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Liquidity shocks, token returns and market capitalization in decentralized finance (DeFi) markets

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Abstract: This paper investigates the market reaction to large positive or negative liquidity shocks on the value of tokens traded on *decentralized exchanges (DEXes)* on the Ethereum blockchain. *Automated market makers (AMMs)* and constant product markets provide transparent and decentralized ways to directly swap two blockchain tokens for each other via the use of liquidity pools. Using trade-by-trade data of 2.77 million swaps of 14 different tokens traded on *Uniswap v2*, *v3* and *SushiSwap*, we find that the size of sell orders significantly correlates with negative future token returns, while buy size positively correlates with future token returns. Using an event study approach, we quantify the market reaction of unusually large sell and buy orders (top 1% percentile) and identify that the market reaction outweighs the economic value of the event by a factor of -7.4 for sell orders and +4.4 for buy orders over a short-span trading window. In the case of sell orders, a high proportion of the abnormal return is already realized before the event, which indicates informed trading in the form of arbitrage or frontrunning via *Miner Extractable Value (MEV)*. Looking at individual crypto assets, we find a mean reassessment of token value following short sales of up to -0.79% within just one follow-up trade (buy orders up to 0.50%). The findings indicate that price shocks may have a signaling effect but also that market capitalization may be an insufficient metric for assessing the liquidity and valuation of (inefficient) crypto assets. The results suggest multiple challenges for investor protection in *decentralized finance (DeFi)* markets.

Keywords: Market efficiency, Liquidity; Informational efficiency, Price discovery, Asset pricing, Event study; Uniswap

1 Introduction

On January 17, 2022, tokens worth $11.3 million of the blockchain project *Olympus DAO (OHM)* were sold on the *decentralized exchange (DEX) SushiSwap* in a single transaction (Etherscan 2022b). Up to that point, the OHM cryptocurrency had a market capitalization of $1.3 billion. As a result, the market capitalization of OHM dropped to $900 million over a short period of time (CoinGecko 2022). The fact that a single transaction with a value of ~0.86% of the implied value of all OHM tokens caused a market cascade or overreaction of ~ -30% suggests that market capitalization is not a meaningful metric for the actual liquidity or "value" of cryptocurrencies and that *decentralized finance (DeFi)* markets are inefficient.

It should be noted that such large transactions on DEXes are by no means a rarity in DeFi markets. In fact, there are already services that automatically track transparent markets on blockchains and report particularly large swaps so that traders or market makers can incorporate the information into their strategies. One example is the *DeFi Sniper* project, which has over 32,000 followers on *Twitter* (DeFi Sniper 2022). However, even if part of the market already knows about the occurrence and timing of large swaps, the actual market impact or relevance remains largely unclear.

The trading of tokens on DEXes has increased significantly in recent years, due in part to the great success of the *automated market making (AMM)* protocol *Uniswap*. *Uniswap* is a system of smart contracts, i.e., decentrally anchored computer code on blockchains (Ante 2021), that functions as an automated liquidity protocol using a constant product market maker formula. More precisely, two assets are anchored in a decentralized liquidity pool and can be swapped directly with each other. Liquidity providers are incentivized via a transaction fee (Adams, Zinsmeister, and Robinson 2020; Adams et al. 2021). Traders can directly interact with the protocol by sending one token to the liquidity pool and receiving the other one in return. The shifting ratio of the tokens in the pool then determines the new exchange rate between them. The use of AMM protocols for token trading makes logins, central authentication or the use of intermediaries superfluous or replaces them with smart contracts, i.e., decentralized trust. The decentralized nature of DEXes such as *Uniswap* offers a unique degree of transparency and certainty of settlement, as all trades and traders' accounts can be monitored in real-time. This is not the case for centralized exchanges that self-report trading volume and trades, which can lead to trust issues due to, e.g., wash trading, as the information cannot be independently validated (e.g., Le Pennec et al., 2021). Additionally, it is usually not possible to monitor individual accounts on centralized exchanges.

AMM protocols are a rather recent phenomenon whose capital efficiency is constantly developing. Older protocols, such as *Uniswap v2* or *SushiSwap*, use the constant product formula of $x * y = k$, where x and y represent the reserves in token A and token B in a liquidity pool. If a user wants to withdraw a number of tokens A from the pool, a proportional amount of token B must be sent to the pool. Thus, the price of token A can be calculated as the reserve of token B divided by the reserve of token A. Other protocols, most of which were released at a later date, use more advanced logic to improve capital efficiency, such as concentrated liquidity (e.g., *Uniswap v3* or *Balancer*) or multi-asset pools (e.g., *Curve*) (Adams et al. 2021; Curve.fi 2022; Martinelli and Mushegian 2019). A key characteristic of AMMs—especially DEXes employing a constant product formula—is that the underlying liquidity for the exchange of two tokens is publicly visible at all times and that swaps are almost exclusively market orders. The fact that each swap shifts the market price by changing the ratio of the two tokens means that large transactions can have a significant impact on prices and liquidity. While the price effect of a swap is immediately obvious, there are currently no precise findings on the extent to which the market interprets (particularly large or significant) swaps as price signals that trigger overreactions, i.e., effects beyond the economic impact of the transaction itself.

There are various reasons why supply or price shocks in the form of exceptionally large cryptocurrency sales or purchases on DEXes could or should cause an abnormal market reaction, i.e., one that exceeds its actual economic impact. The withdrawal or addition of tokens shifts the supply curve or the underlying liquidity of the token, thus making future trading more or less efficient. Accordingly, and in line with *Signaling Theory* (Spence 1973), this suggests that an increase in liquidity should represent a positive market signal for traders and a decrease a negative signal. So if a very strong unforeseen price or liquidity shock occurs, traders will update their expectations of the token price, which may in turn result in direct buying (more liquidity), selling (less liquidity) or temporary absence from any activity in the market (uncertainty due to possible adverse selection) (Beaver 1968; Chae 2005). A higher risk of encountering informed counterparties reduces the willingness of uninformed traders, such as liquidity traders or market makers, to participate in a market (Black 1986; Milgrom and Stokey 1982). However, in the case of liquid assets that are besides DEXes also traded on other (central) trading venues, extraordinary market reactions also provide an opportunity for arbitrageurs to offset these effects and exploit market inefficiencies.

The academic literature has examined price shocks and similar unforeseen events in a wide variety of settings and concluded that they can have both short- and long-term effects on financial markets. This includes, for example, oil price shocks and stock returns (Hu et al. 2018; Kang, Ratti, and Vespignani 2016; Cunado and Perez de Gracia 2014), short sales and stock returns (Aitken et al. 1998) or Bitcoin volatility (Diaconaşu, Mehdian, and Stoica 2022). Other studies focus on the relationship of on-chain ('on-the-blockchain') transactions and financial metrics. Koutmos (2018) finds that the cumulative amount of transaction activity in the Bitcoin network has an effect on the returns and trading volume of Bitcoin, and Wei (2018) identifies that issuances of the stablecoin Tether do not affect returns on Bitcoin but raise its trading volume. For other stablecoins, too, it has been found that issuances and transactions relate to the pricing, return and volume of Bitcoin and other cryptocurrencies (Kristoufek 2021; Griffin and Shams 2020; Ante, Fiedler, and Strehle 2021b; 2021a; Saggu 2022). Ante (2020) identifies that large Bitcoin transfers are part of Bitcoin's microstructure, as informed traders adjust their expectations (trading volume) based on the degree of information asymmetry. For large on-chain transactions of Bitcoin, Ante and Fiedler (2021) further identify different price effects depending on size and type (initiator/receiver) of transactions.

