen the genesis of an entirely new asset class (Nakamoto (2008)). Naturally, with crypto-assets' growth in popularity, exchanges that facilitate trading have developed simultaneously. Most cryptocurrency exchanges use the traditional centralised limit-order book model (CLOB); however, latency and computational constraints with blockchains make trading crypto-assets expensive and inefficient (Angeris, Evans and Chitra (2020)).[2] Decentralised exchanges (DEXs) attempt to alleviate these issues by enabling cryptocurrency trade without a trusted third party to facilitate transactions.[3] The most popular of these DEXs is a new model (protocol) called the automated market maker (AMM). This exchange model uses a supply-based algorithm to price assets rather than a registry of buy and sell orders (Wang (2020)). AMM's simple pricing function and democratised manner of generating liquidity have seen them explode in size and value, averaging $67 billion monthly trading volume in 2021 (DeFiPrime (2021)).[4] However, the novelty and simplicity of AMM design warrants an examination into whether it can sustainably perform the functions of a market and handle the associated challenges.

Facilitating efficient price discovery is one of these essential functions. An extensive body of literature describes how exchanges are vital to providing liquidity and determining the true value of an asset (De Jong (2002); Harris, McInish, Shoesmith and Wood (1995); Harris (2015); Madhavan, Richardson and Roomans (1997)). However, the difficulty in determining crypto-assets' fundamental value complicates how and where price discovery occurs (Dimpfl and Peter (2021)). Combining this with cryptocurrency's high volatility and noise makes finding the price leader challenging (Conrad, Custovic and Ghysels (2018)). Considering AMMs newly-found market share, it is difficult to determine the significance of their role in the unwieldy price discovery of digital-assets. It is reasonable to suspect that the smaller and novel AMMs source their prices from CLOBs, which perform most of the price discovery. My study, however, provides

[2] Blockchain refers to the open, decentralised and immutable network which uses cryptography to facilitate transactions and information transfer. Centralised Limit Order Book refers to the dominant exchange model which keeps a record of outstanding buy and sell orders (see Appendix Table 3A).
[3] A Decentralised Exchange refers to an exchange which allows participants to trade peer-to-peer, without the need for an intermediary (see Appendix Table 3A).
[4] All dollar values within this study are priced in USD terms.

evidence to the contrary. Furthermore, it is ambiguous which AMM is the first to reflect new information in cryptocurrency prices.

Managing the adverse selection costs/risks (ASC) of liquidity provision is another vital function that exchanges must facilitate.[5] Exchanges need to adequately compensate liquidity providers with fees earned from uninformed trades to cover the costs of informed agents performing arbitrage. If the adverse selection proves too great for liquidity providers, they will withdraw from the market, thus reducing the efficiency of the exchange. CLOB exchanges have utilised many innovative approaches such as Bayesian inference from order flow to minimise this ASC and maintain competitiveness (Glosten and Milgrom (1985); Kyle (1985)). In contrast, AMM's unique design amplifies this adverse selection. Since AMM liquidity providers must supply a pair of crypto-assets in a set proportion, arbitrage negatively affects both holdings.[6] This ASC is known as impermanent loss (IL), which describes the risk for liquidity providers of seeing the value of their reserved assets decrease compared to holding them (Wang, Heimbach and Wattenhofer (2021)). Similar to traditional market makers, AMM liquidity providers receive fees as compensation. However, it is unclear whether these fees can sustainably offset the IL within AMMs. Considering that liquidity provision impacts price discovery (Riordan and Storkenmaier (2012)), it is important to understand whether AMMs can manage the IL. My study investigates this tension between 'informed' IL and 'uninformed' fees through the perspective of liquidity providers and whether it impacts AMM price discovery.

I use high-frequency data to investigate eleven AMMs and eight asset pairs within two periods between November 2020 and October 2021. Using this dataset, I determine the price leader, explore the returns generated from liquidity provision and establish a connection between the two within AMMs. I calculate the Hasbrouck (1995) Information Share (IS), Gonzalo and Granger (1995) Component Share (CS), and Putniņš (2013) Information Leadership Share (ILS) to determine the informational efficiency of AMMs and the popular CLOB exchange Binance. Moreover, I examine the relation between IL, fees and returns through the perspective of a liquidity provider. Several fixed effects panel regressions are also performed to determine whether IL and fees are reasonable proxies for the level of trade informativeness within AMMs. Using time and

[5] Adverse Selection refer to the situation where one party has information the other does not have. In this case it refers to informed traders who perform arbitrage on mispriced assets against liquidity providers.

[6] This proportion is determined by the liquidity pool and can vary. The most common split, however, is 50:50.

entity effects, along with clustered standard errors, I explore whether these proxies have a measurable impact on the ILS price discovery measure.

My study reveals that when accounting for noise, AMMs are on average the first to reflect new information in prices 62% of the time compared to the CLOB exchange Binance. Considering the IS and CS' bias against noise, I also find that AMMs are substantially noisier markets than CLOBs. When examining different AMM frameworks, I determine that the popular constant-function market maker (CFMM) is the most price-efficient model (ILS 70%, IS 70%, CS 62%).[7] Furthermore, the most actively traded AMM, QuickSwap, is the definitive price leader in the sample, with an average ILS of 72%.

Additionally, I demonstrate that AMMs can consistently offset the IL through fees in large liquidity pools of stable asset pairs or small pools of volatile pairs. Moreover, Uniswap is the only AMM that nullifies the IL across all pairs and sample periods. I find that providing liquidity to AMMs can be a lucrative investment within pools with one (20% to 180%) and two (20%) low-volatile cryptocurrencies (stablecoins).[8] On the contrary, asset pairs without a stablecoin perform poorly overall, returning between 15% and -45%.[9] I also determine that fee compensation and asset price movements are the main drivers of stablecoin returns and non-stablecoin pairs, respectively. These findings all provide evidence that the IL is primarily a function of the asset's volatility. Lastly, I find that liquidity provider fees and the IL from adverse selection are reasonable proxies for the level of informativity within AMMs. Fee compensation and IL are found to have a significant negative and positive association with the ILS, respectively. These results suggest that liquidity provision has a measurable effect on AMM's ability to perform efficient price discovery.

My findings provide several implications for the sustainability of AMMs. With the current trajectory of DEX retail adoption, there is a real possibility that AMMs could compete with CLOBs for market dominance. With the creation of more cryptocurrencies that are strictly compatible with decentralised systems, AMMs could also be an exclusive market maker for these assets. However, there are concerns that AMMs are another poorly designed and flawed system in the crypto-asset ecosystem. My study, therefore, aims to reduce the uncertainty surrounding the efficiency and

[7] Constant Function Market Maker refers to a type of automated market maker which uses a deterministic pricing rule simplified as the product of the two asset's reserve amounts (see Appendix Table 3A).
[8] Stablecoin refers to a crypto-asset pegged to a fiat currency, commodity or another crypto-asset (see Appendix Table 3A).
[9] Returns are calculated daily and accumulatively over the sample period.

longevity of this new market type. Recognising the novelty and benefits a decentralised exchange can bring, I also hope my study contributes to the advancement of AMMs so that they can reach their potential.

Secondly, my study provides further insights into the properties of crypto-assets. This has implications on the performance of these assets via an alternative investment strategy through liquidity provision. Thirdly, with AMM's price leadership over Binance established, the paper contributes to the highly debated concept of whether markets with little to no human intervention are viable. My study suggests that automation can allow for efficient price discovery, but further research is needed to clarify what properties of AMMs cause this.

My research project provides several contributions to the growing literature on AMMs. Firstly, my study advances the understanding of AMM by providing empirically-based conclusions. Many papers within the literature investigate AMMs on a conceptual basis and therefore lack rigour. My research instead explores the informational efficiency of crypto-asset markets and DEXs using high-frequency data. Secondly, by examining the relation between ASCs and liquidity provision profitability, my paper also helps clarify how asset volatility affects the sustainability of AMMs. Lastly, my study is the first to elucidate whether the tension between IL and fees impact the price discovery capabilities of AMMs.

Quantifying these interesting concepts will be useful in ensuring the future health of AMMs and DEXs. Developers of AMM protocols will benefit substantially, allowing them to identify which AMM protocols can better perform price discovery. I also provide direction to what affects AMM price efficiency by investigating the tension between fees and IL. Moreover, this paper can help attract the attention of regulators by proposing that AMMs are more robust than initially assumed. This could potentially see regulators develop legal frameworks around this new market type and reduce its susceptibility to criminal activity. By contributing to the design of AMMs, my study acts as an anchor for further research, which can generate significant insights when data is more readily available.

The layout of the paper is as follows. Section 2 describes the background of AMMs, price discovery and liquidity provision. Section 3 outlines the structure of the data and some preliminary analysis. Section 4 presents the research design, main results, robustness tests, limitations and implications for future research. Lastly, Section 5 concludes.

2. Literature Review

My study relates to the body of work on automated market making, price discovery and liquidity provision. In this literature review, I discuss the unique traits of AMMs, why price discovery matters, how to measure it, and the ASCs of market-making. I achieve this by referencing both traditional and cryptocurrency-based literature. Additional institutional details on blockchain technology and decentralised finance (DeFi) are detailed in Appendix A.[10]

2.1. Institutional Details of Automated Market Maker Function

Automated market makers consist of a group of liquidity pools.[11] Each liquidity pool is a reserve that comprises a pair of crypto-assets. These two cryptocurrencies are held in a fixed ratio, which the AMM determines. The ratio is based on the total value of each respective crypto-asset. For example, say the total value of the liquidity pool is $100, and the fixed ratio between the two assets is 50:50. If asset A is worth $5, asset B is worth $10; then the quantities within the pool would be ten and five, respectively (both worth $50 each). Since liquidity pools are freely accessible, anyone can deposit or 'stake' their crypto-assets within them. Moreover, liquidity providers receive fees generated from the amount of trading volume within the liquidity pool. Feng, Bhat and Las Marias (2019) claim this accessibility allows AMMs to generate almost instant liquidity to the market, which is highly beneficial for newly-created cryptocurrencies.

With the liquidity pool established, participants can exchange one asset for the other. The AMM uses a pricing function algorithm that mathematically determines the asset's price based on its respective quantity within the liquidity pool (Wang (2020)). For example, a buyer submits an order to purchase one asset B ($10) with two of asset A ($5 each). A smart contract manages this order, which withdraws one asset B from the liquidity pool and adds two asset A's.[12] Assuming no additional liquidity has been deposited by liquidity providers, the pool's total value remains at $100 after the transaction. However, the quantities have changed with only four of asset B and twelve of asset A. The pricing function therefore automatically updates the price of both

[10] Decentralised Finance refers to the blockchain-based financial system which operate using smart contracts instead of intermediaries (see Appendix Table 3A).
[11] Liquidity Pools refer to a crowdsourced reserve of crypto-assets locked in by a smart contract. It provides the funds to facilitate trades within a decentralised exchange.
[12] Smart Contract refer to the specialised coded-protocols that execute complicated transactions when the terms of agreement are met, without relying on a third party.

cryptocurrencies, with asset A and B now worth \$4.17 and \$12.50, respectively.[13] As illustrated, the pricing function follows the negative relation between supply price, i.e., the fewer the quantity, the higher the price.

Since crypto-assets within AMMs are priced relative to each other, the gain made from a price increase in one is offset by the price decrease in the other. Moreover, as buyers and sellers trade with the liquidity pool, the deterministic pricing function means the prices of these assets can deviate substantially from the broader market (e.g., CLOB exchanges). If a large order moves the price of a crypto-asset away from its fundamental value, informed traders will perform arbitrage which equalises the prices. Because liquidity providers passively supply liquidity to AMMs, there is a possibility of being adversely selected when the fundamental value of a cryptocurrency changes. What is unique to AMMs is that this adverse selection affects the value of both assets since their price is bound to each other. Therefore, no matter which asset is mispriced, the total value of the liquidity provider's assets decreases. In comparison, if both assets are held outside of the AMM, then the fundamental price change of one asset would likely not influence the price of the other. This expense is the impermanent loss, which is incurred when the price of an asset changes within an AMM. The loss is considered 'impermanent' because it is only realised when the liquidity provider decides to withdraw their assets from the liquidity pool.

2.2. Automated Market Making

Automated market making is not a new concept, with Hakansson, Beja and Kale (1985) first performing a simulation using a "programmed specialist" market maker to smooth demand. Although limited in scope, they find automatic demand smoothing to be cost-efficient even in thinly traded markets. Robin Hanson's seminal papers on logarithmic market scoring rules further explore an early AMM model within traditional markets (Hanson (2003); Hanson (2007)). They claim that automation brings substantial modularity and cost advantages. However, his logarithmic model could not maintain efficient price discovery between markets with low and high liquidity. Othman, Pennock, Reeves and Sandholm (2013) address this problem by designing a "liquidity sensitive" AMM, which runs at a profit in markets with fluctuating volume. Updating Glosten and Milgrom (1985) model, Gerig and Michayluk (2010) find that automated liquidity provision sets more efficient prices, improves informativeness but increases trader transaction costs. Although

[13] This is assuming the AMM uses a Constant Function Market Maker model.

some functions of exchanges are now commonly automated, traditional markets have still not seen a successful model which is fully automatic. In this paper, I hypothesise that automated market making is a viable exchange model in digital-asset trading.

Of the limited literature on crypto-asset AMMs, most papers conceptually examine the feasibility of the standard CFMM model. Park (2021) says that CFMMs have substantial flaws that are absent from order book models, despite being easy to implement. He elucidates that an exogenous arbitrary pricing function creates undesirable characteristics that reduce token values with low liquidity through IL.[14] How the IL changes between exchanges and assets is still not well understood. I expect that IL is primarily a function of the asset price dynamics such as volatility.

Alternatively, Pourpouneh, Nielsen and Ross (2020) suggest that the AMM pricing mechanism works well for low-volatile assets by exploring conditions when the algorithm is at equilibrium. They, however, agree with Park (2021) that CFMMs inefficiently price more volatile assets. Angeris, Kao, Chiang, Noyes and Chitra (2019) provide a generalised overview of the most popular AMM, Uniswap, and find that the CFMM model appears to work well in practice, despite its simplicity under several common market conditions. Additionally, Wang (2020) investigates the feasibility of other pricing functions, suggesting circle/eclipse algorithms are a better alternative than CFMMs. Although the pricing function is less flexible, they find it more robust against front/backrunning (slippage) attacks since the attacker can only manipulate the token price within a fixed price amplitude. Despite these proposed limitations, I hypothesise that CFMMs are economically sustainable when they have large liquidity pools of stable asset pairs or small pools in volatile pairs.

To help AMMs align their prices with the broader market, they use price oracles that connect off-chain and on-chain information.[15] Angeris, Kao, Chiang, Noyes and Chitra (2019) use an agent-based simulation to demonstrate that Uniswap provides a "censorship-resistant price oracle for smart contracts", which performs well when liquidity pools are liquid enough to facilitate arbitrage. Eskandari, Salehi, Gu and Clark (2021) explain that price oracles are almost essential for the operation of major AMMs. They, alongside Bartoletti, Chiang and Lluch-Lafuente (2021), describe the price oracle's ability to automatically adjust prices with the broader market as

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[14] A token is used to represent an asset of some kind, for example a share of ownership, voting rights or another crypto-asset.
[15] Off-chain refers to anything that is not recorded on the blockchain.

necessary to limit IL. Krishnamachari, Feng and Grippo (2021) agree with this finding, saying it could significantly reduce IL's magnitude. Furthermore, Lo and Medda (2020) empirically test the use of price oracles by cointegrating the ETH-USDT pair on Uniswap with an exchange rate benchmark, concluding that oracles reduced the impact of arbitrage. However, Lo & Medda (2020) only look at one stablecoin pair, which naturally experiences much lower volatility than other crypto-assets. Although price oracles have helped homogenise prices between AMMs and the broader market, I still expect that AMMs are significantly noisier than their CLOB counterparts.

Comparing popular AMMs against each other, Xu, Vavryk, Paruch and Cousaert (2021) demonstrate how the biggest AMMs all utilise a CFMM-like protocol with some variation. Additionally, Jensen, Pourpouneh, Nielsen and Ross (2021) support the idea of homogeneity between CFMMs, and Engel and Herlihy (2021) create a mathematical model to allow compatibility between different AMMs. This model theoretically enables AMMs with varying asset classes to communicate, reducing the discrepancies between values and thus improving price stability. These findings are important for my study because they allow a generalised formula to be applied to different AMMs, while still providing valuable insights.

Literature comparing DEXs with centralised exchanges has recently received attention from academics. Lehar, Parlour and Berkeley (2021) show minor pricing and trading volume differences between Uniswap and Binance. Moreover, they notice that the price impact for the popular USDC/ETH pair on Binance almost always exceeds Uniswap. This finding implies that AMMs can better handle price action within large and stable liquidity pools. Similar to my study, Barbon and Ranaldo (2021) compare DEX and CLOB exchanges, demonstrating that CLOBs provide better market quality overall. Regarding similarities between both market types, Young (2020) states that CLOBs and AMMs are mathematically equivalent. He claims that the characteristics of both models could be interchangeable in the future, giving rise to hybrid market systems which combine AMMs transparency with limit order book's liquidity protection.

Looking at how traders interact with both, Aspris, Foley, Svec and Wang (2021) empirically show that AMMs serves as a "vehicle for on-ramping" to centralised exchanges. Not only do they show that DEX to centralised exchange cross-listings results in much higher overall trading volume, but they also show that DEX trading activity drops significantly. This conclusion is consistent with Domowitz, Glen and Madhavan (1998) study on order flow migration between traditional foreign and emerging markets, which demonstrates market segmentation. My paper contributes to this discussion by forecasting that the lower trading activity in AMMs does not impede their ability to perform efficient price discovery against centralised exchanges.

Concerning the sustainability of AMMs, most studies focus on their susceptibility to illegal trading activity. Xu, Vavryk, Paruch and Cousaert (2021) explain that AMMs are highly vulnerable to front/backrunning, wash trading, rug pulling and sandwich/vampire attacks. They, along with Angeris, Evans and Chitra (2021), express privacy concerns when using AMMs, as attackers can bridge between virtual account transactions and people's identities with relative ease (Zhang, Xue and Liu (2019)). Moreover, Park (2021) finds that manipulative frontrunning opportunities within CFMMs are always profitable compared to limit order book models; however, this is only substantial for trading pairs with low liquidity. Although not strictly illegal, Mohan (2020) identifies the presence of generalised bots programmed to "snipe" arbitrage transactions entered by others. These bots disincentivise participants to engage in arbitrage, thus resulting in greater mispricings within AMMs than usual. Eskandari, Salehi, Gu and Clark (2021) also identify the threat of oracle-based attacks and discusses several mitigation strategies. I expect these threats to not significantly hinder AMM's ability to perform price discovery.

2.3. Price Discovery

Price discovery is one of the central functions of financial markets and is extensively discussed within traditional literature (Baillie, Booth, Tse and Zabotina (2002); De Jong (2002); Hasbrouck (1995); Thomas and Karande (2001)). However, there are different definitions of price discovery which confuses the interpretation. Some refer to it as purely the speed of adjustment (Booth, Lin, Martikainen and Tse (2002)), whereas others refer to it as the first to reflect new information (Chakravarty, Gulen and Mayhew (2004); Rittler (2012)). Lehmann (2002) combines both concepts, defining price discovery as the "efficient and timely incorporation of investor trading information into asset prices". To clarify Lehmann (2002) definition further, Putniņš (2013) describes efficiency as the relative absence of noise and timely as the speed at which new information reflects the fundamental value. I use Putniņš (2013) understanding of price discovery for my research project.

Price discovery across market types is of particular interest to many published studies. For the fundamental value of the same asset to be accurately reflected, each market is responsible for quickly adjusting to new information (Easley and O'Hara (2004)). A seminal paper by Hasbrouck (1995) demonstrates that prices for the same asset over multiple markets converge long term, yet they deviate in the short term due to trading frictions. This assumption is supported exhaustively within the literature that compare price discovery between spot and futures markets (Thomas and Karande (2001)), bond and foreign exchange markets (Andersen, Bollerslev, Diebold and Vega (2007)), as well as stock and options markets (Patel, Putniņš, Michayluk and Foley (2020)). I forecast these same relations are present when comparing CLOBs to AMMs.

When measuring price discovery, there are two primary metrics that market microstructure literature use: the Gonzalo and Granger (1995) Component Share (CS) and the Hasbrouck (1995) Information Share (IS). Gonzalo and Granger (1995) propose that a cointegrated price series can be decomposed into temporary and permanent components using the error correction term's coefficients. They postulate that contribution to price discovery is identified through the weight of each market's permanent component, with the temporary component representing noise. Furthermore, Gonzalo and Granger (1995) also highlight that the permanent component is a linear combination of every variable in the cointegration system (Putniņš (2013)).

Alternatively, Hasbrouck (1995) assesses how variance within efficient price innovation is decomposed and how that contributes between varying markets. He proposes that the relative informativeness of trades represent the proportion of efficient price variation within those trades (Hasbrouck (1991)). The CS and IS were initially thought to be competing measures; however, the works of Baillie, Booth, Tse and Zabotina (2002) prove them to be similar since both rely on the vector error correction model (VECM) coefficients. Baillie, Booth, Tse and Zabotina (2002) conclude that the IS is simply the CS adjusted for variance. I calculate both of these well-established metrics to provide comparability with other price discovery papers.

Previous to Yan and Zivot (2010), it was still unclear what the CS and IS were measuring. They revealed that the IS and CS measure which market is faster but also which market is less noisy. Therefore, these measures tend to attribute the less noisy market as the informational leader, which can be misleading. To remediate this issue, Yan and Zivot (2010) combined the IS and CS estimates to help account for microstructure noise, thus providing a metric that strictly measures which market is faster at impounding new information into prices. Putniņš (2013) builds upon Yan and Zivot (2010) metric, creating the Information Leadership Share (ILS). The ILS allows for easier comparability between the IS and CS as well as interpretation. The combination of the ILS' simplicity and handling of microstructure noise; which is high in crypto-markets, is why I consider it the primary measure of price discovery in my study. Additionally, I hypothesise that the ILS will often contradict the IS and CS due to the large noise variability between AMMs.

