European Journal of Operational Research 323 (2025) 253–266

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/eor

Innovative Applications of O.R.

An adoption model of cryptocurrencies

Khaladdin Rzayev [a,b,c,*], Athanasios Sakkas [d], Andrew Urquhart [e]

[a] University of Edinburgh Business School, The University of Edinburgh, Edinburgh, UK
[b] Koç University, Istanbul, Turkey
[c] Systemic Risk Centre, London School of Economics, United Kingdom
[d] Department of Accounting and Finance, Athens University of Economics and Business (AUEB), Athens, Greece
[e] Birmingham Business School, University of Birmingham, Birmingham, UK

ARTICLE INFO

Keywords:
Cryptocurrency adoption
Innovators
Imitators
Network effects
Predictive modelling
Market quality

ABSTRACT

The network effect, measured by users' adoption, is considered an important driver of cryptocurrency market dynamics. This study examines the role of adoption timing in cryptocurrency markets by decomposing total adoption into two components: innovators (early adopters) and imitators (late adopters). We find that the innovators' component is the primary driver of the association between user adoption and cryptocurrency returns, both in-sample and out-of-sample. Next, we show that innovators' adoption improves price efficiency, while imitators' adoption contributes to noisier prices. Furthermore, we demonstrate that the adoption model captures significant cryptocurrency market phenomena, such as herding behaviour, more effectively, making it better suited for forecasting models in cryptocurrency pricing. These results suggest that our methodology for linking early and late adopters to market dynamics can be applied to various domains, offering a framework for future research at the intersection of operational research and financial markets.

1. Introduction

Cryptocurrencies are growing in importance and influence in the financial system. At their height, cryptocurrency market capitalization reached nearly $3 trillion, putting it on a par with some of the largest stocks worldwide. They may have begun life being traded by only a select few computer programmers, but with the introduction of Bitcoin futures in 2017 and the approval of Bitcoin spot ETFs in January 2024, more investors are taking notice of this innovative asset class. While it may have begun as an investment tool for retail investors, very large institutions are also now exposed to the market and more intend to in the future.[1,2]

The increase in institutional investor interest makes it necessary to understand the factors driving cryptocurrency market behaviour (Bhambhwani et al., 2023; Liu & Tsyvinski, 2021; Liu et al., 2022), and the relevant literature suggests that users' adoption is one of the most important factors in explaining competition and dynamics in these markets (Jiang et al., 2022; Naoum-Sawaya et al., 2023; Zhang et al., 2022). However, while the financial economics literature focuses on general adoption, the business studies and operational research (OR) literature suggest that the timing of product adoption is more critical for a product's success (Bass, 1969; Mansfield, 1961; Paç et al., 2018). Consistent with this intuition, Cong et al. (2021) theoretically suggest that the users' adoption has the highest effect on cryptocurrency prices during the early stages of adoption. However, there is little empirical evidence in the existing literature on how adoption timing impacts cryptocurrency market dynamics, primarily because only general adoption measures are available. To circumvent this issue and bridge the gap between theoretical and empirical literature, we adopt an innovation adoption model from business studies.

Our framework is based on the adoption model initially proposed in Bass (1969) and Mansfield (1961) and allows to estimate the innovators' and imitators' adoptions magnitudes from the total adoption. The economic intuition behind this model is that innovators actively acquire information and disseminate it, while late adopters use innovators-sourced information in their adoption decisions. This implies that late adopters' decision is influenced by the number of existing users. To test whether this mechanism is applicable to the cryptocurrency adoption process, we start our analysis by estimating innovators' and imitators' adoptions. Based on the data on the number of active addresses for 77 cryptocurrencies, we show that, on average, the adoption of cryptocurrencies by innovators makes it more desirable for imitators to adopt.

* Corresponding author.
E-mail addresses: khaladdin.rzayev@ed.ac.uk (K. Rzayev), asakkas@aueb.gr (A. Sakkas), a.urquhart@bham.ac.uk (A. Urquhart).

[1] https://www.bloomberg.com/news/audio/2022-10-08/high-frequency-trader-says-institutions-are-taking-over-crypto.

[2] https://www.forbes.com/sites/lawrencewintermeyer/2021/08/12/institutional-money-is-pouring-into-the-crypto-market-and-its-only-going-to-grow/?sh=1a5424261459.

https://doi.org/10.1016/j.ejor.2024.11.024
Received 14 May 2024; Accepted 14 November 2024
Available online 23 November 2024
0377-2217/© 2024 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

This result suggests that the cryptocurrency adoption mechanism is consistent with the general product adoption process modelled by Bass (1969) and Mansfield (1961).

We then examine the effects of the innovators and imitators components of the adoption model on the realized and expected returns. This inquiry is critical as developing methodological tools for predicting cryptocurrency prices is a key focus in OR (Akyildirim et al., 2023), and understanding the economic drivers behind these prices is essential in the financial economics literature (Biais et al., 2023). We expect that cryptocurrencies with higher exposure to innovators' adoption experience higher expected returns. Conversely, we do not expect any significant association between imitators' adoption and returns. Our explanation follows Cong et al. (2021), who provide theoretical evidence that cryptocurrency prices increase sharply in the early stages of adoption as transactional demand is at its highest level during this period. Along this line, Hackethal et al. (2022) argue that early adopters take more risks, indicating the higher impact of early adopters on pricing. Consistent with these explanations, we find that innovators' adoption is significantly related to future realized returns both in- and out-of-sample. As noted above, we use the number of active addresses to estimate the innovators' and imitators' adoptions. Interestingly, we fail to document a significant association between total adoption and cryptocurrency returns in our sample. A plausible explanation is that total adoption measures are noise proxies of the network effects.

To test this explanation, we extend our analysis by conducting a horse race between total adoption and innovators/imitators' adoptions in a formal asset pricing test. We show that a cryptocurrency strategy with exposure to the innovators' adoption warrants a positive and sizable risk premium of 18.20% per month, which is statistically significant at the 5% level. In contrast to this, we do not find any significant association between total users' and imitators' adoptions and expected returns. This result confirms our interpretation of the noisy nature of general adoption measures.

Cong et al. (2021) develop a parsimonious asset pricing model of cryptocurrencies and theoretically show that adoption is a priced factor owning to users' demand for transactions. Given that a high (low) innovators' adoption portfolio is associated with increased (decreased) demand from transactions, our findings regarding the positive association between innovators' adoption and expected return are consistent with Cong et al. (2021). As noted above, Cong et al. (2021) model indeed also predict that cryptocurrency prices should increase sharply during early adoption stages. In addition, a key finding is that our innovators' adoption factor has statistically significant positive exposure to the cryptocurrency size factor. This result is in line with Liu et al. (2022), which conjectures that the size premium is related to the trade-off between capital gain and convenience yield (Cong et al., 2021; Sockin & Wei, 2023), in which larger and more mature cryptocurrencies exhibit larger convenience yield at the expense of lower capital profits. This implies that the cryptocurrency size premium should be larger when transactional demand is high (Liu et al., 2022). Our result on the association between innovators' adoption and size premium is consistent with this explanation.

While the association between users' adoption and *expected* return is a more interesting research question, the fact that only innovators' adoption is a significant determinant of future *realized* return may have further implications. We further explain this result in the market microstructure dimension. The literature shows that the main difference between innovators and late adopters is the information content of their transactions (Bass, 1969; Rogers et al., 2014). Innovators have better technological skills and are more active in information search, while late adopters are generally uninformed users, and their adoption is based on the information generated by innovators. Interestingly, this characteristic of innovators and imitators makes them comparable to informed and uninformed traders, with the former being able to use technology to better interpret public information and profit from it, as described in the relevant market microstructure literature (Aquilina et al., 2022; Rzayev & Ibikunle, 2019).[3] We therefore test whether the effects of innovators and late adopters on financial markets are consistent with the empirical literature on the role of informed and uninformed traders in market quality.