To our knowledge, there is currently no scientific research that addresses the question of how positive or negative price shocks on DEXes affect the prices of crypto-assets. This study therefore aims to investigate and quantify these effects. An accurate understanding of the factor liquidity is a strikingly important aspect of understanding financial markets and an essential criterion for the behavior of market participants such as liquidity traders. In traditional financial markets or centralized cryptocurrency exchanges, order books with bids and asks serve a similar role as liquidity pools in DeFi markets. The same cryptocurrencies that are traded in centralized order books are also traded in DeFi markets. Thus, arbitrageurs, for example, need to understand exactly how these markets interact and differ from each other. Academic research on order book dynamics and its information content has a long history (e.g., Cao et al., 2009; Chen et al., 2019;

Cornelli and Goldreich, 2003), which is why assessing the liquidity and risk factors of assets and prices is easier on traditional exchanges than it is for novel forms of supply and demand matching. Accordingly, we see a significant research gap in studying the relationship between liquidity and prices in DeFi markets. The analysis of price shocks can play a small part in filling the research gap and contributes to research on DeFi in general, the role of information for financial markets and cryptocurrency market efficiency. Furthermore, we include the extremely important cryptocurrency market metric 'market capitalization' in our analysis (=market price multiplied by circulating token supply) to analyze how high relative swaps and market reactions turn out to be. If the market capitalization metric represents a proper proxy for the realizable value of a crypto asset, then the relative economic impact of a large swap should be at most as high as it is large relative to the market capitalization. However, we suspect that this is not the case, especially for comparatively illiquid cryptocurrencies. It seems reasonable to assume that the market capitalization metric sometimes puts the actual value of crypto assets much higher than is realistically the case. Therefore, if the price impact of a large swap is higher than it would rationally be using market capitalization as a fair proxy for value, we can interpret this as an indication that our assumption is correct.

To assess the significance of price and liquidity shocks in DeFi markets, we use trade-by-trade data from three major DEXes (*Uniswap v2*, *Uniswap v3* and *SushiSwap*) on the largest blockchain infrastructure for DeFi, *Ethereum*. These DEXes likely represent over 95% of the respective DeFi market for the time frame considered. Based on a sample of 2.77 million individual trades of 14 tokens (i.e., crypto assets), we determine the extent to which the swap size of buy and sell orders relates to token returns at different intervals. We find that the size of sell orders is significantly related to negative future token returns, while the size of buy orders positively relates to future token returns. Using an event study approach, we identify and quantify the market reaction to unusually large sell and buy orders and find that the resulting short-term market reaction is 640% higher than the actual swap for sales and 340% higher for buys. For sales, a high proportion of the abnormal return is realized before the event, suggesting informed trading in the form of arbitrage via *Miner Extractable Value (MEV)* (Daian et al. 2020; Strehle and Ante 2020). Looking at individual crypto assets, we show that token prices on average drop by -0.79% after sales in the 1% percentile within just one subsequent trade (up to 0.50% for buy orders). However, the relative size of the swaps is only 0.059% for sells and 0.043% for buys. The results thus suggest that price shocks on decentralized exchanges may have a signaling effect, but they also indicate that market capitalization may be an insufficient metric for assessing the liquidity and value of (inefficient) crypto assets.

This article proceeds as following. Section 2 describes the data collection, the sample and the empirical approach. Section 3 presents correlations between swap size and token returns as well as the event study results. Section 4 reflects on the main results of the study, its limitations, future research paths and implications. Section 5 concludes.

2 Data and methods

2.1 Data and sample description

There are thousands of different trading pools for DEXes (especially for *Uniswap v2*), making it difficult to select specific pairs for swap data extraction and subsequent analysis. We adopt a multi-step approach to selecting tokens for our analysis. The first step is the exploratory identification of tokens with exceptionally large swap activity. For this purpose, we use a *Python* script to extract all large swaps published by market intelligence bot *DeFi Sniper* between June 05, 2021, and January 23, 2022, from their *Telegram* channel (t.me/defisniper). This yields 29,654 swaps with an average size of $1.16 million (SD = $1.54 million) involving 511 unique crypto assets.

We then exclude the major reference currencies from the sample. This includes *Ether (ETH)*, *Wrapped Ether (WETH)*, and their interest bearing (e.g., *Aave*'s *aETH* or *aWETH*), staked (e.g. *Lido*'s *stETH* or *Ankr*'s *aETH*) and leveraged (e.g., *ETH 2x Flexible Leverage Index*; *ETH2x-FLI*) variations. *Wrapped Bitcoin (WBTC)*, *renBTC* and *HBTC* are likewise dropped from the sample, as are stablecoins, (e.g., *USDT*, *USDC*, *MIM*, *EURT* and *UST*), their interest-bearing variations (e.g., *Compound*'s *cUSDC*), and mirrored stocks such as *Mirrored Apple (mAAPL)* and *Mirrored Tesla (mTSLA)*. We individually check the suitability of the remaining tokens for swap activity analysis based on the following criteria: Is there a high number of unusually large swaps? Does the token have a high average trade volume and *token value locked (TVL)*, i.e. the liquidity anchored in AMM pools, on DEXes? These checks leave a sample of 14 tokens, for which we use subsequently collect data and conduct the analyses: *Aave (AAVE)*, *Alchemix (ALCX)*, *Compound (COMP)*, *Ethereum Name Service (ENS)*, *Chainlink (LINK)*, *LooksRare (LOOKS)*, *Decentraland (MANA)*, *Maker (MKR)*, *Olympus DAO (OHM)*, *Ribbon Finance (RBN)*, *The Sandbox (SAND)*, *Shiba Inu (SHIB)*, *Spell Token (SPELL)* and *Sushi (SUSHI)*. Of course, this selection of tokens is subject to some extent arbitrary, but given the lack of research or approaches to systematically select tokens on this topic, we consider our approach suitable for such an explorative analysis.

We use *Flipside Crypto* (flipsidecrypto.xyz) to generate custom *application programming interfaces (APIs)* for each of the 14 tokens, which provide us with a historic dataset of all swaps made on the DEXes *Uniswap v2*, *Uniswap v3* and *Sushiswap* from May 20, 2021, to March 20, 2022. The number of liquidity pools depends on the token—for example, the highest number of different pools is 46 for LINK. However, 99% of the volume accrues to a few trading pairs with ETH or stablecoins as the reference pairs (i.e., *LINK/ETH* or *LINK/USDT*). The swap data is enriched with the circulating supply of each token, which is obtained via the *CoinGecko* API (coingecko.com). This data is updated daily (while the swaps are specific to seconds or rather Ethereum blocks) and is curated by *CoinGecko*. This means that vested or burned tokens are excluded from the calculation, which allows a meaningful assessment of the actually circulating supply of a token. This results in the justifiable limitation that intraday fluctuations or inflation of the circulating token supply are not accounted for. Accordingly, the price of a token in USD is multiplied by its daily circulating supply to calculate the market capitalization at the time of the swap. Table 1 shows an overview of the 14 tokens, their average market capitalization, the periods under consideration, their swap count and distribution across the DEXes.

Table 1. Overview of token samples.