Price discovery literature within crypto-assets is expanding as academics apply traditional assumptions and methods to this new market. The first study to observe the informational efficiency of crypto-asset exchanges was Brandvold, Molnár, Vagstad and Valstad (2015), who examined Bitcoin within early exchanges between 2013 and 2014. They conclude that Mt. Gox and BTC-e were the leaders in price discovery during the period. However, they both were shut down soon after due to hacking events. Next, Urquhart (2016) investigates Bitcoin's market efficiency determining that the market was inefficient at impounding new information until the end of the study's sample period. Using tick data for 34 exchanges and across 19 countries, Makarov & Schoar (2020) find that arbitrage deviations of Bitcoin prices are large, persistent and greater across countries. Another paper investigates the relationship between liquidity and price discovery within seven popular cryptocurrencies, finding that they become more efficient as liquidity increases (Brauneis and Mestel (2018)). My study extends this research, hypothesising that AMMs with the most trading activity will be the price leaders across all sampled assets.

The discussion of price discovery between traditional and cryptocurrency markets is also growing. Giudici and Polinesi (2021) find that Bitcoin exchange prices are unaffected by conventional asset prices, although volatilities are interrelated with a negative and lagged relationship. They also determine that Bitcoin exchange prices are positively related to each other. Similarly, Pagnottoni and Dimpfl (2019) explore whether fiat currency exchange rates affect Bitcoin's price discovery. They conclude that they had no discernible impact. Highly related to my study, Dimpfl and Peter (2021) extend the literature by observing the price discovery contributions of different exchanges accounting for noise. They determine that the cryptocurrency market includes much more microstructure noise than the NYSE or NASDAQ. Moreover, compared with CLOBs, Barbon and Ranaldo (2021) conclude that DEXs are not competitive regarding transaction costs and price efficiency. Alternatively, I hypothesise that AMM's deterministic pricing function is favourable for informed traders as it allows DEXs to compete with CLOBs by being the first to impound new information into prices.

2.4. Adverse Selection Costs & Liquidity Provision

The literature is comprehensive surrounding adverse selection costs as they are present within all markets. (Collin-Dufresne and Fos (2015); Easley and O'Hara (1992); Wilson (1980);

Wilson (1989)). The ASC describes the informational asymmetry that informed traders have to exploit the uninformed for financial gain. This risk is characterised by arbitrage which is necessary to equalise mispricings between markets (Nosal and Wang (2004)). Foucault, Kozhan and Tham (2017) explore the tension between market efficiency and adverse selection, showing that the price efficiency gain from high-frequency arbitrage comes at the cost of greater ASCs. The impact of this ASC is deemed considerable, with Muravyev (2016) showing that it has a “first-order effect” on option prices. Considering that Bitcoin markets are known to have substantial price spreads, arbitrage’s impact on market efficiency is likely more substantial than traditional markets (Kroeger and Sarkar (2017); Krückeberg and Scholz (2020)). In my study, I hypothesise that the ASC of IL can be a proxy for the level of informed trading within an AMM.

CLOB market makers have developed several ways to mitigate ASCs. One such technique is Bayesian inference from order flow, as described by Kyle (1985) and Glosten and Milgrom (1985). Using Bayesian inference, liquidity providers can reliably charge the lowest possible “fee”, thus limiting their expenses. Brahma, Chakraborty, Das, Lavoie and Magdon-Ismail (2012) also show that the Bayesian market maker offers lower expected loss at the same liquidity. They also conclude a “rapid convergence when there is a jump in the underlying true value of the security”. With the development of high-frequency trading (HFT), market makers can also refresh quotes quickly with Jovanovic and Menkveld (2016) finding HFT reduces adverse selection by 23% and increases trade by 17%.

There is limited literature examining how AMMs deal with ASCs (characterised through the IL). Aigner and Dhaliwal (2021) observe the risk profile of liquidity providers by accounting for IL within Uniswap. They provide a derivation of the IL function and find liquidity providers may not always receive less return than a buy and hold strategy under specific circumstances. Similarly, Wang, Heimbach and Wattenhofer (2021) cite the same IL formula and suggest that liquidity providers perform different trading strategies depending on the asset pair. They find that staking in stablecoin pools provide an almost risk-free profitable return, whereas staking in riskier pools generates substantial losses. Additionally, based on their equilibrium modelling, Barbon and Ranaldo (2021) theorise “an optimal level of stacked liquidity”. This theory assumes that IL is a function of the asset’s volatility, and fees are a function of liquidity pool size and volume. I agree with Barbon and Ranaldo (2021) and forecast that there is an optimal level of IL and fees within an AMM which has a measurable impact on the price efficiency of the exchange.

3. Data

I collect price and other exchange-related data from a collection of eleven AMMs using two sample periods. Sample Period 1 is from 1st November 2020 to 1st October 2021, and Sample Period 2 is from 1st June 2021 to 1st October 2021. The second sample period includes newer exchanges established within 2021 that account for substantial market share (e.g., QuickSwap). These eleven exchanges make up around 60% of the total market share of DEXs, with almost $2 billion in daily trading volume (CoinGecko (2021)). Uniswap is the largest AMM within the sample, with Uniswap 2.0 (v2) and Uniswap 3.0 (v3) accounting for over 30% market share (CoinGecko (2021)). The rationale for selecting these AMMs is based on a combination of data availability, commonly traded asset pairs and high trading volume. The primary reason to examine many AMMs was to include enough variation between protocols that trade the same asset pairs.

From these eleven AMMs, I examine eight asset pairs segmented into categories based on their respective volatility. The assets are segmented into two main categories - stable denotes a stablecoin, and risky represents a non-stablecoin. This identification is useful when looking at an asset pair. For example, a pair with a stablecoin and a non-stablecoin is referred to as ‘stable/risky’. The chosen trading pairs represent a substantial share of DeFi ecosystem, with a total market capitalisation valuing around $591 billion (CoinMarketCap 2021). The stablecoins used in this study are all pegged to the US dollar. The most prominent digital asset in this study is Wrapped-Ether (WETH), which is the cryptocurrency that runs the Ethereum blockchain. For this reason, it is considered the ‘base currency’ within pairs without a stablecoin (e.g., risky/risky). Additionally, since most AMMs are built on the Ethereum blockchain, each exchange and asset has its own unique 40-character address (see Tables 1A and 2A in the Appendix). I use these smart-contract addresses (see Table 3A for definition) to locate the relevant asset pairs and exchanges through blockchain explorers: Etherscan.io, BscScan, and Polygonscan. Not every AMM trades all eight asset pairs within this study. I summarise the organisation of AMMs and asset pairs in Table 1.

Table 1

Asset Pair and AMM Configuration

This table shows the asset pairs that trade on each AMM, represented by a tick mark. Pairs are in three categories: Stable/Stable, Stable/Risky and Risky/Risky. Stable refers to a stablecoin and Risky refers to a non-stablecoin. Shaded pairs denote pairs with lower trading frequency. Sample Period 1 is from November 2020 to October 2021. Sample Period 2 is from June 2021 to October 2021. The Binance sample period is from November 2020 to March 2021. No tick means that the asset pair is not traded on that particular AMM.

	Stable/Stable		Stable/Risky		Risky/Risky			
AMM	**USDC/ USDT**	**USDC/ DAI**	**USDC/ WETH**	**DAI/ WETH**	**WBTC/ WETH**	**LINK/ WETH**	**AAVE/ WETH**	**YFI/ WETH**
Decentralised Exchange (AMM)								
Panel A: Sample Period 1								
Uniswap v2	✓	✓	✓	✓	✓	✓	✓	✓
SushiSwap	✓	✓	✓	✓	✓	✓	✓	✓
Balancer		✓	✓	✓	✓	✓	✓	✓
Bancor		✓	✓	✓	✓	✓	✓	✓
0x	✓	✓	✓	✓	✓	✓	✓	✓
Dodo	✓		✓					
Curve	✓	✓	✓					
Panel B: Sample Period 2								
QuickSwap	✓	✓	✓	✓	✓	✓	✓	✓
Uniswap v3	✓	✓	✓	✓	✓	✓	✓	✓
PancakeSwap	✓		✓		✓			
1inch Liquidity Protocol			✓	✓	✓	✓		✓
DeFi Swap	✓	✓	✓	✓	✓	✓	✓	✓
Panel C: Centralised Exchange								
Binance	✓	✓	✓	✓	✓	✓	✓	

Table 2 highlights the different asset properties of stablecoins and other cryptocurrencies. The stablecoins exhibit low volatility, as seen with the small average standard deviation in prices (0.003) and returns (0.355%). As for the non-stablecoins, we can see that they exhibit high volatility, with large fluctuations evident in both mid and large-cap assets.[16] Volatility is highlighted through the daily minimum and maximum returns, with mid and large caps having an average spread of 71% and 42%, respectively. These large daily price movements are further supported the average standard deviation of 7% in non-stablecoins Although considered extreme within traditional markets, this volatility is typical within the crypto-asset industry.

Table 2
Descriptive Statistics of Daily Asset Prices and Returns

This table displays the descriptive statistics of daily prices and returns for the eight assets. Data for this table is sourced from market aggregator CoinGecko at daily intervals. Prices are calculated based on US dollar terms. Data is winsorized at 1%. Stablecoin denotes a cryptocurrency pegged to the USD and a non-stablecoin refers to a cryptocurrency. Large-cap and mid-cap refers to a cryptocurrency with over $100 billion and $1 billion market capitalisation, respectively.

			Prices				Returns %			
Category	**Asset**	**Obs.**	**Mean**	**Std.**	**Min.**	**Max.**	**Mean**	**Std.**	**Min.**	**Max.**
Stablecoin	USDC	334	1.00	0.002	0.98	1.01	0.003	0.367	-1.572	1.944
	USDT	334	1.00	0.003	0.99	1.01	0.002	0.352	-1.394	1.746
	DAI	334	1.00	0.003	0.99	1.01	0.001	0.345	-1.325	1.258
Non-Stablecoin (Large-Cap)	WETH	334	2,007	975	384	4,183	0.782	5.733	-26.302	24.534
	WBTC	334	39,921	12,919	13,558	63,577	0.439	4.300	-13.468	19.247
Non-Stablecoin (Mid-Cap)	LINK	334	24	9	10	52	0.498	7.326	-35.647	30.377
	AAVE	334	294	138	28	631	0.995	8.102	-33.475	29.744
	YFI	334	34,817	10,396	8,521	82,071	0.622	8.086	-36.349	45.999

[16] I classify, crypto-assets with greater than $100 billion market capitalisation as large-cap and greater than $1 billion market capitalisation as mid-cap.

Table 3 provides an overview of the daily AMM trading frequency between the two sample periods. Firstly, trade activity appears highly varied between exchanges, more so than between asset pairs. QuickSwap is the most active exchange with an average of 3,815 daily trades. This result is surprising considering QuickSwap was released in May 2021. Looking at Uniswap, it appears v2 is more popular than the newer v3, with 164 more daily trades. Due to infrequent trading activity, several AMMs are merged and labelled as ‘non-CFMM’ (see Appendix Table 4A and Table 5A for the merge order). The low liquidity of these individual exchanges means I am unable to estimate the price discovery shares (Refer to Appendix Table 6A). Conversely, these AMMs still have enough liquidity for me to calculate the liquidity provider metrics (Section 4.2).

Binance’s trading activity of the pairs described in Table 2 is far above its AMM counterparts at 20,519 daily transactions. This high liquidity is expected since Binance is one of the largest global CLOBs, processing more trades than the following four biggest exchanges combined (Kowsmann and Ostroff (2021)). Lastly, Table 3 shows that the stable/risky pairs USDC/WETH and DAI/WETH are the most popular, averaging 5,003 and 1,470 daily trades across AMMs. The YFI/WETH pair is the least popular, with a daily average of 146.

Table 3
Average Number of Daily Trades

This table shows the average daily number of trades for each exchange across asset pairs. Stable refers to a stablecoin, and Risky refers to a non-stablecoin. Some exchanges are merged into non-CFMMs due to low trading activity. These include Bancor, Balancer, 0x, Curve and Dodo for Sample Period 1 (November 2020 to October 2021), and DeFi Swap, 1inch and PancakeSwap for Sample Period 2 (June 2021 to October 2021) (see Appendix Table 4A). Not all exchanges trade every asset pair; these are left blank. Binance’s sample period is from November 2020 to March 2021.

Asset Pair		Sample Period 1			Sample Period 2			Centralised
		Uniswap v2	SushiSwap	Non-CFMMs	QuickSwap	Uniswap v3	Non-CFMMS	Binance
Stable/Stable	USDC/USDT	672		157	4,368	821	238	49,749
	USDC/DAI	290		102	3,445	501	1	8,150
Stable/Risky	USDC/WETH	6,562	1,329	495	14,997	6,259	374	19,177
	DAI/WETH	2,481	878	140	3,440	1,805	75	17,194
Risky/Risky	WBTC/WETH	874	420	243	2,037	1,038	81	31,604
	LINK/WETH	645	266	103	1,038	304	27	11,562
	AAVE/WETH	313	209	235	1,127	75	5	6,194
	YFI/WETH	325	376	53	71	47	4	
	Average	**1,520**	**580**	**191**	**3,815**	**1,356**	**101**	**20,519**

Table 4 represents the average trading volume per transaction. Transaction sizes are substantially larger than expected, with SushiSwap, non-CFMMs and Uniswap v3 ranging between $40,729 and $57,385. The high volume in non-CFMMs is attributed mainly to the Curve and Dodo exchanges, whose average transaction size in stablecoin pairs is $214,007. This volume suggests Curve and Dodo are popular AMMs for trading stablecoins. Surprisingly, Binance transaction sizes are much smaller than many AMMs, with an average volume of $10,541. The higher traded volume in AMMs is likely because there is no intention to split trades since the price is algorithmically determined. Additionally, by only performing one transaction, AMM agents reduce the amount of gas fees they are charged.[17] QuickSwap has the smallest transaction sizes at $1,057, indicating that traders prefer to make smaller, more frequent trades on this AMM.

Table 4
Average Trading Volume Per Transaction

This table displays the average trading size per transaction across AMMs and Binance. Stable refers to a stablecoin, and Risky refers to a non-stablecoin. Several exchanges are merged into non-CFMMs due to low trading activity. These include Bancor, Balancer, 0x, Curve and Dodo for Sample Period 1 (November 2020 to October 2021), and DeFi Swap, 1inch and PancakeSwap for Sample Period 2 (June 2021 to October 2021) (see Appendix Table 5A). All values are priced in USD terms. Note, not all exchanges trade every asset pair; these are left blank. The trading activity on Binance is also displayed from November 2020 to March 2021.

		Sample Period 1			**Sample Period 2**			**Centralised**
Asset Pair		**Uniswap v2**	**SushiSwap**	**Non-CFMMs**	**QuickSwap**	**Uniswap v3**	**Non-CFMMS**	**Binance**
Stable/Stable	USDC/USDT	6,228		162,601	573	41,672	203	2,161
	USDC/DAI	4,519		65,211	371	43,334	9	1,463
Stable/Risky	USDC/WETH	11,956	39,706	32,742	1,784	83,315	1,552	1,698
	DAI/WETH	13,915	40,216	46,509	1,178	32,974	1,796	674
Risky/Risky	WBTC/WETH	22,283	63,822	58,267	1,663	68,833	2,801	39,616
	LINK/WETH	14,443	32,163	33,081	1,312	43,735	1,320	26,358
	AAVE/WETH	15,756	38,392	40,424	1,564	19,495	857	1,817
	YFI/WETH	10,107	30,075	20,247	10	11,052	369	
	Average	**12,401**	**40,729**	**57,385**	**1,057**	**43,051**	**1,113**	**10,541**

[17] Gas fees refer to the computational expense for validating a transaction on the blockchain (see Appendix Table 3A).

Shifting focus towards the frequency of my dataset, I use prices recorded at ten-second intervals to estimate the daily VECM variables and, by extension, the price discovery metrics.[18] I choose this frequency for two reasons: (i) to allow comparison across AMMs on different blockchains, (ii) to limit contemporaneous correlation. Using 10-second intervals is granular enough for the VECM to capture which market is the first to change prices. Although using the blockchain's unique time interval block time would be ideal, it is unsuitable for this study as some AMMs are incompatible (e.g. PancakeSwap and QuickSwap).[19] Utilising an interval slightly shorter than block time, I can still capture its granularity without removing these unique AMMs. Moreover, the difference in price discovery shares when using block time and ten-second intervals is marginal (see Appendix Table 8A).

In addition to high-frequency price data, I collect daily volume, trades and gas fees through the Bitquery Application Programming Interface (API). Bitquery provides access to the eleven AMM blockchains through the GraphQL programming language. Furthermore, I collect the daily total-value locked (TVL) amounts from IntoTheBlock, DeFi Prime, and DeBank, and daily market prices from coinGecko's API.[20] Prices from coinGecko are required since the price data from Bitquery are recorded in relation to the asset pair. I use CoinGecko prices as the representative market price to convert the assets values in the pair to US dollar terms.

I winsorize my dataset to minimise the influence of outliers while still retaining a portion of their explanatory power. For price data, I determine the percentage level of winsorization by visually observing the price series. Since my price series has millions of observations, I set a low range between 1% and 0.00001% to avoid removing too much natural variation. For non-price data, I set the level of winsorization at 1%.

Table 5 displays the average correlation matrix of the variables used in the fixed effects panel regression in Section 4.3. I also include the three price discovery metrics: the Information Leadership Share (ILS), Component Share (CS) and the Information Share (IS), which act as the study's dependent variables. The IL variable represents the daily expense liquidity providers incur for investing in a liquidity pool, and the FeeYield variable denotes the daily compensation liquidity

[18] I use UTS' Interactive High Performance Computing Cluster (iHPC) to estimate the VECM.
[19] Block time refers to the timestamp that the blockchain has verified a group of transactions, and can occur anywhere between 2-20 seconds, averaging at about 15 seconds. PancakeSwap is run on the Binance chain, and QuickSwap is run on the Polygon/Matic chain.
[20] Total Value Locked refers to the sum of all assets deposited or 'staked' within a liquidity pool (see Appendix Table 3A).

providers receive. Both of these variables are explained in detail within Section 4.2. The variables in Table 6 are log-transformed to help normalise the data and account for the notable differences in values between asset pairs. Normalisation is particularly relevant for the IL and FeeYield variables as they have a skewed distribution with a narrow range of values.

Table 5 provides an initial observation of whether there is a positive or negative relation between variables. For the ILS, we see a negative coefficient with the CS (-0.40) and IS (-0.15), which is consistent with my hypothesis that these measures will contradict. Additionally, we see that IL has a positive association with the ILS at 0.11, which is expected. Interestingly, we see FeeYield with a positive coefficient with the ILS (0.24), indicating that higher fees lead to better price discovery. Lastly, daily trades and gas fees also display a positive coefficient.

Table 6 represents the descriptive statistics of the independent variables used in the fixed effects panel regression (Section 4.3). Here we see the disparity in variables between pair categories at daily observations. On average, the stable/stable pairs exhibit notably lower IL than the other two pair categories. This is likely because of the stablecoin's low volatility and is consistent with expectations. Additionally, the daily fee yield between categories is similar, indicating that each generates similar fees. Looking at the control variables, the risky/stable pairs appear to have the highest daily trades, and all categories accrue comparable gas fees.

Table 5
Pearson's Correlation Matrix

This table displays the correlation matrix between all daily price discovery, liquidity provider and control variables. This is averaged across the eight asset pairs between November 2020 and October 2021. The ILS is the Information Leadership Share, CS is the Component Share and IS is the Information Share. IL is the impermanent loss liquidity providers incur for investing in a liquidity pool. FeeYield is the compensation liquidity providers receive for investing in a liquidity pool. Trades is the daily number of trades, and GasValue is the expense of running on the blockchain. The logarithm of the IL, FeeYield, Trades and GasValue variables is used within this matrix and remains consistent throughout the rest of the paper.

	ILS	CS	IS	IL	FeeYield	Trades	GasValue
ILS	1.00						
CS	-0.40	1.00					
IS	-0.15	0.78	1.00				
IL	0.11	-0.15	-0.07	1.00			
FeeYield	0.24	-0.05	0.10	0.08	1.00		
Trades	0.47	-0.20	0.12	0.04	0.46	1.00	
GasValue	0.31	-0.11	0.11	0.06	0.42	0.82	1.00

Table 6
Descriptive Statistics of Regression Variables

This table displays the descriptive statistics of the daily liquidity provider and control variables. The eight pairs are averaged within their respective category between November 2020 and October 2021. Stable/Stable includes USDC/USDT and USDC/DAI. Risky/Stable includes USDC/WETH and DAI/WETH. Risky/Risky includes WBTC/WETH, LINK/WETH, AAVE/WETH and YFI/WETH. IL is the impermanent loss liquidity providers incur for investing in a liquidity pool. FeeYield is the compensation liquidity providers receive for investing in a liquidity pool. Trades is the daily number of trades, and GasValue is the expense of running on the blockchain. The logarithm of the IL, FeeYield, Trades and GasValue variables is used within this matrix and remains consistent throughout the rest of the paper

	Stable/Stable					**Risky/Stable**					**Risky/Risky**				
Variable	**Obs.**	**Mean**	**Std.**	**Min.**	**Max.**	**Obs.**	**Mean**	**Std.**	**Min.**	**Max.**	**Obs.**	**Mean**	**Std.**	**Min.**	**Max.**
IL	366	-17.3	3.4	-32.2	-9.1	912	-9.6	2.3	-19.0	-5.5	727	-8.2	2.0	-16.6	-0.8
Fee Yield	366	-9.3	1.3	-12.5	-6.0	912	-7.4	1.0	-9.8	-4.6	727	-6.6	0.9	-9.7	-4.3
Trades	366	6.5	1.3	4.2	9.7	912	7.7	0.9	5.2	10.1	727	4.4	0.9	0.8	6.5
Gas Value	366	1.8	1.5	-1.3	5.9	912	3.7	1.2	0.8	7.6	727	1.0	1.5	-5.1	5.0

4. Research Design & Main Results

In this section, I describe the research design of my study and provide the main results. I then draw out and discuss several implications that relate to my hypotheses. I categorise my main results into three sections: AMM price discovery, liquidity provision dynamics, and the fixed effects panel regression model.

4.1. AMM Price Discovery

I utilise prices at ten-second intervals to estimate three daily price discovery shares. My objective is to determine which AMM is first to reflect a change in the fundamental value of an asset. I calculate the following metrics: the Hasbrouck (1995) Information Share, Gonzalo and Granger (1995) Component Share and Putniņš (2013) Information Leadership Share. They attempt to disentangle the price series by examining the market's speed in impounding new information. The ILS will serve as the dependent variable for the main regression in Section 4.3. The CS and IS will be used as the dependent variable as a robustness test in Section 4.6.