For this purpose, we study the association between innovators/late adopters components and volatility/price discovery. Volatility is driven by two factors: information and noise (Menkveld et al., 2007). Given that we argue the innovators (imitators) component of the adoption model captures informed (uninformed/noise) trading, we expect that the innovators (imitators) component will be positively related to the information (noise) component of the price discovery. First, we find that both components are positively and statistically significantly related to volatility. More importantly, our results suggest that the innovators' (imitators') adoption is significantly related to the information-driven (noise-driven) volatility. These results are in line with our expectations and confirm our argument that the adoption model offers us some important market microstructure insights.

We contribute to two streams of literature. First, we contribute to the OR literature by examining the adoption dynamics of cryptocurrencies. Investigating the adoption mechanisms of new products has long been an interesting research question in OR. For instance, Stummer et al. (2015) suggest that providing tools to help decision-makers adopt new products can impact the pricing and distribution strategies of these products. Paç et al. (2018), by using the Bass model that we also employ, shows the importance of adoption timing in the success of innovation. Similarly, understanding cryptocurrency markets is also an important stream in the OR literature. There is significant literature investigating the pricing dynamics of cryptocurrencies (e.g., Akyildirim et al., 2023; Atsalakis et al., 2019), the transaction fee dynamics of cryptocurrencies (Shang et al., 2023), and the trading processes in cryptocurrencies (Schnaubelt, 2022). Therefore, merging these two streams and investigating the role of adoption dynamics of cryptocurrencies in various stakeholders' decision-making processes is a natural area for OR to contribute to, which is what we aim to do with this paper.

Another important research domain in the OR area is developing new methodological tools to contribute to decision-making. While the Bass diffusion model and its variations have been widely applied to study the adoption of various consumer products and technologies, our work is among the first to adapt and extend this framework to analyse the diffusion of cryptocurrencies. We argue that cryptocurrencies, as a new class of financial assets with unique characteristics and therefore adoption patterns, requires a specialized approach that accounts for the distinct roles of early adopters (innovators) and late adopters (imitators) in driving market dynamics and quality. We evaluate this theoretical proposition through an empirical analysis of two critical aspects of cryptocurrency trading: (i) the pricing dynamics of cryptocurrencies and (ii) herding behaviour.

First, we demonstrate that early adoption plays a crucial role in explaining price variations in cryptocurrencies, showing a stronger impact than traditional network proxies, such as the total number of active addresses. We contribute to a growing body of literature that focuses on examining the performance of cryptocurrency portfolios based on characteristics such as size (Liu et al., 2022), momentum (Dobrynskaya, 2023; Liu et al., 2022), liquidity (Bianchi & Babiak, 2022), trading volume and liquidity provision (Bianchi et al., 2022), blockchain characteristics (Bhambhwani et al., 2023; Sakkas & Urquhart, 2024) and trend (technical) indicators (Fieberg et al., 2024), amongst others. Our study builds on this literature by offering empirical evidence that early adoption can be used as a signal for cryptocurrency investors

[3] Our definition of informed trading differs from the standard informed trading described in traditional market microstructure models, such as Glosten and Milgrom (1985) and Kyle (1985). In these standard models, informed traders possess private information about firms' fundamentals, which is not applicable in cryptocurrency markets.

to develop effective long-only and long–short investment strategies exhibiting significant performance over holding periods up to three months.

Second, while there is significant literature on price discovery in cryptocurrency markets, proposing that investor sentiment (e.g., Entrop et al., 2020), manipulation and speculation (e.g., Alexander & Heck, 2020), and trading activity (e.g., Hung et al., 2021) impact the price discovery process, our results reveal distinct roles for early and late adopters: early adopters tend to enhance price efficiency, while late adopters tend to introduce price noise. This finding is important because efficient prices are crucial for investment strategies and risk management. When prices are efficient and accurately reflect all available information, investors can make informed decisions, leading to optimal portfolio allocation. For instance, Wurgler (2000) show that efficient and informed prices improve capital allocation in financial markets (Tadesse, 2004). Along this line, De Long et al. (1990) demonstrate that noise can create short-term mispricing risks, which provide profit opportunities for speculators (Zhang & Zhang, 2024). The practical implication is that long-term investors aiming to hedge against mispricing risks may find it advantageous to invest in cryptocurrencies with a higher proportion of early adopters, as these participants tend to have a deeper understanding of the technology. In contrast, speculative investors seeking profit from short-term mispricing may prefer cryptocurrencies dominated by late adopters. More broadly, these findings contribute to a more comprehensive understanding of market maturation in the cryptocurrency space. As these markets evolve, the changing dynamics between early and late adopters may signal shifts in overall market efficiency and stability. This knowledge is beneficial for policymakers and regulators seeking to create appropriate frameworks for these emerging markets, as well as for institutional investors considering entry into the cryptocurrency space.

Third, the herding effect identified by our adoption model has a stronger correlation with cryptocurrency markets than past returns alone. Notably, while past returns alone fail to predict future performance, the coefficient of past returns derived from the adoption model predicts future returns, confirming its superior suitability in capturing herding behaviour in cryptocurrency markets. These results contribute to a growing body of OR aimed at developing predictive models for cryptocurrency prices (e.g., Akyildirim et al., 2023; Atsalakis et al., 2019). Our findings suggest that prediction models should differentiate between early and late adoption stages.

With evolving market dynamics, such as the introduction of Bitcoin ETFs, understanding the informational content of cryptocurrency prices and investor herding behaviour has become crucial. Our tool offers valuable insights into adoption dynamics, allowing investors to understand and measure efficient price discovery and herding behaviour better, and optimize investment strategies. By demonstrating this model's relevance and application in the cryptocurrency context, we open up the way for future research at the nexus of OR and financial markets. This methodology could be readily adapted to study other financial innovations, including blockchain-based assets and decentralized finance (DeFi) applications. Moreover, our approach provides a framework for analysing the success factors of new cryptocurrencies, offering insights that could be useful for both investors and developers in this rapidly evolving market.

We also contribute to the growing financial economics literature on the pricing dynamics of cryptocurrencies. Cong et al. (2021) build a cryptocurrency asset pricing model and show that endogenous platform adoption builds on user network externality and exhibits an S-curve, while inter-temporal feedback between user adoption and cryptocurrency price accelerates adoption and dampens user-base volatility. One of the important predictions of Cong et al. (2021) model is that not only users' adoption but also the timing of this adoption matters. We complement Cong et al. (2021) by providing empirical evidence on the distinctive effects of innovators (early adopters) and imitators (late adopters) on cryptocurrency pricing. The importance of this point is magnified because our results show that innovators' and late adopters' adoptions have heterogeneous impacts on the market quality. This has important practical implications for new cryptocurrencies. For instance, given the historically high rate of failure among new cryptocurrencies, our analysis underscores the critical importance of initial user adoption in shaping the successful trajectory of these innovative financial products. This importance emanates from their capability to produce and disseminate new information.

The remainder of the paper is structured as follows: Section 2 discusses the relevant literature, and introduces the adoption model. Section 3 presents our data and the estimation results for the adoption model. Sections 4 and 5 provide evidence on the asset pricing and market microstructure implications of the adoption model. Section 6 summarizes and concludes. All additional tests referenced but not presented in this paper can be found in the Online Appendix.

2. Theoretical framework

2.1. Early versus late adoption and its implications for cryptocurrency markets

According to Frame and White (2004), *"financial innovations can be grouped as new products (e.g., adjustable-rate mortgages, exchange-traded index funds); new services (e.g., online securities trading, internet banking); new "production" processes (e.g., electronic record-keeping for securities, credit scoring); or new organizational forms (e.g., a new type of electronic exchange for trading securities, internet-only banks)"*. Cryptocurrencies meet these criteria of financial innovation since they are new products, and moreover, they provide new services (e.g., decentralized exchanges) with a new production process (e.g., blockchain-based data storage). This implies that cryptocurrencies should be classified and studied as innovative product within the financial ecosystem.

