How Does Payment for Order Flow Influence Markets? Evidence from Robinhood Crypto Token Introductions*

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Abstract:

In contrast to equities and options markets that have SEC Rule 606 reports and reported wholesaler trades, payment for order flow (PFOF) in crypto asset markets is subject to wide-spread non-compliance with securities law. PFOF rates for crypto assets, however, are 4.5 (45) times higher than options (equities) markets. We use staggered Robinhood Crypto token introductions (i.e., when crypto tokens are made available for trading on their platform) as a shock to PFOF to examine their effects on crypto asset trading platform activity. We find that volume shifts away from other trading platforms but increases for the largest crypto assets (i.e., BTC and ETH). Order imbalances shift to net sales and average trade sizes increase for transactions made in USD terms. Implied spreads and return volatility both increase but the largest crypto assets are unaffected. Overall, our results show PFOF introduction changes trading activity and increases costs for participants at crypto asset trading platforms by approximately $4.8 million daily.

Keywords: bitcoin; crypto; crypto assets; cryptocurrency; digital assets; ethereum; payment for order flow; pfof; Robinhood

JEL Codes: D43; G12; G18

1. Introduction

In June of 2023, the Council of the European Union and the European Parliament agreed on several trading rules aimed at improving transparency in the EU's capital markets.[1] Among the changes was a general ban on the practice of payment for order flow (PFOF), which refers to wholesalers paying (retail) brokers to send the broker's clients' orders to them. PFOF creates a conflict of interest between the broker's performance for its client and the payment it may receive for directing order flow to a particular market, such as selling order flow to a wholesaler. When the ban is fully implemented, the EU will join other countries including Australia, Canada, Singapore, and the UK that have acted to curb PFOF. While U.S. regulatory officials have publicly discussed PFOF,[2] PFOF remains legal, and represents a significant source of revenue for U.S. brokers. According to a recent Congressional Research Service report, PFOF generated $3.8 billion in revenue for the twelve largest U.S. brokerages in 2021.[3] In that same year, Robinhood Markets, Inc. ("Robinhood") reported that transaction-based revenues (primarily PFOF), were responsible for over 77% of the company's net revenue.[4] Robinhood's $1.4 billion in transaction-based revenues that year was split across options (49%), crypto assets (30%), and equities (21%). Uninformed retail order flow, such as that from Robinhood, is particularly valuable to wholesalers seeking to take advantage of information advantages due to limited adverse selection risk. This leads wholesalers to pay to execute against segmented retail orders,[5] where the wholesalers profit

[1] https://www.consilium.europa.eu/en/press/press-releases/2023/06/29/capital-markets-union-council-and-parliament-agree-on-proposal-to-strengthen-market-data-transparency/

[2] See, for example, Barron's "SEC Chairman Says Banning Payment for Order Flow Is 'On the Table'" https://www.barrons.com/articles/sec-chairman-says-banning-payment-for-order-is-on-the-table-51630350595?mod=hp_LEAD_2

[3] https://crsreports.congress.gov/product/pdf/IF/IF12594

[4] https://www.sec.gov/ix?doc=/Archives/edgar/data/0001783879/000178387922000044/hood-20211231.htm

[5] Segmented retail orders are marketable orders of individual investors identified and routed by brokers to wholesalers. This is in contrast to orders which may be routed to exchanges or other liquidity sources for execution.

from the bid-ask spread.[6]

The allure of PFOF for brokers and market makers is obvious; however, its impact on investors is less clear. Proponents argue that PFOF makes possible low or no-commission trading and offers the potential for price improvement as market makers often internalize orders at prices slightly better than the NBBO.[7] However, as Hu and Murphy (2024) detail, the potential savings for investors from internalization are small in comparison to recent trading commissions, which suggests that other factors (e.g., technology) have contributed to the drop in commissions. With respect to price improvement, the evidence is mixed. Levy (2022) performs a randomized controlled trial and finds that, while PFOF is generally associated with price improvement, the effect is more pronounced at some brokers (e.g., TD Ameritrade) than others (e.g., Robinhood Financial, LLC). Ernst and Spatt (2022) find differences across asset classes. In equity markets, wholesalers offer smaller bid-ask spreads than the exchanges; however, the opposite is true in options markets where PFOF is associated with worse trading costs. Additionally, despite best execution requirements that, for example, brokers execute customer trades at a price "as favorable as possible under prevailing market conditions,"[8] the PFOF practice creates a conflict of interest by incentivizing brokers to route trades to the PFOF-paying liquidity providers and not necessarily the liquidity provider offering the best price. Levy (2022) posits that this could explain the broker-based heterogeneity in price improvement he uncovers.

Because brokers engaged in PFOF target uninformed retail order flow, market makers on the exchanges face greater adverse selection risk because a larger fraction of the remaining order flow is information based (Glosten and Milgrom, 1985; Kyle, 1985). Furthermore, orders that are

[6] See Eaton et al. (2022) for an analysis of Robinhood order flow.
[7] See Congressional Research Services. February 20, 2024. Payment for Order Flow (PFOF) and Broker-Dealer Regulation. Available at https://crsreports.congress.gov/product/pdf/IF/IF12594.
[8] https://www.finra.org/rules-guidance/rulebooks/finra-rules/5310

internalized by wholesalers are hidden (non-displayed) liquidity, which has negative implications for price discovery and market quality (Lee and Chung, 2022). Consistent with this notion, Hu and Murphy (2024) show that greater internalization is associated with higher spreads and worse price improvement for equities. Contrary to the notion that market makers use internalization profits to lower quoted spreads, they find that the effect is amplified when PFOF is more concentrated amongst fewer wholesalers. Ernst and Spatt (2022) report similar effects in the options markets – PFOF is associated with less price improvement and worse prices for retail options traders. Perhaps more interestingly, they note that the typical PFOF fee paid for a 100 share options trade is twice that for a 100 share equity trade (40 cents versus 20 cents). The difference is more glaring when zero commissions and differences in prices between stocks and options are considered. They argue that this exacerbates adverse selection concerns – because market makers pay more for some assets' order flow than others, brokers may be tempted to encourage investors to trade securities that offer higher PFOF fees.