The three price discovery metrics rely on the assumption that both price series are cointegrated. This assumption is based on economic intuition, being that both series reflect the same asset and hence the same fundamental value (Hasbrouck (1995)). Although the prices will deviate in the short-term due to mainly noise and trading frictions, they will converge in the long-term since arbitrage will enforce similarity between the two prices.

The economic assumption of cointegration makes applying a vector error correction model (VECM) logical. Moreover, all three price discovery measures derive from estimates of a reduced form VECM. I estimate the VECM in a bi-variate setting,

$$\begin{aligned}\Delta p_{1,t} &= \alpha_1\left(p_{1,t-1} - p_{2,t-1}\right) + \sum_{i=1}^{n} \gamma_i \Delta p_{1,t-i} + \sum_{j=1}^{n} \delta_j \Delta p_{2,t-j} + \varepsilon_{1,t},\\ \Delta p_{2,t} &= \alpha_2\left(p_{1,t-1} - p_{2,t-1}\right) + \sum_{k=1}^{n} \varphi_k \Delta p_{1,t-k} + \sum_{m=1}^{n} \phi_m \Delta p_{2,t-m} + \varepsilon_{2,t},\end{aligned} \tag{1}$$

where $\Delta p_{1,t}$ and $\Delta p_{2,t}$ are the changes in log prices of price series one and two respectively at time t. The error correction term $\left(p_{1,t-1} - p_{2,t-1}\right)$ explains the actual difference between the two prices, with α_i being its coefficient and n denoting the number of lags estimated within the VECM. Estimating two price series keeps the computational requirements for my study at a manageable level. Since the study compares markets with varying liquidity levels, the number of lags is intuitively determined for each asset pair. I also use the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to determine the optimal VECM lag length as a robustness check (Akaike (1973); Akaike (1974)).[21] Although Lütkepohl (2005) claims the AIC is worse at estimating lag lengths for a VECM compared to a VAR, he still considers it a reasonable estimation compared to other criteria. Since there are only two price series within the VECM, the maximum number of cointegrating vectors is one; however, I prove this separately using the Johansen Cointegration test.

My study uses the Putniņš (2013) Information Leadership Share as the primary metric for measuring the informational efficiency of AMMs. It uses the Component Share and Information Share as inputs to form the Yan and Zivot (2010) structural cointegration model, [22]

$$ILS_1 = \frac{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right|}{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| + \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|}, \qquad ILS_2 = \frac{\left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|}{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| + \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|}, \tag{2}$$

where ILS_2 is simplified to,

$$ILS_2 = 1 - ILS_1. \tag{3}$$

I only consider the ILS estimates when determining the price leader in my study. This is because the ILS accounts for the many microstructure features that would contribute to overall market noise between exchanges. Alternatively, the Component and Information Shares provide supplementary insights to my study as they only accurately estimate price discovery when markets exhibit a similar level of noise (see Appendix C for additional information on the CS and IS). Considering the open-source nature and lower technical sophistication of AMMs, many present vastly different levels of noise which therefore reduce the informativeness of the CS and IS.

Additionally, to improve the validity of results, three diagnostics are used to control for contemporaneous correlation and accuracy. The first diagnostic is the correlation of the VECM reduced form errors,

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[21] Refer to Table 12 for AIC and BIC lag estimations in Section 4.4.

[22] Refer to Eqs. (3A) and (7A) in Appendix C for the Component Share and Information Share calculations.

$$\rho = \frac{\sigma_{1,2}}{\sqrt{\sigma_1^2 \sigma_2^2}}, \tag{4}$$

where σ_1 and σ_2 are the standard deviations of price series one and two, respectively. The second diagnostic is the difference between the upper and lower bound of IS_1,

$$UmL = \left| IS_{1,x} - IS_{1,y} \right|, \tag{5}$$

where x and y denote orders configuration one and two, respectively. These two diagnostics help identify whether the sampling frequency is high enough to capture which market moves first in reflecting new prices. An initial average upper bound of UmL is set at 0.20 for the price series. Although this is still relatively high, I deem it necessary to account for the lower sophistication of AMM markets. If the average UmL variable is greater than 0.20, I deem the sampling frequency too low and rerun the VECM at a higher interval to reduce the impact of contemporaneous correlation. However, I find that using ten-second intervals is sufficient in maintaining the UmL below the 0.20 cut-off. The third diagnostic is the spread between upper and lower bounds of the 95% confidence interval (CI). The tightness of the spread ensures that the price discovery shares accurately represent the results of the VECM estimation.

I structure the results by first comparing the price discovery estimates between AMMs and the CLOB exchange Binance. I then break down AMMs into two model types: constant function market makers (CFMMs) and non-CFMMs. I continue to estimate the price shares between individual AMMs until a final price leader is determined.

Table 7 reports the ILS, IS and CS estimates between Binance and AMMs, demonstrating which market is the first to reflect new information. The CS and IS metrics attribute most of the price discovery within Binance on average 94% of the time. Contrastingly, AMMs have a minimal effect on price discovery when considering the CS and IS measures, with an average of 6%. The story changes when looking at the ILS measure, as it attributes AMMs as the overall informational leader across the sampled pairs at 62%. However, Binance does appear to still lead the LINK/WETH and AAVE/WETH pairs at 56% and 70%, respectively. As highlighted within Putniņš (2013), the disparity between measures in Table 7 illustrates the strong bias CS and IS have towards the less noisy market. These results support their findings as stripping out microstructure noise clarifies which market is the leader. The average correlation estimate is 0.02, and the average spread of IS bounds is 0.01, implying there is very little contemporaneous correlation when sampled at ten-second intervals. The CI bounds are moderately sized, averaging at 0.10.

Table 7
Estimates of Price Discovery Shares between Binance and AMMs

This table shows the Informational Leadership Shares (ILS), Information Shares (IS), and Component Shares (CS) from the CLOB exchange Binance and a collection of sampled AMMs. Individual AMM price series are merged, giving preference to exchanges with more trade activity (see Table 4A for exact order). The respective market is denoted by the subscript. The shares are estimated between November 2020 and March 2021. The informational leader for a particular share is shaded. Three diagnostics are also computed: the correlation of reduced form errors (Correl), the spread of the IS between orderings (UmL) and the spread between the confidence intervals set at 95% (CI_{ILS}). Shares for YFI/WETH are not estimated since Binance does not trade that pair.

	Price Discovery Shares						Diagnostics		
Asset Pair	$\mathbf{ILS_{Binance}}$	$\mathbf{ILS_{AMM}}$	$\mathbf{IS_{Binance}}$	$\mathbf{IS_{AMM}}$	$\mathbf{CS_{Binance}}$	$\mathbf{CS_{AMM}}$	Correl	UmL	CI_{ILS}
USDC/USDT	0.25	0.75	0.99	0.01	0.99	0.01	-0.01	0.01	0.11
USDC/DAI	0.20	0.80	0.98	0.02	0.99	0.01	-0.01	0.01	0.10
USDC/WETH	0.32	0.68	0.94	0.06	0.95	0.05	0.04	0.01	0.10
DAI/WETH	0.30	0.70	0.90	0.10	0.94	0.06	0.04	0.02	0.10
WBTC/WETH	0.34	0.66	0.97	0.03	0.98	0.02	0.02	0.01	0.10
LINK/WETH	0.56	0.44	0.93	0.07	0.92	0.08	0.03	0.01	0.11
AAVE/WETH	0.70	0.30	0.86	0.14	0.81	0.19	0.04	0.02	0.07
Average	**0.38**	**0.62**	**0.94**	**0.06**	**0.94**	**0.06**	**0.02**	**0.01**	**0.10**

These results are interesting in several ways. Firstly, the AMM market type tends to be the first to impound new information when accounting for noise, rather than the CLOB Binance. This result demonstrates that informed traders tend to use the new AMM model instead of the well-established CLOB. One explanation for this finding is that AMM's algorithmic pricing function is easier to predict. Therefore, this greater predictability can allow the more sophisticated traders to maximise their gains. Another potential explanation is that because of AMM's novelty, traders in these markets often have a more sophisticated understanding of crypto-asset markets. As a result, there potentially could be fewer noise traders within AMMs compared to centralised exchanges. Considering that Binance is the largest cryptocurrency exchange in the world, this finding gains significance. Table 7 also highlights how AMM prices are substantially noisier than centralised exchange prices through the IS and CS estimates. This difference in noise is likely a result of two things. The first reason is that AMMs have a much lower trading frequency, as evident in Table 3.

The second explanation is that AMM's relatively inflexible pricing algorithm can cause significant deviations in price when large trades occur within a short period. These findings are novel and informative, supporting the idea that AMMs can sustainably perform price discovery.

With AMMs being established as the overall market leader when accounting for noise, the next logical step is to drill down into which AMM model leads price discovery. I estimate the price discovery shares between CFMMs and non-CFMMs in Table 8. The results in Table 8 show CFMMs as the leading exchange type. All three estimates are consistent, with CFMMs leading price changes 62% (CS) and 70% (IS and ILS) of the time. However, the estimates are more varied between pairs than in Table 7, with the differences in ILS ranging between 16% and 52%.

Interestingly, the CS and IS attribute non-CFMMs as the informational leader within the USDC/USDT stablecoin pairs at 82% and 76%, respectively. Similar to Table 7, this likely implies that there is significantly more noise within the CFMMs than the non-CFMMs within this asset pair. Low correlations and IS bounds indicate that estimates are unaffected by contemporaneous correlation. The average CI is also smaller than Table 7 at 0.07, implying higher accuracy.

Table 8

Estimates of Price Discovery Shares between CFMMs and non-CFMMs

This table displays the Informational Leadership Shares (ILS), Information Shares (IS), and Component Shares (CS) from the constant-function market maker type (CFMM) and non-CFMM AMMs. Individual AMM price series are merged, giving preference to larger exchanges (see Appendix Table 4A for exact order). The respective market is denoted by the subscript. Non-CFMM is denoted by the 'Other' subscript. The shares are estimated between June 2021 and October 2021. The informational leader for a particular share is shaded. Three diagnostics are also computed: the correlation of reduced form errors (Correl), the spread of the IS between orderings (UmL) and the spread between the confidence intervals set at 95% (CI_{ILS}).

	Price Discovery Shares						Diagnostics		
Asset Pair	**ILS_{CFMM}**	**ILS_{Other}**	**IS_{CFMM}**	**IS_{Other}**	**CS_{CFMM}**	**CS_{Other}**	Correl	UmL	CI_{ILS}
USDC/USDT	0.69	0.31	0.24	0.76	0.18	0.82	0.01	0.01	0.08
USDC/DAI	0.58	0.42	0.56	0.44	0.51	0.49	0.01	0.01	0.09
USDC/WETH	0.66	0.34	0.97	0.03	0.91	0.09	0.01	0.01	0.09
DAI/WETH	0.69	0.31	0.94	0.06	0.87	0.13	0.02	0.01	0.08
WBTC/WETH	0.76	0.24	0.66	0.34	0.57	0.43	0.01	0.01	0.06
LINK/WETH	0.75	0.25	0.90	0.10	0.77	0.23	0.02	0.01	0.07
AAVE/WETH	0.73	0.27	0.72	0.28	0.62	0.38	0.07	0.05	0.05
YFI/WETH	0.70	0.30	0.64	0.36	0.55	0.45	0.04	0.03	0.07
Average	**0.70**	**0.30**	**0.70**	**0.30**	**0.62**	**0.38**	**0.02**	**0.02**	**0.07**

With the CFMM market type established as the clear informational leader, I split CFMMs into individual exchanges and their respective sample periods.[23] Table 9 displays the price discovery metrics between Uniswap v2 and SushiSwap, and between Uniswap v3 and QuickSwap, respectively. I compute the price shares for these exchanges as they are the only CFMMs within their respective sample periods. The price shares for non-CFMMs are not estimated for two reasons. The first is that the ILS in Table 8 does not consider non-CFMMs to lead price discovery. The second reason is that individually, they have too little liquidity to run the VECM accurately.

Similar to Table 8 results, the IS and CS in Table 9 attribute SushiSwap as the price discovery leader at 57% and 64%. The ILS again contradicts this finding, attributing Uniswap v2 as the first to impound new information on average 63% of the time. However, unlike the past estimates, the difference between SushiSwap and Uniswap v2 is smaller, with an overall spread of 22%. The tighter range suggests that both markets exhibit similar levels of microstructure noise. The correlations and IS bounds are the largest of the study, averaging at 0.12 and 0.11, respectively. These diagnostics indicate that both prices are more closely aligned than other AMMs. This finding is understandable, considering SushiSwap is a direct copy of the Uniswap v2 exchange.[24] Uniswap v2 being the price leader is consistent with my hypothesis that the most actively traded exchanges tend to be more price efficient.

Alternatively, Panel B exhibits that QuickSwap is the informational leader when compared to Uniswap v3. Table 9 again demonstrates the CS and IS' preference for lower noise levels, with Uniswap v3 being considered the price leader at 77% and 64% on average. Conversely, the ILS concludes that QuickSwap is the first to change the fundamental value of prices 75% of the time when accounting for noise. Looking at pair categories, QuickSwap dominates the price discovery of stablecoin and risky pairs more than the stable/risky pairs. This finding is likely because these pairs are the largest and most popular within Uniswap. Initially, QuickSwap's price leadership was unexpected. However, considering that the AMM has more than double the average daily trades of Uniswap v3 (see Table 3), this supports my trade activity hypothesis.

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[23] SushiSwap and Uniswap v2 are in Sample Period 1, and QuickSwap and Uniswap v3 are in Sample Period 2.

[24] In 2020, the SushiSwap exchange was created by performing a 'vampire attack' on Uniswap v2. It achieved this by offering Uniswap users incentives to bridge their assets onto the SushiSwap exchange resulting a large amount of liquidity being "sucked out" and transferred to SushiSwap (Stone (2021)).

Table 9

Estimates of Price Discovery Shares of Uniswap v2/v3, SushiSwap, and QuickSwap

This table shows the Informational Leadership Shares (ILS), Information Shares (IS), and Component Shares (CS) of Uniswap v2/v3, SushiSwap and QuickSwap AMMs. The shares between Uniswap v2 and SushiSwap are estimated between November 2020 and October 2021. The shares between Uniswap v3 and QuickSwap are estimated between June 2021-October 2021. Uniswap v2 and v3 are denoted by the subscript 1, SushiSwap and QuickSwap are denoted by the subscript 2. The informational leader for a particular share is shaded. Three diagnostics are also computed: the correlation of reduced form errors (Correl), the spread of the IS between orderings (UmL) and the spread between the confidence intervals set at 95% (CI_{ILS}). The stablecoin pairs for Table 9 are unable to be estimated as SushiSwap does not trade those pairs

	Price Discovery Shares						Diagnostics		
Asset Pair	**ILS_1**	**ILS_2**	**IS_1**	**IS_2**	**CS_1**	**CS_2**	Correl	UmL	CI_{ILS}
Panel A: Uniswap v2 - SushiSwap									
USDC/WETH	0.78	0.22	0.59	0.41	0.42	0.58	0.08	0.08	0.03
DAI/WETH	0.66	0.34	0.45	0.55	0.37	0.63	0.09	0.09	0.04
WBTC/WETH	0.66	0.34	0.48	0.52	0.38	0.62	0.07	0.06	0.04
LINK/WETH	0.65	0.35	0.41	0.59	0.33	0.67	0.13	0.12	0.03
AAVE/WETH	0.53	0.47	0.35	0.65	0.33	0.67	0.18	0.16	0.03
YFI/WETH	0.49	0.51	0.31	0.69	0.31	0.69	0.14	0.13	0.05
Average	**0.63**	**0.37**	**0.43**	**0.57**	**0.36**	**0.64**	**0.12**	**0.11**	**0.04**
Panel B: Uniswap v3 - QuickSwap									
USDC/USDT	0.11	0.89	0.60	0.40	0.87	0.13	-0.01	0.01	0.10
USDC/DAI	0.05	0.95	0.54	0.46	0.90	0.10	0.01	0.01	0.06
USDC/WETH	0.35	0.65	0.92	0.08	0.95	0.05	0.04	0.02	0.10
DAI/WETH	0.43	0.57	0.69	0.31	0.73	0.27	0.03	0.02	0.10
WBTC/WETH	0.13	0.87	0.94	0.06	0.98	0.02	0.01	0.01	0.09
LINK/WETH	0.34	0.66	0.45	0.55	0.53	0.47	0.01	0.01	0.08
AAVE/WETH	0.13	0.87	0.24	0.76	0.48	0.52	0.01	0.01	0.08
YFI/WETH	0.47	0.53	0.71	0.29	0.75	0.25	0.01	0.01	0.13
Average	**0.25**	**0.75**	**0.64**	**0.36**	**0.77**	**0.23**	**0.01**	**0.01**	**0.09**

To clarify which two exchanges should be considered in the final estimation, I compute the price discovery shares for all additional orderings between CFMMs (see Appendix Table 7A). From those results, I find Uniswap v2 and QuickSwap to be the most price-efficient AMMs within Sample Periods 1 and 2, respectively. To determine the price leader of the study, Table 10 exhibits the price discovery shares between Uniswap v2 and QuickSwap. Looking at the ILS, Table 10 declares QuickSwap as the definitive price leader of my study, with a value of 72%. YFI/WETH is the only pair that attributes Uniswap v3 as the slightly more price efficient exchange at 51%. Contemporaneous correlation is minimal, with the correlation and IS bounds averaging at 0.01. The bounds of confidence intervals are similar to past estimations at 0.10, implying the estimates are relatively robust. The CS results are consistent, attributing Uniswap v2 as the less noisy and, therefore, the first to react to information. Alternatively, the IS estimates are mixed, finding that QuickSwap is more price efficient within the USDC/DAI, USDC/WETH, DAI/WETH and AAVE/WETH pairs.

Table 10

Estimates of Price Discovery Shares between Uniswap v2 and QuickSwap

This table shows the Informational Leadership Shares (ILS), Information Shares (IS), and Component Shares (CS) from the Uniswap v2 and QuickSwap AMMs. The shares are estimated between June 2021 and October 2021. The respective market is denoted by the subscript. The informational leader for a particular share is shaded. Three diagnostics are also computed: the correlation of reduced form errors (Correl), the spread of the IS between orderings (UmL) and the spread between the confidence intervals set at 95% (CI_{ILS}).

Asset Pair	Price Discovery Shares						Diagnostics		
	ILS_{Uni}	**ILS_{Quick}**	**IS_{Uni}**	**IS_{Quick}**	**CS_{Uni}**	**CS_{Quick}**	Correl	UmL	CI_{ILS}
USDC/USDT	0.23	0.77	0.53	0.47	0.68	0.32	-0.01	0.01	0.13
USDC/DAI	0.24	0.76	0.19	0.81	0.43	0.57	0.01	0.01	0.14
USDC/WETH	0.35	0.65	0.49	0.51	0.57	0.43	0.03	0.03	0.08
DAI/WETH	0.31	0.69	0.39	0.61	0.51	0.49	0.02	0.02	0.09
WBTC/WETH	0.12	0.88	0.92	0.08	0.96	0.04	0.01	0.01	0.09
LINK/WETH	0.38	0.62	0.51	0.49	0.59	0.41	0.01	0.01	0.10
AAVE/WETH	0.11	0.89	0.33	0.67	0.60	0.40	0.01	0.01	0.05
YFI/WETH	0.51	0.49	0.69	0.31	0.71	0.29	0.02	0.02	0.13
Average	**0.28**	**0.72**	**0.51**	**0.49**	**0.63**	**0.37**	**0.01**	**0.01**	**0.10**

Table 10's conclusion that QuickSwap is the most price-efficient AMM out of the study provides several novel insights. This result further supports my hypothesis that the most actively traded AMM is likely the most price-efficient exchange. The explanation for QuickSwap's price leadership likely stems from it being run on the Polygon chain. The Polygon blockchain has significantly lower gas fees and faster transaction times compared to the Ethereum blockchain, making it highly attractive for traders. Despite being released in May 2021, it shows informed traders have quickly switched markets to take advantage of the lower costs and faster transaction speeds. Considering that Uniswap has the biggest liquidity pools, the most active users and has undergone three major protocol updates to improve its pricing function, my results imply that these qualities are not as attractive to informed participants.

Additionally, my findings also suggest that price leadership is mostly consistent across asset pairs. This conclusion implies that informed traders either trade across multiple asset pairs or tend to gravitate towards the same exchanges. Moreover, these results further prove that the IS and CS estimates are inaccurate when comparing markets with different noise levels. Their contradiction with the ILS supports my hypothesis, indicating that they are biased towards less noisy markets. Since the ILS accounts for different market microstructure noise, it provides a more precise conclusion. I also find that using ten-second intervals is a reasonable frequency to examine AMMs from a price discovery perspective. Across all estimations, contemporaneous correlation had a minimal impact on results, and the tight IS, and confidence interval bounds further support that the interval chosen is appropriate.

4.2. Liquidity Provision Dynamics

In this sub-section, I compute several liquidity provider metrics over Sample Periods 1 and 2. The objective is to demonstrate the differences in price movements, fee generation and handling of IL. My study computes these components with a formula designed for CFMMs described in Putniņš (2021). Although calculated differently, these equations are empirically equivalent to other studies (Barbon and Ranaldo (2021); Jensen, Pourpouneh, Nielsen and Ross (2021); Wang, Heimbach and Wattenhofer (2021)), which I prove as a robustness check (see Figure 9). Although AMMs have different pricing algorithms, Xu, Vavryk, Paruch and Cousaert (2021) demonstrate that most are slight variations of the CFMM pricing function. Therefore, using this generalised formula to calculate the IL is considered appropriate since it still captures meaningful variation through each AMM's price action.

Impermanent Loss

I first calculate the IL, which represents the adverse selection cost of providing liquidity in an AMM liquidity pool,

$$Impermanent\ Loss = \sqrt{\frac{P_T}{P_0}} - \frac{1}{2}\left(\frac{P_T}{P_0} + 1\right), \tag{6}$$

where P_0 and P_T are the price of the risky asset upon entering and exiting the pool, respectively. Naturally, the IL will always be negative because of the order imbalance between both assets. In risky/risky pairs, WETH is considered the stable asset.

Figures 1 and 2 show the daily accumulative IL that liquidity providers experience over Sample Periods 1 and 2, respectively. Overall, we see that the magnitude of IL is considerably different amongst asset pairs. The most significant discrepancies are between assets of differing volatilities, exemplified between the stablecoin pairs (USDC/USDT and USDC/DAI) and the rest of the sample. Contrastingly, many AMMs appear to exhibit very similar IL within each pair. The values of USDC/USDT range between -0.001% and -0.040%, with Uniswap v2 and PancakeSwap having the highest IL in their sample periods. These losses are similar to USDC/DAI in Figure 1, except for Balancer, which saw an IL of -5%. Within Figure 2, Uniswap v3 in USDC/DAI appears to exhibit almost zero IL.