One of the unique features of innovative products' adoption is the importance of the *timing* of adoption for the success of the adoption process. Bass (1969) classify investors into two main groups (consisting of five small sub-groups) according to the timing of their adoption process: (i) innovators (i.e., early adopters) and (ii) imitators (i.e., late adopters). The main difference between innovators and imitators is generally explained by their information-processing capacities. Richins and Bloch (1986) show that the reason for imitators being late to adopt products is the information asymmetry. Specifically, the study finds that innovators acquire and disseminate more information about products, and this allows them to adopt first. Consistently, Ram and Jung (1994) document that innovators are highly active in information search and opinion leadership.

Along similar lines, Chau and Hui (1998) and Soh et al. (1997) investigate the difference in behaviours of innovators and imitators in the adoption and use of Information Technology products. Soh et al. (1997) focus on the use of the Internet for business and find that innovators produce information that is later used by imitators for their adoption decisions. Chau and Hui (1998) use Windows 95 as an innovative product and demonstrate that information collection is done by innovators (Lynn et al., 2017). Rogers et al. (2014) state this crucial relationship between early and late adopters as *"[p]otential adopters look to early adopters for advice and information about the innovation. The early adopter is considered by many as 'the individual to check with' before using a new idea"*.

The implication of the above discussion is that the dynamics of users' cryptocurrency adoption and more broadly, cryptocurrency markets should be studied by making a distinction between early and late adopters. However, the literature primarily focuses on general adoption and its impact on cryptocurrency markets. For instance, Cong et al. (2021) propose one of the first theoretical models linking users' adoption to cryptocurrency pricing. Unlike traditional valuation models, their model indicates that cryptocurrency values are primarily driven by transactional demand stemming from endogenous user adoption, enhanced by network effects—more users simplify finding transaction counterparts, increasing token utility. Additionally, exogenous factors such as technological advances and regulatory frameworks, termed "platform productivity" in the study, also influence cryptocurrency utility and, hence, value.

Empirical evidence supporting this theoretical model is provided by Liu et al. (2022), who demonstrate the significance of user adoption in explaining variations in cryptocurrency returns across different contexts. Further, Cong et al. (2022) identify not only traditional market factors like size and momentum but also significant premiums associated with network adoption and value in cryptocurrencies, documenting that creating a factor that longs crypto with high network adoption generates excess returns of up to 4% per year (see also Bhambhwani et al., 2023; Shams, 2020).[4]

While no explicit theoretical model and study address the distinction between early and late adoption and its impact on cryptocurrency markets, a few studies offer some insights. For instance, Cong et al. (2021) categorize blockchain platforms in terms of their adoption stages into early, intermediate, and late adoption, showing that users' adoption and network effects drive the largest cross-sectional variation in the early stages of adoption. The main reason for this is that higher adoption during the early stages signals more transactional demand. Along this line, Hackethal et al. (2022) also discuss the importance of understanding the implications of early users' adoption in cryptocurrency markets. The study finds that early adopters are more likely to take risks and follow price trends, and more importantly, early adopters of cryptocurrency securities are also more likely to invest in other innovative products in the future. The fact that early adopters are more likely to take risks and follow price trends indicates that, consistent with Cong et al. (2021), the magnitude of their impacts on cryptocurrency prices is expected to be higher.

While a few papers examine the timing of adoption and its implications for cryptocurrencies, to the best of our knowledge, there is no empirical study on the relative effects of early and late adopters on the cryptocurrency market. The main reason for this is data availability, as we can only observe total adoption measures. Our main aim in this study is to address this limitation by using a product adoption model proposed in the business studies literature that allows us to decompose total adoption into early and late users' adoption.

2.2. Adoption model

As discussed in Section 2.1, it is vital to make a distinction between innovators and imitators to have a more nuanced understanding of the adoption dynamics of cryptocurrencies and its implications. The first adoption model that makes this distinction is proposed by Bass (1969) and Mansfield (1961) in the marketing literature to study the adoption process of consumer products. This adoption model and its variations are also used in the finance literature as they provide new insights about the adoption/diffusion processes of financial innovations (Ibikunle, 2018; Molyneux & Shamroukh, 1996). Mathematically, the simple innovation adoption model is as follows:

$$\begin{aligned}\Delta Adopters_t = {} & \alpha(PAdopters - Adopters_{t-1}) + \beta\left(\frac{Adopters_{t-1}}{PAdopters}\right) \\ & \times(PAdopters - Adopters_{t-1}) + \\ & \gamma \times Adopters_{t-1} \qquad (1)\end{aligned}$$

where $Adopters_{t-1}$ is the cumulative number of adopters at time $t-1$, $PAdopters$ is the market potential or the potential number of adopters (this is also called market penetration ceiling), and $\Delta Adopters_t$ is the number of new adopters at time t and computed as the difference between $Adopters_t$ and $Adopters_{t-1}$. There are two important coefficient estimates in Eq. (1): α (the coefficient of innovation/early adoption) and β (the coefficient of imitation/late adoption).[5]

Eq. (1) offers a few important insights. First, it shows that the only difference between innovators (α) and imitators (β) is the fact that the latter component depends on the ratio of existing adopters ($Adopters_{t-1}$) to the potential adopters ($PAdopters$). To illustrate, consider a scenario with no prior adopters ($Adopters_{t-1} = 0$); in this case, the imitators' coefficient (β) cannot be estimated since its calculation depends on the presence of existing adopters. Conversely, for innovators, the absence of prior adopters means their influence is solely based on the pool of potential adopters. In another extreme, where the market reaches its potential ($PAdopters = Adopters_{t-1}$), it implies market saturation, leading to a halt in adoption as the market has reached its full potential; under these conditions, neither α nor β would be estimated. Notably, as $Adopters_{t-1}$ approaches $PAdopters$, the gap between $PAdopters$ and $Adopters_{t-1}$ narrows linearly, whereas the second component ($\frac{Adopters_{t-1}}{PAdopters}$) $\times$ ($PAdopters - Adopters_{t-1}$) displays a nonlinear trajectory, initially increasing to a peak before declining. This pattern aligns with the expectation that while the number of initial adopters may decrease over time, the number of late adopters can rise to a certain point as they are influenced by the forerunners (discussed in the next paragraph in detail). However, once the market nears its capacity, the incentive for late adoption also diminishes, reflecting the declining economic benefits of adopting the innovation at this stage.

According to Bass (1969), the impact of early adopters on late adopters is underpinned by two interrelated theories. The "information hypothesis" posits that early adopters' experiences inform later adopters about the benefits and drawbacks of the innovation, helping them balance the cost of updating their knowledge against the potential losses from not adopting a profitable innovation promptly. As Bass (1969) states, *"...imitators are influenced by the number of previous buyers. Imitators "learn" in some sense, from those who have already bought"*. This learning process can be influenced by various factors, such as changes in the environment that decrease the expected cost of adoption or increase the expected return and positive externalities associated with the number of earlier adopters (Farrell & Saloner, 1985; Katz & Shapiro, 1985), and reduced adoption costs due to the fixed costs component associated with developing new markets and promotional activities (Reinganum, 1981). Thus, as more firms adopt an innovation, more information about its true cost and return characteristics becomes available and is disseminated from adopters to non-adopters, leading to a greater number of subsequent adoptions.

Beyond this information exchange, the adoption by innovators exerts a "bandwagon effect" on late adopters, compelling their adoption independent of information dissemination. Here, the decision of late adopters to adopt is not directly informed by early adopters' experiences but rather driven by the growing number of early adopters, which triggers fears of losing legitimacy and competitive edge (Abrahamson & Bartner, 1990). This channel is explained in Bass (1969) as follows: *"..., adopters are influenced in the timing of adoption by the pressures of the social system, the pressure increasing for later adopters with the number of previous adopters"*. The bandwagon effect can manifest in two forms: institutional and competitive. Institutional bandwagon pressure arises from the threat of lost legitimacy and stockholder support, as firms that do not adopt an innovation may appear abnormal or illegitimate to their stakeholders when more firms adopt it. Competitive bandwagon pressure, on the other hand, stems from the threat of lost competitive

[4] The importance of users' adoption in cryptocurrency markets has not only been studied in the asset pricing context. For instance, Wei and Dukes (2021) show that price bubbles accelerate the adoption process, suggesting the endogenous nature of the adoption process with respect to price. Additionally, Bhimani et al. (2022) provide an excellent discussion on the development factors affecting individual country cryptocurrency adoption, showing that the legal environment, governance, democracy level, human development, GDP, income inequality, education level, economic freedom, and network readiness determine countries' ability to adopt cryptocurrencies into their society.