Token	Avg. market cap ($b)	First swap	Swaps			Distribution across DEXes		
			All	Buys	Sells	Uniswap v2	Uniswap v3	Sushiswap
AAVE	3.751	May 2021	58,503	54%	46%	26%	38%	36%
ALCX	0.224	May 2021	61,443	43%	57%	0%	11%	89%
COMP	1.943	May 2021	59,492	45%	55%	26%	36%	38%
ENS	0.864	Nov 2021	145,356	33%	67%	8%	70%	22%
LINK	10.539	May 2021	186,072	49%	51%	35%	44%	21%
LOOKS	0.525	Jan 2022	317,837	52%	48%	44%	56%	0%
MANA	3.444	May 2021	95,625	52%	48%	36%	31%	33%
MKR	2.449	May 2021	52,022	48%	52%	29%	45%	25%
OHM	1.546	Dec 2021	107,084	55%	47%	1%	11%	88%
RBN	0.116	Oct 2021	36,022	56%	44%	24%	75%	1%
SAND	2.981	May 2021	222,653	59%	41%	72%	28%	<1%
SHIB	10.917	May 2021	1,060,915	61%	39%	68%	31%	1%
SPELL	1.001	Jun 2021	174,319	57%	43%	<1%	26%	74%
SUSHI	1.761	May 2021	192,334	47%	52%	15%	9%	76%
All	3.004	May 2021	2,769,677	55%	45%	44%	35%	21%

Blocks and thus transactions on the *Ethereum* blockchain are confirmed on average every 12-14 seconds (Etherscan 2022a). Miners bundle initiated transactions from the *Mempool* and confirm them. They can independently determine the order of settlement, which has significant implications for activity and trading on DEXes. Via MEV, users can bid to be placed in front of and/or behind specific transactions, which, in conjunction with flash loans (loans that are reimbursed within the same block), enables applications such as sandwich attacks, frontrunning or arbitrage (Daian et al. 2020). The ordering of settled transactions therefore represents a direct sequence and can be considered as a time series (with irregular intervals). So to quantify the short-term impact of an individual token swap on the price of a token, the calculation must include the immediate successor swap(s), even if they may have the exact same timestamp as the actual swap event. We therefore define the sequence of swaps as a time series, with each swap as a unit of time, and use this basis to calculate log returns. Table 2 shows descriptive statistics for the log returns of each token.

The statistics clearly show that the log returns are not normally distributed, as the very large kurtosis indicates thick tails. Ten of the tokens have a negative average return over the respective periods, four have a positive average return. The fact that the minimum swap-to-swap returns per token range between -14.38% (MKR) and -68.48% (RBN) illustrates how volatile the tokens are and that there are significant downward outliers. Likewise, there are outliers on the upside, as evidenced by the maximum swap-to-swap log returns ranging from 10.53% (LINK) to 38.19% (ENS).

Table 2. Descriptive statistics for token log returns. For the number of observations, see Table 1.

Token	Mean (%)	SD (%)	Min (%)	Max (%)	Skewness	Kurtosis
AAVE	-0.0020	0.51	-17.08	13.39	-1.23	199.07
ALCX	-0.0042	0.49	-59.08	16.02	-27.37	3,455.01
COMP	-0.0032	0.48	-23.06	12.79	-2.93	245.94
ENS	-0.0002	0.29	-27.56	38.19	17.16	3,130.91
LINK	-0.0003	0.26	-18.26	15.01	-3.31	653.97
LOOKS	-0.0003	0.22	-63.05	21.56	-68.69	30,965.39
MANA	0.0005	0.43	-20.69	20.13	1.83	287.26
MKR	-0.0019	0.47	-14.38	12.14	-0.29	154.25
OHM	-0.0025	0.20	-29.10	12.09	-32.44	5,455.47
RBN	-0.0038	0.73	-68.48	25.59	-19.66	2,332.22
SAND	0.0011	0.30	-15.47	17.84	5.80	562.03
SHIB	0.00003	0.14	-16.27	20.04	14.74	3,831.42
SPELL	0.0008	0.53	-36.94	37.73	4.53	1,750.85
SUSHI	-0.0007	0.31	-21.82	14.88	-1.84	639.22

For each swap we collect basic metrics like timestamps, transaction ID, direction of the swap (sell or buy order), pool name, the exchanged number of tokens, and the USD value of these tokens at the time of the swap. The latter refers only to the side of the swap that contains the respective token. For example, an exemplary swap of 1 SUSHI for 16.88 USDT only counts for \$16.88 USD, rather than the total volume of the swap (\$37.66). From this absolute swap size, we calculate the relative size by dividing the former by the current market capitalization of the token. Table 3 shows descriptive statistics for absolute and relative swap sizes for each token sample and for subsamples based on the direction of the swap. “in” indicates that the token in question is sent to the pool and is thus being sold for another token, while “out” means that other tokens are sent to the pool and the tokens under consideration are transferred out of the pool, i.e., they are being purchased.

On average, the absolute size of the swaps ranges between \$11,984 (MANA) and \$29,093 (LINK). Half of the tokens considered feature an excess of sales (out transactions). The share of sales is highest for ENS (67%), which is probably due to its distribution by airdrop (ENS 2022). On average, sales of ENS were significantly larger than purchases (Δ=\$13,370***), which indicates that an overselling of ENS has taken place—at least on the DEXes considered. The other tokens with statistically significantly larger sells compared to buys show the opposite picture. LOOKS, MANA, OHM, RBN, SAND, SHIB (the lowest share of sales, at 39%) and SPELL all exhibit significantly higher average sales than purchases. This could indicate that smaller (retail/individual) investors buy tokens on DEXes and larger/professional investors or stakeholders use DEXes to sell tokens. Another picture emerges with tokens like AAVE, ALCX, COMP or MKR which, have a larger overall share of buys than sells. In relation to the tokens’ market capitalization, ALCX has the largest swaps (average swap of 0.01% of the "total value" of all tokens / market capitalization) and SHIB the smallest, at 0.00008%.

Table 3. Descriptive statistics for token swap size. 'Swap $' indicates the mean dollar value of the swaps of a given token. 'Swap %' shows the mean swap size in relation to the crypto assets' market capitalization in percent. The Δ columns show the difference between the sell and buy orders group and the significance level of a Mann—Whitney U test. The asterisks *** indicate significance at the 1% level.

	All			Sell orders			Buy orders				
	N	Swap $ (SD)	Swap % (SD)	N	Swap $ (SD)	Swap % (SD)	N	Swap $ (SD)	Swap % (SD)	Δ Swap $ (SE)	Δ Swap % (SE)
AAVE	58,503	26,995	0.0007	31,301	26,870	0.0007	27,202	27,140	0.0007	270***	0.0001***
		(288,650)	(0.0071)		(389,943)	(0.0097)		(70,964)	(0.0017)	(2,393)	(0.0006)
ALCX	61,443	23,443	0.0100	35,283	21,122	0.0091	26,160	26,573	0.0112	5,451***	0.0021***
		(107,165)	(0.0458)		(112,478)	(0.0485)		(99,467)	(0.0420)	(874)	(0.0004)
COMP	59,492	18,774	0.0010	32,463	17,454	0.0009	27,029	20,359	0.0011	2,905***	0.0002***
		(66,729)	(0.0036)		(82,907)	(0.0044)		(39,252)	(0.0022)	(549)	(0.00003)
ENS	145,356	18,068	0.0022	97,535	13,670	0.0017	47,821	27,039	0.0033	13,370***	0.0016***
		(43,649)	(0.0052)		(38,616)	(0.0045)		(51,280)	(0.0064)	(241)	(0.00003)
LINK	186,072	29,093	0.0002	95,527	28,931	0.0003	90,545	29,264	0.0003	333***	0.00003***
		(93,705)	(0.0009)		(92,435)	(0.0008)		(95,027)	(0.0009)	(435)	(0.00004)
LOOKS	317,837	15,104	0.0041	153,057	15,577	0.0042	164,780	14,665	0.0039	-912***	-0.0003***
		(48,264)	(0.0143)		(50,289)	(0.0136)		(46,301)	(0.0148)	(171)	(0.00005)
MANA	95,625	11,984	0.0004	45,695	12,366	0.0004	49,930	11,635	0.0004	-731***	-0.00002***
		(24,498)	(0.0008)		(25,025)	(0.0008)		(23,999)	(0.0007)	(159)	(0.000002)
MKR	52,022	22,789	0.0009	27,117	22,501	0.0009	24,905	23,102	0.0010	601***	0.00003***
		(77,470)	(0.0033)		(100,283)	(0.0043)		(39,833)	(0.0017)	(680)	(0.00003)
OHM	107,084	22,481	0.0020	47,826	25,519	0.0023	59,258	20,029	0.0018	-5,090***	-0.0005***
		(75,306)	(0.0065)		(91,729)	(0.0079)		(58,682)	(0.0052)	(463)	(0.00004)
RBN	36,022	35,320	0.0336	15,891	41,585	0.0395	20,131	30,375	0.0290	-11,209***	-0.0105***
		(120,978)	(0.1289)		(150,171)	(0.1593)		(91,286)	(0.0982)	(1,282)	(0.0014)
SAND	222,653	12,017	0.0009	92,039	13,241	0.0011	130,614	10,379	0.0007	-3,963***	-0.0003***
		(32,710)	(0.0023)		(35,710)	(0.0025)		(30,342)	(0.0021)	(141)	(0.000001)
SHIB	1,060,915	7,950	0.00008	410,006	10,193	0.0001	650,909	6,537	0.00007	-3,656***	-0.00004***
		(34,533)	(0.0004)		(39,986)	(0.0004)		(30,520)	(0.0003)	(68)	(0.0000008)
SPELL	174,319	23,949	0.0062	74,442	27,617	0.0073	99,877	21,215	0.0055	-6,401***	-0.0018***
		(58,611)	(0.0314)		(63,389)	(0.0357)		(54,620)	(0.0278)	(283)	(0.0002)
SUSHI	192,334	27,046	0.0016	101,516	25,655	0.0015	90,818	28,601	0.0017	2,946***	0.0002***
		(79,659)	(0.0044)		(84,249)	(0.0045)		(74,161)	(0.0042)	(364)	(0.00002)
All	2,769,664	15,697	0.0020	1,259,698	17,265	0.0018	1,509,979	17,166	0.0013	-98****	-0.0006***
		(58,550)	(0.0081)		(50,501)	(0.0073)		(92,517)	(0.0067)	(579)	(0.0002)