Looking at the stable/risky pairs (USDC/WETH and DAI/WETH), the IL averages at -10% and -2.5% in Figures 1 and 2, respectively. What is visually apparent in Figure 1's stable/risky pairs are that Bancor experiences significantly more IL than its peers at -42% in USDC/WETH and -57% in DAI/WETH. Similarly, Figure 2 shows that DeFi Swap has far higher IL than its peers, highlighted with a return of -7.6% in DAI/WETH. Excluding these two exchanges, most AMMs experience similar IL across the stable/risky pairs.

Shifting focus towards the risky/risky pairs, we see that WBTC/WETH sustains the least amount of IL over both sample periods averaging at -4.8% and -0.62%. Figure 1's average excludes Bancor, which had a remarkable accumulative IL value of -56%. Next, the LINK/WETH asset pair also experiences moderate IL averaging at -4.5% in Figure 1 and -0.9% in Figure 2. Lastly, AAVE/WETH and YFI/WETH suffer the greatest average IL in Figure 1 at -11% and -11.5%, respectively. This IL decreases substantially in Figure 2, where AAVE/WETH averages -

2.2%, and YFI/WETH averages -0.85%. DeFi Swap again sees large IL in AAVE/WETH, and QuickSwap surprisingly experiences much higher IL than its peers within YFI/WETH.

The results in Figures 1 and 2 support my second hypothesis that IL is primarily a function of the asset price dynamics. This is evident through the substantial differences in IL returns between asset pairs. As expected, pairs with stablecoins experience much less IL due to their minimal price volatility. The understanding that IL is highly dependent on the volatility of the asset is also consistent with the current literature (Angeris and Chitra (2020); Angeris, Kao, Chiang, Noyes and Chitra (2019); Evans (2020); Wang, Heimbach and Wattenhofer (2021)).

When observing each pair in isolation, my results also demonstrate that AMMs mostly exhibit very similar levels of IL. This finding implies that most AMMs are closely priced with each other and further reinforces my hypothesis that individual AMM models impact the IL less than the asset price dynamics. Additionally, the lower overall IL within Sample Period 2 is expected as the IL was estimated over less time. Interestingly, the Bancor and DeFi Swap AMMs consistently exhibit the largest IL, implying that these exchanges are priced less accurately with respect to the market, resulting in higher price deviations and IL.

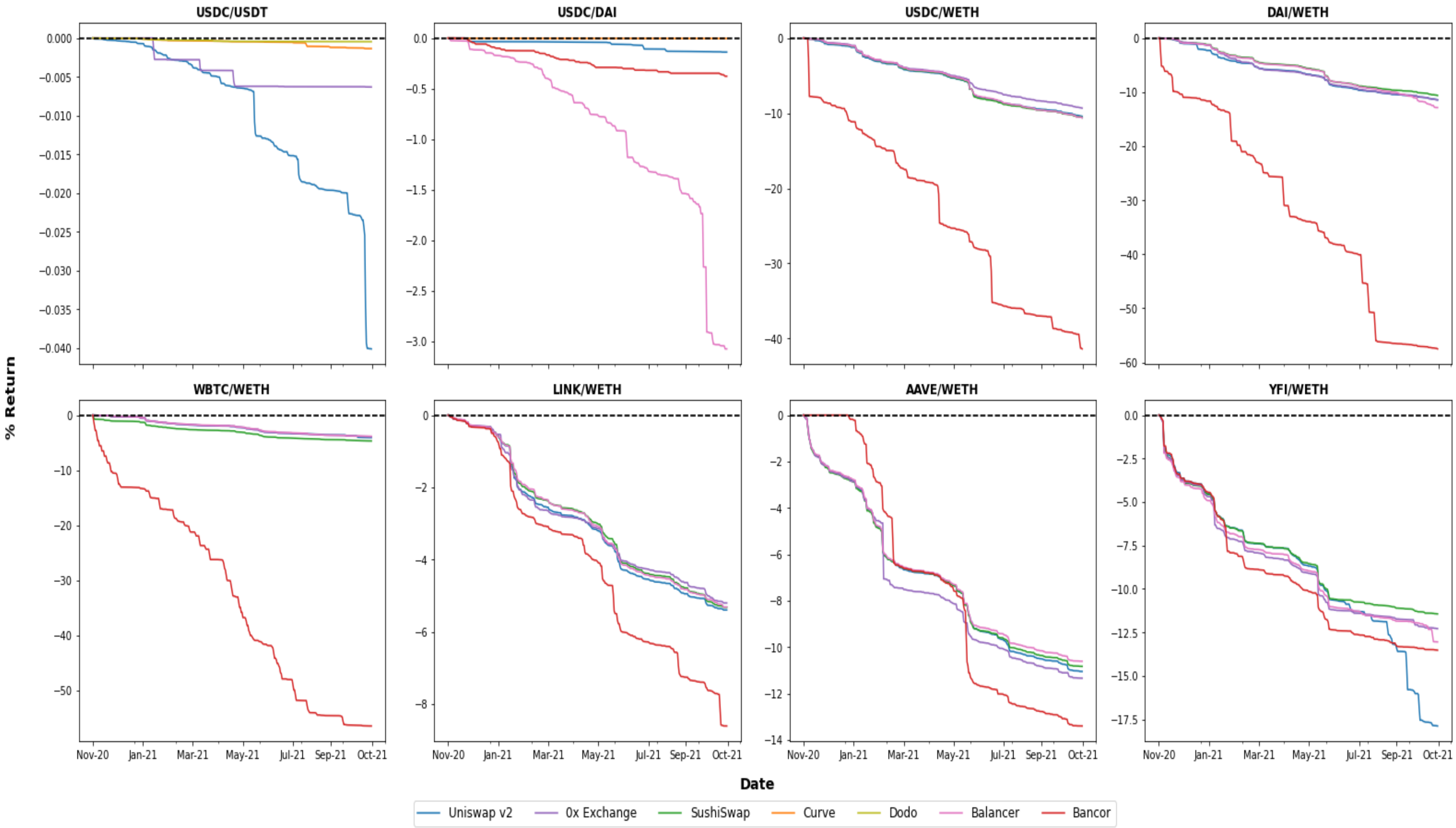

Figure 1. Total Accumulative Impermanent Loss, Sample Period 1.

This figure displays the total accumulative impermanent loss liquidity providers suffer for each asset pair between November 2020 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 1 displays the AMMs and its respective colour code. The x-axis is shared.

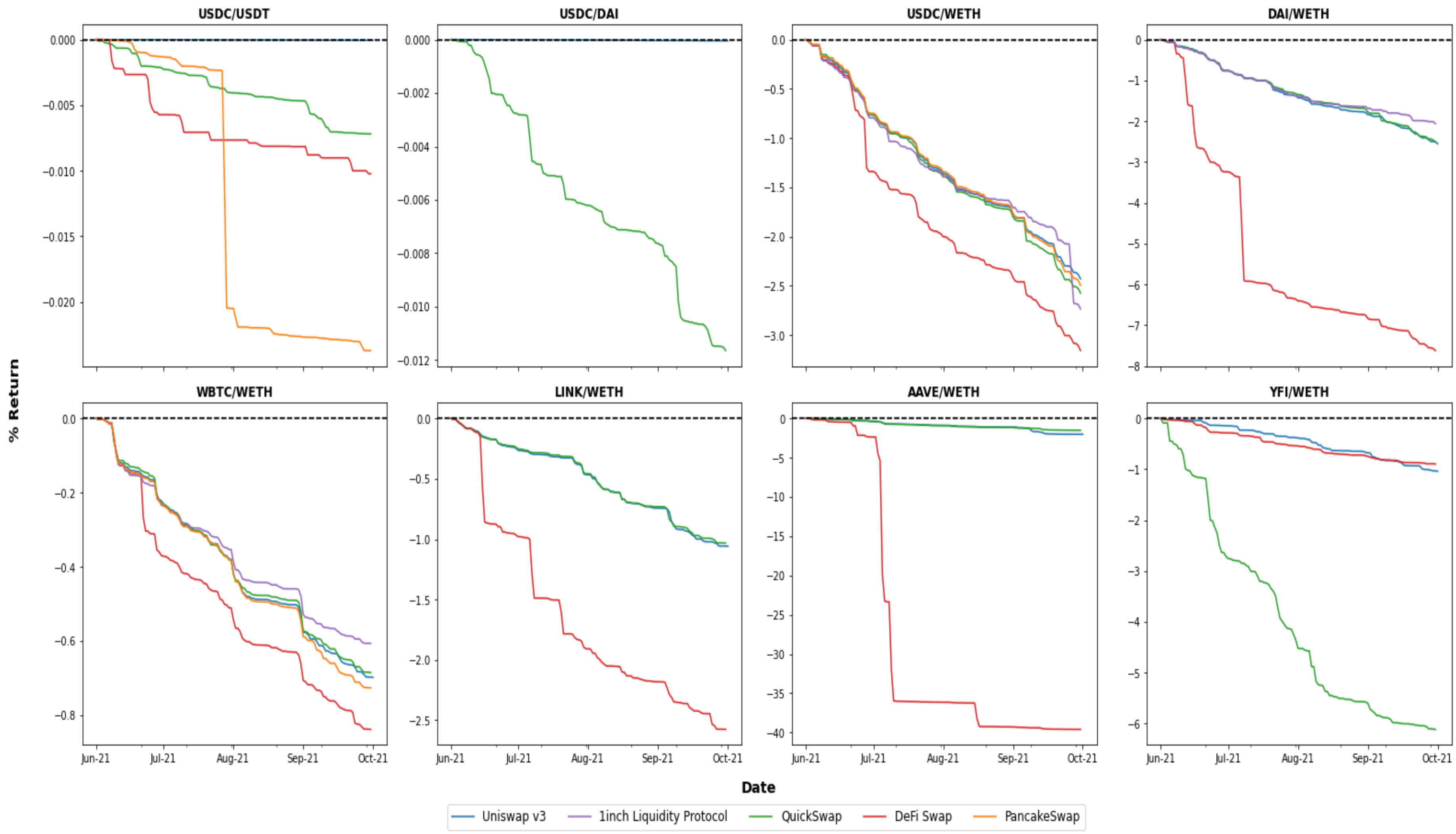

Figure 2. Total Accumulative Impermanent Loss, Sample Period 2.
This figure displays the total accumulative impermanent loss liquidity providers suffer for each asset pair between June 2021 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 2 displays the AMMs and its respective colour code. The x-axis is shared.

Fee Yield

Similar to how market makers in traditional finance receive a maker-taker fee for acting on both sides of the market, liquidity providers also receive similar compensation. The fees are rewarded to liquidity providers to offset the IL incurred and therefore provide an incentive for supplying assets to liquidity pools. I calculate these fees by the following equation,

$$Fee\ Yield = Fee\frac{Q_T}{V_0}, \tag{7}$$

where Q_T denotes the total trade volume between pool entry and exit and V_0 represents the total value locked (TVL). Fee represents the percentage of trade volume that liquidity providers receive as fees and varies between AMMs and liquidity pools. The percentages for each exchange/pair are found in Table10A within the Appendix.

Figures 3 and 4 display the daily accumulative fee yield liquidity providers receive over both sample periods. Overall fee yields appear to vary more between exchanges compared to the IL results. Uniswap v2 and v3 generate the highest fee yields, often well above its peers, averaging 16.3% and 20.9%, respectively. Surprisingly Uniswap v3 in Figure 4 produces significantly higher returns than v2 within the stable/risky pairs. Other AMMs also achieve high yields in Figure 3, with Curve in USDC/USDT, Balancer in AAVE/WETH and DeFi Swap in DAI/WETH and WBTC/WETH. Looking at the magnitude of returns, we see the stable/risky pairs are best performing across Figures 3 and 4, ranging between 2.5% and 50% as well as 4% and 70%, respectively. Yields across risky/risky pairs are similar, averaging around 9% in Sample Period 1 and 4.5% in Sample Period 2. In contrast to the IL results, Bancor and DeFi Swap have the lowest accumulative average fee yield, averaging 1.7% and 3.6%.

Ultimately, the results in Figures 3 and 4 are consistent with expectations, showing that substantial fee yields can be generated through high trading volume. Examples supporting this conclusion include Uniswap v2/v3, Curve and QuickSwap, which consistently outperform many of their peers. Moreover, the 0x Exchange and Balancer also demonstrate that small liquidity pools can generate reasonable returns, as seen in the DAI/WETH and WBTC/WETH pairs. Uniswap v3 returning higher yields than v2 within less time implies that the AMM has very high trade activity and volume, which is reinforced in Table 3. Alternatively, Bancor consistently ranks at the bottom of fee yield generation, suggesting very low trade volume (see Table 4A).

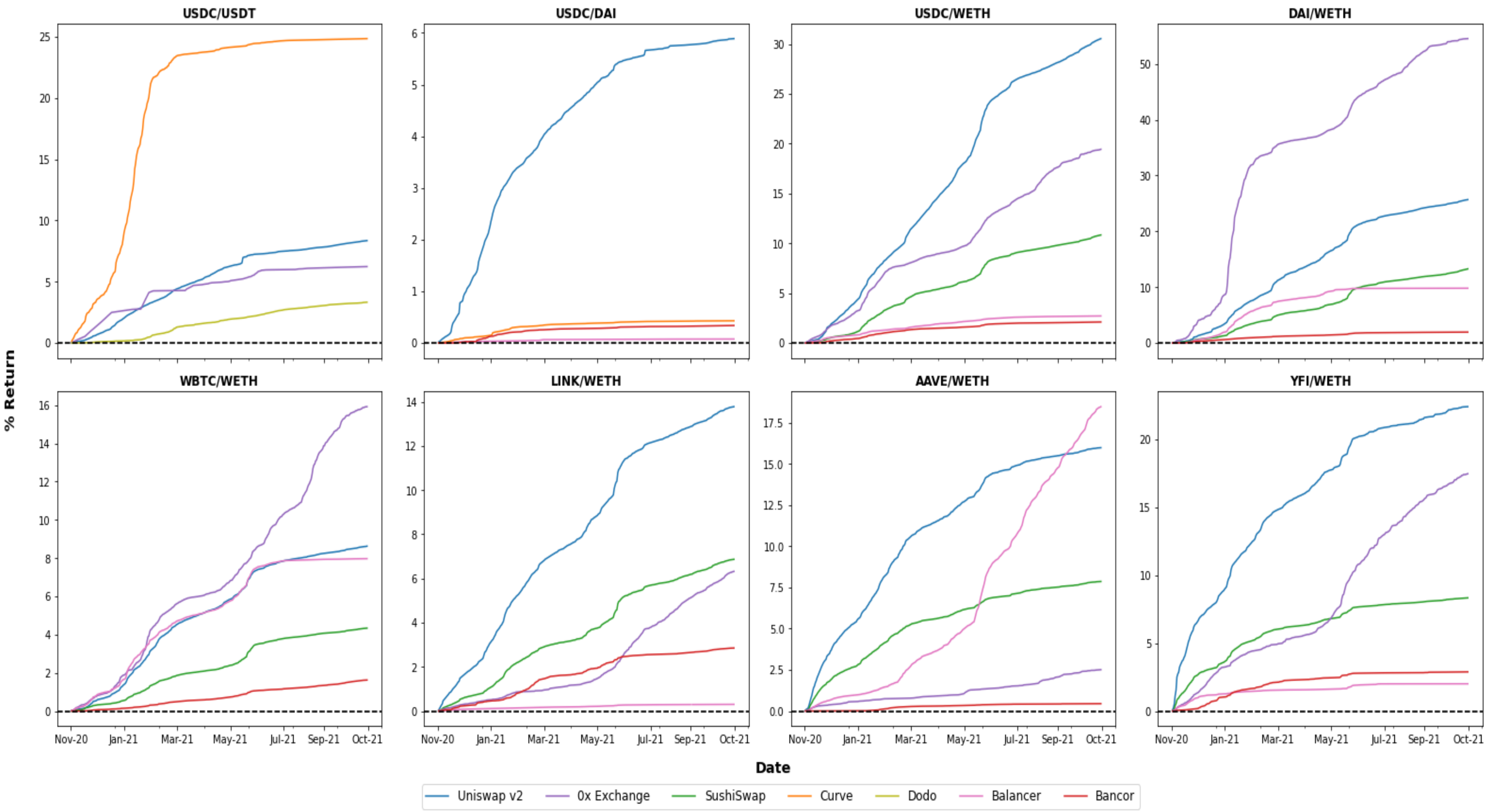

Figure 3. Total Accumulative Fee Yield, Sample Period 1.

This figure displays the accumulative daily fee yield liquidity providers receive for each asset pair between November 2020 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 3 displays the AMMs and its respective colour code. The x-axis is shared.

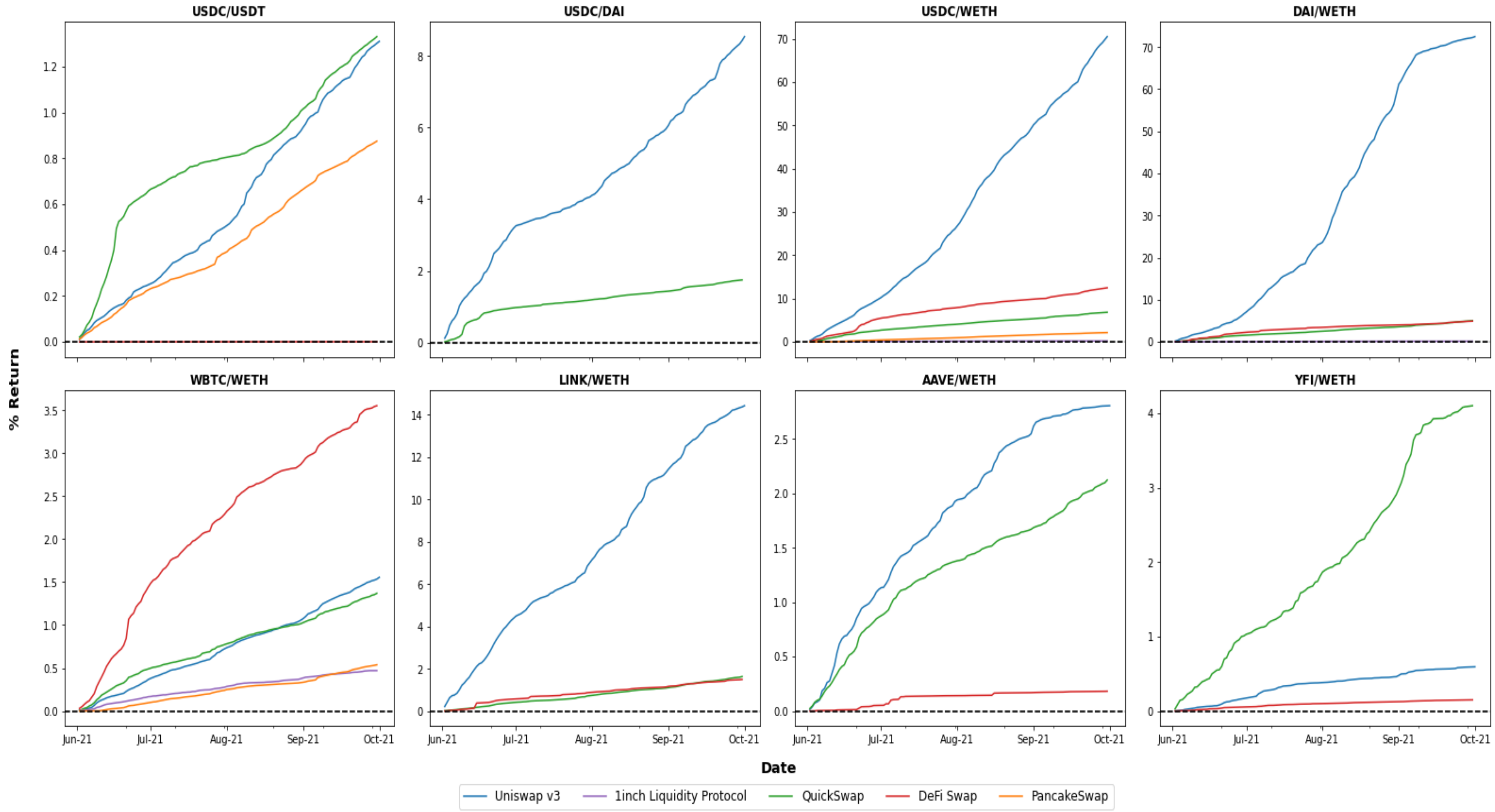

Figure 4. Total Accumulative Fee Yield, Sample Period 2.

This figure displays the accumulative daily fee yield liquidity providers receive for each asset pair between June 2021 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 4 displays the AMMs and its respective colour code. The x-axis is shared.

Fee Yield & Impermanent Loss

I combine both metrics to determine which drives liquidity provider returns. The objective is to understand the relative informativeness of each AMM. Since IL is a result of arbitrage, I consider it a proxy for the level of informed trades within an exchange. On the contrary, since fee yield is primarily based on trade volume, I consider it a proxy for un-informativeness.

Figures 5 and 6 show the accumulative net return of IL and fee yield for Samples 1 and 2, respectively. Looking at Figure 5, we see substantial variation between AMMs, with Uniswap v2 being the only exchange to achieve positive returns (5% to 20%) over all asset pairs. The other AMMs have mixed performance, with Bancor consistently seeing substantial negative returns (-6% to -55%), SushiSwap breaking even or experiencing slightly negative returns (1% to -3%) and Balancer with minor negative returns (-6% to -55%). Interestingly, 0x sees a surge of strong performance after May 2021 within LINK/WETH and YFI/WETH and similarly with Balancer in AAVE/WETH. The USDT/USDC returns also look identical to Figure 3, highlighting the minimal IL sustained within stablecoin pairs.

Continuing onto Figure 6, we see less variation amongst asset pairs. It appears most exchanges either deliver flat or positive performance on every pair except for YFI/WETH. Uniswap v3 is the clear outperformer ranging from 1% to 70% return. On average, QuickSwap achieves mostly low returns except for the YFI/WETH pair (-2.5%). Similar to Bancor in Figure 5, DeFi Swap consistently sees significant negative returns highlighted in AAVE/WETH. The pair experiences a sharp drop to -40% by the end of the period. PancakeSwap and 1inch mostly deliver flat performance (+/- 1%), implying there is just enough volume to cover the IL.