We extend this line of research by studying the impact of PFOF on market quality for crypto assets. To our knowledge, this issue has not been examined previously, presumably due to a lack of transparency in the crypto asset markets. While Regulation NMS Rule 606 requires broker-dealers to make public reports with detailed information about payment for order flow paid from market makers to retail brokers in equities and options markets and wholesaler trades are printed to the consolidated tape, the majority of crypto asset market participants are not registered with financial regulators.[9] Therefore, much less is known about PFOF in crypto assets and its effects on market quality.[10] We overcome this challenge by identifying a shock to PFOF in the crypto

[9] Much of this comes from non-compliance with existing securities laws and regulations by market participants trading in crypto asset securities.
[10] https://www.sec.gov/files/rules/final/2019/34-85714.pdf

markets, which we expect to have a significant information-based effect on trading platform activity. Namely, we use Robinhood Crypto's[11] ("RHC") staggered introduction of trading capability in certain crypto assets from 2018 through 2022 as an information-based shock to liquidity providers that allow them to better avoid adverse selection risk by paying for RHC's order flow. We examine this effect on crypto asset market quality. Over this period, RHC introduced trading in 19 crypto assets, beginning with Bitcoin and Ethereum on January 25, 2018 and ending with Aave and Tezos on October 24, 2022. As noted above, Robinhood generates significant revenue from crypto PFOF, which suggests that these product introductions may have had a meaningful impact on PFOF in crypto assets RHC made available for trading. Additionally, RHC's retail order flow, which is largely uninformed orders, is particularly attractive to wholesalers engaged in PFOF.

If the market quality effects for crypto assets are in line with prior research on the impact of PFOF on equities and options, we expect to observe a deterioration in market quality following the RHC crypto asset trading availability. However, we expect the detrimental effects will be even greater for crypto assets. Dollar for dollar, wholesalers pay more for crypto retail order flow than they do for equity and option order flow. For example, wholesalers like B2C2 and Tai Mo Shan Trading pay 35 basis points per dollar of crypto trading volume from RHC.[12] According to Ernst and Spatt (2022), this compares to 8 basis points for options and just 0.8 basis points for equities. This relatively large PFOF rate suggests that retail order flow in crypto assets is even more uninformed than it is for options and equities; therefore, any detrimental effects of PFOF may be amplified in the crypto markets. Our findings are consistent with this prediction. Specifically, RHC crypto asset trading availability are associated with lower trading volume, greater level of order

[11] Robinhood Crypto is a subsidiary of Robinhood Markets, Inc.
[12] https://robinhood.com/us/en/support/articles/how-robinhood-makes-money/

imbalances, wider implied spreads, and greater volatility. The economic magnitude of the effect of PFOF introduction on crypto markets is substantial. For example, the increase in spreads costs crypto asset traders an estimated $4.8 million daily.

Our findings bridge two rapidly growing areas of research: PFOF and crypto assets. Specifically, we add to the literature on PFOF by providing new evidence that the detrimental effects of PFOF, previously documented for stocks and options, are also present in the crypto asset markets. This is important given the exponential growth in annual crypto trading volume, which surged from $258 million in 2013 to over $76 trillion by 2023.[13] By focusing on PFOF following RHC's introduction of crypto asset trading, we position ourselves at the intersection of financial and technological innovation – a union that Goldstein et al. (2019) suggest is "revolutionizing the financial industry." (Abstract) This focus allows us to highlight an important implication of these innovations for modern financial markets and contribute to the ongoing debate on PFOF, which has important economic and policy implications.

2. Background and Literature Review

2.1. Crypto asset trading

The market for crypto assets has grown exponentially since the introduction of Bitcoin in 2009. As reported in Figure 1, estimated annual trading volume grew at a compound annual rate of over 300% from 2013 to 2023. Crypto assets differ from traditional financial assets such as National Market System securities in important ways. First, as Detzel et al. (2021) point out, crypto assets' source of intrinsic value is, at best, uncertain. Heightening this valuation uncertainty is the absence or limited availability of many of the information sources that benefit investors in other assets (e.g., analyst reports, accounting disclosures). This constraint, coupled with their utility as a

[13] https://coincodex.com/trading-volume/

medium of exchange, may introduce other valuation considerations for crypto assets. For instance, Cong et al. (2021) study platform-specific tokens and conclude that "In contrast to financial assets whose values depend on cash flows, tokens derive value by enabling users to conduct economic transactions on the digital platform, making them a hybrid of money and investable assets." (p. 1106) Second, crypto trading takes place in a competitive global market that encompasses a variety of regulatory regimes, which allows investors to switch trading platforms when it is advantageous (Feinstein and Werbach, 2021; Borria and Shakhnov, 2020). Jasperse (2023) states "At the moment, the United States has no federally regulated framework for digital assets". The U.S. Securities and Exchange Commission, however, has alleged in many enforcement actions that certain crypto assets meet the definition of a security under the U.S. securities laws, and multiple courts have agreed with these assessments. Additionally, the Commodities Futures Trading Commission regulates some crypto assets such as virtual currencies.[14] Notably, Makarov and Schoar (2020, pp. 293-294) state that "in contrast to traditional, regulated equity markets, the cryptocurrency market lacks any provisions to ensure that investors receive the best price when executing trades," which, as noted previously, may be more accurately thought of as non-compliance with securities laws. Third, crypto assets trade under a variety of market structures. While most trading in the most actively traded crypto assets occurs on centralized crypto asset trading platforms (e.g., Binance and Coinbase), many crypto assets trade exclusively on so-called decentralized crypto asset trading platforms. (Aspris et al., 2021).[15] Trading costs on the centralized trading platforms vary widely and include maker/taker fees and deposit/withdrawal fees; while fees and gas fees – payments to network validators – are the primary costs on so-called