2.2 Empirical approach

The analysis comprises two parts. We first investigate the link between relative swap size and returns and then examine the extent to which particularly large and unexpected buys and sells trigger a market reaction. For this purpose, we define several time intervals based on swaps to test the effect of information propagation. These are 1) single-trade windows of t = -1 (*the preceding swap*), 0 (*the event itself*) and +1 (*the subsequent swap*) to quantify short-run effects, and 2) multi-swap windows of t = -15 to -1, 0 to 15, 0 to 50, 0 to 100 and 0 to 500, for each of which we calculate the cumulative returns. Using Spearman rank correlation analysis, we first identify the extent to which a relationship exists between relative swap size and future returns for sells and buys. This is followed by an event study to calculate abnormal returns around exceptionally large buys and sells.

In line with MacKinlay's (1997) essential steps for conducting event studies, we first identify the events as those "outlier swaps" that rank in the top 1% in terms of relative swap size of each of the 14 tokens. The same percentile-events are also identified for the sales and purchases subsamples. In line with, e.g., Demir et al. (2022) or Diaconaşu et al. (2022), the model's expected return is calculated over the full sample period (excluding the individual event window or each event), as swaps occur irregularly and we would be unable to prevent event-specific estimation windows of the various events from overlapping. We calculate the expected return (ER_{it}) as the average log return over the estimation period: $ER_{it} = \overline{R_{it}} + e_{it}$. The term *i* refers to a specific event and *t* denotes the swap within the estimation period. R_{it} is the token's observed log return over *t* for *i*. e_{it} is the error term. The bar over R_{it} denotes the mean over the estimation window. The difference between the expected and the observed return is the *abnormal return (AR)* that can be attributed to the event (Brown and Warner 1985): $AR_{it} = R_{it} - ER_{it}$. Aggregated across multiple swaps, the *cumulative abnormal return* can be calculated as: $CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$. Since the statistics from Table 2 and the financial literature in general (Brown and Warner 1985) suggest that such data is non-normally distributed, we test the significance of the results using the non-parametric *Wilcoxon sign-rank test* (Wilcoxon 1945).

3 Results

Table 4 shows results for the *Spearman* rank correlation coefficient between the relative swap size of buy and sell orders and token returns over the eight different event windows. The results for the two subsamples – buy orders versus sell orders – are almost diametrically opposed, which suggests that the effects in the overall sample cancel each other out.

With a few exceptions, such as ENS, we find significant negative correlations between the relative size of sales and future token returns. The opposite holds for purchases, where the relationship is almost exclusively positive. This finding of widespread significant correlation between the metrics suggests that very large swaps from the tail of the distribution have a particularly large impact on token returns. This hunch is tested in the following event study.

Table 4. Spearman rank correlations between relative swap size and future token log returns. This table shows *Spearman* correlation coefficients for sell and buy orders. Token returns are based on single swaps (t = -1, 0, and +1); five returns relate to aggregate windows of multiple swaps: t = -15 to -1, 0 to +15, 0 to +50, 0 to +100, and 0 to +500. For the number of observations, see Table 3. An asterisk (*) indicates statistical significance at the 0.1% level.

	Sell orders								Buy orders							
	Single swap windows			Multi-swap windows					Single swap windows			Multi-swap windows				
Token	-1 swap	0 (event)	+1 swap	-15 swaps	+15 swaps	+50 swaps	+100 swaps	+500 swaps	-1 swap	0 (event)	+1 swap	-15 swaps	+15 swaps	+50 swaps	+100 swaps	+500 swaps
AAVE	-0.042*	-0.023*	-0.018*	0.132*	-0.063*	-0.048*	-0.028*	-0.031*	0.033*	0.020*	0.014	-0.114*	0.079*	0.093*	0.074*	0.003
ALCX	-0.017*	-0.007	-0.018*	0.076*	-0.040*	-0.031*	-0.036*	-0.037*	0.020*	0.024*	0.008	-0.089*	0.053*	0.083*	0.063*	0.019
COMP	-0.033*	-0.034*	-0.009	0.079*	-0.063*	-0.046*	-0.039*	-0.036*	0.024*	0.019*	0.008	-0.085*	0.054*	0.044*	0.020	0.051*
ENS	-0.001	-0.003	-0.009	0.014*	0.004	0.018*	0.026*	0.044*	0.009	0.001	0.008	-0.019*	0.036*	0.038*	0.039*	0.041*
LINK	-0.007	-0.005	-0.003	0.081*	-0.051*	-0.053*	-0.039*	0.002	0.007	0.006	0.006	-0.093*	0.061*	0.078*	0.073*	0.047*
LOOKS	-0.005	-0.004	-0.000	0.005	-0.009*	-0.011*	-0.013*	-0.007	0.002	0.004	-0.002	-0.009*	0.003	0.001	-0.003	0.007*
MANA	-0.017*	-0.014*	-0.011	0.057*	-0.037*	-0.026*	-0.012	0.057*	0.014*	0.015*	0.012	-0.101*	0.062*	0.066*	0.065*	0.082*
MKR	-0.028*	-0.023*	-0.021	0.048*	-0.030*	-0.009	-0.005	-0.012	0.015	0.013	0.005	-0.045*	0.037*	0.048*	0.039*	0.005
OHM	-0.007	-0.007	0.004	0.026*	-0.007	-0.028*	-0.037*	-0.028*	0.001	0.004	0.001	-0.006	0.017*	0.009	-0.000	-0.001
RBN	-0.011	-0.017	-0.020*	0.040*	-0.055*	-0.049*	-0.027*	-0.000	0.010	0.009	0.009	-0.005	0.042*	0.039*	0.038*	0.030*
SAND	-0.015*	-0.018*	-0.010*	0.053*	-0.038*	0.035*	-0.007	0.048	0.024*	0.021*	0.011	-0.091*	0.057*	0.074*	0.076*	0.084*
SHIB	-0.001	-0.000	-0.002	0.009*	-0.006*	-0.006*	-0.008*	0.009*	0.002	0.002	0.005	-0.016*	0.012*	0.016*	0.019*	0.022*
SPELL	-0.013*	-0.009	-0.002	0.016*	-0.028*	-0.010	-0.001	0.040*	0.009	0.004	0.005	-0.029*	0.022*	0.031*	0.026*	0.019*
SUSHI	-0.014*	-0.014*	-0.003	0.073*	-0.056*	-0.058*	-0.047*	-0.017*	0.007	0.005	0.005	-0.091*	0.051*	0.073*	0.073*	0.029*