Both Figures 5 and 6 provide some noteworthy findings. Firstly, the results imply that offsetting IL is beneficial from a price discovery perspective as Uniswap and QuickSwap are the only AMMs that achieve a positive return across pairs. This conclusion is reasonable as liquidity providers, on average, would only supply their assets if they expect to make a profit. If the IL proves too great, they will withdraw their assets, reducing the AMMs liquidity and price efficiency. This situation can be explained with Bancor and DeFi Swap's returns, which are consistently the lowest out of all AMMs. Additionally, these results show that IL is less adequately compensated within riskier asset pairs. This is likely a result of two things: the higher IL experienced due to higher volatility and their lower popularity (namely YFI and AAVE). Lastly, the results suggest that trading volume is the main factor when offsetting the IL.

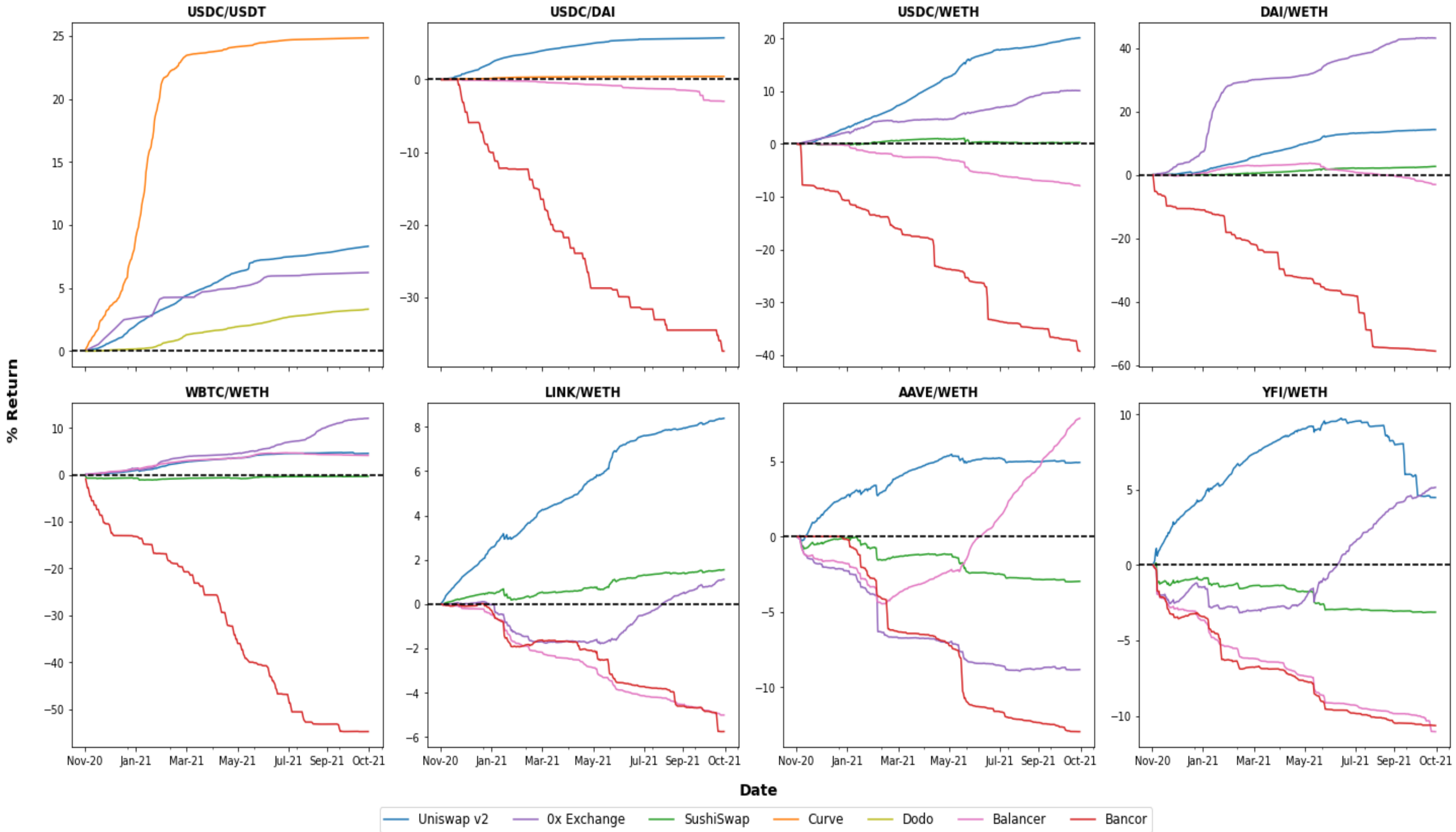

Figure 5. Accumulative Fee Yield and Impermanent Loss Return, Sample Period 1.

This figure displays the accumulative daily fee yield and impermanent loss liquidity providers receive for each asset pair between November 2020 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 5 displays the AMMs and its respective colour code. The x-axis is shared.

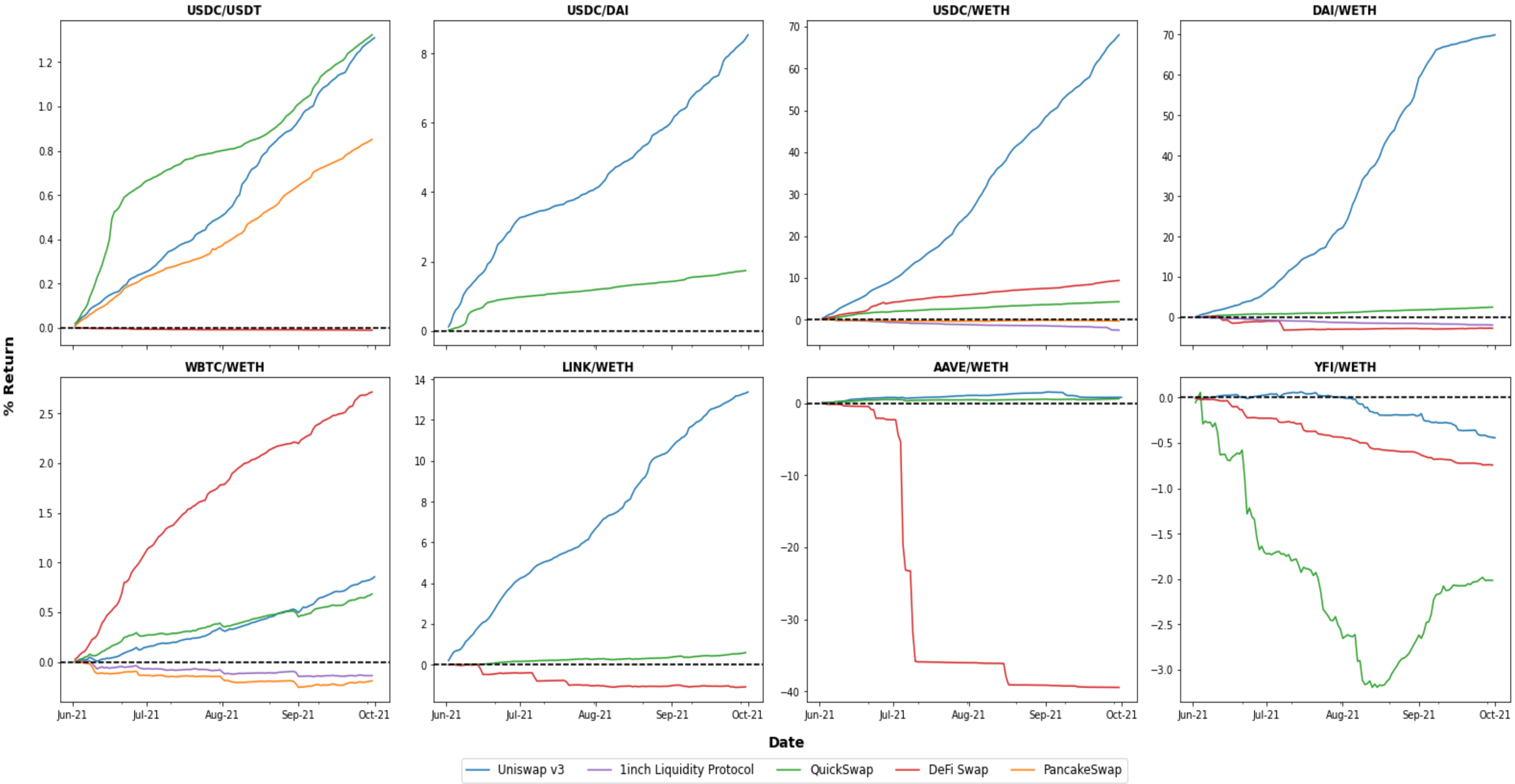

Figure 6. Accumulative Fee Yield and Impermanent Loss Return, Sample Period 2.
This figure displays the accumulative daily fee yield and impermanent loss liquidity providers receive for each asset pair between June 2021 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 6 displays the AMMs and its respective colour code. The x-axis is shared.

Liquidity Provider Total Return

To complete our understanding of AMM liquidity provision, I add the holding return to the fee and IL equations to calculate the overall profitability.[25] The inventory holding return is simply the return on the risky asset between entering and exiting the liquidity pool. Equation (8) shows the total return for liquidity providers within the sample period,

$$R_{TOTAL} = \underbrace{\frac{1}{2}\left(\frac{P_T}{P_0} - 1\right)}_{Inventory\ Holding\ Return} + \underbrace{\sqrt{\frac{P_T}{P_0}} - \frac{1}{2}\left(\frac{P_T}{P_0} + 1\right)}_{Impermanent\ Loss} + \underbrace{Fee\ \frac{Q_T}{V_0}}_{Fee\ Yield} . \quad (8)$$

Figures 7 and 8 show the total accumulative returns for the eight asset pairs in Samples 1 and 2, respectively. Observing the stable/stable pairs, USDC/USDT averages at 10% and 0.76% and DAI/WETH averages at 4% (excluding Bancor) and 5.1%. The similarity in returns between these results and Figures 5 and 6 highlights the minimal holding returns stablecoins experience. In contrast, both stable/risky pairs generate high returns, ranging between 100% and 170% in Figure 7 and 17% to 79% in Figure 8. Moving onto the risky pairs, WBTC/WETH, LINK/WETH and YFI/WETH in Figure 7 exhibit an overall negative return of -32%, -53% and -26%, respectively. These negative returns are consistent within Figure 8, except for WBTC/WETH, which ended with a slightly accumulative positive return of 4%. Surprisingly, AAVE/WETH is the only risky pair with a positive average return of 39% in Figure 7. Regarding AMMs, most experience similar returns within asset pairs. Examples of the contrary include Bancor in USDC/DAI, Uniswap v3 in USDC/WETH, and DeFi Swap in AAVE/WETH.

Overall, the total liquidity provider returns provide a couple of insights. Firstly, pairs with a stablecoin prove to be a lucrative investment for liquidity providers, with stable/stable pairs producing modest positive returns. The profitability of liquidity provision significantly increases when investing in either USDC/WETH or DAI/WETH. However, most risky/risky pairs generate moderate negative returns over both periods. These results imply that stablecoins are required for sustainable liquidity provision as it creates a positive feedback loop between attracting more liquidity providers and increasing fee yields which further offsets the IL. Additionally, my results demonstrate that fee yields and holding return are the primary drivers of profitability within stable/stable and risky pairs, respectively. Lastly, the higher severity in losses within risky pairs implies that IL has a measurable impact on the overall profitability of liquidity provision.

[25] Refer to Figures 1A and 2A in the Appendix to see holding returns generated over both sample periods.

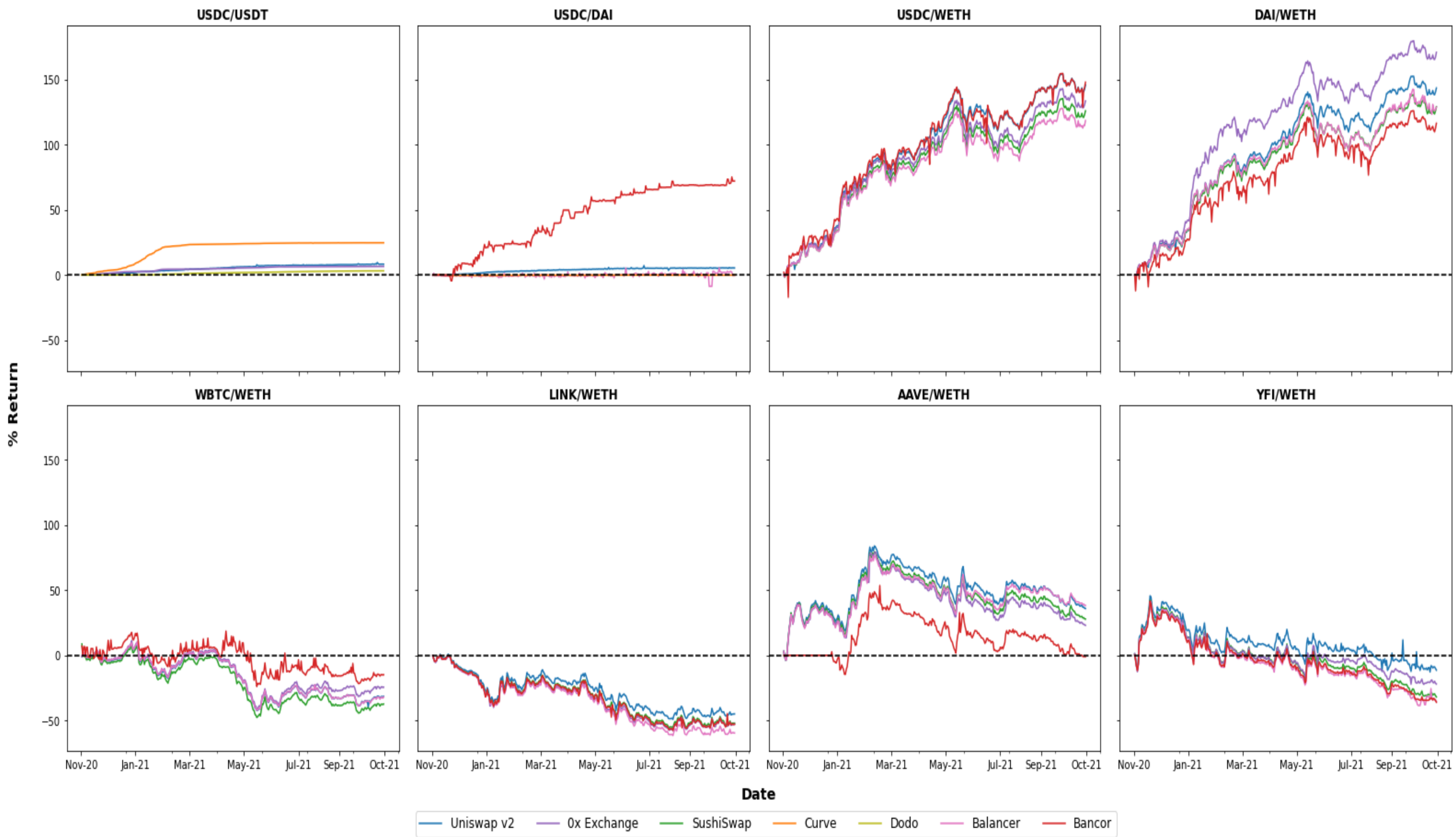

Figure 7. Total Accumulative Daily Return, Sample Period 1.

This figure displays the total accumulative daily return liquidity providers receive for each asset pair between November 2020 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 7 displays the AMMs and its respective colour code. The x and y axes are shared.

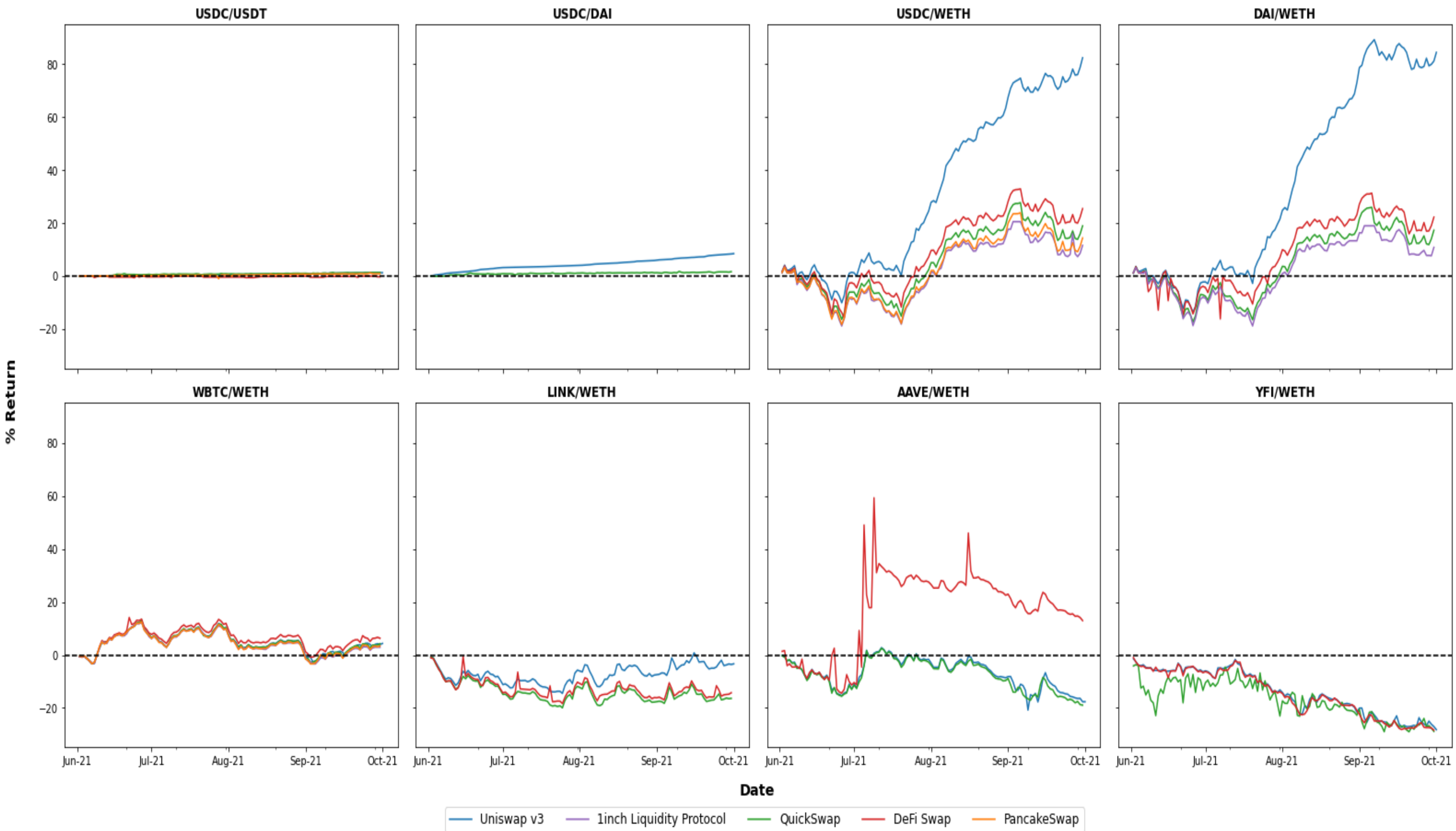

Figure 8. Total Accumulative Daily Return, Sample Period 2.

This figure displays the total accumulative daily return liquidity providers receive for each asset pair between June 2021 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 8 displays the AMMs and its respective colour code. The x and y axes are shared.

4.3. Fixed Effects Panel Regression Model

I perform a standard fixed effects panel regression combining the price discovery and liquidity provider metrics over a daily time horizon. The regression's objective is to establish if IL and fees have a measurable impact on the informational efficiency of AMMs. Equation (9) specifies the dependent variable $ILS_{i,t}$ as the information leadership share. This price discovery metric is regressed on the logarithm of the absolute value of impermanent loss $IL_{i,t}$, and the logarithm of $FeeYield_{i,j,}$ which are calculated in Section 4.2. Two control variables are included: the daily number of trades, $Trades_{i,t}$, and the daily gas fees, $gasValue_{i,t}$. The $Trades_{i,t}$ variable captures the liquidity of the asset pair, and the $gasValue_{i,t}$ variable is used as a proxy for AMM efficiency. I also include four dummies that represent each of the CFMMs and CLOB ILS scores.[26] Since I only calculate the price discovery estimates in a bi-variate setting, I take the average ILS value from all possible combinations. Moreover, I use the previously determined price leader QuickSwap as the reference category for the dummy variables. The u_t and n_i coefficients represent time and asset-specific effects, which help control for the large market-wide trends and differences between asset properties. The model is also estimated using clustered standard errors, which is common practice when performing fixed effects regressions.

$$\begin{gathered} ILS_{i,t} = u_t + n_i + \ B_1 \cdot IL_{i,t} + B_2 \cdot FeeYield_{i,t} + B_3 \cdot Trades_{i,t} + B_4 \cdot \\ gasValue_{i,t} + B_5 \cdot Binance + \ B_6 \cdot UniswapV2 + B_7 \cdot UniswapV3 + B_8 \cdot \\ SushiSwap + \varepsilon_{i,t}. \end{gathered} \tag{9}$$

The output of the regression is presented in Table 11. The fixed effects regression is implemented with clustered standard errors and robust to entity and time effects to help control for endogeneity. I perform the same regression on all eight asset pairs to isolate the impact of the fees and IL on each pair.

[26] Other AMMs (namely non-CFMMs) were not included within the regression since they did not have enough liquidity to estimate the VECM.

Table 11
Fixed Effects Panel Regression Results

This table reports the estimates from the fixed effects panel regression. The dependent variable, $ILS_{i,t}$, is the Information Leadership Share. Impermanent loss ($IL_{i,t}$) is the expense liquidity providers incur for investing in a liquidity pool. $FeeYield_{i,t}$ is the compensation liquidity providers receive for investing in a liquidity pool. $Trades_{i,t}$ is the daily number of trades and $GasValue_{i,t}$ is the expense of running on the blockchain. The logarithm of the $IL_{i,t}$, $FeeYield_{i,t}$, $Trades_{i,t}$ and $GasValue_{i,t}$ variables is used within this matrix and remains consistent throughout the rest of the paper**.** Binance, Uniswap v2, Uniswap v3 and SushiSwap are categorical variables representing the respective CFMMs. The QuickSwap exchange is the reference category. p < 0.1 *, p <0.05 **, p < 0.001 ***, t-statistics are in parenthesis.