[14] See https://www.cftc.gov/media/4636/VirtualCurrencyMonitoringReportFY2020/download

[15] Lehar and Parlour (2023) compare a centralized exchange (Binance) and decentralized exchange (Uniswap), while Lehar et al. (2024) explore investor segmentation across low- and high-fee decentralized exchanges.

decentralized crypto trading platforms (Barbon and Ranaldo, 2023).[16]

[Place Figure 1 about here]

Crypto market microstructure research is growing rapidly.[17] Brauneis et al. (2021) discuss the unique challenges researchers face in measuring liquidity in the crypto markets (e.g., transparency, large number of trading platforms). They compare several low- and high-frequency liquidity measures and find that the Corwin and Schultz (2012) and Abdi and Ranaldo (2017) measures work best for capturing time-series variation in crypto asset liquidity, while the Amihud (2002) and Kyle and Obizhaeva (2016) measures are better at capturing liquidity levels and cross-sectional differences. Marshall et al. (2019) use high-frequency trade and order book data to study Bitcoin liquidity and find substantial heterogeneity across countercurrencies and crypto asset trading platforms. For instance, average effective spreads in Bitcoin are 0.30% and range from 0.04% (Chinese Yuan) to 1.28% (Canadian Dollars). They also find a causal relation between currency market liquidity changes and Bitcoin liquidity.

The efficiency of crypto markets has also garnered substantial attention, albeit with mixed results. Burggraf and Rudolf (2021) suggest that the crypto market is generally efficient, while Alvarez-Ramirez and Rodriguez (2021) find that efficiency in Bitcoin and Ethereum markets continues to improve from prior inefficient periods. Other studies report that Bitcoin is the most efficient crypto asset, which is not surprising given its position as the bellwether of the crypto world (Brauneis and Mestel, 2018; Yaya et al., 2021). However, others find evidence of inefficiency in crypto markets generally. Makarov and Schoar (2020) find that prices often deviate significantly and persistently across crypto asset trading platforms, although capital controls may

[16] Miller (2024) is one of many sources that compares trading fees across crypto exchanges: https://dailycoin.com/crypto-exchange-fees-comparison/

[17] Almeida and Gonçalves (2024) provide a systematic review of crypto asset market microstructure.

restrict arbitrage strategies; Barbon and Ranaldo (2023) find that gas fees make prices less efficient on so-called decentralized trading platforms compared to centralized trading platforms; Hashemi Joo et al. (2020) find that event-induced information is not immediately impounded into crypto asset prices; and Kozlowski et al. (2021) report return reversals over daily, weekly, and monthly holding periods. Evidence of inefficiency extends to Bitcoin, which Hattori and Ishida (2020) suggest presents arbitrage opportunities for investors. Marshall et al. (2019) find that Bitcoin liquidity and price efficiency are positively correlated.

2.2. Payment for order flow

Payment for order flow (PFOF) refers to the practice in which a broker is paid in exchange for routing customer orders to a particular venue. In practice this is typically a retail broker being paid to route order flow to a wholesaler who typically internalize the orders (i.e., trade against their own inventory). PFOF has been practiced in the U.S. since at least the mid-1980s and started to attract attention from regulators around the same time.[18] While PFOF remains legal in the U.S., concerns about the practice led to bans in Australia, Canada, Singapore, and the U.K., while the EU member states recently agreed to phase out PFOF by mid-2026.[19] Among the main concerns are broker incentives; namely, the temptation to sacrifice execution quality for client orders to capture higher PFOF fees (Battalio et al., 2016a). Recent regulatory actions against firms engaged in PFOF suggest this is a valid concern,[20] as is Levy's (2022) finding that price improvement for PFOF orders is negatively correlated with the amount of revenue a broker derives from PFOF. Early academic studies predicted similar issues in markets with minimum tick sizes (Chordia and Subrahmanyam, 1995) but argued that decimalization would improve broker incentives and lead

[18] https://www.sec.gov/news/speech/1993/042993roberts.pdf
[19] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024R0791
[20] Robinhood Financial, LLC (sec.gov) (settled action)

to more transparent order flow and lower cost order execution. However, this did not come to pass, as PFOF continues to capture a substantial portion of overall trading activity not only for stocks, but also for options (Bryzgalova et al., 2023).

Besides broker incentives, concerns have been raised about the impact of PFOF on market quality. If wholesalers siphon off uninformed retail trades, trades sent to the exchanges are more likely to be informed (Easley et al., 1996). This should lead to an increase in the adverse selection component of bid-ask spreads and, more generally, have a negative impact on trading costs. However, Battalio (1997) examines bid-ask spreads in NYSE-listed stocks for which Bernard L. Madoff Investment Securities ("Madoff") purchased and internalized order flow and, contrary to the notion that Madoff was exploiting an information advantage, finds evidence consistent with a cost advantage – i.e., spreads tighten and trading costs are unchanged in the securities targeted by Madoff. Battalio and Holden's (2001) model reconciles this apparent contradiction by showing that it is possible for primary listing market orders to be more informed than internalized orders and for trading costs to fall. More recently, Hu and Murphy (2024) show that greater internalization is associated with higher spreads and worse price improvement for equities. They attribute the difference between their findings and Battalio's (1997) to changes in markets in the past 30 years (legal, technological, and economic) and the fact that, while internalizers today tend to be both wholesalers and market makers, Madoff was not a market maker.

Related research on PFOF in options markets, which have rules that enable internalization of on-exchange orders, uncovers interesting results. Comparing PFOF for stocks and options, Ernst and Spatt (2022) find that retail stock traders benefit from price improvement from wholesalers (0.5 bps, on average). Retail option traders, on the other hand, receive worse prices from market makers engaged in PFOF. Additionally, they find that PFOF payments are substantially larger for options than for stocks and posit that this may incentivize retail brokers to encourage options trading. Battalio et al. (2016b) compare PFOF venues with venues that pay maker-taker fees and find that PFOF venues tend to offer lower liquidity costs, except for high-priced options.