The cumulative swap-to-swap abnormal returns for sell and buy order swaps from t = -15 to +15 are presented graphically in Figure 1. Before the actual event (from t = -15 to -1), the cumulative abnormal return is much lower for sell orders (-0.11%) than for buys (0.009%). This suggests that some adverse information contained in a sell order is already impounded before the actual swap, likely due to MEV trading or arbitrage. For buy orders, the cumulative abnormal return remains relatively stable until the last individual swap before the actual event. At that point, the mean abnormal return amounts to 0.019% ($p < 0.01$), which is much higher than at the time of the actual event (0.008%). It is also striking that the cumulative abnormal returns after the actual event are also higher: 0.015% in t = +1, 0.016% in t = +2 and 0.018% in t = +3 (all $p < 0.01$). For a large buy order, the cumulative abnormal return over the next 15 swaps is 0.12%. For sell orders, it is -0.01%; however, as the figure shows, the abnormal return drops between the swaps and t = +7 (by 0.07% in total) before rising again by 0.06.

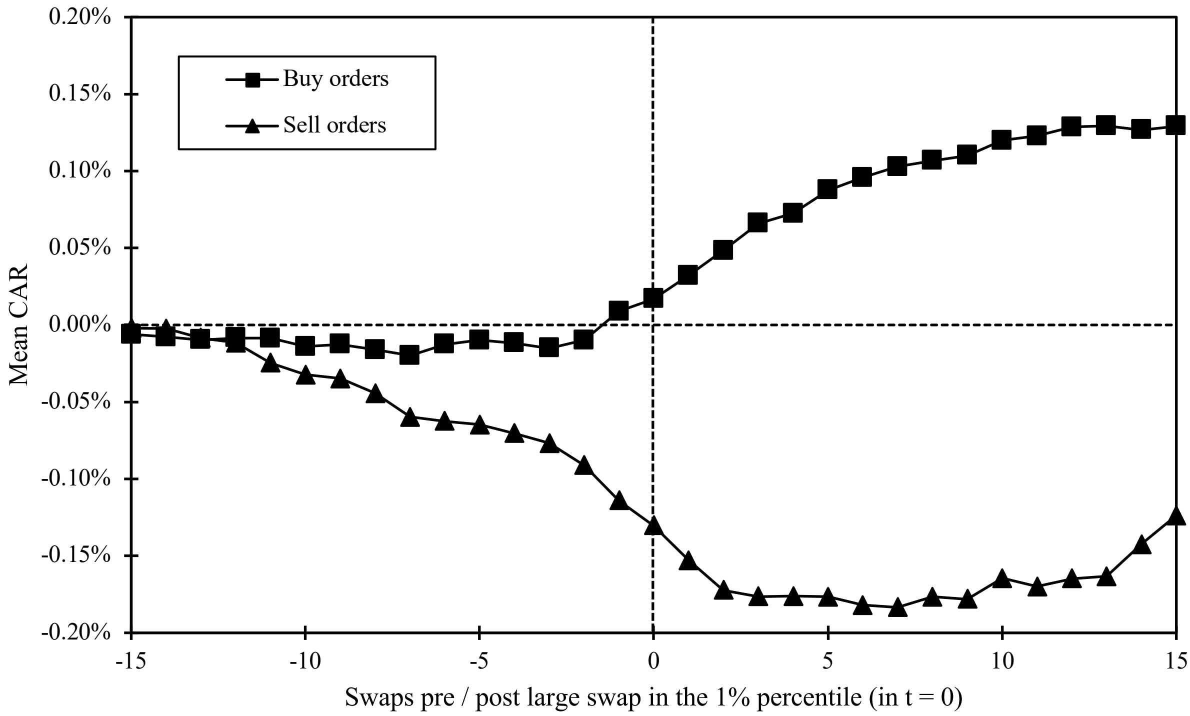

Figure 1. Mean cumulative abnormal returns (CARs) attributable to large sell or buy orders on a transaction-by-transaction basis from t = -15 to 15 swaps. The data comprise all 2,769,677 swaps of the 14 crypto assets shown in Table 1. The number of events is 16,586 for buy orders and 13,848 for sell orders (top 1% percentile of each token).

On average, the order volume in the top 1% percentile is \$0.747 million for sell orders and \$0.824 million for buy orders. In relation to the market capitalization of the respective assets, this amounts to an average of 0.059% for sales and 0.043% for buys. With an average market capitalization of about \$3 billion (cf. Table 1), a cumulative abnormal return of -0.11% in the swaps before the actual event already means a loss of \$3.3 million, which is 4.4 times the economic value of the average sell order. This value drops further in the subsequent swaps to a minimum of -0.18% (factor of 7.37) before recovering slightly. In the case of buy orders, in t-1 there is already an abnormal increase in value of \$0.266 million, which corresponds to about 32% of the event volume. Subsequently, the market capitalization increases by another \$3.62 million on average, which corresponds to a factor of 4.39.

Table 5 shows event study results for the market reaction to the occurrence of buy and sell order swaps of the largest one percent by crypto asset. For sell orders, the average swap size per asset is between \$120,000 (SPELL) and \$1,134,000 (RBN) in absolute terms and between 0.003% (SHIB) and 1.185% (RBN) in relation to market capitalization. For buy orders, the average transaction size is between \$113,000 (SAND) and \$660,000 (RBN). In relative terms, the swaps average between 0.002% (SHIB) and 0.735% (RBN).

Looking at the individual swap windows of t = -1, 0 and +1 for sale swaps, it is immediately clear that the effects are very similar across all crypto assets. With a single exception (COMP in +1 swap), we identify significant negative abnormal returns in all three periods. The results for t = -1, at -0.006% (SHIB) to -0.3% (SPELL), suggest that traders have moved ahead of the transaction as part of Mempool monitoring (cue MEV, sandwich attacks and frontrunning). At the time of the swap, abnormal returns on sells range from -0.002% (SAND) to -0.699% (SPELL). In t = +1, the range is -0.001% (ENS) to -0.56% (RBN). A critical observation here is the relationship between the relative size of the swap and the market reaction (or rather anticipation) in t-1. For eight of the fourteen crypto assets, the abnormal and statistically significant token return in t = -1 is so strongly negative that it exceeds the economic value of the swap. For example, an average swap in the top 1% of AAVE amounts to about 0.017% of the asset's market capitalization, but the significant abnormal return already equals 0.015% in t-1 (similarly for COMP, LINK, MANA, OHM, SHIB and SPELL). At the time of the swap and in t = +1, this phenomenon is amplified, with ten of the fourteen projects (71%) exhibiting a significantly higher economic market reaction than assumed. The differences are particularly significant for the MKR and SHIB tokens, whose abnormal returns are -18.8 and -17.66 times as large, respectively, as the swap size. The average factor across all 14 tokens is -4.32, i.e., for every dollar sold in a swap, the market capitalization of the tokens declines by \$4.32. Clearly such averaging can only serve as an indication. It can be interpreted as evidence of inefficiency and suggests that the (reported) market capitalization of the tokens is not a meaningful metric for assessing their liquidity or value.