Dependent Variable	**Putniņš Information Leadership Share**							
	USDC/USDT	USDC/DAI	USDC/WETH	DAI/WETH	WBTC/WETH	LINK/WETH	AAVE/WETH	YFI/WETH
	1	2	3	4	5	6	7	8
Impermanent Loss	0.002	0.005	0.004***	-0.004	0.004**	0.007*	0.005	0.022**
	(0.010)	(0.778)	(3.372)	(0.006)	(2.172)	(1.974)	(0.988)	(2.256)
Fee Yield	0.012	-0.131**	-0.039*	-0.008**	0.034	-0.221***	0.011	-0.066***
	(0.035)	(-2.852)	(-1.804)	(2.283)	(1.107)	(-7.344)	(0.542)	(-2.758)
No. of Trades	0.094	0.367***	0.249***	0.383***	0.175***	0.185***	0.192***	0.154***
	(1.572)	(4.131)	(7.260)	(16.376)	(6.375)	(4.860)	(6.626)	(3.158)
Gas Value	-0.116**	0.054	0.006	-0.059	0.105***	-0.110***	-0.073***	-0.041
	(-2.216)	(0.039)	(0.181)	(0.031)	(3.869)	(-5.072)	(-3.652)	(-0.787)
Binance	-0.246***	-0.197***	-0.323***	-0.306***	-0.357***	-0.560**	0.697***	
	(-9.028)	(-7.708)	(-13.135)	(-12.459)	(-2.750)	(-2.572)	(9.951)	
Uniswap v3	-0.677***	0.088	-0.002	0.136***	-0.283***	-0.267***	-0.408***	-0.559***
	(-6.048)	(0.634)	(-0.058)	(5.885)	(-12.367)	(-7.016)	(-11.779)	(-2.497)
Uniswap v2	-0.340***	0.225	0.142***	-0.044**	-0.186***	-0.001	-0.375***	-0.031
	(-3.515)	(1.285)	(8.654)	(-2.219)	(-6.871)	(-0.012)	(-20.335)	(-0.308)
SushiSwap			-0.003	-0.065***	-0.412***	-0.231***	-0.456***	-0.016
			(-0.093)	(-2.675)	(-12.965)	(-4.153)	(-25.897)	(-0.144)
Observations	366	366	912	912	912	912	912	790
AMM Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Estimator	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
R - squared	0.524	0.569	0.791	0.800	0.755	0.613	0.644	0.447

Examining Table 11, we see that IL and fee yield can significantly affect the ILS between November 2020 and October 2021. Seven asset pairs exhibit a positive IL between 0.002 and 0.022, with columns (3), (5), (6) and (8) being significant at various levels. The positive coefficients are consistent with expectations, suggesting a 1% increase in IL leads to a 0.007 rise in the ILS. Alternatively, column (4) contradicts this with a negative IL coefficient of -0.004, indicating that IL decreases the ILS within DAI/WETH. Shifting focus towards the fee yield variable, five pairs show a negative coefficient ranging between -0.008 to -0.221. Additionally, all columns except for (1), (5) and (7) are significant at several levels. The negative association between fee yields and the ILS is consistent with expectations, where a 1% increase in fee yield leads to an average 0.093 decrease in the ILS coefficient. Columns (1), (5) and (7) show a positive coefficient between 0.011 and 0.034, implying the alternative. However, these positive coefficients are deemed statistically insignificant.

Continuing onto the control variables, Table 11 shows positive coefficients for daily trades in all pairs significant at the 1% level. These coefficients range from 0.094 to 0.383, averaging at 0.225. This result implies, on average, that a 1% increase in the number of trades changes the ILS coefficient by 0.225. The trades variable having a positive association with the ILS supports my hypothesis that more liquid exchanges have higher price discovery estimates. Alternatively, the gas expense variable appears to primarily have a negative relation with the ILS, with five pairs exhibiting negative coefficients between -0.041 to -0.116. However, columns (2), (3) and (5) display a positive association with (5) being significant at the 1% level. Since the other significant pairs (1, 6 and 7) are negative, it suggests gas expenses lower the ILS. This negative relation is expected as higher gas fees means it is more expensive for the AMM to verify transactions, thus decreasing their efficiency.

Observing the exchange dummies, we see that Table 11 supports the findings in the price discovery section. Firstly, all Binance dummies are significant at 1%, with six out of seven pairs displaying negative coefficients. On average, this demonstrates that the Binance ILS is 0.332 lower than the QuickSwap ILS. Interestingly, column (7) shows that the ILS in Binance is higher than QuickSwap, with a positive coefficient of 0.697. Table 5 in Section 4.1 reaches the same conclusion with Binance leading the AAVE/WETH pair 70% of the time. Looking at Uniswap v3, we see negative coefficients within all columns except for (2) and (4), ranging between -0.002 to -0.677. Additionally, only (2) and (3) are not significant at the 1%. Column (4) shows a strong positive coefficient suggesting Uniswap v3 has a higher average ILS than QuickSwap. However, overall, the results imply that Uniswap v3 has a lower ILS across asset pairs when compared to QuickSwap. The Uniswap v2 dummy shows similar results with an average coefficient of -0.076, concluding that QuickSwap is the price leader. On the contrary, the USDC/DAI and USDC/WETH pairs in columns (2) and (3) have a positive association. Consistent with the other dummies, all pairs that were deemed significant were at the 1% level. Lastly, all SushiSwap coefficients are negative, with columns (4) to (7) significant at the 1% level. These results are consistent across the rest of the dummies. Lastly, all regressions have large adjusted R-squared values ranging between 0.45 and 0.80, suggesting the variables have a high explanatory power on the ILS.

Overall, the regression supports several of my hypotheses as well as my price discovery results. Firstly, IL's positive association with the ILS demonstrates that IL improves the ability of AMMs to impound new information into prices. This is consistent with my hypothesis, indicating that IL can be considered a reasonable proxy for the level of informed trades occurring within an AMM. The significant p-values and larger coefficients within USDC/WETH, WBTC/WETH, LINK/WETH and YFI/WETH further imply that IL has more impact within riskier asset pairs. This makes intuitive sense when considering the results in Section 4.2, where IL was found to be substantially higher in more volatile pairs. Furthermore, we also see a negative association between ILS and fee yields, supporting my hypothesis that fees are an adequate proxy for the level of uninformed trades occurring within the AMM. Table 11 also highlights that fees impact the stable/risky pairs more, which is expected because they are the biggest and most popular assets.[27]

Additionally, the negative IL coefficient within DAI/WETH hints that IL improves price discovery up to a point supporting my optimal balance hypothesis. Looking at DAI/WETH in Figures 1 and 2, the substantial IL displayed within both sample periods further supports the existence of an optimal level. The positive association found between FeeYield and ILS within USDC/USDT, WBTC/WETH and AAVE/WETH reinforces this concept, implying that an increase in round-trip trades can improve price efficiency likely due to the increased liquidity.

Table 11 also demonstrates that trade activity improves an AMM's ability to perform price discovery substantially. This finding is consistent with my price discovery results as the more liquid markets tend to be more price efficient. This claim is augmented through Uniswap's and QuickSwap's price leadership in Section 4.1. This conclusion is also supported by traditional

[27] See the USDC/WETH and DAI/WETH asset pairs in Tables 3 and 4.

literature examining the impact of liquidity on price efficiency in traditional markets (O'Hara (2003); Riordan and Storkenmaier (2012)). Gas expenses appear to be a decent proxy for AMM efficiency, conveying that AMMs with higher gas fees are perhaps slower and less efficient at reacting to new information. Lastly, the exchange dummies improved the validity of my price discovery estimates, demonstrating their ILS values were on average lower than QuickSwap across most asset pairs. Since I average the AMM's ILS over all possible combinations, Table 11's results reinforce my conclusion that QuickSwap is the definitive price leader within my sample.

4.4. Optimal Lag Order Selection

I perform a number of robustness checks to further validate my conclusions regarding price discovery and liquidity provision within AMMs. To ensure that the price discovery estimates are accurate, I re-run the VECM using the lags determined by Akaike Information Criterion (AIC) and Schwarz (1978) Bayesian Information Criterion (BIC). These two criteria are well-established in econometric literature when determining the number of lags in a model. In the main results, I intuitively choose the lag number based on the difference in liquidity between the two markets (see Appendix Table 9A).

Table 12 presents the estimates between Binance and AMMs when using the AIC and BIC to determine the number of lags. Observing the AIC, we see that it has a minimal effect on the price shares compared to the main results. Most estimates within the CS and IS measures are almost identical, the USDC/WETH and WBTC/WETH pairs having a deviation between 1 and 2%. The more considerable variations occur solely within the ILS, where USDC/WETH and LINK/WETH have sizeable deviations of 10% and 9%, respectively. Although rather substantial, these results claim that AMM's price leadership is greater than what is found in the main results, thus enhancing my original conclusions. Overall, most pairs have a marginal difference of 2%.

Conversely, the ILS estimates when using the BIC show more substantial deviations, with all pairs exhibiting greater than 3% variation. The most considerable deviations again occur within the USDC/WETH and WETH/LINK pairs with a difference of 16% and 15%, respectively. Using the BIC appears to attribute more price leadership to Binance, which conflicts with my main results. However, we can safely assume my original conclusion since the average still favours AMMs as the overall price leader at 53%. Additionally, Table 12 shows more variation within the IS estimates than the AIC, with most pairs differing by 3%. The magnitude of deviations between CS and IS and the ILS metrics suggest that the AIC and BIC measures are affected by noise.

Additionally, the BIC consistently estimates substantially lower lags than the AIC (see Table 9A in the Appendix), which is the likely reason for this discrepancy. Considering that the AIC is better for determining the minimum prediction error and the substantial liquidity difference between markets, it is reasonable to assume a larger lag length is more appropriate. For these two reasons, I conclude that the AIC is the better lag estimator than the BIC, which provide similar findings to my main results. Lastly, all diagnostic measures in Table 12 exhibit little to no difference, implying the lag length has a negligible effect on contemporaneous correlation.

Table 12
Price Discovery Estimation with Optimal AIC and BIC Lags

This table shows the Informational Leadership Shares (ILS), Information Shares (IS), and Component Shares (CS) between Binance and AMMs with the lag number determined by the AIC and BIC. The respective market is denoted by the subscript. Deviation of 1% *, deviation of 3% **, deviation of 5% ***. Price leader is shaded. Three diagnostics are also computed: the correlation of reduced form errors (Correl), the spread of the IS between orderings (UmL) and the spread between the confidence intervals set at 95% (CI_{ILS}).

Asset Pair	Price Discovery Shares						Diagnostics		
	$ILS_{Binance}$	**ILS_{AMMs}**	**$IS_{Binance}$**	**IS_{AMMs}**	**$CS_{Binance}$**	**CS_{AMMs}**	Correl	UmL	CI_{ILS}
Panel A: AIC									
USDC/USDT	0.25	0.75	0.99	0.01	0.99	0.01	-0.01	0.01	0.11
USDC/DAI	0.20	0.80	0.98	0.02	0.99	0.01	-0.01	0.01	0.10
USDC/WETH	0.42	0.58***	0.95*	0.05	0.95	0.05	0.04	0.01	0.09*
DAI/WETH	0.35	0.65***	0.90	0.10	0.94	0.06	0.04	0.02	0.10
WBTC/WETH	0.36	0.64**	0.98*	0.02	0.98	0.02	0.02	0.01	0.10
LINK/WETH	0.56	0.44	0.93	0.07	0.92	0.08	0.03	0.01	0.09*
AAVE/WETH	0.65***	0.35	0.86	0.14	0.81	0.19	0.04	0.02	0.07
Average	**0.40**	**0.60****	**0.94**	**0.06**	**0.94**	**0.06**	**0.02**	**0.01**	**0.10**
Panel B: BIC									
USDC/USDT	0.22	0.78**	0.99	0.01	0.99	0.01	-0.01	0.01	0.10
USDC/DAI	0.25	0.75***	0.99	0.01	0.99	0.01	-0.01	0.01	0.11
USDC/WETH	0.48	0.52***	0.96**	0.04	0.96*	0.04	0.04	0.02	0.09
DAI/WETH	0.42	0.58***	0.92**	0.08	0.95*	0.05	0.04	0.02	0.09
WBTC/WETH	0.45	0.55***	0.99**	0.01	0.98	0.02	0.02	0.01	0.11
LINK/WETH	0.71***	0.29	0.94*	0.06	0.91	0.09	0.03	0.01	0.06*
AAVE/WETH	0.75***	0.25	0.88**	0.12	0.82	0.18	0.04	0.02	0.04
Average	**0.46**	**0.53*****	**0.95***	**0.05**	**0.94**	**0.06**	**0.02**	**0.01**	**0.09**

4.5. Alternative Impermanent Loss

Next, to help prove the validity of my IL results, I compute a variation of the IL formula, which is widely used amongst practitioners and academics alike,

$$Impermanent\ Loss = \frac{2 \cdot \sqrt{\frac{p_{t_2}}{p_{t_1}}}}{1 + \frac{p_{t_2}}{p_{t_1}}} - 1, \tag{10}$$

where p_1 and p_2 are the risky asset's price when entering and exiting the liquidity pool, respectively. I visually demonstrate that these two formulas are mathematically equivalent in Figure 9 by looking at the USDC/USDT, USDC/WETH and WBTC/WETH pairs in Uniswap v2. Figure 9 elucidates that for all three pairs, the accumulative IL is almost equivalent between formulas. Although Equation (10) computes slightly less IL than Equation (6), this difference is minuscule and, therefore, likely a cause of rounding error.

Figure 9 confirms the legitimacy of the Putniņš (2021) equation, which can accurately calculate the IL. Many previous studies estimate the IL based on the amounts of both assets within the liquidity pool. This method is exemplified within Wang, Heimbach and Wattenhofer (2021), who similarly calculate the return, fees and IL using asset amounts. What Figure 9 shows that is computing the IL can be achieved by simply using the prices of the risky asset within the pair. This extends towards calculating the fee yield and total return, supporting the accuracy of my estimations.

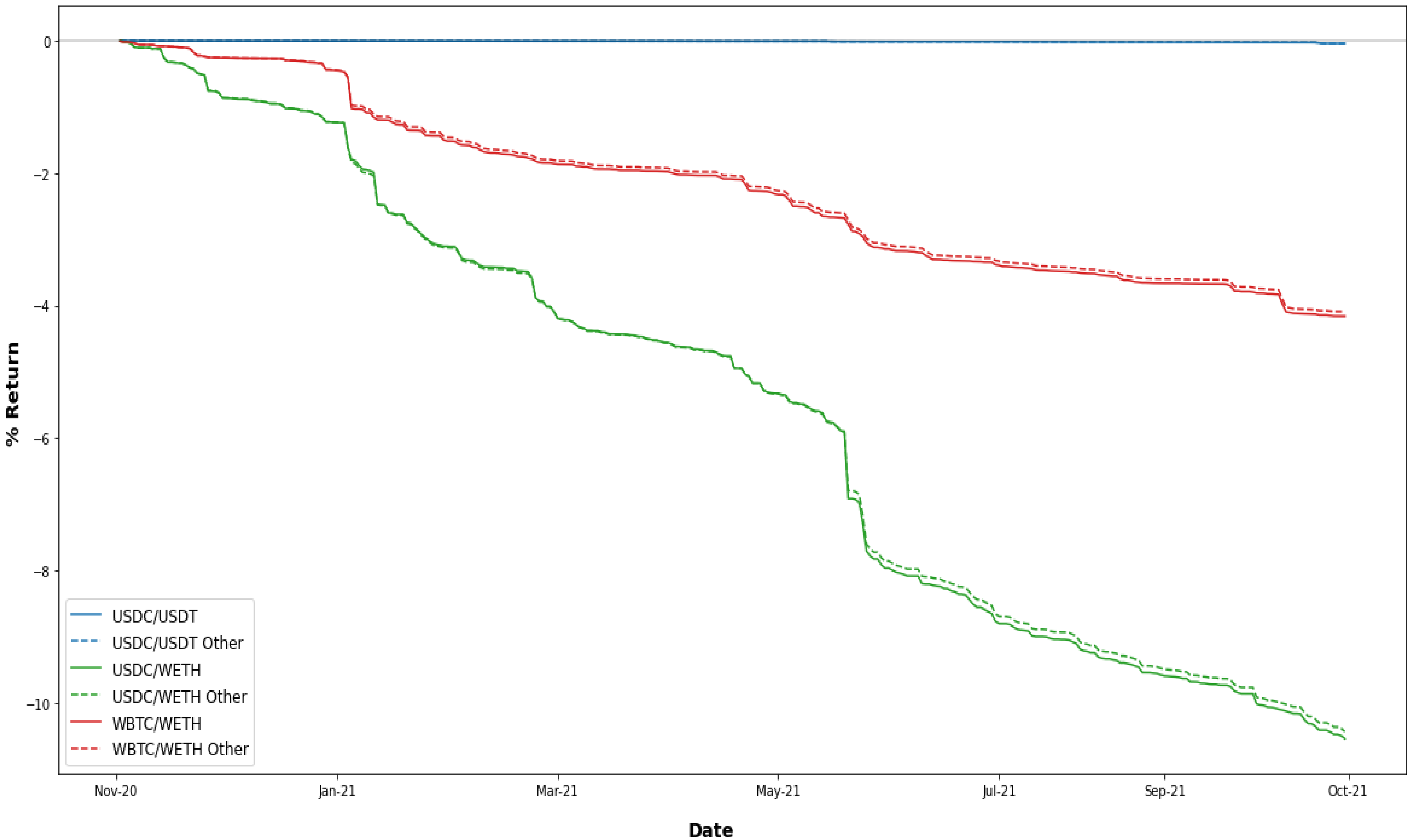

Figure 9. Accumulative Impermanent Loss Comparison.

This figure shows the accumulative impermanent loss (IL) for USDT/USDC, USDC/WETH and WBTC/WETH in the Uniswap v2 exchange using two different formulas. The sample period is from November 2020 to October 2021. Returns are in % and calculated in USD terms. The dotted line (Other) denotes the alternative IL calculation.

4.6. Alternative Regression Model

I perform the same fixed effect regressions with the CS and IS metrics replacing the ILS as the dependent variable. This robustness test aims to understand whether fees and IL impact price discovery when not accounting for different market microstructure noise between AMMs. Table 13 shows the regression results of the eight pairs with CS as the dependent variable. Firstly, I find that IL and fees are still reasonable proxies to explain the informativeness of the AMM. Moreover, I find that the adjusted R-squared ranges between 0.51 and 0.84, indicating the variables have slightly more explanatory power than in Table 11. Five pairs display a positive coefficient in the IL variable, with columns (4), (5) and (7) being significant at the 10% and 1% levels. Additionally, columns (3), (6) and (8) lose their significance within Table 13. The fee yield variable shows five pairs with a negative coefficient ranging between -0.018 to -0.218. Although column (1) is significant at the 10% level with a positive coefficient, the remaining four significant results imply that fees still reduce the price discovery metrics.

Interestingly, the trade activity variable is negative with a value of -0.066 on average which is different from the main results. This result persists within columns (3), (4), (6) and (7), which are significant at 1%. Regarding gas value, coefficients are mostly positive, with columns (1), (6) and (7) significant at the 5% level. AMM dummies are consistent with expectations, with nearly all coefficients being positive, averaging at 0.443 and significant at the 1% level. The Uniswap v2 dummy variable in column (2) is the only negative coefficient at -0.187; however, this result was considered statistically insignificant.

A couple of conclusions can be drawn from Table 13, which contribute to the study. Firstly, it appears IL's impact on price discovery slightly loses significance when not accounting for noise. In contrast, fee yield retains its effectiveness at describing the level of uninformed trading within the exchange, which inhibits AMM price discovery. Furthermore, trade activity appears to have an overall negative association with the CS. This is consistent with expectations as the CS also measures the relative avoidance of noise, meaning more trades would increase noise and hence reduce the CS. Similarly, the AMM dummy variables are in accordance with the main results highlighting that all other exchanges exhibit higher CS than QuickSwap. This result is consistent with my previous findings as QuickSwap is one of the noisiest AMMs, therefore, would have a lower CS. Ultimately, Table 13 supports the conclusions made from the project's main results.

Table 13

Alternative Measure (CS) Regression Results

This table reports the estimates from the fixed effects panel regression. The dependent variable, $CS_{i,t}$, is the Component Share. Impermanent loss ($IL_{i,t}$) is the expense liquidity providers incur for investing in a liquidity pool. $FeeYield_{i,t}$ is the compensation liquidity providers receive for investing in a liquidity pool. $Trades_{i,t}$ is the daily number of trades and $GasValue_{i,t}$ is the expense of running on the blockchain. The logarithm of the $IL_{i,t}$, $FeeYield_{i,t}$, $Trades_{i,t}$ and $GasValue_{i,t}$ variables is used within this matrix and remains consistent throughout the rest of the paper**.** Binance, Uniswap v2, Uniswap v3 and SushiSwap are categorical variables representing the respective CFMMs. The QuickSwap exchange is the reference category. p < 0.1 *, p <0.05 **, p < 0.001 ***, t-statistics are in parenthesis.