Another source of concern is concentration in the wholesaler market for PFOF. Bryzgalova et al. (2023) note that three wholesalers are responsible for 70-82% (73-90%) of PFOF in the stock (options) markets, with the top five wholesalers generating almost all PFOF. Similarly, Hu and Murphy (2024) find that seven market makers purchase most retail order flow and that two firms (Citadel and Virtu) account for 60-70% between 2017-2021. While some argue the resulting economies of scale may benefit investors, concentration has the potential to limit competition for retail order flow and constrain price improvement. Consistent with the latter, Hu and Murphy (2024) find that the negative effect of PFOF on bid-ask spreads and price improvement is amplified in more concentrated wholesale markets.

PFOF is also prevalent in crypto markets, although much less is known about the practice and its effects. The largest wholesalers in this space include B2C2 and Tai Mo Shan.[21] As the first to study this topic, we provide critical evidence that advances our understanding of PFOF in several important ways. First, regulatory stances on both crypto assets and PFOF differ substantially across countries. However, because crypto asset trading occurs continuously in a competitive global market, investors can act strategically and trade in the market that fits them best (Feinstein and Werbach, 2021; Borria and Shakhnov, 2020). Second, we find PFOF rates are substantially larger in the crypto markets (~35 bps) compared to options (8 bps) and equities (0.8 bps) found by Ernst and Spatt, 2022. To the extent that PFOF creates an adverse selection problem (e.g., Battalio and

[21] As of August 2023, Tai Mo Shan (the crypto trading division of Jump Trading) no longer provides crypto trading services for Robinhood. See https://www.coindesk.com/business/2023/08/29/robinhood-and-jump-trading-no-longer-have-crypto-partnership-source/ . The article notes that B2C2 "now handles the lion's share of Robinhood's crypto flow", further increasing wholesaler concentration.

Holden, 2001), the effects should be more prominent in the crypto markets because uninformed traders may be easier to detect in crypto markets. Third, evidence suggests that information asymmetries tend to be large in the crypto markets, driven in part by the technological complexity related to crypto asset creation and mining and the prevalence of institutional investors (Tiniç et al., 2023). Therefore, the order flow segmentation effects that result from PFOF documented for other types of securities should also be observable in the crypto markets (e.g., Hu and Murphy, 2024).

3. Data

3.1. Robinhood Crypto dates

Our empirical strategy centers on RHC's staggered crypto product introductions. RHC introduced trading in 19 crypto assets in two clusters, which we summarize in Table 1. The first occurred on January 25, 2018, when Bitcoin and Ethereum were made available for trading. Later that same year, Bitcoin Cash, Litecoin, Dogecoin, Ethereum Classic, and Bitcoin SV were also made available for trading. Four years later, RHC added 12 more crypto assets to its platform. Compound, Polygon, Shiba Inu, and Solana were all added on April 12, 2022, while Chainlink, Uniswap, Avalanche, Stellar Lumens, Cardano, USD Coin, Aave, and Tezos were added in subsequent months.

[Place Table 1 about here]

We argue that the addition of these crypto assets to RHC's platform represented shocks to PFOF in the crypto asset market for two reasons. First, RHC is a popular trading platform that provides commission-free crypto trading to retail investors. Thus, their investor base fits perfectly with the uninformed retail order flow targeted by wholesalers. Second, crypto asset trading on RHC is substantial, as is the revenue related to PFOF. For instance, in 2021 Robinhood reported an average of 1.2 million daily revenue trades from generating crypto assets and crypto-related PFOF fees of nearly $420 million for the full year.[22] Figure 2 summarizes Robinhood's PFOF revenue by asset class from 2019 through 2023.

[Place Figure 2 about here]

3.2. Kaiko data

To examine the impact of PFOF on crypto asset markets, we follow previous studies using Kaiko market data (Makarov and Schoar, 2020; Marshall et al., 2019). We obtain trade level data from Kaiko in the [-90,+90] day window around the addition of each crypto asset to RHC's platform. These data include a trade date-timestamp (to the nanosecond), the platform on which the trade occurred, a unique trade identifier, the price at which that the trade occurred (in US dollars or Tether terms, depending on the market), the amount of crypto assets in the trade, and a variable indicating whether the trade is buyer or seller initiated.

We search for trades in US dollar (USD) and Tether (USDT) terms across all trading platform listed in Kaiko's instruments explorer.[23] While Kaiko captures trades from hundreds of crypto asset trading platforms (both centralized and so-called decentralized) historically, our data represent trades from 52 unique active platforms and total almost 1.54 billion trades (105 gigabytes of raw data). We aggregate trades to crypto-hour level observations for our main analyses.

One trading platform dominates the trade data across each countercurrency. By trade count, Binance represents approximately 49.5% (38.2%) of Tether based (total) trading while Coinbase makes up 47.5% (10.87%) of US dollar based (total) trading. Other international, USDT based

[22] For perspective, daily average revenue generating trades for options and equities were 0.8 million and 3.1 million, respectively. https://www.sec.gov/ix?doc=/Archives/edgar/data/0001783879/000178387922000044/hood-20211231.htm
[23] Crypto trading platforms transact in other crypto assets (e.g., BUSD and USDC). We choose to focus on USD-based transactions because Robinhood's crypto assets are USD-based and we include Tether because it is involved in the majority of crypto asset transactions. See https://instruments.kaiko.com/ for more information on Kaiko's data availability.

trading platforms Huobi, Kucoin, and OKX represent 9.9%, 9.1%, and 6.9% of total trading, respectively. Of the remaining trading platforms, none makes up more than 4% of total trade count activity during the RHC crypto introduction event windows.