A similar effect, but with the reverse sign, is identified for buy orders, which consistently lead to significant positive abnormal returns in t = -1, 0 and +1. In t = -1, for 64% of the tokens, the return effect exceeds the relative size of the swap. The effects range from 0.007% (SHIB) to 0.495% (SPELL). At the time of the swap, they range from 0.004% (SHIB) to 0.429% (SPELL), and in t = +1, from 0.003% (LOOKS) to 0.180% (RBN). Accumulated over all three time points, again for 71% of the tokens, the abnormal return exceeds the relative size of the swap. The differences are particularly large for AAVE (factor of 11.9), COMP (10.6), MANA (16.6) and SHIB (17.0). Using SHIB as an example, this means that an average swap in the 1% percentile worth \$157,000 raises the market capitalization of the crypto asset by \$2,669,000.

Table 5. Effects of large DEX swaps (top 1% percentile) on token returns. The table shows event study results for returns around swap events that range in the top 1% in terms of swap size relative to the asset's market capitalization. The panels include swaps whose tokens were sent to the liquidity pool, i.e., sell orders, and ones whose tokens were withdrawn (buy orders). The *swap size* columns show means for the size of the swap in relative (*Mcap*, in percent) and in absolute (*$k*, in thousands of dollars) terms. The mean (cumulative) abnormal return ((*C*)*AR*) in percent and results of the Wilcoxon sign-rank test (*z-test*) are shown for the single swap periods t = -1, 0, and +1, and for aggregated series of t = -15 to -1, 0 to +15, 0 to +50, 0 to +100, and 0 to +500 swaps after the event. The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

				Single swap windows						Multi-swap windows									
		Swap size		-1 swap		Event		+1 swap		-15 swaps		+15 swaps		+50 swaps		+100 swaps		+500 swaps	
Type	N	Mcap	$k	AR	*z*-test	AR	*z*-test	AR	*z*-test	CAR	*z*-test	CAR	*z*-test	CAR	*z*-test	CAR	*z*-test	CAR	*z*-test
Panel A: Sell orders																			
AAVE	344	0.017	637	-0.051	-10.95***	-0.016	-12.98***	-0.017	-14.97***	-1.053	-2.53***	0.131	3.07***	0.516	1.73*	-0.197	-0.57	-1.513	-1.09
ALCX	388	0.300	694	-0.080	-10.66***	-0.023	-10.80***	-0.124	-10.29***	-0.679	-2.75***	-0.290	-3.88***	-0.594	-2.85***	-0.231	-0.72	-0.549	-1.01
COMP	357	0.016	280	-0.036	-10.42***	-0.077	-11.01***	0.096	-1.94	-0.465	-3.21***	-0.531	0.20	-0.332	-1.02	-0.605	-0.19	-0.096	-1.96**
ENS	1,072	0.032	259	-0.025	-27.03***	-0.004	-27.03***	-0.001	-28.26***	0.177	1.02	-0.199	-18.37***	0.036	7.89***	0.144	5.38***	1.090	2.39**
LINK	1,050	0.005	527	-0.008	-24.78***	-0.002	-23.84***	-0.005	-24.79***	0.039	0.32	0.110	7.22***	1.615	4.38***	2.302	6.08***	2.634	5.15***
LOOKS	1,681	0.093	284	-0.003	-39.99***	-0.006	-40.09***	-0.001	-40.20***	-0.117	0.86	-0.606	-31.98***	-0.164	-14.32***	-0.297	-9.80***	-0.313	1.95*
MANA	502	0.005	139	-0.026	-16.09***	-0.008	-16.54***	-0.018	-18.17***	-0.223	-2.66***	-0.099	-2.34**	0.595	1.66*	0.977	2.07**	0.414	4.03
MKR	298	0.015	347	-0.078	-8.63***	-0.067	-9.32***	-0.152	-10.04***	-0.451	-4.15***	0.143	-0.52	-0.416	1.14	0.089	1.09	-0.191	0.01
OHM	526	0.047	445	-0.057	-17.82***	-0.074	-19.24***	-0.022	-20.27***	-0.084	-3.02***	-0.304	-4.15***	-0.694	-3.92***	0.902	-4.55***	-0.992	-1.23
RBN	174	1.185	1,134	-0.287	-6.40***	-0.221	-6.49***	-0.560	-5.30***	-0.195	-2.99***	-0.384	-5.00***	-2.392	-5.03***	-2.306	-3.73***	0.040	-0.48
SAND	1,012	0.016	137	-0.006	-28.14***	-0.002	-26.63***	-0.012	-27.68***	-0.407	-4.56***	-1.611	-5.31***	0.535	4.46***	1.203	4.48***	4.475	8.94***
SHIB	4,510	0.003	217	-0.009	-19.29***	-0.006	-20.20***	-0.041	-19.33***	-0.001	-2.89***	-0.259	-47.31***	-0.217	-14.12***	-0.087	-7.14***	-0.093	-0.89
SPELL	818	0.235	120	-0.300	-5.31***	-0.699	-7.12***	-0.006	-65.15***	-0.139	-7.23***	-0.028	-3.85***	0.719	0.56	2.261	3.44***	10.429	8.80***
SUSHI	1,116	0.030	494	-0.024	-8.17***	-0.025	-6.61***	-0.005	-28.59***	-0.036	-2.09**	-0.111	-2.11**	-0.117	-0.99	0.247	1.39	0.482	1.65*
Panel B: Buy orders																			
AAVE	299	0.011	422	0.075	9.11***	0.039	10.47***	0.017	13.43***	-0.295	-4.32***	0.318	6.11***	0.254	1.90*	-1.007	-0.75	-1.717	-1.84*
ALCX	287	0.313	728	0.149	11.96***	0.156	13.88***	0.105	14.00***	-0.566	-6.11***	0.720	6.89***	0.420	2.58**	0.220	1.29	0.136	0.07
COMP	297	0.014	251	0.070	7.98***	0.055	10.43***	0.023	12.05***	-0.633	-3.76***	0.574	-0.84	-0.408	-0.17	-0.327	1.62	-0.062	-2.31**
ENS	526	0.046	322	0.077	19.63***	0.023	19.62***	0.008	20.27***	-0.097	-7.33***	0.031	14.52***	0.433	9.44***	1.001	9.17***	3.160	5.65***
LINK	944	0.005	528	0.003	24.10***	0.023	24.93***	0.009	25.31***	0.089	0.29	0.158	10.87***	0.375	5.80***	0.587	6.25***	0.855	3.23***
LOOKS	1,812	0.104	235	0.013	42.04***	0.006	42.19***	0.003	42.28***	-0.071	-3.88***	0.052	38.28***	0.112	25.00***	0.214	17.49***	0.864	5.89***
MANA	549	0.005	130	0.026	15.24***	0.017	18.45***	0.040	18.92***	-0.165	-4.44***	0.064	1.77*	-0.264	-0.17	-0.003	-1.25	1.552	2.09**
MKR	273	0.012	271	0.084	10.09***	0.011	10.43***	0.025	11.32***	-0.234	-8.34***	0.163	2.39**	1.370	3.35***	1.614	3.27***	2.027	1.96**
OHM	651	0.036	354	0.008	23.85***	0.001	24.10***	0.056	23.53***	-0.463	-11.01***	0.021	13.03***	0.297	4.28	0.307	2.51**	0.172	1.72*
RBN	221	0.735	660	0.046	9.77***	0.022	8.38***	0.180	10.93***	-0.322	-2.98***	1.063	5.90***	0.540	1.32	-0.969	-1.07	1.537	0.27
SAND	1,436	0.014	113	0.035	31.35***	0.031	32.37***	0.032	34.21***	0.052	5.43***	0.208	8.29***	0.817	7.35***	1.285	8.20***	3.112	8.52***
SHIB	7,195	0.002	157	0.007	82.26***	0.004	82.66***	0.023	12.05***	-0.100	-12.89***	0.006	65.39***	0.119	23.17***	0.269	7.85***	0.412	2.91***
SPELL	1,098	0.136	118	0.495	3.43***	0.429	4.63***	0.136	21.69***	-0.014	-5.17***	0.857	4.87***	1.572	5.78***	2.270	6.43***	2.700	3.97***
SUSHI	998	0.030	497	0.123	8.26***	0.004	7.42***	0.006	28.17***	0.008	0.78	0.032	7.64***	0.181	2.73***	0.312	3.04***	0.757	3.33***