Dependent Variable	**Gonzalo & Granger Component Share**							
	USDC/USDT	USDC/DAI	USDC/WETH	DAI/WETH	WBTC/WETH	LINK/WETH	AAVE/WETH	YFI/WETH
	1	2	3	4	5	6	7	8
Impermanent Loss	0.007	-0.006	0.004	0.027***	0.002***	-0.002	0.009*	-0.001
	(0.886)	(-1.164)	(0.641)	(3.154)	(2.490)	(-0.608)	(1.838)	(-0.157)
Fee Yield	0.073*	-0.057**	0.023	-0.218***	0.005	-0.018	-0.058***	-0.051**
	(2.127)	(-2.311)	(1.379)	(-6.878)	(0.214)	(-0.896)	(-2.744)	(-2.213)
No. of Trades	0.018	-0.060	-0.080***	-0.107***	-0.029	-0.129***	-0.091***	-0.050
	(0.313)	(-0.905)	(-4.206)	(-3.419)	(-1.379)	(-5.551)	(-3.264)	(-1.265)
Gas Value	0.126**	0.017	0.017	-0.047	-0.071	0.037**	0.053**	0.003
	(2.526)	(0.502)	(0.780)	(-1.304)	(-4.089)	(2.377)	(2.552)	(0.056)
Binance	0.100***	0.995***	0.956***	0.946***	0.985***	0.916***	0.809***	
	(3.128)	(9.410)	(10.550)	(8.050)	(3.040)	(4.590)	(8.975)	
Uniswap v3	0.650***	0.540***	0.661***	0.177***	0.801***	0.175***	0.022	0.443***
	(6.621)	(5.412)	(2.583)	(4.730)	(6.102)	(7.199)	(0.633)	(4.234)
Uniswap v2	0.423***	-0.187	0.118***	0.004	0.367***	0.157***	0.051***	0.313***
	(4.515)	(-1.490)	(9.090)	(0.202)	(8.314)	(4.444)	(2.550)	(6.525)
SushiSwap			0.217***	0.232***	0.555***	0.423***	0.342***	0.648***
			(7.563)	(8.664)	(7.119)	(2.522)	(7.664)	(10.206)
Observations	366	366	912	912	912	912	912	790
AMM Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Estimator	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
R - squared	0.518	0.767	0.844	0.514	0.869	0.674	0.629	0.561

A final regression is performed using the IS metric as the dependent variable, and its output is displayed in Table 14. Similar to the main results, we see that IL has a positive coefficient within seven asset pairs averaging at 0.009. Moreover, the same columns (4), (5) and (7) that are significant in Table 12 are also significant in Table 13 at the 10%, 5% and 1% level, respectively. Alternatively, five pairs show a positive association with the IS metric, which differs from Table 11 and Table 13. Moreover, these unexpected coefficients are significant within columns (2) to (4) and (6) at the 1%, suggesting fees increase the IS measure between 0.036 to 0.193.

Shifting the focus to the trade variable, we see positive coefficients across six pairs averaging at 0.108. Unlike the main results, only four columns are deemed significant at the 5% and 1% levels (3, 4, 6 and 7). This conflicts with Table 13's coefficients which mainly exhibited a negative association. Moving onto the gas value, we see five negative coefficients between -0.002 to -0.068. However, the impact of the gas variable appears to decrease when regressing on the IS, as column (5) is the only significant coefficient at -0.068. Lastly, the dummy variables are consistent with my main results, with significant positive coefficients across all three AMMs and Binance. Interestingly, the AAVE/WETH pair has negative values for both Uniswap AMMs significant at the 1% level. This is consistent with Tables 9 and 10 in Section 4.1, with IS attributing QuickSwap as the leader 76% and 67% of the time, respectively. The adjusted R-squared values are high, ranging between 0.46 to 0.77 making them slightly lower than the past two regression models.

In terms of insights, Table 14 generally reinforces the findings found in Tables 11 and 13. The IL and trade activity variables are still considered a reasonable explanation for informed trading and are consistent with the main results. In contrast Table 14, implies that fee yields improve the ability for AMMs to perform price discovery. This finding is likely due to the IS being influenced by the market's noise, with higher noise resulting in higher IS estimates. Lastly, the exchange dummies reiterate that QuickSwap is a very noisy exchange, seen with the large positive coefficients within all exchange dummies. With the overall findings of Tables 13 and 14 providing similar conclusions to the main results, it is suitable to conclude that IL, fee yields and trade activity substantially impact AMM price discovery.

Table 14

Alternative Measure (IS) Regression Results

This table reports the estimates from the fixed effects panel regression. The dependent variable, $IS_{i,t}$, is the Information Leadership Share. Impermanent loss ($IL_{i,t}$) is the expense liquidity providers incur for investing in a liquidity pool. $FeeYield_{i,t}$ is the compensation liquidity providers receive for investing in a liquidity pool. $Trades_{i,t}$ is the daily number of trades and $GasValue_{i,t}$ is the expense of running on the blockchain. The logarithm of the $IL_{i,t}$, $FeeYield_{i,t}$, $Trades_{i,t}$ and $GasValue_{i,t}$ variables is used within this matrix and remains consistent throughout the rest of the paper**.** Binance, Uniswap v2, Uniswap v3 and SushiSwap are categorical variables representing the respective CFMMs. The QuickSwap exchange is the reference category. p < 0.1 *, p <0.05 **, p < 0.001 ***, t-statistics are in parenthesis.

Dependent Variable	**Hasbrouck Information Share**							
	USDC/USDT	USDC/DAI	USDC/WETH	DAI/WETH	WBTC/WETH	LINK/WETH	AAVE/WETH	YFI/WETH
	1	2	3	4	5	6	7	8
Impermanent Loss	0.013	-0.002	0.010	0.031***	0.001**	0.001	0.012*	0.002
	(1.367)	(-0.433)	(1.221)	(2.967)	(2.037)	(0.113)	(1.950)	(0.314)
Fee Yield	0.060	0.121***	0.036**	0.193***	-0.006	0.104***	-0.022	-0.024
	(1.482)	(4.091)	(1.872)	(6.461)	(-0.236)	(3.806)	(-0.951)	(-0.999)
No. of Trades	0.181**	0.055	0.098***	0.117***	0.156***	-0.030	-0.023	0.041
	(2.147)	(0.755)	(4.551)	(3.336)	(4.967)	(-0.911)	(0.730)	(0.965)
Gas Value	0.089	0.029	0.034	-0.066	-0.068**	-0.022	-0.002	-0.034
	(1.514)	(0.678)	(1.645)	(-1.585)	(-2.572)	(-1.102)	(-0.086)	(-0.724)
Binance	0.990***	0.982***	0.938***	0.905***	0.979***	0.928***	0.856***	
	(5.472)	(9.84)	(10.07)	(8.656)	(7.060)	(3.510)	(6.609)	
Uniswap v3	0.415***	0.255**	0.472***	0.259***	0.826***	0.014	-0.283***	0.341***
	(3.256)	(2.220)	(6.004)	(6.741)	(6.892)	(0.426)	(-6.984)	(3.003)
Uniswap v2	0.396***	-0.403	-0.041***	0.031	0.434***	0.133***	-0.223***	0.262***
	(3.077)	(-2.704)	(-3.178)	(1.234)	(2.801)	(2.792)	(-9.908)	(5.152)
SushiSwap			0.025	0.200***	0.481***	0.279***	0.032	0.582***
			(0.740)	(6.703)	(2.748)	(6.087)	(1.491)	(9.300)
Observations	366	366	912	912	912	912	912	790
AMM Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Estimator	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
R - squared	0.458	0.643	0.766	0.390	0.735	0.593	0.502	0.498

4.7. *Limitations*

The availability of a structured high-frequency dataset for AMMs has been the primary challenge for my study. Given the novelty and open-source nature of DeFi, many proprietary and open-source data providers offer incomplete datasets. Although all data is available within blockchains, accessing it is technically challenging and would be too time-consuming given the constraints of this study. I strike a balance by leveraging the Bitquery API to access the blockchains; however, the functionality is limited. This issue extends towards my CLOB dataset, which only includes data for Binance between November 2020 and March 2021. Furthermore, the novelty of the DEX industry means that many AMMs do not have enough liquidity to estimate the price discovery shares accurately. This limitation reduces the scope of the study. These data constraints are coupled with the lack of cohesiveness seen within the asset pairs. It is challenging to find pairs commonly traded across multiple AMMs. These data issues will likely resolve if AMMs continue to grow and develop in sophistication and popularity. Moreover, my use of a generalised CFMM formula also inhibits the accuracy of my results, as AMMs incorporate several pricing functions which calculate the IL differently. Lastly, relying on univariate estimations in the regression limits the amount of insight gained when comparing between asset pairs.

4.8. *Implications for Future Research*

Future avenues of research that could prove interesting include a deeper examination of the relation between CLOB exchanges and AMMs. Valuable insights can be found by investigating the similarities and differences and how market participants interact with both market types. Moreover, understanding why informed agents prefer to use AMMs (and CFMMs) could generate exciting findings. Analysing trade activity within AMMs would also yield novel outcomes. Additionally, studies could extend my research by incorporating the different pricing functions within AMMs and re-calculating the liquidity provider metrics. This would clarify how AMMs manage the dynamics between IL, holding return and fees. With AMMs constantly being updated, research into the impact of new versions would likely yield interesting results and help indicate the future direction of the ecosystem. Furthermore, the use of a difference-in-differences model could help capture the systematic changes between protocol updates. Lastly, an investigation into the merits of automation and algorithmic pricing functions would also be exciting. These future works would all highly benefit from the increasing availability of AMM data.

5. Conclusion

Automated market making is a fascinating blend of market microstructure and technology. Although this new exchange model has seen rapid adoption due to its simplicity and accessibility, there are concerns about whether it is economically sustainable. A limited body of literature examines how AMMs perform price discovery and handle the ASCs of liquidity provision (Angeris, Kao, Chiang, Noyes and Chitra (2019); Barbon and Ranaldo (2021); Dimpfl and Peter (2021); Pagnottoni and Dimpfl (2019); Wang, Heimbach and Wattenhofer (2021)).

Considering the growing prominence of AMMs, I fill a necessary gap in the literature by assessing their informational efficiency between themselves and with CLOB exchanges. Furthermore, I investigate whether AMMs can manage the ASCs associated with IL and if it impacts the informativeness of the market. I achieve this by estimating three well-known price discovery measures (CS, IS, ILS) for eleven AMMs and the CLOB exchange Binance. Moreover, I calculate the IL, fees and holding return to understand if AMM liquidity provision is sustainable. I regress the IL and fee variables, along with trade activity and gas fees on the ILS, to establish a connection between managing ASCs and price discovery. I perform this study across two sample periods between November 2020 to October 2021, examining eight asset pairs with different levels of volatility.

When compared to Binance, I find that AMMs are on average the first to impound new information into prices 62% of the time. Additionally, I demonstrate that the CFMM model leads price discovery 70% of the time and that QuickSwap is the definitive price leader for the sample period. Furthermore, I demonstrate that AMMs can consistently offset the IL through fees in large liquidity pools of stable asset pairs or small pools of volatile pairs. I also prove that being a liquidity provider with a stablecoin is a profitable endeavour, achieving average returns upwards of 50% over the sample period. However, this profitability does not apply to riskier asset pairs, which saw average negative returns of -20%. When regressing these variables, I demonstrate that IL and fee yields are reasonable proxies for measuring the level of informed/uninformed trades within AMMs. Lastly, my regression supports QuickSwap as the price leader through exchange dummies and shows a strong positive association between trade activity and informational efficiency.

The findings from my study provide exciting implications for the sustainability of AMMs. Firstly, I demonstrate that AMMs are more sophisticated at performing price discovery than initially assumed, even outperforming the largest CLOB exchange Binance. Considering that

AMMs were created in 2018, this result supports that AMMs are price efficient despite being new and automated. More broadly, my study contributes to the discussion around the applicability of pure automation within finance by providing evidence of its success. Furthermore, this result indicates a shift within cryptocurrency markets, where people are increasingly using AMMs to trade crypto-assets rather than CLOBs. This conclusion introduces more avenues of research in determining what characteristics of the AMM model appeal to market participants.

Secondly, my study highlights that AMM liquidity provision can be a lucrative alternative investment opportunity. I find that AMMs with either high trading volume or small liquidity pools can consistently compensate liquidity providers for the IL suffered. Moreover, I provide strong evidence that IL is primarily a function of volatility, with riskier pairs experiencing greater IL. These findings benefit developers looking to improve AMM design as they can better identify the primary drivers of price efficiency and liquidity provision.

Thirdly, establishing a link between price discovery, IL, and fees lays the foundation for future research into how these unique dynamics drive each other. With IL and fees being effective representations of trade informativity, this deepens our understanding of how adverse selection impacts price efficiency. By providing evidence that AMMs are a sustainable exchange model, my research is also beneficial for institutional investors and regulators concerned with the safety and longevity of this market marker. My study aids regulators in better understanding how AMMs perform the roles of a market, allowing them to make more informed decisions and thus improve the safety of the ecosystem.

Ultimately, an understanding of how AMMs perform the functions of exchange is still in its infancy. My study aims to prove that automated market making is not a passing trend, but a robust market type that is economically sustainable. By providing evidence of their sustainability, I suggest that AMMs have the potential to compete with CLOBs for market dominance in both DeFi and traditional finance.

Appendix A: Institutional Details on Blockchain & DeFi

1.1A. Intermediation & Blockchain Technology

Financial intermediation has long been a staple of the modern financial system (Allen and Santomero (1997); Beck, Degryse and Kneer (2014); Hellwig (1991)). Intermediaries expand transaction possibilities, increase security and reduce transaction costs by creating trust between buyers and sellers (Chen and Bellavitis (2020); Roth (2015)). However, there is extensive literature and countless publicised scandals of large intermediaries abusing their power for personal gain (Cohen (2019); Srnicek (2017); Zuboff (2019)). Furthermore, the oligopolistic landscape of global financial intermediaries results in a central point of failure. The Global Financial Crisis highlighted how their interdependency cascaded into a worldwide downturn.

In contrast, the blockchain's immutable open ledger network design, which uses cryptography to facilitate transactions and information transfer (Anderson (2019)), has enabled a paradigm shift in how markets build trust (Werbach (2018)). Blockchains removes the need for any intermediation, with its direct peer-to-peer network allowing faster and cheaper transactions with greater security. Seidel (2018) claims that blockchain technology replaces the traditional financial system's reliance on opportunism for distributed trust. Additionally, Ammous (2018) suggests that the decentralised nature of blockchains makes them incredibly resistant since there is no central point of failure. Moreover, Ammous (2018) emphasises that the complete transparency of the network creates public verifiability, thus resulting in a "trustless" system. These qualities of disintermediation, transparency and potential have greatly appealed to retail investors and academics alike.

1.2A. Decentralised Finance (DeFi)

DeFi refers to the crypto-asset sub-industry that converts traditional financial instruments such as loans and derivatives onto the blockchain (Werner, Perez, Gudgeon, Klages-Mundt, Harz and Knottenbelt (2021)). It replaces the need for intermediaries with smart contracts – specialised coded protocols that execute a function when the agreement terms are met (Hertig (2020)). These smart contracts are highly adjustable, allowing them to perform countless functions such as representing an asset, a share of ownership or even voting rights (Blémus and Guégan (2019)). Kuhn (2021) states that DeFi is an antithesis to the current financial system by replacing custodians with code.

Despite mainly being practitioner-led, the academic literature surrounding DeFi is growing. A systematisation of knowledge (SoK) performed by Werner, Perez, Gudgeon, Klages-Mundt, Harz and Knottenbelt (2021) summarises the DeFi industry as a blend between promise and challenge. They believe that the DeFi system is non-custodial, permissionless, openly auditable and composable in an ideal world, posing substantial benefits for loans, derivatives and exchanges. Although Werner, Perez, Gudgeon, Klages-Mundt, Harz and Knottenbelt (2021), along with Schär (2021), heed caution about DeFi's future, mentioning concerns surrounding technical, security and economic challenges. These concerns conflict with Narayanan, Bonneau, Felten, Miller and Goldfeder (2016) and Lo and Medda (2020), who suggest that the open-source nature of DeFi allows external parties to freely audit protocols for risks and fix bugs and glitches. Brynjolfsson and McAfee (2014) comment on the benefits of open-source networks, saying that it accelerates innovation as technologies build upon one another at incredible speeds.

One looming concern that followed crypto-assets and DeFi's development is its vulnerabilities towards criminal activity. Hammond and Ehret (2021) believe it is due to cryptocurrency's unregulated and pseudo-anonymous nature. Unlawful activities such as drug dealing, tax evasion and money laundering have been recorded in abundance within cryptocurrencies as these events can occur far away from traditionally regulated markets (Barratt, Ferris and Winstock (2016); Foley, Karlsen and Putniņš (2019); Kethineni and Cao (2020)). Furthermore, cryptocurrencies have catalysed a paradigm shift in cyber-attacks (Zimba, Wang, Mulenga and Odongo (2020)), with Connolly and Wall (2019) saying mining hacks and ransomware pose a challenging problem for cyber-security. Alternatively, two reports state that criminal activity in the space has drastically reduced, with around 1% of all cryptocurrency transactions considered illegal payments (CipherTrace (2021)) and 54% of those being scams, not terrorism or other severe crimes (Chainalysis (2021)).

However, the lack of empirical research in much of the DeFi literature makes it difficult to substantiate any claims made. Unlike these studies, my paper is empirically driven, providing data-based insights on the largest market type within DeFi.

Appendix B: Additional Descriptive Statistics

Table 1A
Asset Smart Contract Addresses

This table shows the smart contract addresses of assets used within my study. These addresses are used to locate the relevant cryptocurrency on the blockchain. The study examines AMMs over three different Ethereum chains which require a unique address. Assets not provided on a particular chain are left as blank.

Ticker	Name	Ethereum Address	Polygon Address	Binance Address
USDC	USD-Coin	0xa0b86991c6218b36c1d19d 4a2e9eb0ce3606eb48	0x2791bca1f2de4661ed88a30c99a7 a9449aa84174	0x8ac76a51cc950d9822d68b83fe1a d97b32cd580d 0xe9e7cea3dedca5984780bafc599b d69add087d56 *
USDT	USD-Tether	0xdac17f958d2ee523a220620 6994597c13d831ec7	0xc2132d05d31c914a87c6611c1074 8aeb04b58e8f	0x55d398326f99059ff77548524699 9027b3197955
DAI	Dai	0x6b175474e89094c44da98b 954eedeac495271d0f	0x8f3cf7ad23cd3cadbd9735aff9580 23239c6a063	0x1af3f329e8be154074d8769d1ffa4 ee058b1dbc3
WETH	Wrapped Ether	0xc02aaa39b223fe8d0a0e5c4f 27ead9083c756cc2	0x7ceb23fd6bc0add59e62ac255782 70cff1b9f619	0x2170ed0880ac9a755fd29b268895 6bd959f933f8
WBTC	Wrapped Bitcoin	0x2260fac5e5542a773aa44fb cfedf7c193bc2c599	0x1bfd67037b42cf73acf2047067bd 4f2c47d9bfd6	0x7130d2a12b9bcbfae4f2634d864a 1ee1ce3ead9c
LINK	Chainlink	0x514910771af9ca656af840d ff83e8264ecf986ca	0x53e0bca35ec356bd5dddfebbd1fc 0fd03fabad39	
AAVE	Aave	0x7fc66500c84a76ad7e9c934 37bfc5ac33e2ddae9	0xd6df932a45c0f255f85145f286ea0 b292b21c90b	
YFI	yearn-finance	0x0bc529c00C6401aEF6D22 0BE8C6Ea1667F6Ad93e	0xda537104d6a5edd53c6fbba9a898 708e465260b6	

Table 2A

AMM Smart Contract Addresses

This table shows the smart contract addresses of the sampled AMMs. These addresses are used to locate the relevant AMM on the blockchain. Note some exchanges use a number of proxy addresses rather than a single address. These particular AMMs were accessed by using Bitquery's AMM naming conventions which are provided. PancakeSwap's address is on the Binance blockchain. QuickSwap's address is on the Polygon blockchain. The other addresses are on the Ethereum blockchain.

Exchange Name	Address
0x Exchange	"Zerox Exchange"
1inch Liquidity Protocol	"1inch Liquidity Protocol"
Balancer	0x9424B1412450D0f8Fc2255FAf6046b98213B76Bd
Bancor	0x2f9ec37d6ccfff1cab21733bdadede11c823ccb0
Curve	"Curve"
DeFi Swap	"CRO DeFi Swap"
Dodo	"Dodo"
PancakeSwap	0xcA143Ce32Fe78f1f7019d7d551a6402fC5350c73
QuickSwap	0x5757371414417b8c6caad45baef941abc7d3ab32
SushiSwap	0xc0aee478e3658e2610c5f7a4a2e1777ce9e4f2ac
Uniswap v2	0x5C69bEe701ef814a2B6a3EDD4B1652CB9cc5aA6f
Uniswap v3	0x1F98431c8aD98523631AE4a59f267346ea31F984

Table 3A
Glossary

Term	Definition
Adverse Selection Cost/Risk (ASC)	Situation where one party has information the other does not have. In this case it refers to informed traders who perform arbitrage on mispriced assets against liquidity providers.
Automated Market Maker (AMM)	A type of decentralised exchange that uses a mathematical algorithm to price assets.
Blockchain	An open, decentralised and immutable network which uses cryptography to facilitate transactions and information transfer (Anderson (2019)).
Limit Order Book (CLOB)	The dominant exchange model which keeps a record of outstanding buy and sell orders.
Constant Function Market Maker (CFMM)	A type of automated market maker which uses a deterministic pricing rule simplified as the product of the two asset's reserve amounts.
Crypto	Short-hand term often referring to digital assets secured by cryptography.
Decentralised Exchange (DEX)	An exchange which allows participants to trade peer-to-peer, without the need for an intermediary.
Decentralised Finance (DeFi)	A blockchain-based financial system which operate financial instruments using smart contracts instead of intermediaries.
Gas Fees	The computational expense for validating a transaction on the Ethereum blockchain.
Impermanent Loss (IL)	The risk for liquidity providers of seeing the value of their reserved tokens decrease in comparison to holding the assets (Wang, Heimbach and Wattenhofer (2021)).
Liquidity Pool	A crowdsourced reserve of crypto-assets locked in by a smart contract. It provides the funds to facilitate trades within a decentralised exchange.
Liquidity Provider	A participant who supplies their own digital-assets to the liquidity pool. They are compensated with the fees generated from trade volume.
Price Discovery	The efficient and timely incorporation of the information implicit in investor trading into market prices (Lehmann 2002).
Total Value Locked (TVL)	Represents the sum of all assets deposited or 'staked' within a DeFi protocol.
Smart Contract	Specialised protocols that execute complicated transactions when the terms of agreement are met, without relying on a third party (Hertig (2020)).
Stablecoin	A crypto-asset pegged to a fiat currency, commodity or another crypto-asset.

Table 4A

Average Daily Trades of Merged AMMs

This table displays the daily average number of trades for the merged AMMs across asset pairs. AMMs are marked 1 to 6 demonstrating the order they were merged in. Stable refers to a stablecoin, and Risky refers to a non-stablecoin. Sample Period 1 is between November 2020 and October 2021, and Sample Period 2 is between June 2021 and October 2021. The * in PancakeSwap and Curve explains that they are the first and second to be merged if trading that pair. The other AMMs are shifted down if this is the case. Not all exchanges trade every asset pair; these are left as blank.