Summary statistics at the crypto asset event level are provided in Table 2. We obtain the average unit price (in USD), market capitalization, and daily dollar volume from CoinMarketCap historical data on each crypto introduction event date.[24] All but two crypto assets exceed one billion USD in market capitalization, the exceptions being Compound and Dogecoin. Despite their introductions occurring four years earlier than many of the crypto assets in the sample, Bitcoin and Ethereum dominate market capitalization. Bitcoin has daily dollar volume of close to one billion USD, second only to the Shiba Inu token.

[Place Table 2 about here]

We also report the number of average daily trades and the number of active trading platforms from the Kaiko data during the [-90,+90] RHC crypto introduction event window. The level of liquidity across the crypto assets exhibits substantial heterogeneity. Three crypto assets have more than one million trades per day (Bitcoin, Shiba Inu, and Solana) while some, notably Bitcoin SV and Dogecoin, have far less. Crypto assets in the 2022 (2018) time cluster tend to have more (fewer) active trading platforms.

4. Results

We employ five market quality variables to examine the impact of PFOF on crypto markets. These variables include *Dollar Volume*, *Trade Size, Order Imbalance*, *C-S Spread* (Corwin and Schultz, 2012), and *Volatility*. Each variable is winsorized at the 1% level to mitigate the influence

[24] See https://coinmarketcap.com/

of outliers. We present summary statistics in Table 3 for each of these variables across token-hour observations in the ninety days before and after each crypto asset trading introduction on RHC.

[Place Table 3 about here]

We examine each of these dependent variables in three different regression specifications with the effect our treatment variable *PFOF Introduction*, which equals one (zero) on and in the 90 days after (before) each RHC token introduction date. First, the base specification includes both USD and USDT markets for all crypto assets and includes hour of day, countercurrency, and token fixed effects. As we expect autocorrelation in our dependent variables, we include lagged dependent variable observations as a control. Second, we use only observations for markets denominated in USD. RHC conducts transactions for its crypto assets available for trading only in US dollars (as opposed to Tether or some other stablecoin), therefore we expect that the impact of PFOF introduction will be more pronounced for markets with USD as a countercurrency. Our third specification includes only Bitcoin (Nakamoto, 2008) and Ethereum (Buterin, 2014) crypto assets. These two crypto assets represent an economically large proportion of total crypto market capitalization and liquidity.

Dollar Volume, the average hourly trading volume in USD, is our first dependent variable examined in Table 4. RHC trading introduction may move overall volume from trading platforms to wholesalers. On the other hand, RHC may raise awareness of crypto assets that they introduce and increase trading volume on trading platforms. Alternatively, wholesalers may make counter trades on the trading platforms against internalized retail volume and no net change in trading volume would result. Results in Table 4 are mixed on the effect of token introduction on dollar volume. Columns 1 and 2 show a reduction in on-platform trading volume for all crypto assets while column 3 points to an increase in trading volume for the two largest crypto assets.

[Place Table 4 about here]

Using Kaiko provided trade initiator data, our next dependent variable is *Order Imbalance* defined as buyer-initiated trade volume minus seller-initiated trade volume divided by total trade volume within each token-hour observation. If buy volume moves from the trading platforms to wholesalers after PFOF introduction, we expect more net selling and the coefficient on *PFOF Introduction* to be negative. Alternatively, wholesalers may transact on the trading platforms, as opposed to making transactions directly on-chain, to deliver crypto assets to RHC and increase buy volume. We find support for the former in Table 5 as the impact of *PFOF Introduction* is negative and highly significant in columns 2 and 3.

[Place Table 5 about here]

Next, we examine the effect of PFOF introduction on average hourly trade size in USD. Larger trades convey more information (Hasbrouck, 1991). We therefore expect that, as more small, uninformed retail trades move from the trading platforms to RHC, *Trade Size* will increase. Column 2 of Table 6 displays evidence supporting our conjecture.

[Place Table 6 about here]

We also examine the informational effects of RHC's PFOF introduction on bid-ask spreads. Specifically, we estimate Corwin and Schultz (2012) implied bid-ask spreads using the close, high, and low prices across each token-hour observation.[25] As more uninformed trading moves off of the trading platforms, we anticipate that spreads will increase after RHC's crypto introductions. Columns 1 and 2 show a positive and highly statistically significant influence of *PFOF Introduction* on *C-S Spread*. Excluding Bitcoin and Ethereum (which are not significant in

[25] Kaiko produces a crypto-token level NBBO-equivalent across trading platforms but it is unavailable historically. Therefore, we rely on using trade data to calculate Corwin and Schultz (2012) implied bid ask spreads. Crypto asset trading platforms are open 24 hours a day and we thus use hourly instead of daily intervals to calculate the implied bid-ask spread.

insolation in column 3), the economic impact of this increase in spreads costs traders of crypto assets on trading platforms an estimated $4.83 million daily.[26]

[Place Table 7 about here]

Finally, the effects of PFOF introduction on *Volatility* are presented in Table 8. Bhushan et al. (1997) find that "the volatility of prices declines as the number of noise traders increases." We therefore expect that, if uninformed noise traders leave the crypto trading platforms for commission free trading at RHC, volatility will increase. Evidence in columns 1 and 2 of Table 8 support our conjecture. However, in column 3 we find no impact of RHC crypto introductions on the largest two crypto assets.

[Place Table 8 about here]

5. Conclusion

While many studies have examined the influence of PFOF on equities and options markets (see, for example, Bryzgalova et al., 2023; Ernst and Spatt, 2022; Hu and Murphy, 2024), we are, to the best of our knowledge, the first to examine payment for order flow and its interaction with crypto markets. There is reason to believe that wholesalers pay more to trade against crypto assets because the order flow is highly uninformed. This is because crypto PFOF rates per dollar of trading value are 45 (4.5) times higher than in equities (options).