[5] In addition to these two key variables, we also include the effects of repeat adopters (γ) (Molyneux & Shamroukh, 1996).

advantage. As more firms adopt an innovation, non-adopters face a worse relative performance if the innovation succeeds, making adoption more attractive as a means to reduce uncertainty and maintain an average industry performance (Abrahamson & Bartner, 1990).

The empirical validity of the adoption model is well-supported by existing literature, highlighting its capability to accurately depict both the early and late stages of the adoption process. For instance, Bass (1969) applies the adoption model to 11 consumer products, finding a notable resemblance between the model's predictions and the actual historical adoption patterns, especially in terms of peak adoption timings. Easingwood et al. (1983) extend the model and apply it to five categories of consumer durables, again finding it effectively captures the adoption dynamics. Moreover, the financial economics literature also demonstrates that the adoption model's predictions are consistent with the theory of the adoption of financial innovations (Akhavein et al., 2005; Ibikunle, 2018).

In this study, drawing from the strong evidence in the aforementioned literature confirming the adoption model's relevance in capturing the early and late adoption process, we employ Eq. (1) and use the number of active addresses to model the adoption process of cryptocurrencies. Specifically, we estimate the following model:

$$
\begin{aligned}
\Delta AAddresses_t = {} & \alpha(PAAddresses - AAddresses_{t-1}) \\
& + \beta\left(\frac{AAddresses_{t-1}}{PAAddresses}\right) \times (PAAddresses - AAddresses_{t-1}) \\
& + \gamma \times AAddresses_{t-1} + \phi \times ret_{t-1} \qquad (2)
\end{aligned}
$$

where $AAddresses_t$ is the number of active addresses on day t, $PAAddresses$ is the market potential or potential number of active addresses, and $\Delta AAddresses_t$ is computed as the difference between $AAddresses_t$ and $AAddresses_{t-1}$. In addition to the primary variables, our model incorporates one more explanatory variable: the lagged returns of the cryptocurrency. By including this variable, our model accounts for potential herding behaviours, positing that past returns may influence the decisions of new market entrants (Ballis & Drakos, 2020; King & Koutmos, 2021).[6]

The adoption of cryptocurrencies can be measured using various variables, including trading volume, the number of transactions, and the number of active addresses. We use the number of active addresses because a change in active addresses provides a clear signal about the adoption and fits the theoretical justification discussed above. For instance, a change in trading volume in cryptocurrencies can be solely driven by the existing users/addresses, i.e., trading volume can increase without any actual adoption process. Active addresses, however, give us a measure of the number of users participating and using the cryptocurrency. Cong et al. (2021) also suggest that the number of active addresses can be a very good measure of users' adoption.

One of the difficulties in estimating the innovation adoption models is using the correct proxy for the market potential ($PAAddresses$ in our model). Bass (1969) shows that the distribution of the cumulative number of adopters can help us to make a plausible guess on the size of the market. In this study, we set the market potential to the maximum value plus three standard deviations of $AAddresses_t$ for each crypto (de Bondt & Ibáñez, 2005). This approach assumes $PAAddresses$ to be constant over time for each cryptocurrency. Considering the critical role of $PAAddresses$ and its unobservability, we implement two additional robustness checks. First, we experiment with different market potential rates by setting $PAAddresses$ to the maximum value plus two and four standard deviations. Second, we allow for time variation in $PAAddresses$, assigning a monthly market potential calculated as the maximum value plus three standard deviations of $AAddresses_t$ for each cryptocurrency and month. In both tests, we obtain consistent results in the multivariate regression models estimated in Section 4. More details are in Section 4 and in the Online Appendix.

[6] Thanks to the anonymous referee for this suggestion.

3. Data and the estimation of the adoption model

3.1. Data and variables

3.1.1. Data sources

We collect data from two main sources. First, we collect daily data on the number of users of cryptocurrencies from www.intotheblock.com, which is an aggregator of cryptocurrency data and collects a wealth of indicators for the cryptocurrency market across a range of cryptocurrencies. Here, we include as many cryptocurrencies as we possibly can that provide a 7-day average of all addresses that have interacted with the network. We exclude stablecoins as they are pegged to the US dollar and their adoption is influenced by a number of different factors.[7] Second, we collect price and volume data for our sample of cryptocurrencies from www.coinmarketcap.com, a widely used source of cryptocurrency market data in the literature. For instance, both Liu and Tsyvinski (2021) and Liu et al. (2022) use data from www.coinmarketcap.com. The price is defined by taking the volume-weighted average of all market pair prices reported for the cryptoasset. We consider the market close as 23:59 UTC and the market open as 00:00, consistent with www.coinmarketcap.com. Our final sample includes 77 cryptocurrencies up to 31st July 2022, which is smaller than the samples used in Liu and Tsyvinski (2021) and Liu et al. (2022) due to data availability; however, it is considerably larger than those used in recent papers such as Bhambhwani et al. (2023), Filippou et al. (2022) and Sakkas and Urquhart (2024). Including many cryptocurrencies in our sample poses the risk that small, illiquid, and failing cryptocurrencies may drive our results while having too few means we cannot obtain a good representation of the cryptocurrency market. We argue that we achieve a balance by including all cryptocurrencies and ensuring that they are liquid and tradeable coins. Our sample includes over 90% of the total cryptocurrency market cap, with most of the remaining market capitalization we do not capture are from stablecoins which, as explained above, are not appropriate to include in our analysis. Table A1 of Online Appendix reports the tickers and cryptocurrency names we use in this study.

3.1.2. Variables and descriptive statistics

To study the respective effects of innovators' and imitators' adoption on cryptocurrency markets, we conduct various analyses; in this section, we discuss the variables that we use in these tests. We have two adoption measures. The first measure is the change in the number of active addresses, denoted as $\Delta AAddresses_{i,m}$, which reflects overall adoption. $\Delta AAddresses_{i,m}$ is calculated as the difference in the number of active addresses between months m and $m-1$ for each cryptocurrency (i). This measure captures the fluctuation in active addresses over time. We use changes in the variable rather than its raw values to ensure consistency with our second set of adoption measures, namely innovators' and imitators' adoption (α and β), which are estimated using Eq. (2) and discussed in the next section. Specifically, since our model in Eq. (2) uses $\Delta AAddresses_{i,m}$ as the dependent variable to estimate innovators' and imitators' adoption, it is essential to base the total adoption measure on the same variable. Our supplementary variables capture return, liquidity, order imbalance and volatility in cryptocurrency markets.

We compute all variables at monthly intervals and then estimate various multiple regressions to understand the effects of innovators' and late adopters' adoption on cryptocurrency markets. Our first test examines the asset pricing implications of innovators and late adopters. In this test, our main variable is the monthly return ($Return_{i,m}$) computed as the monthly average of daily returns. Daily returns are calculated using the daily closing prices. We use two measures to capture liquidity.

[7] See Dionysopoulos et al. (2024) for an explanation for the growth of stablecoins.

The first measure is trading volume ($Volume_{i,m}$), which is computed as the monthly average of daily traded volume. The second liquidity measure is the Amihud illiquidity measure ($Amihud_{i,m}$) that captures the price impact and is computed as the monthly average of the ratio of the absolute value of daily return to daily dollar trading volume (Amihud, 2002). We proxy volatility with the monthly standard deviation of daily returns ($\sigma_{i,m}$). To decompose volatility into information- and noise-driven components ($\sigma_{i,m}^{EPD}$ and $\sigma_{i,m}^{NPD}$), we use the state-space modelling approach developed in Menkveld et al. (2007). Our last market quality variable is the order imbalance, $OIB_{i,m}$, which is computed as the difference between buy and sell volumes over the sum of buy and sell volumes; thus, a higher $OIB_{i,m}$ indicates greater net purchases. Trade classification is done using the Bulk Volume Classification method described in Easley et al. (2012). We use the above-stated variable as dependent and control variables in various specifications; all regression models are specified and discussed in Sections 4 and 5. The definitions of these variables are also provided in Table A2 of Online Appendix.