		Sample Period 1					**Sample Period 2**		
Category	**Asset Pair**	**Balancer (1)**	**Bancor (5)**	**0x (2)**	**Curve (2*)**	**Dodo (6)**	**DeFi Swap (3)**	**1inch (4)**	**Pancake Swap (1*)**
Stable/Stable	USDC/USDT		3		70	84	2		236
	USDC/DAI	18	3		81		1		
Stable/Risky	USDC/WETH	245	45	165		40	168	12	194
	DAI/WETH		32	108			69	6	
Risky/Risky	WBTC/WETH	187	18	38			24	5	52
	LINK/WETH	57	26	20			25	2	
	AAVE/WETH	214	9	12			5		
	YFI/WETH	29	10	14			3	1	
	Average	**125**	**18**	**60**	**76**	**62**	**37**	**5**	**161**

Table 5A

Average Trading Volume Per Transaction of Merged AMMs

This table displays the mean trade amount for the merged AMMs across asset pairs. Stable refers to a stablecoin, and Risky refers to a non-stablecoin. Sample Period 1 is between November 2020 and October 2021, and Sample Period 2 is between June 2021 and October 2021. Not all exchanges trade every asset pair; these are left as blank. The * in PancakeSwap and Curve explains that they are the first and second to be merged if trading that pair. The other AMMs are shifted down if this is the case. Values are in USD terms.

		Sample Period 1					**Sample Period 2**		
Category	**Asset Pair**	**Balancer (1)**	**Bancor (5)**	**0x (2)**	**Curve (2*)**	**Dodo (6)**	**DeFi Swap (3)**	**1inch (4)**	**Pancake Swap (1*)**
Stable/Stable	USDC/USDT		18,473		150,169	319,161	25		380
	USDC/DAI	1,480	21,463		172,691		9		
Stable/Risky	USDC/WETH	4,782	30,966	70,156		25,063	2,855	1,761	40
	DAI/WETH		30,802	62,216			2,801	790	
Risky/Risky	WBTC/WETH	29,555	65,959	79,287			5,990	2,192	221
	LINK/WETH	3,761	62,443	33,038			2,594	45	
	AAVE/WETH	59,992	33,744	27,537			857		
	YFI/WETH	5,843	26,727	28,171			676	61	
	Average	**17,569**	**36,322**	**50,067**	**161,430**	**172,112**	**214**	**1,975**	**970**

Appendix C: Price Discovery Interpretation & Additional Estimates

The model assumes that the unobservable true value of the asset follows a random walk:

$$m_t = m_{t-1} + u_t, \qquad u_t \sim N(0, \sigma_u), \tag{1A}$$

with m_t denoting the natural log of the fundamental value and u_t representing the i.d.d white noise processes at time t. Building on (1A) to apply to asset price series,

$$p_{i,t} = m_{t-\delta_i} + s_{i,t}, \qquad s_{i,t} \sim N\left(0, \sigma_{s_i}\right), \tag{2A}$$

$p_{i,t}$ denotes the natural log of price series i at the time t, and similarly, $s_{i,t}$ represents the i.d.d noise processes that are uncorrelated with other price series. The δ_i and σ_{s_i} variables characterise the speed of impounding new information and its noise of price series i.

Following Baillie, Booth, Tse and Zabotina (2002), I calculate the Component Share as the normalised orthogonal to the error correction term coefficients α_1 and α_2,

$$CS_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, \quad CS_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2}. \tag{3A}$$

Since there are only two price series, and CS is normalised, CS_2 can be simplified to:

$$CS_2 = 1 - CS_1, \tag{4A}$$

The second price discovery measure is the Hasbrouck (1995) Information Share. The IS incorporates the CS along with variables from the Cholesky factorisation matrix.
The covariance matrix of the VECM error terms,

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}, \tag{5A}$$

is used to formulate the Cholesky factorisation matrix **Ω** = MM',

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{\frac{1}{2}} \end{pmatrix}, \tag{6A}$$

and when combined provides,

$$IS_1 = \frac{(CS_1 m_{11} + CS_2 m_{12})^2}{(CS_1 m_{11} + CS_2 m_{12})^2 + (CS_2 m_{22})^2},$$

$$IS_2 = \frac{(CS_2 m_{22})^2}{(CS_1 m_{11} + CS_2 m_{12})^2 + (CS_2 m_{22})^2}. \tag{7A}$$

Due to the normalisation factor, IS_2 can be simplified to:

$$IS_2 = 1 - IS_1, \tag{8A}$$

Since the IS estimates are dependent on the price series ordering within the VECM, I compute the IS under both orderings then take the average following past literature (Baillie, Booth, Tse and Zabotina (2002); Booth, Lin, Martikainen and Tse (2002); Cao, Hansch and Wang (2009); Chen and Gau (2010); Korczak and Phylaktis (2010); Putniņš (2013)).

Table 6A
Supplementary Estimates of Price Discovery Shares

This table displays the Informational Leadership Shares (ILS), Information Shares (IS), and Component Shares (CS) of Uniswap v2, Curve and PancakeSwap and QuickSwap AMMs. The shares between Uniswap v2 and Curve are estimated between November 2020 and October 2021. The shares between PancakeSwap and QuickSwap are estimated between June 2021 and October 2021. Uniswap v2 and PancakeSwap are denoted by the subscript 1, Curve and QuickSwap are denoted by the subscript 2. Many of the pairs in my sample are not traded on Curve or PancakeSwap. The informational leader for a particular share is shaded. Three diagnostics are also computed: the correlation of reduced form errors (Correl), the spread of the IS between orderings (UmL) and the spread between the confidence intervals set at 95% (CI_{ILS}).

	Price Discovery Shares						Diagnostics		
Asset Pair	**ILS_1**	**ILS_2**	**IS_1**	**IS_2**	**CS_1**	**CS_2**	Correl	UmL	CI_{ILS}
Panel A: Uniswap v2 – Curve									
USDC/USDT	0.87	0.13	0.05	0.95	0.01	0.99	0.01	0.01	0.06
USDC/DAI	0.75	0.25	0.05	0.95	0.01	0.99	0.01	0.01	0.09
Average	**0.81**	**0.19**	**0.05**	**0.95**	**0.01**	**0.99**	**0.01**	**0.01**	**0.08**
Panel B: PancakeSwap – QuickSwap									
USDC/USDT	0.43	0.57	0.79	0.21	0.82	0.18	-0.01	0.01	0.09
USDC/WETH	0.07	0.93	0.37	0.63	0.67	0.33	0.03	0.03	0.10
WBTC/WETH	0.10	0.90	0.93	0.07	0.99	0.01	0.01	0.01	0.09
Average	**0.20**	**0.80**	**0.70**	**0.30**	**0.82**	**0.18**	**0.01**	**0.02**	**0.09**

Table 7A

Supplementary Estimates of CFMM Price Discovery Shares

This table displays the Informational Leadership Shares (ILS), Information Shares (IS), and Component Shares (CS) of Uniswap v2/v3, SushiSwap and QuickSwap CFMMs. All the price discovery shares are estimated between June 2021 and October 2021. Uniswap v2 and SushiSwap are denoted by the subscript 1, Uniswap v3 and QuickSwap are denoted by the subscript 2. The informational leader for a particular share is shaded. Three diagnostics are computed: the correlation of reduced form errors (Correl), the spread of the IS between orderings (UmL) and the spread between the confidence intervals set at 95% (CI_{ILS}).

	Price Discovery Shares						Diagnostics		
Asset Pair	**ILS_1**	**ILS_2**	**IS_1**	**IS_2**	**CS_1**	**CS_2**	Correl	UmL	CI_{ILS}
Panel A: Uniswap v2 – Uniswap v3									
USDC/USDT	0.76	0.24	0.38	0.62	0.25	0.75	-0.01	0.01	0.06
USDC/DAI	0.41	0.59	0.07	0.93	0.07	0.93	0.01	0.01	0.08
USDC/WETH	0.61	0.39	0.07	0.93	0.06	0.94	0.08	0.03	0.10
DAI/WETH	0.38	0.62	0.25	0.75	0.28	0.72	0.06	0.04	0.07
WBTC/WETH	0.38	0.62	0.13	0.87	0.16	0.86	0.05	0.03	0.09
LINK/WETH	0.53	0.47	0.56	0.44	0.54	0.46	0.08	0.07	0.09
AAVE/WETH	0.52	0.48	0.64	0.36	0.64	0.36	0.07	0.06	0.08
YFI/WETH	0.52	0.48	0.47	0.53	0.46	0.54	0.06	0.06	0.07
Average	**0.52**	**0.48**	**0.32**	**0.68**	**0.37**	**0.63**	**0.05**	**0.04**	**0.08**
Panel B: SushiSwap – Uniswap v3									
USDC/WETH	0.43	0.57	0.07	0.93	0.08	0.92	0.10	0.04	0.09
DAI/WETH	0.45	0.55	0.30	0.70	0.31	0.69	0.08	0.05	0.08
WBTC/WETH	0.36	0.64	0.18	0.82	0.21	0.79	0.07	0.04	0.08
LINK/WETH	0.53	0.47	0.66	0.34	0.65	0.35	0.10	0.09	0.05
AAVE/WETH	0.54	0.46	0.75	0.25	0.74	0.26	0.08	0.06	0.08
YFI/WETH	0.63	0.37	0.69	0.31	0.64	0.36	0.07	0.06	0.09
Average	**0.49**	**0.51**	**0.44**	**0.56**	**0.44**	**0.56**	**0.08**	**0.06**	**0.08**
Panel C: SushiSwap – QuickSwap									
USDC/WETH	0.22	0.78	0.47	0.53	0.63	0.36	0.03	0.03	0.06
DAI/WETH	0.30	0.70	0.45	0.55	0.55	0.45	0.03	0.02	0.08
WBTC/WETH	0.12	0.88	0.93	0.07	0.97	0.03	0.01	0.01	0.08
LINK/WETH	0.35	0.65	0.58	0.42	0.68	0.32	0.01	0.01	0.08
AAVE/WETH	0.14	0.86	0.49	0.51	0.73	0.27	0.01	0.01	0.05
YFI/WETH	0.49	0.51	0.75	0.25	0.78	0.22	0.02	0.01	0.13
Average	**0.27**	**0.73**	**0.61**	**0.39**	**0.72**	**0.28**	**0.02**	**0.01**	**0.08**

Table 8A

Supplementary Estimates of Price Discovery Shares using Block-Time Interval

This table shows the Informational Leadership Shares (ILS), Information Shares (IS), and Component Shares (CS) estimates between Uniswap v2 and SushiSwap using block time intervals instead of ten-second intervals. The price discovery shares are estimated between November 2020 and October 2021. Deviation of 1% *, deviation of 3% **, deviation of 5% ***. Price leader is shaded. Three diagnostics are also computed: the correlation of reduced form errors (Correl), the spread of the IS between orderings (UmL) and the spread between the confidence intervals set at 95% (CI_{ILS}).

	Price Discovery Shares						Diagnostics		
Asset Pair	**ILS_{Uni}**	**ILS_{Sushi}**	**IS_{Uni}**	**IS_{Sushi}**	**CS_{Uni}**	**CS_{Sushi}**	Correl	UmL	CI_{ILS}
USDC/WETH	0.85***	0.15	0.71***	0.29	0.53***	0.47	0.09*	0.07*	0.02*
DAI/WETH	0.65*	0.35	0.46	0.54*	0.37	0.63	0.09	0.09	0.05*
WBTC/WETH	0.67*	0.33	0.49	0.51*	0.39*	0.61*	0.07	0.06	0.04
LINK/WETH	0.65	0.35	0.42	0.58*	0.33	0.67	0.13	0.12	0.03
AAVE/WETH	0.54	0.46*	0.34	0.66*	0.31*	0.69*	0.17*	0.16	0.04*
YFI/WETH	0.49	0.51	0.31	0.69	0.31	0.69	0.14	0.12*	0.05
Average	**0.64***	**0.36**	**0.46**	**0.54****	**0.37***	**0.63***	**0.11***	**0.10***	**0.04**

Table 9A

Lag Lengths for Estimation of VECM

This table details the lag lengths used when estimating the VECM. Main denotes the lag length used in the main results and are intuitively determined. AIC and BIC lags are used as a robustness check for the Binance-AMM sample. The shares are estimated between November 2020 and March 2021. Any additional exchange pairings not listed here had a lag length of 200. Binance does not trade YFI/WETH and is therefore left as blank.

	Binance - AMM			**CFMMs - Non CFMMs**	**Uniswap v2 – SushiSwap**	**Uniswap v3 – QuickSwap**	**Uniswap v2 - QuickSwap**	
Asset Pair	Main	AIC	BIC	Main	Main	Main	Main	AIC
USDC/USDT	200	75	42	100	100	200	200	241
USDC/DAI	200	244	38	100	100	200	200	246
USDC/WETH	200	197	52	100	100	200	200	222
DAI/WETH	200	199	34	100	100	200	200	76
WBTC/WETH	200	195	48	100	100	200	200	241
LINK/WETH	200	195	36	100	100	200	200	203
AAVE/WETH	200	99	47	100	100	200	200	149
YFI/WETH				100	100	200	200	220

Appendix D: Liquidity Provision Holding Returns & Fee Rate

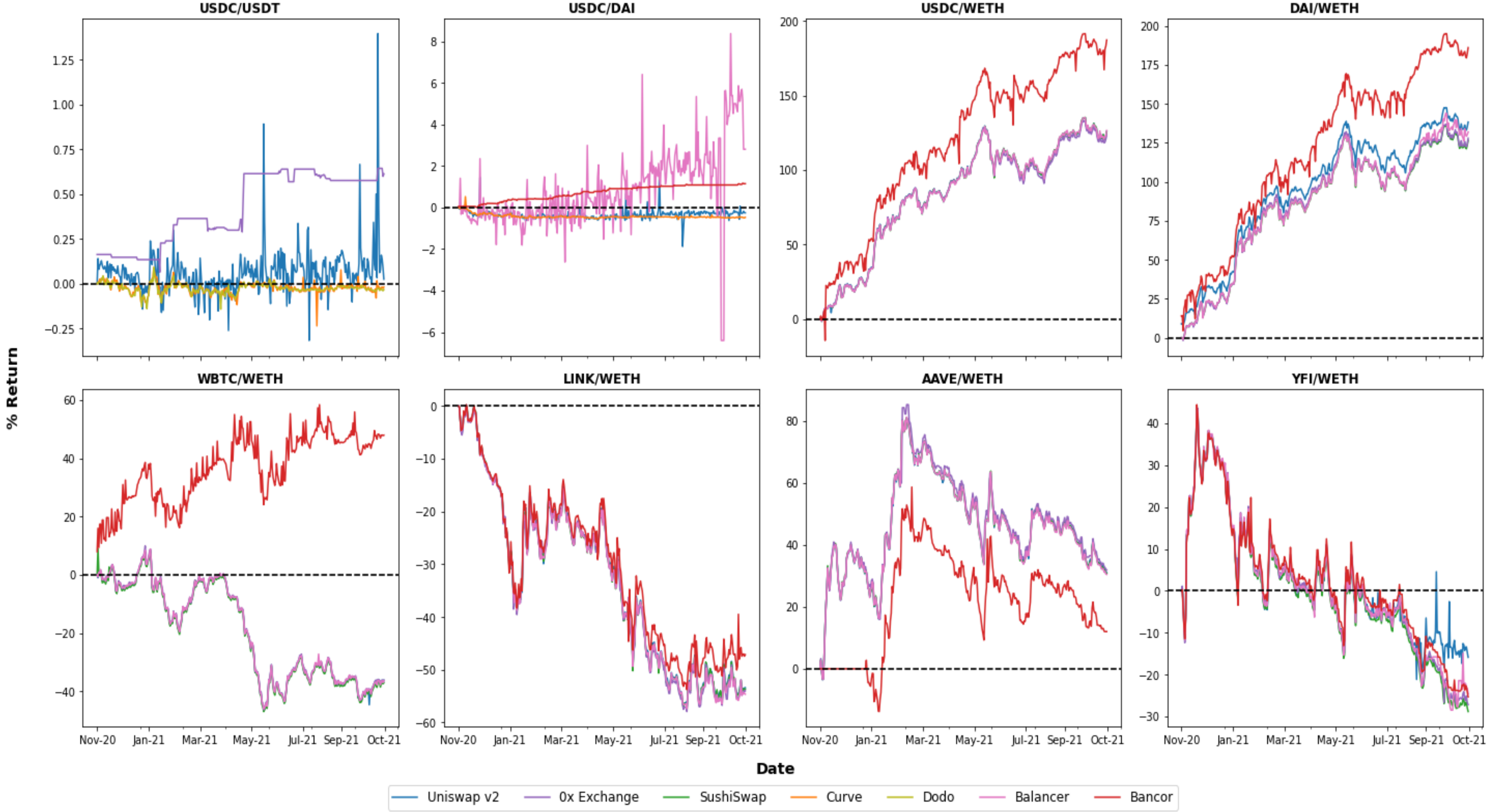

Figure 1A. Total Accumulative Inventory Holding Return, Sample Period.

This figure displays the total accumulative inventory holding return liquidity providers suffer for each asset pair between November 2020 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 1A displays the AMMs and its respective colour code.

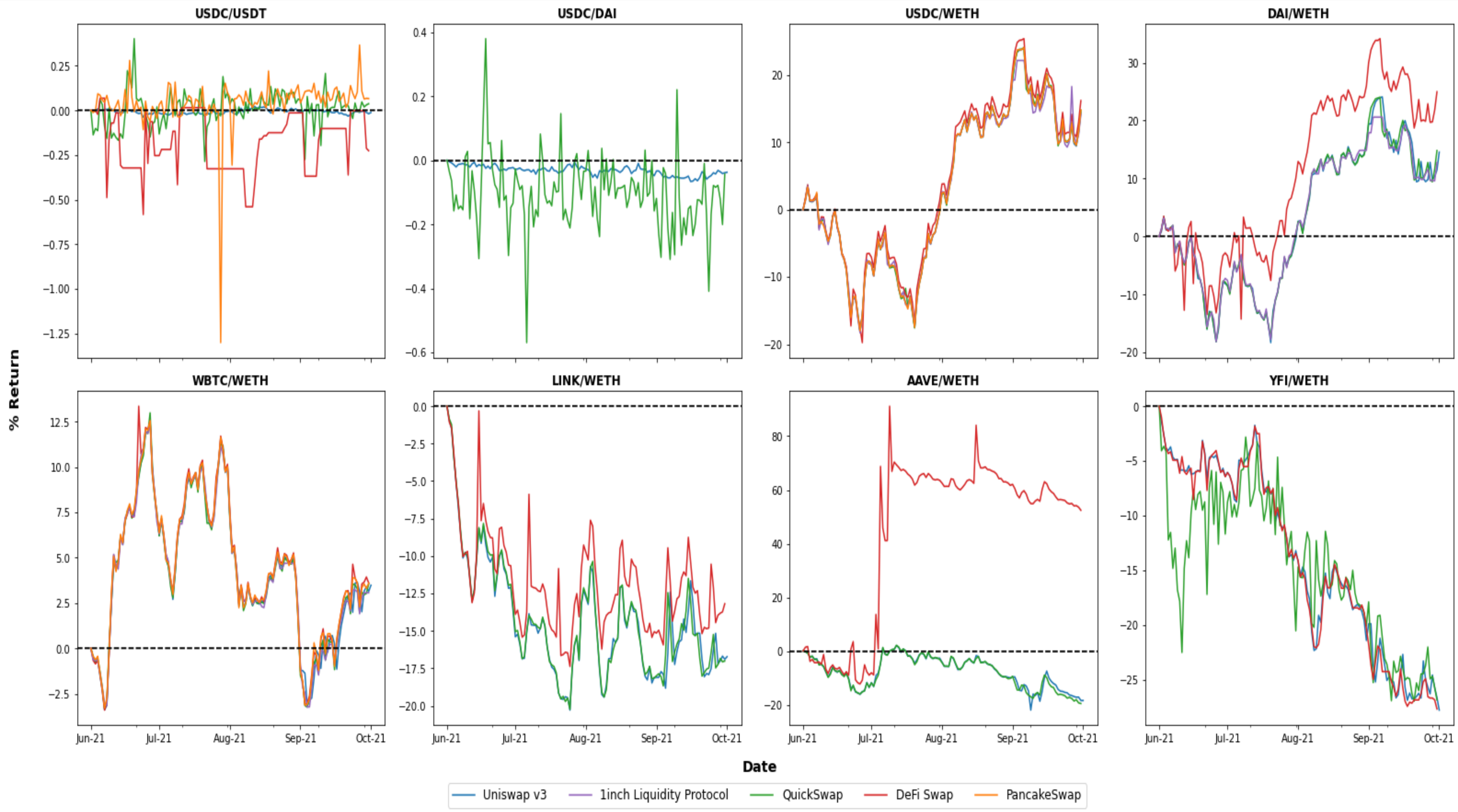

Figure 2A. Total Accumulative Inventory Holding Return, Sample Period.

This figure displays the total accumulative inventory holding return liquidity providers suffer for each asset pair between June 2021 to October 2021. Returns are calculated as percentages. The legend at the bottom of Figure 2A displays the AMMs and its respective colour code.

Table 10A

Percentage Fee Rate for Asset Pairs

This table shows the fee percentage set by the AMM/liquidity pool for the eight sampled asset pairs. Sample Period one is between November 2020 and October 2021, and Sample Period 2 is between June 2021 to October 2021. Note that not all AMMs trade every pair; these are left as blank.

	Sample Period 1							**Sample Period 2**				
Asset Pair	**Uniswap v2**	**Sushi Swap**	**Balancer**	**Bancor**	**0x**	**Curve**	**Dodo**	**Quick Swap**	**Uniswap v3**	**DeFi Swap**	**1inch Liquidity Protocol**	**Pancake Swap**
USDC/ USDT	0.30	0.25		0.20	0.10	0.3	0.008	0.30	0.30	0.30		0.17
USDC/ DAI	0.30	0.25	0.32	0.20		0.03		0.30	0.30	0.30		
USDC/ WETH	0.30	0.25	0.35	0.20	0.10		0.008	0.30	0.30	0.30	0.80	0.17
DAI/ WETH	0.30	0.25	0.25	0.20	0.10			0.30	0.30	0.30	0.56	
WBTC/ WETH	0.30	0.25	0.22	0.17	0.10			0.30	0.30	0.30	0.80	0.17
LINK/ WETH	0.30	0.25	0.25	0.20	0.10			0.30	0.30	0.30		
AAVE/ WETH	0.30	0.25	0.30	0.20	0.10			0.30	0.30	0.30		
YFI/ WETH	0.30	0.25	0.25	0.20	0.10			0.30	0.30	0.30		

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