We use Robinhood Crypto token introduction dates to examine the impact of PFOF on crypto markets. Overall, we find that PFOF introduction in crypto markets leads to lower trading volume on trading platforms, seller-driven order imbalances, larger average trade sizes, higher implied bid-ask spreads, and greater volatility. This evidence is consistent with uninformed trading moving from the trading platforms to wholesalers. The economic magnitude of increased trading costs on

[26] We estimate this economic effect based on a *C-S Spread* coefficient in column 2 of 0.001513 and daily crypto volume of $3.192 billion in Table 2. Including Bitcoin and Ethereum, the impact rises to $6.77 million.

trading platforms is large, potentially as much as $4.8 million per day. Future research with access to wholesaler trade data could shed more light on how PFOF influences crypto markets.

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Figure 1 – Crypto asset trading volume

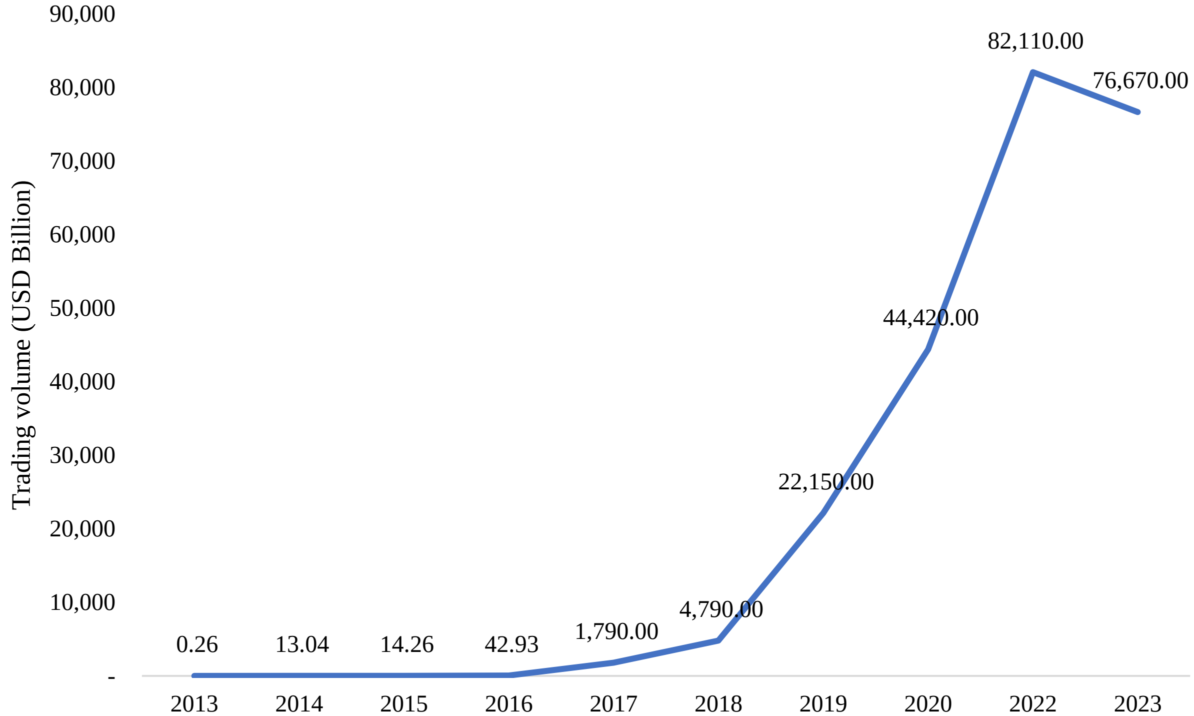

Figure 1 displays estimated crypto asset trading volume by year, as reported by Coincodex (https://coincodex.com/trading-volume/).