A similar effect, but with the reverse sign, can be identified for buy orders, which consistently lead to significant positive abnormal returns in t-1, 0 and +1. In t-1, the return effect exceeds the relative size of the swap for 64% of the tokens. The effects range from 0.007% (SHIB) to 0.495% (SPELL). At the time of the swap, they range from 0.004% (SHIB) to 0.429% (SPELL), and in t+1, from 0.003% (LOOKS) to 0.180% (RBN). Accumulated over all three time points, the abnormal return exceeds the relative size of the swap for 71% of the tokens. The differences are particularly large for AAVE (factor of 11.9), COMP (10.6), MANA (16.6) and SHIB (17). Again using SHIB as an example, this means that a swap worth $157,000 (the average swap size in the top 1%) raises the crypto asset's market capitalization by $2,669,000. The average factor across all tokens for these three swap dates is 7.02, i.e., for every dollar invested in a token, its market capitalization grows by $7.02. As with sell orders, this suggests that the market capitalization metric poorly reflects the views and valuation of the market.

Looking at the aggregate period of 15 swaps before the large transactions, a similar picture emerges for sells and buys. In both subsamples, eleven of the fourteen crypto assets show significant negative abnormal returns. Only one token (SAND) experiences a significant positive abnormal return of 0.052%. Twelve of the tokens show significant negative abnormal returns after fifteen swaps with large sell orders, five after 50 swaps, four after 100 and two after 500. However, significant positive abnormal returns also occur. Already 15 swaps after a large sell order, AAVE (0.13%) and LINK (0.11%) show significant positive abnormal returns. After 50 swaps, ENS, MANA and SAND join the group. Particularly striking are the extremely high significant abnormal returns of SAND (4.48%) and SPELL (10.43%) after 500 swaps.

For the larger multi-swap windows of buy orders, we obtain more consistent results. There are significant positive abnormal returns for all periods considered, but also two negative returns at +500 (AAVE and ALCX). In the short term (+15 swaps), ALCX, RBN and SPELL feature the highest abnormal returns, ranging from 0.72% to 1.06%. In relation to the relative volume of the swap, AAVE and LINK are clearly ahead. The market capitalization of AAVE increases by $28.91 per dollar of purchasing power within 15 swaps, and that of LINK by $31.6. For LINK, this value even increases to $75 by the 50th swap, to $117.4 by the 100th, and to $171 by +500. The highest ratios of abnormal returns to relative swap size are found for SHIB ($206 per dollar spent on buying into the crypto asset), SAND ($222.29), and MANA ($310.4).

4 Discussion

DeFi is a rather recent phenomenon but has quickly grown into a multi-billion-dollar market, making it a significant aspect of cryptocurrency or crypto asset markets. This study uses an event study approach to examine price and liquidity shocks in DeFi markets and contributes to understanding the market efficiency of crypto assets in general and DeFi markets in particular. It also questions the validity of the ubiquitous "market capitalization" metric.

4.1 Reflection on the main results

Dividing DEX trades into sells and buys (or in and out) yields statistically significant differences between the dollar equivalent of buys and sells on DEXes for all crypto assets examined. For example, $49 million more ALCX were sold than bought over the period, which translates to a significant difference of $5,451 per swap between sells and buys. This suggests that DeFi users were on average acquiring ALCX via DEXes—be it just to hold ALCX, to stake it for yield, lend it out or to send it to centralized exchanges. Similar results apply to COMP or SUSHI—both of which can also be staked by DeFi users for yield. The largest discrepancy between buys and sells is observed for the ENS token ($13,370), which is distributed by airdrop. Many ENS holders received the tokens quasi-free (for historical actions), which explains why many smaller sales took place.

In contrast to ALCX or ENS, some of the examined crypto assets, however, feature significantly larger sell swaps. For example, the average sell swaps exceed the average buy swaps of RBN and SPELL by $11,209 and $6,401, respectively. Overall, $50 million more RBN was sold than bought, which can potentially be explained by a drop in the token's price (cf. the negative mean return in Table 2). SPELL, however, has positive average token returns over the considered period, and $2b billion in sales are offset by $2.1 billion in buys. The smaller average size of buys may indicate buying from individual / retail investors and selling by larger investors, or that traders are more likely to use DEXes to sell SPELL—while possibly buying it on centralized exchanges.

On average, buy orders of AAVE are slightly larger than sell orders ($26,879 vs. $27,140). However, the standard deviations of these two measures differ significantly: $389,943 for sells versus $70,964 for buys. This indicates that sell swaps tend to be more extreme in size (both very large and very small) than buy swaps. It seems that individual investors or DeFi users buy AAVE for smaller amounts while very large investors use DEXes to liquidate AAVE positions. This result of significantly larger variability in the size of sell compared to buy orders similarly applies to COMP, MKR, OHM, and RBN.

Using an event-study approach, we estimate cumulative swap-to-swap abnormal returns for sell and buy order swaps that are in the top 1% based on swap size in USD. For the 15 transactions before the large and unexpected swap, we identify abnormal returns that are significantly negative for sell orders and positive for buy orders. Sell orders show a semi-linear negative trend until t = 0. This abnormal price effect may suggest that large sells usually occur in extremely negative market conditions (herding or cascading). Herding, overreactions, overconfidence and sell-offs have already been identified for crypto assets in different settings (e.g., Ajaz and Kumar, 2018; Ballis and Drakos, 2020; Bouri et al., 2019; Youssef, 2022). Another explanation would be that traders (i.e., bots) pick up the information about initiated but not yet confirmed large swaps in the Ethereum Mempool and place themselves in front of and/or behind the transaction in order to arbitrage it. This process is known as MEV and represents a rapidly growing and quite opaque market. Scientific studies show that MEV arbitrage and frontrunning are common on the Ethereum network (e.g., Daian et al., 2020; Qin and Gervais, 2021).

For buy orders, we also identify a significant effect before very large swaps take place. However, abnormal returns from t = -15 to -2 are insignificant and hardly worth mentioning. Yet in t = -1, the abnormal return increases by 0.009%. The fact that there is no quasi-linear trend as in the case of sell orders rules out the explanation of fundamentally rising prices. A much more likely cause is that here, too, we are looking at informed trading in the form of MEV and traders are pushing their own transactions in front of the swap. After the large swap takes place, abnormal returns increase continuously over the following swaps, suggesting that the market takes the information about the increased demand for the token to be a positive price signal. Another major result of this study pertains to the discrepancy between liquidity and valuation of crypto assets in DeFi markets, which can be seen as a sign of market inefficiency. We show that large swaps on DEXes have a significantly higher impact on crypto asset prices than should be the case if market capitalization were a meaningful metric. This applies to both sell orders and buy orders, although the effect is significantly larger on average for sells (factor of -7.4 for sells compared to +4.4 for buys). The results call for some skepticism regarding the suitability of market capitalization as a metric for valuing crypto assets.

The analysis of individual crypto assets shows that significant abnormal returns around very large sell swaps are already greater than the economic value of the swap by $t = -1$ for more than half of the crypto assets considered. If $t = 0$ to 1 are added, this applies to 71% of the assets. In some cases, the extent of these differences is astonishing. For example, a large sale of the crypto assets MKR and SHIB results in a price drop of $18.8 and $17.66, respectively, per dollar of sale value. This means that in the short term, it would be quite cheap to shift the price and market capitalization of these crypto assets. Of course, such behavior could be exploited very quickly by arbitrageurs, and prices on other (centralized) exchanges need not follow suit. Accordingly, the results are particularly relevant for tokens that are either traded only in DeFi markets or for which a DEX is the leading or most liquid market.