3.2. Estimation of the adoption model

Our key variables are coefficients of innovators' (α) and late adopters' (β). These variables are estimated using Eq. (2), where we employ the number of active addresses as our adoption measure. The available highest frequency data for the number of addresses is daily. Hence, we estimate Eq. (2) for each cryptocurrency (i) and month (m) by using daily data, meaning that we have cryptocurrency-month observations of α and β, $\alpha_{i,m}$ and $\beta_{i,m}$. The main assumption of the monthly estimation is that there is at least one monthly technological update that incentivizes or disincentives innovators to adopt and use cryptocurrencies. To the extent that cryptocurrencies are highly innovative products, this assumption is plausible. This is also consistent with Molyneux and Shamroukh (1996), who argue that a single-adoption model is not consistent with the reality of the adoption process as new innovators may start to adopt the product due to the significant changes in the production process.[8] Ignoring this point in the adoption model would cause modelling of these new innovators as late adopters.

One of the initial methods recommended for estimating diffusion parameters is the ordinary least squares (OLS) approach, introduced by Bass (1969). This technique involves estimating the parameters by applying a (discrete) regression-based version of the differential equation formulation found in the Bass (1969) model. However, the OLS procedure has several drawbacks related to (i) plausible multicollinearity issues that might arise between the independent variables in Eq. (2), which in turn can produce parameter estimates that are either unstable or have incorrect signs, (ii) the fact that it does not directly provide standard errors for the estimated parameters making it difficult to assess the statistical significance of these estimates,[9] and (iii) time-interval bias, as the procedure uses discrete time-series data to estimate a continuous model (i.e., the solution to the differential equation in the Bass (1969) model). To address the above limitations, Schmittlein and Mahajan (1982) and Srinivasan and Mason (1986) propose using maximum likelihood estimation (MLE) and non-linear estimation, respectively. Schmittlein and Mahajan (1982) show that the MLE provides improved forecasting accuracy and more stable parameter estimates compared to OLS. Srinivasan and Mason (1986) argue that the fitting and forecasting performance of non-linear least squares estimation is very similar to MLE and both methods are superior to OLS. However, MLE tends to underestimate the standard errors of parameters as it fails to account for the effects of excluded variables and potential misspecification of the probability density function, making non-linear least squares a more reliable approach.[10] The non-linear estimation of the Bass (1969) model parameters has been employed in several studies in the literature (i.e., Ibikunle, 2018; Jain & Rao, 1990; Meade & Islam, 1995; Molyneux & Shamroukh, 1996). Taken together the discussion above, we estimate Eq. (2) using non-linear ordinary least squares.

We use SAS's `proc model` procedure, details of which are provided on SAS's documentation.[11] Due to the model's non-linearity, the standard errors are approximations, necessitating cautious interpretation of the standard error and associated statistics, despite the coefficients' magnitudes being reliably interpretable. While the referenced documentation offers extensive details on the estimation process, we briefly discuss a key consideration in this section: the impact of potential correlations between variables in the estimation process. In Eq. (2), the dynamics of innovation and late adoption are captured through two correlated variables: (i) the net potential increase in adoption, represented by the difference between the potential and past active addresses ($PAAddresses - AAddresses_{t-1}$) and (ii) a ratio reflecting late adopters' adoption pace ($\frac{AAddresses_{t-1}}{PAAddresses} \times (PAAddresses - AAddresses_{t-1})$). This correlation is intentional, reflecting the intrinsic linkage between these two adoption phases. Although the use of this method in business and finance literature typically does not highlight collinearity as a significant issue (Akhavein et al., 2005; Bass, 1969; Molyneux & Shamroukh, 1996), it remains important for us to assess whether collinearity could affect the validity of the estimations in our specific context.[12]

First, it is essential to note that the variables' correlation coefficient is 0.59, below the commonly accepted threshold of 0.80 for linear estimations in scholarly research (Lindner et al., 2020). Second, the `proc model` procedure's convergence criteria is pivotal in understanding the collinearity's effect on our estimation. The procedure adopts an iterative approach, initiating with a nominal parameter value guess (defaulted to 0.0001) and iteratively refining these values to minimize the estimation method's objective function. However, convergence is not guaranteed, with parameter estimate correlations – sourced from variable correlations – potentially introducing bias or even impeding this process. In relation to this, two aspects of our estimation process merit discussion. First, our procedure consistently achieves convergence, demonstrating that collinearity within our variables does not negatively impact the estimation.[13] This consistent convergence, despite potential theoretical concerns about collinearity in nonlinear models, underscores the robustness of our methodological approach. Second, our collinearity diagnostics[14] reveal that the highest condition number is below 5 in our estimations, indicating a lack of significant multicollinearity issues within our model.

While the findings above collectively support the reliability of our estimation methods and mitigate concerns about correlation, it is also important to emphasize that our choice of non-linear least squares estimation also helps address the potential impact of correlation on

[8] For robustness, we also estimate the model (2) quarterly and use them in the secondary models. The results are qualitatively similar.

[9] The model representation of Eq. (2) is essentially of the form: $Y_t = z_0 + z_1 X_{t-1} + z_2 X_{t-1}^2 + \phi[\![ret]\!]_{t-1}$, where $Y = [\![\Delta AAddresses]\!]$, $X = [\![AAddresses]\!]$, $z_0 = \alpha PAAdresses$, $z_1 = (\beta + \gamma - \alpha)$, $z_2 = -\beta / PAAddresses$. Once z's are estimated, then α, β and γ can be estimated.

[10] An analytical discussion on the drawbacks of using OLS for estimating the Bass (1969) diffusion model and the superiority of non-linear estimation over MLE and OLS can be found in Mahajan et al. (1990).

[11] https://support.sas.com/documentation/onlinedoc/ets/132/model.pdf.

[12] We thank the anonymous referees for this suggestion.

[13] The iteration algorithm is affected by collinearity when near singularity is encountered, which results in the algorithm becoming numerically unstable and, hence, failing to converge. See Adkins (2022) and Adkins et al. (2015) for a detailed discussion.

[14] Collinearity diagnostics are conducted using the approach described in Belsley et al. (2005).

our results. As discussed earlier, adoption models are estimated using three approaches: (i) OLS, (ii) MLE, and (iii) non-linear least squares. Mahajan and Sharma (1986) and Srinivasan and Mason (1986) highlight that multicollinearity poses a significant issue in the OLS approach, warranting caution when applying OLS to estimate adoption models. In contrast, both MLE and non-linear least squares are less affected by correlation. Given the various advantages outlined in Srinivasan and Mason (1986) and our earlier discussion, we chose non-linear least squares as our primary estimation approach. To further ensure that collinearity does not substantially affect our estimates, we also employ the MLE approach, finding consistent results across all subsequent regression frameworks. The results of the in-sample return analysis are presented in the Online Appendix Section F.

We report the estimation results of Eq. (2) for each crypto in Table A3 of Online Appendix. The mean and median values of α and β are positive, and the mean values are statistically significantly different from zero. A positive β is observed in 73 out of 77 cryptocurrencies, and interpreting the positive average β is relatively straightforward. It implies that the adoption of these assets is self-reinforcing: as more investors adopt a cryptocurrency, it becomes more desirable for others to do the same. This reflects the strong network effects typical in digital assets, where the perceived value increases with the number of users. This positive β suggests that the overall speed of adoption rises as the user base grows, driven by the cumulative influence of both innovators and early imitators (Bass, 1969; Ibikunle, 2018).