Figure 2 – Robinhood PFOF revenue

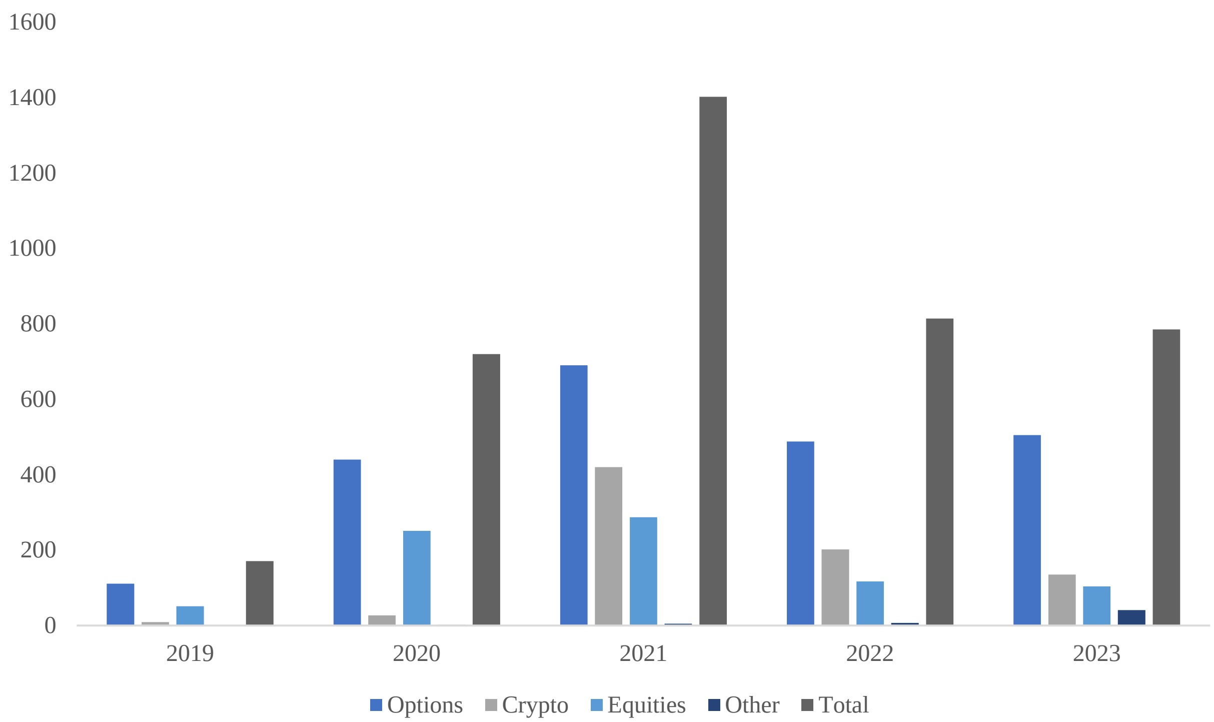

Figure 2 displays Robinhood's transaction-based revenues (i.e., PFOF) by product category from 2019 through 2023 as reported in the company's annual reports.

Table 1 – RHC Crypto Introductions

Table 1 displays crypto asset names, Kaiko symbols, RHC introduction dates, and the crypto announcement URLs for 19 RHC crypto introductions from 2018 through 2022.

Name	Kaiko Symbol	Listing Date	Information URL
Aave	aave	10/24/2022	https://twitter.com/robinhoodapp/status/1584532320551174145
Avalanche	avax	8/8/2022	https://twitter.com/robinhoodapp/status/1556624446093373440
Bitcoin	btc	1/25/2018	https://twitter.com/RobinhoodApp/status/956557558017179648
Bitcoin Cash	bch	7/12/2018	https://blog.robinhood.com/news/2018/7/12/litecoin-and-bitcoin-cash-now-on-robinhood-crypto
Bitcoin SV	bsv	11/29/2018	https://twitter.com/askrobinhood/status/1068346552341561344?lang=en
Cardano	ada	9/1/2022	https://twitter.com/RobinhoodApp/status/1565323169409351681
Chainlink	link	6/28/2022	https://twitter.com/RobinhoodApp/status/1541765004885577730
Compound	comp	4/12/2022	https://blog.robinhood.com/news/2022/4/12/robinhood-lists-four-new-crypto-assets
Dogecoin	doge	7/16/2018	https://blog.robinhood.com/news/2018/7/15/dogecoin-is-now-on-robinhood-crypto
Ethereum	eth	1/25/2018	https://twitter.com/RobinhoodApp/status/956557558017179648
Ethereum Classic	etc	8/6/2018	https://blog.robinhood.com/news/2018/8/5/ethereum-classic-is-now-on-robinhood-crypto
Litecoin	ltc	7/12/2018	https://blog.robinhood.com/news/2018/7/12/litecoin-and-bitcoin-cash-now-on-robinhood-crypto
Polygon	matic	4/12/2022	https://blog.robinhood.com/news/2022/4/12/robinhood-lists-four-new-crypto-assets
Shiba Inu	shib	4/12/2022	https://blog.robinhood.com/news/2022/4/12/robinhood-lists-four-new-crypto-assets
Solana	sol	4/12/2022	https://blog.robinhood.com/news/2022/4/12/robinhood-lists-four-new-crypto-assets
Stellar Lumens	xlm	8/8/2022	https://twitter.com/robinhoodapp/status/1556624446093373440
Tezos	xtz	10/24/2022	https://twitter.com/robinhoodapp/status/1584532320551174145
Uniswap	uni	7/14/2022	https://twitter.com/RobinhoodApp/status/1547608038860697606
USD Coin	usdc	9/20/2022	https://twitter.com/RobinhoodApp/status/1572215405791580164

Table 2 – Crypto Asset Summary Statistics

Table 2 displays the average crypto asset unit price, market capitalization, and daily dollar trading volume from CoinMarketCap.com at the date of each RHC crypto introduction. The table also displays the number of average daily trades across all trading platforms and the number of unique active trading platforms for each crypto asset using Kaiko trade data in the [-90,+90] window around each RHC token introduction date provided in Table 1. All variables are averages calculated across crypto markets denominated in US Dollar and Tether countercurrency terms.

Name	Unit Price	Market Capitalization	Daily Dollar Volume	Daily Trades	Active Trading Platforms
Aave	$75.740	$1,105,053,320	$30,352,776	213,449	29
Avalanche	$21.296	$7,563,894,885	$152,979,480	526,477	22
Bitcoin	$10,252.060	$200,174,661,561	$974,400,000	1,001,481	25
Bitcoin Cash	$828.961	$16,198,567,369	$70,454,280	126,008	14
Bitcoin SV	$79.530	$1,532,259,166	$2,522,275	11,507	7
Cardano	$0.450	$15,856,258,810	$199,666,920	670,354	22
Chainlink	$8.685	$4,835,374,220	$113,497,728	435,061	35
Compound	$103.262	$816,884,230	$23,386,457	150,343	29
Dogecoin	$0.004	$571,843,952	$419,848	8,701	4
Ethereum	$667.741	$80,300,992,176	$307,200,000	612,983	22
Ethereum Classic	$13.929	$2,001,573,042	$49,179,888	117,786	12
Litecoin	$92.817	$6,849,506,322	$58,716,768	165,426	18
Polygon	$1.218	$11,335,066,980	$259,200,000	846,788	30
Shiba Inu	$0.00002	$11,740,334,448	$1,123,200,000	1,110,413	25
Solana	$81.064	$33,869,298,882	$640,800,000	1,651,827	18
Stellar Lumens	$0.116	$3,236,822,298	$31,923,696	244,432	23
Tezos	$1.288	$1,233,238,799	$8,163,278	84,563	20
Uniswap	$6.499	$3,825,061,652	$48,716,184	327,057	35
USD Coin	$1.000	$43,537,884,267	$379,200,000	250,093	28

Table 3 – Hourly Summary Statistics

Table 3 displays summary statistics for five market quality variables for crypto-hour observations during the [-90,+90] day interval around each Robinhood crypto introduction date. *Dollar Volume* is the total trading volume in USD for the crypto asset during each hourly observation, *Order Imbalance* is the buyer-initiated trade volume minus seller-initiated trade volume (based on initiator indicators provided by Kaiko) divided by total trade volume, *Trade Size* is the average trade size in USD, *C-S Spread* is the Corwin-Schultz (2012) implied bid-ask spread calculated using high/low/last across crypto-hour observations, and *Volatility* is the hourly return volatility.