4.2 Limitations and future research paths

This study is subject to a number of limitations, some of which have already been outlined in the methodology section. DeFi markets cover thousands of assets, only 14 of which were selected for this exploratory study. In particular, since inclusion in the sample was conditioned on an asset featuring extremely large swaps, it is unclear to what extent the results can be truly generalized. Future studies could seek to validate the results based on the same crypto assets and methodology or use different assets and methodologies to address similar questions. Basically, we have dealt only with the tip of the iceberg, so the possibilities for follow-up studies are vast.

Many potentially significant explanatory variables have not been considered in this study. The addition of detailed trading volumes, liquidity, and additional explanatory factors such as market sentiment or momentum could help to better understand the phenomena investigated here. In the context of MEV as a possible explanation of ex-ante abnormal returns, future studies could collect Mempool and on-chain data to examine when a transaction first became public and to what extent MEV bots reacted to it. Furthermore, it can be an exciting research avenue to supplement the analysis with data from centralized exchanges to evaluate information or volatility transmission between DeFi markets and centralized trading venues (for related studies, see, e.g., Alexander et al., 2021; Barbon and Ranaldo, 2021; Makarov and Schoar, 2020). The fact that Ethereum on-chain transactions are settled only every 12-14 seconds while centralized exchanges have no significant time lag may entail significant differences between these markets.

The data basis of this study is twofold: on the one hand, blockchain data on tokens with timestamps on a per second basis, and on the other hand, daily data on circulating supply. Calculating the market capitalization metric from these two asynchronous sources logically leads to the limitation that intraday fluctuations in the number of tokens are not taken into account. While this leads to an overweighting or underweighting of the metric depending on the time of day, the size of the samples should serve to curb this limitation at least on average. However, it may be helpful for future studies to improve on this form of calculation.

A final fundamental point for future research is to further challenge the ubiquitous metric of market capitalization and develop new metrics that better incorporate the illiquidity and inefficiency of crypto assets.

4.3 Implications

Probably the most significant implication of this study is that ‘market capitalization’ is quite unsuitable for determining the "true value" of crypto assets. The main reason for this is that the metric completely disregards the underlying liquidity of the assets. An example shall serve to illustrate this shortcoming. Unlike in traditional markets, it is an extremely simple process to create, say, a million tokens in no time at all, to trade only one of them on a decentralized exchange and to deposit the rest in one or more blockchain wallets. The value of the token can then be increased via wash trading, so that a public market price of, say, $1,000 is now used as the basis for calculating the market capitalization of all tokens. That way, in theory, a crypto asset with a market cap of $1 billion can quickly be created. As long as the major data providers like *CoinGecko* or *Coinmarketcap* rank all cryptocurrencies by market cap, it will always be possible to drive up the listed value of illiquid and highly centralized crypto assets to attract investors.[1] However, these investors may then find it difficult to liquidate their crypto holdings. While the above example is clearly fictitious and extreme, phenomena such as so-called “rug-pulls”, scam tokens or “pump-and-dumps” show that the cryptocurrency market, and the DeFi market in particular, faces significant challenges of fraud and investor deception (e.g., Scharfman, 2022; Wronka, 2021; Xia et al., 2021). Research and practice should strongly question the market capitalization metric and generate alternative approaches to objectively valuing crypto assets.

This study contributes to existing research in multiple ways: It studies a transparent blockchain-based market and ecosystem in which information about market orders, liquidity and pricing is openly available and to some extent known even prior to actual execution. The results can thus

[1] For the sake of completeness, it should of course be noted that these sites, which are listed here as examples, also have listing criteria against which they evaluate the inclusion of projects. For example, Coinmarketcap reports an evaluation framework that includes, 1) *trading volume and liquidity*, 2) *community interest and engagement*, 3) *traction/progress*, 4) *team*, 5) *product/market fit*, 6) *impact & practicality*, 7) *uniqueness & innovation*, and 8) *project longevity & activity* (Coinmarketcap 2022). It remains unclear to what extent these criteria are consistently checked. It is important to keep in mind that there is a potential conflict of interest, as customers could potentially pay for a listing. However, Coinmarketcap states that “We don’t ask for payment on listings, period.” (Coinmarketcap 2022).

contribute to the topic of market transparency and efficiency and question to what degree transparency is even desirable in financial markets (Bloomfield and O'Hara 2000). While transparency offers significant informational benefits to market participants and market makers, research in equity markets has already shown that higher transparency can reduce liquidity, which is in turn associated with lower stock prices (Madhavan, Porter, and Weaver 2005). Individual investors, who generally underperform the market (Barber and Odean 2013; Ante et al. 2022), are discouraged from participating in the market, as professional traders have an information advantage over them (H.-K. Chen, Hsieh, and Ma 2011). Accordingly, it seems reasonable to assume that full transparency is not optimal for financial markets; instead, an optimal tradeoff must be found. The results described here and the assumption of frontrunning attacks on transparently initiated DEX swaps are in line with the findings for stock markets. Professional traders likely benefit from their information advantage, which tend to dissuade individual investors from participating in such a market.

The study analyzes the price behavior of crypto assets based on abnormal returns on an intraday trade-by-trade (or rather swap-by-swap) basis. In particular, we investigate the market reaction to, and anticipation of, large unexpected trades on DEXes. The results thus contribute to research on herding, overreaction and information cascades in cryptocurrency markets. Accordingly, they may inform the development of crypto asset pricing models, risk metrics and models, or trading strategies (e.g., Liu et al., 2022; Petukhina et al., 2021; Ren et al., 2022).

Dividing the samples into sell and buy orders (or rather swaps in and out of a pool) permits a differentiated view of crypto assets that can potentially proxy retail investor attention or sell-offs from large holders. The results suggest that the user or investor base of different DEX trading pairs varies substantially. For example, some tokens predominantly attract individual investors (e.g., SHIB), whereas others may be rather or additionally be used to liquidate larger positions (e.g., AAVE). While this study cannot clarify why these differences exist, it contributes to a better assessment of liquidity pools and their users (e.g., Heimbach et al., 2021), on which little research has been conducted as yet.

5 Concluding remarks

This study applies quantitative analysis to explore the interplay between DEX swaps, i.e., buys and sells of crypto assets, and token returns in DeFi. Based on a sample of 2.77 million swaps of 14 crypto assets on three major DEXes, we identified that the size of sell (buy) orders is negatively (positively) correlated with future token returns. Using an event study approach, we quantified how the market reacts to extremely large unanticipated swaps, finding significant overreaction. On average, this amounts to a factor of -7.4 (+4.4) for sells (buys) in relation to the reported market capitalization of the tokens, with much larger effects accruing to individual tokens. This suggests that some of the crypto assets are overvalued and that market capitalization is only of limited value in determining the actual recoverable value of (possibly illiquid) crypto assets. We also identify that the market reacts before the actual execution of the swap, suggesting that market participants monitor unconfirmed transactions in order to generate returns via so-called sandwich or frontrunning attacks. This is by no means illegal activity, but it is likely to deter individual investors from participating in the market.

The results point to various challenges for investors and their protection in DeFi markets. Besides price, market capitalization is likely the most important metric for ranking and evaluating crypto assets. Major data aggregators such as *CoinGecko* or *Coinmarketcap* (both of which are among the top 500 websites globally based on *Alexa* ranking) sort crypto assets by market capitalization and rank them accordingly. The top 100 assets in terms of market capitalization are shown directly on the main page and accordingly receive the most attention from website visitors. This approach needs to be questioned, and more suitable metrics should be developed that integrate liquidity as an essential factor, among other things. Ultimately, the protection of investors should be paramount so that crypto markets become as safe a place to invest in as possible.

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Declarations

Availability of data and materials

The datasets used for the study are available from the corresponding author on reasonable request.

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