This phenomenon can be attributed to both the information and bandwagon pressure hypotheses previously discussed. From the information perspective, the initial adoption by cryptocurrency innovators can act as a pivotal source of insights for potential adopters. As these early adopters navigate the complexities and explore the benefits of cryptocurrencies, they generate a wealth of information that can mitigate the perceived risks and uncertainties for late adopters. This effect is further amplified as the initial adoption of cryptocurrencies spurs extensive research within the academic and financial communities, leading to a surge in publicly available information. This dissemination of knowledge and experiences can significantly lower the barriers to entry for those who are hesitant, making the decision to engage with cryptocurrencies more informed and less daunting. Supporting this notion, Shahzad et al. (2024) illustrates how heightened awareness of cryptocurrencies positively correlates with increased adoption rates.

On the flip side, from the bandwagon effect perspective, the expansion of early adopter groups generates momentum, imposing social and market pressures on potential adopters who remain on the sidelines. This sense of urgency, driven by the fear of missing out on profitable opportunities or falling behind in a swiftly changing market, often compels late adopters to overcome their hesitations and engage with cryptocurrencies. For example, the recent trend of institutional investors flocking to cryptocurrencies, driven by rising prices to maintain competitive edges, may exemplify this phenomenon, often referred to as the "Bitcoin bandwagon" in public debates.[15] The concept of bandwagon effect in cryptocurrencies is also supported by academic studies such as those by Nepp and Karpeko (2022), further validating its impact in the context of cryptocurrency markets.

Interpreting innovators' adoption coefficient (α) is more nuanced. An average positive α suggests that, overall, the gap between market potential and current adoption continues to drive further adoption, indicating that innovators still play a role in increasing adoption as long as the market is not fully penetrated. However, a positive α does not necessarily mean that the rate of innovator adoption is increasing over time; rather, it reflects the ongoing influence of innovators when the market is under-penetrated.

[15] https://www.portfolio-institutional.co.uk/news-and-analysis/are-institutional-investors-jumping-on-the-bitcoin-bandwagon/.

Interestingly, for more mature cryptocurrencies, such as BTC, ETH, and LTC, a negative α suggests a different dynamic. This could indicate that these cryptocurrencies have reached a stage where the initial phase of adoption led by innovators has largely concluded, reflecting their relative maturity compared to newer digital assets. In these cases, the role of innovators in driving new adoption may have diminished, signalling a transition to a market where adoption is more influenced by broader market acceptance and network effects rather than the novelty-driven behaviour of early adopters.

To understand this further, we split the lifetime of each cryptocurrency into four distinct periods and estimate the adoption model for each period (Figure A.1 of Online Appendix). Specifically, instead of estimating α and β for each cryptocurrency, we now estimate them for each period. We observe a clear pattern that is consistent with our explanation of the negative α for mature cryptocurrencies. Specifically, during the early periods, α tends to be positive while β is negative. This combination suggests that in the initial stages, adoption is primarily driven by innovators who are motivated by the unique benefits of the cryptocurrency, independent of the actions of others. The negative β indicates that imitation effects or network externalities are either weak or non-existent during this early phase, as early adopters are less influenced by social proof and more by their intrinsic interest in the technology.

As cryptocurrencies transition into later periods, we observe a reversal: α becomes negative while β turns positive. The negative α in these later stages suggests that the role of innovators in driving further adoption has diminished, likely due to the market reaching a higher level of saturation among these early adopters. This shift reflects a transition from an innovation-driven market to one where broader market forces and network effects become more prominent. The positive β observed in these later periods underscores the increasing importance of social proof and network effects in driving adoption. As more users adopt the cryptocurrency, it becomes increasingly attractive for others to follow suit—whether due to informational advantages or bandwagon effects, as discussed above—creating a self-reinforcing cycle of growth that is characteristic of more mature markets.

Estimating the adoption model across different time periods also highlights an important advantage of these models. While generic measures such as trading volume and the number of active addresses offer valuable information about market activity, they fail to reveal the critical transition point when adoption shifts from innovators to late adopters. Adoption models, however, provide a deeper understanding of this transition, offering essential insights into the lifecycle of cryptocurrency adoption that cannot be discerned from basic metrics alone.

4. The asset pricing implications of the adoption model

4.1. Adoption and return predictability

In the first analysis, we link the cryptocurrency users' adoption to future returns using the panel data of 77 cryptocurrencies included in our sample. We estimate two specifications of the return model. First, we use the changes in the number of active addresses as our key explanatory variable. Second, we replace the total adoption measure with the coefficients of innovators and imitators estimated using Eq. (2). This approach allows us to do the horse race between two adoption measures: (i) general adoption measure or (ii) innovators' and imitators' adoptions. Specifically, we estimate the following two multivariate predictive models:

$$Return_{i,m+1} = \theta_i + \mu_m + \gamma_1 \Delta AAddresses_{i,m} + \gamma_2 \sigma_{i,m} + \gamma_3 OIB_{i,m} + \gamma_4 Amihud_{i,m} + \gamma_5 Volume_{i,m} + \gamma_6 Return_{i,m} + \varepsilon_{i,m+1} \quad (3)$$

$$Return_{i,m+1} = \theta_i + \mu_m + \gamma_1\alpha_{i,m} + \gamma_2\beta_{i,m} + \gamma_3\sigma_{i,m} + \gamma_4 OIB_{i,m} + \gamma_5 Amihud_{i,m} + \gamma_6 Volume_{i,m} + \gamma_7 Return_{i,m} + \gamma_8\phi_{i,m} + \varepsilon_{i,m+1} \quad (4)$$

where $Return_{i,m+1}$ is the monthly return for crypto i and month $m+1$, θ_i and μ_m are crypto and month fixed effects. $\sigma_{i,m}$ is the standard deviation of cryptocurrency returns for crypto i and month m, $OIB_{i,m}$ is the order imbalance for crypto i and month m, $Volume_{i,m}$ is an average trading volume for crypto i and month m, and $Amihud_{i,m}$ is the Amihud measure of price impact for crypto i and month m. In addition to these variables, we control for the herding effects in cryptocurrencies by including the lagged values of return ($Return_{i,m}$) and the coefficient of the lagged return ($\phi_{i,m}$) obtained from the adoption model described in Eq. (2). The calculation details of the control variables are provided in Table A2.

The inclusion of control variables in our analysis is motivated by the financial economics literature. Central to traditional asset pricing theories is the risk-return paradigm, with the standard deviation of stock returns serving as a proxy for risk in our framework (Brandt & Kang, 2004). Chordia et al. (2002) show the relationship between order imbalance/volume and stock returns, positing that order imbalances – sourced from informational asymmetries or the costs associated with inventory management – prompt market makers to adjust prices, thereby influencing returns. Liquidity's role in shaping both realized and expected returns is also widely recognized (Amihud, 2002). Furthermore, to account for the serial correlation often observed in asset returns (Lewellen, 2002), we incorporate lagged returns. Tables B1 and B2 in the Online Appendix tabulate the descriptive statistics and the correlation matrix of the variables. Table B3 in the Online Appendix provides the panel unit root test of Im et al. (2003). The Im et al. (2003) test does not require balanced panel datasets and can be employed for fixed N and T. Our findings suggest that all variables employed in the regression models of Eqs. (3) and (4) are stationary.

We standardized all variables to make a valid comparison between the magnitudes of the independent variables. This is particularly important in Eq. (4) because we aim to study the relative return prediction abilities of innovators' and imitators' adoption. The estimation results of Eqs. (3) and (4) are provided in Table 1. For robustness, we estimate Eqs. (3) and (4) with and without liquidity proxies ($Amihud_{i,m}$ and $Volume_{i,m}$). The results are qualitatively identical.

Three important points stand out. First, the results show that our total adoption measure, $\Delta AAddresses_{i,m}$, is not a statistically significant predictor of cryptocurrency returns. Second, when we split the total adoption into innovators' and imitators' adoptions, we find that only the former component is a significant predictor of future return with a t-value of 3.06 (1% significance level). This evidence is also confirmed out-of-sample (OOS), with Section C of the Online Appendix providing a detailed analysis.

This result is consistent with the predictions of product adoption and cryptocurrency literature. First, Bass (1969) and Akhavein et al. (2005), and the references therein suggest that innovators produce and disseminate information about the products. Along this line, we show that innovators' adoption predicts future returns. Second, Cong et al. (2021) and Hackethal et al. (2022) argue that cryptocurrency prices change most during the early adoption stage; our results confirm these studies, too.