	(1)	(2)	(3)	(4)	(5)
Variables	*Mean*	*Std. Dev.*	*Median*	*Min*	*Max*
log(Dollar Volume)	14.408	2.218	14.663	6.337	18.207
Order Imbalance	0.052	0.300	0.006	-0.650	1.000
log(Trade Size)	6.015	1.135	6.130	2.051	8.263
C-S Spread	0.020	0.048	0.006	0.000	0.314
Volatility	0.003	0.007	0.001	0.000	0.048

Table 4 – Volume

Table 4 displays regressions of the natural logarithm of trading volume in USD for crypto-hour observations. Column 1 includes all observations for trades made in USD and USDT terms. Column 2 includes only observations made in USD terms. Column 3 includes only observations trading in Bitcoin and Ethereum crypto assets. Standard errors are clustered by hour of day. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Variables	*log(Dollar Volume)*	*log(Dollar Volume)*	*log(Dollar Volume)*
PFOF Introduction	-0.057***	-0.152***	0.069***
	(-16.916)	(-34.229)	(5.329)
log(Dollar Volume)$_{t-1}$	0.777***	0.682***	0.872***
	(192.296)	(117.279)	(111.283)
Subsample	Full	USD Only	BTC/ETH Only
Hour of Day FE	Yes	Yes	Yes
Token FE	Yes	Yes	Yes
Countercurrency FE	Yes	No	Yes
N	240,532	80,262	25,920
R^2	0.933	0.939	0.861

Table 5 – Order Imbalance

Table 5 displays regressions of order imbalance (i.e., the buyer-initiated trade volume minus seller-initiated trade volume divided by total trade volume) for crypto-hour observations. Column 1 includes all observations for trades made in USD and USDT terms. Column 2 includes only observations made in USD terms. Column 3 includes only observations trading in Bitcoin and Ethereum crypto assets. Standard errors are clustered by hour of day. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Variables	(1) *Order Imbalance*	(2) *Order Imbalance*	(3) *Order Imbalance*
PFOF Introduction	0.001	-0.008***	-0.010***
	(0.942)	(-5.705)	(-3.695)
Order Imbalance$_{t-1}$	0.464***	0.112***	0.267***
	(110.881)	(18.312)	(22.473)
Subsample	Full	USD Only	BTC/ETH Only
Hour of Day FE	Yes	Yes	Yes
Token FE	Yes	Yes	Yes
Countercurrency FE	Yes	No	Yes
N	240,478	80,244	25,914
R^2	0.452	0.473	0.077

Table 6 – Trade Size

Table 6 displays regressions of the natural logarithm of trade size in USD for crypto-hour observations. Column 1 includes all observations for trades made in USD and USDT terms. Column 2 includes only observations made in USD terms. Column 3 includes only observations trading in Bitcoin and Ethereum crypto assets. Standard errors are clustered by hour of day. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Variables	(1) *log(Trade Size)*	(2) *log(Trade Size)*	(3) *log(Trade Size)*
PFOF Introduction	0.006	0.032***	-0.005
	(1.481)	(7.009)	(-0.400)
log(Trade Size)$_{t-1}$	1.031***	1.100***	1.024***
	(293.583)	(176.832)	(184.703)
Subsample	Full	USD Only	BTC/ETH Only
Hour of Day FE	Yes	Yes	Yes
Token FE	Yes	Yes	Yes
Counter crypto asset FE	Yes	No	Yes
N	240,478	80,244	25,914
R^2	0.862	0.888	0.795

Table 7 – Implied Spread (Corwin-Schultz)

Table 7 displays regressions of Corwin-Schultz (2012) implied bid-ask spread for crypto-hour observations. Column 1 includes all observations for trades made in USD and USDT terms. Column 2 includes only observations made in USD terms. Column 3 includes only observations trading in Bitcoin and Ethereum crypto assets. Standard errors are clustered by hour of day. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Variables	*C-S Spread*	*C-S Spread*	*C-S Spread*
PFOF Introduction	0.001***	0.002***	0.000
	(7.966)	(12.024)	(0.176)
C-S Spread$_{t-1}$	0.899***	0.935***	0.780***
	(190.057)	(345.869)	(90.186)
Subsample	Full	USD Only	BTC/ETH Only
Hour of Day FE	Yes	Yes	Yes
Token FE	Yes	Yes	Yes
Countercurrency FE	Yes	No	Yes
N	240,397	80,225	25,896
R^2	0.842	0.944	0.609

Table 8 – Volatility

Table 8 displays regressions of return volatility for crypto-hour observations. Column 1 includes all observations for trades made in USD and USDT terms. Column 2 includes only observations made in USD terms. Column 3 includes only observations trading in Bitcoin and Ethereum crypto assets. Standard errors are clustered by hour of day. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Variables	*Volatility*	*Volatility*	*Volatility*
PFOF Introduction	0.012***	0.023***	-0.003
	(6.620)	(7.837)	(-0.851)
Volatility$_{t-1}$	0.888***	0.886***	0.970***
	(189.572)	(155.673)	(234.715)
Subsample	Full	USD Only	BTC/ETH Only
Hour of Day FE	Yes	Yes	Yes
Token FE	Yes	Yes	Yes
Countercurrency FE	Yes	No	Yes
N	240,452	80,234	25,914
R^2	0.836	0.903	0.942