Third, our results support the notion of herding effects in cryptocurrency markets (Ballis & Drakos, 2020; King & Koutmos, 2021). We specifically find a significant relationship between past returns, as determined by our adoption model in Eq. (2) ($\phi_{i,m}$), and future returns ($Return_{i,m+1}$). This significant link does not extend to the relationship between future ($Return_{i,m+1}$) and past returns ($Return_{i,m}$) when examined with traditional methods. This leads to two important conclusions: first, that past returns can indeed forecast future market movements as suggested by the herding literature; second, that the herding effect is more accurately identified through the adoption model's past return coefficients, demonstrating the model's capability in reflecting the complex behaviours of the cryptocurrency market better than the conventional methods. Beyond the primary findings, the positive correlation between $Return_{i,m+1}$ and $OIB_{i,m}$ is expected, as higher $OIB_{i,m}$ reflects greater net purchases, which typically leads to an increase in prices (Barucci et al., 2023).

Table 1
The impact of users' adoption on future returns: In-sample evidence.

Variable	$Return_{i,m+1}$	$Return_{i,m+1}$	$Return_{i,m+1}$	$Return_{i,m+1}$
$\Delta AAddresses_{i,m}$	0.013	0.012	–	–
	(1.25)	(1.17)	–	–
$\alpha_{i,m}$	–	–	0.077***	0.069***
	–	–	(3.50)	(3.06)
$\beta_{i,m}$	–	–	0.013	0.005
	–	–	(0.77)	(0.29)
$\sigma_{i,m}$	0.052**	0.038	0.042	0.029
	(2.13)	(1.57)	(1.59)	(1.14)
$OIB_{i,m}$	0.732***	0.716***	0.457***	0.448***
	(8.23)	(7.68)	(10.90)	(10.87)
$Volume_{i,m}$	–	−0.078***	–	−0.069**
	–	(−5.07)	–	(−2.39)
$Amihud_{i,m}$	–	0.111***	–	0.106***
	–	(3.73)	–	(2.67)
$Return_{i,m}$	0.030	0.025	0.030	0.031
	(0.84)	(0.97)	(0.90)	(0.92)
$\phi_{i,m}$	–	–	0.063***	0.061***
	–	–	(3.94)	(3.82)
Crypto FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
R^2	55.44%	56.35%	55.94%	56.79%
N	3008	3008	3008	3008

This table reports the results for the estimation of the impacts of the total, innovators' and late adopters' adoptions on future returns where the sample comprises 77 cryptocurrencies (see Table A1) and spans the period January 1, 2014, to July 31, 2022. All variables are defined in Table A2. All variables are standardized and the standard errors used to compute the t-statistics (in brackets) are double clustered by cryptocurrency and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively.

We also estimate alternative specifications to confirm the robustness of our results. As detailed in Section 2.2, we set the market potential for each cryptocurrency to the maximum value plus three standard deviations of $AAddresses_t$. We then expand this method in two ways. First, we adjust the market potential rates by setting $PAAddresses$ to the maximum value plus two and four standard deviations. Second, we incorporate time variation into $PAAddresses$, calculating a monthly market potential for each cryptocurrency and month at the maximum value plus three standard deviations of $AAddresses_t$. The findings, as reported in Online Appendix Section D, align with our primary results. Additionally, our main sample consists of 77 cryptocurrencies for which we can obtain data. To address the concern that some of these cryptocurrencies may not be liquid enough, we conduct a robustness check by restricting our sample to the 20 most liquid cryptocurrencies. We obtain similar results in this restricted sample (see Online Appendix Section E). Finally, we estimate our innovators' and imitators' coefficients ($\alpha_{i,m}$ and $\beta_{i,m}$) using the MLE approach instead of non-linear least squares, applying these new coefficients in Eqs. (3) and (4). The results reported in the Online Appendix Section F are in line with our main specification.

The results obtained in this section have important implications for the OR and finance literature, particularly in studies exploring the role of user adoption in cryptocurrency markets and the predictors of cryptocurrency prices. For instance, using machine learning techniques to predict cryptocurrency prices is common in the OR literature (e.g., Atsalakis et al., 2019). We demonstrate that autocorrelation in cryptocurrency returns and herding behaviours in cryptocurrency markets are more effectively captured using the adoption model, and hence, research aiming to predict cryptocurrency prices should increasingly use adoption models. More broadly, we find that the general adoption measures often used in the cryptocurrency literature are limited in terms of the scope of the insights they offer. A better alternative is decomposing users' adoption into early and late adoption components and studying their relative impacts on the cryptocurrency markets. This is crucial for cryptocurrency pricing, as theory suggests that the explanatory power of user adoption may vary by adoption stage (Cong et al., 2021); we formally test this in Section 4.2.

4.2. Asset pricing implications: cross-sectional evidence

In this section, we examine the asset pricing implications of the total, innovators', and imitators' adoption factors in explaining cross-sectional differences in cryptocurrency returns. Our first hypothesis posits that portfolios with high exposure to total adoption should not yield higher returns than those with lower exposure because, based on the results provided in the previous section, total adoption is a noisy proxy of transactional demand. On the other hand, Cong et al. (2021) emphasize that users' adoption impacts cryptocurrency prices most during the early adoption stage, and Hackethal et al. (2022) underline that early adopters are more prone to investing in high-risk products. Consistent with these papers, we also find that our innovators' adoption measure (denoted α) is a significant factor in explaining changes in future cryptocurrency prices. Hence, we posit that the innovators' adoption (α) should capture a significant consideration of demand for transactions, and investors will demand a premium for holding cryptocurrencies with high α. Therefore, our second hypothesis expects the α portfolio, which is the high minus low portfolio with exposure to innovators' adoption, to deliver significantly positive returns on average. Conversely, imitators' adoption (β) reflects exposure to lower early transactional demand and is unrelated to future unrealized returns, suggesting that investors receive no additional compensation for holding cryptocurrencies exposed to β.

To this end, we form tercile portfolios based on the total adoption, α and β at the beginning of the month and calculate the equally weighted return of the top and bottom 30 percent portfolios of cryptocurrencies at the end of the month. We base our analysis on monthly data covering the period from January 2014 to July 2022. The cryptocurrency monthly returns are constructed from daily prices. Table 2 presents the portfolio sorting results. For benchmarking purposes, we also form portfolios based on the size (market capitalization of the last day of the previous month) and momentum (the past one month's return). Liu et al. (2022) have shown that, taken together, the value-weighted cryptocurrency market, size, and momentum factors can summarize the cross-sectional variations in cryptocurrency returns. We calculate the return of the cryptocurrency market factor as the capitalization-weighted return of the 77 cryptocurrencies, rebalanced monthly. Finally, all cryptocurrency returns are in excess returns defined as the difference between the cryptocurrency return and the one-month Treasury bill rate (r_f) sourced from Kenneth R. French Data Library.

Consistent with our first hypothesis, the low and high total adoption portfolios achieved premia of 13.04% (statistically significant at the 10% level) and 18.30% (statistically significant at the 1% level), respectively, but a long–short portfolio, taking a long position in the high total adoption portfolio and a short position in the low one, yields a statistically insignificant average return of 8.06% per month. In addition, we do not document monotonic cross-sectional patterns across portfolios when we sort the cryptocurrencies by total adoption. The above evidence suggests that total adoption is a noisy variable. This is plausible as Cong et al. (2021) also show that the users' adoption affects price significantly during the early adoption stage; it is, therefore, vital to distinguish between adoption stages.

In line with our second hypothesis, we observe monotonic cross-sectional patterns across portfolios when we sort the cryptocurrencies by the innovators' adoption (α). Panel C shows that the low, medium

Table 2
Cryptocurrency factor portfolios.

	AVG	SD	SKEW	KURT
	Panel A. Value weight market portfolio			
	6.03%	24.80%	−0.719	0.803
	Panel B. Total adoption			
Low	13.04% *	70.42%	6.130	49.051
Medium	22.38% ***	79.59%	4.390	25.488
High	18.30%***	57.86%	2.044	4.747
Long short (High-Low)	8.06%	57.87%	−2.432	23.444
	Panel C. Innovators' adoption α			
Low	9.60% **	43.97%	1.881	4.863
Medium	15.98% ***	55.66%	2.932	11.979
High	27.80%**	111.19%	5.306	32.957
Long short (High-Low)	18.20%**	96.85%	5.407	38.737
	Panel D. Imitators' adoption β			
Low	35.00%***	125.73%	4.495	22.865
Medium	7.91%*	34.71%	1.387	3.187
High	18.01%**	68.51%	3.186	14.027
Long short (High-Low)	−16.99%	110.33%	−4.644	29.395
	Panel E. Momentum			
Low	10.21% **	39.64%	1.998	8.136
Medium	13.22% **	50.54%	2.348	6.558
High	27.56% ***	95.25%	4.513	25.059
Long short (High-Low)	17.35%**	78.45%	5.704	40.635
	Panel F. Size			
Low	42.14% ***	130.69%	3.942	17.126
Medium	9.94% *	43.67%	1.609	3.476
High	9.15% **	35.92%	1.672	3.511
Long short (Low-High)	32.98% ***	112.65%	4.080	17.760

This table presents the descriptive statistics for the period January 2014–July 2022 of the cryptocurrency market portfolio (Panel A) and the cryptocurrency factor portfolios of the low, medium, high and long–short with exposure to total adoption (Panel B), innovators' adoption α (Panel C), imitators' adoption β (Panel D), momentum (Panel E) and size (Panel F). The low, medium and high cryptocurrency portfolio returns are returns of equally weighted portfolios of the bottom 30 percent and top 30 percent of the cryptocurrencies we have in our sample. All cryptocurrency returns are in excess returns, defined as the difference between the cryptocurrency return and the one-month Treasury bill rate. The mean (AVG), standard deviation (SD), Skewness (SKEW) and Kurtosis (KURT) are on a monthly basis. We test the statistical significance of the mean portfolio excess returns using Newey and West (1987) standard errors. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively.

and high α portfolios achieved premia in excess of 9.60% (statistically significant at the 5% level), 15.98% (statistically significant at the 1% level) and 27.80% (statistically significant at the 5% level), respectively. A portfolio that takes a long position in the high α portfolio and a short position in the bottom one yields an average return of 18.20% per month, statistically significant at the 5% level.

In contrast, we do not observe cross-sectional patterns when we sort the cryptocurrencies by imitators' adoption (β). Panel D shows that the monthly average excess return for the low, medium and high β portfolios are equal to 35.00% (statistically significant at the 1% level), 7.91% (statistically significant at the 10% level) and 18.01% (statistically significant at the 5% level), respectively. A portfolio that buys the high β group and sells the low β one gives a statistically insignificant negative premium of −16.99% per month. Therefore, our results are in line with the suggested hypotheses. Finally, consistent with the cryptocurrencies asset pricing literature (Liu & Tsyvinski, 2021; Liu et al., 2022), we observe statistically and economically significant momentum and size premia (see Panels D and E, respectively). The long–short size portfolio (32.98%) achieved the highest premia, followed by the α portfolio (18.20%), and the β portfolio exhibits the highest volatility amongst the long–short cryptocurrency portfolios.

Correlation comparisons amongst the cryptocurrency long–short factors (Table G1 of Online Appendix) show that over our sample period, the cryptocurrency total adoption factor is negatively correlated

Table 3
Sources of risk of the α premium.

	$R_{\alpha,t}$
Constant	−0.023
	(−0.537)
$R_{M,t} - r_{f,t}$	0.432
	(1.428)
$R_{SIZE,t}$	0.820***
	(3.144)
$R_{MOM,t}$	−0.527**
	(−2.035)
R-squared	61.07%

This table reports the results from the estimation of Eq. (6). R_α denotes the return on the long–short α portfolio, R_M the return on the value weighted cryptocurrency market portfolio, R_{SIZE} the return on the long–short size portfolio, R_{MOM} the return on the long–short momentum portfolio and r_f the risk free rate. t-statistics are calculated using Newey and West (1987) standard errors and are shown in parenthesis. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively.

with the α factor (correlation = −0.317) and very low correlated β factor (correlation = 0.115). In addition, the correlation between the cryptocurrency α and β factor portfolios are negatively correlated (−0.739). Interestingly, α and size factor premia exhibit a high correlation (0.710), whilst the correlation between the total adoption with size portfolio is low (−0.173). Finally, α portfolio possess low correlation with momentum, i.e., 0.237 and β portfolio is negatively correlated with momentum, i.e., −0.488, respectively, whilst the correlation of the total adoption factor with momentum is equal to −0.170.

Our analysis so far suggests that a cryptocurrency long–short portfolio with exposure to the innovators' adoption (α) warrants a positive and sizable risk premium, whilst a cryptocurrency long–short portfolio with exposure to the total adoption and the imitators' adoption (β) does not achieve a statistically significant premium, while in the latter portfolio the premium is negative. What are the sources of risk that underlie this α premium? To answer this question, we regress the α factor against the three cryptocurrency factors proposed by Liu et al. (2022), i.e. the value-weighted cryptocurrency market, the size and the momentum cryptocurrency long–short portfolios, as follows:

$$R_{\alpha,t} = \delta_0 + \delta_1(R_{M,t} - r_{f,t}) + \delta_2 R_{SIZE,t} + \delta_3 R_{MOM,t} + e_t \tag{5}$$

where R_α denotes the return on the long–short α portfolio, R_M the return on the value weighted cryptocurrency market portfolio, R_{SIZE} the return on the long–short size portfolio, R_{MOM} the return on the long–short momentum portfolio and r_f the risk free rate. Table 3 tabulates the results. The model suggests that the α factor has a statistically insignificant $\hat{\delta}_0$ of −0.023, an insignificant $\hat{\delta}_1$ of 0.432 against the value-weighted cryptocurrency portfolio, and a significant exposure ($\hat{\delta}_2$) of 0.820 (t-statistic 3.144) to the size long–short cryptocurrency portfolio. Moreover, a statistically significant (at 5% level) and negative exposure ($\hat{\delta}_3$) of −0.527 to the momentum long–short cryptocurrency factor. This model explains 61.07% of the total variance of the return of the innovation measure (α) portfolio.

Thus, the innovators' (α) portfolio loads positively and statistically significant at the 1% significance level on the size factor, consistent with our earlier finding on the high correlation between the α and size portfolios. This implies that the α and size factors capture a very similar variation. This is an indeed interesting and important finding and corroborates with the study by Liu et al. (2022), which posits that the size premium is related to the trade-off between capital profits and convenience yield. This trade-off suggests that larger and more mature cryptocurrencies demonstrate larger convenience yield at the expense of lower capital gains (Cong et al., 2021; Sockin & Wei, 2023). Hence the cryptocurrency size premium should be larger when demand from transactions is high, with Liu et al. (2022) to empirically confirm this. The association of the high (low) innovators' adoption portfolio with increased (decreased) transactional demand supports the positive association of innovator's adoption premium with the size premium in the cryptocurrency market. Further, the innovators' (α) portfolio loads negatively and statistically significant at the 5% significance level on the momentum factor. Finally, our regression analysis shows that in the cryptocurrency universe, our innovators' adoption factor is subsumed by the size factor (the intercept in the regression is statistically insignificant), suggesting that innovators' adoption and size capture similar information.

We also study the nature of the total adoption, α and β portfolios by analysing the composition of the long and short legs of each portfolio. To this end, we calculate the number of months in which each cryptocurrency enters the long and short portfolios of the long–short total adoption, α and β factors. Table H1 of Online Appendix tabulates the results where we see in Panel A, certain cryptocurrencies tend to be in the high or low portfolio a lot of the time. For instance, Dogecoin (DOGE) is in the low total adoption portfolio 41.18% of the time, while it is also in the higher portfolio 40.20% of the time, while DASH is in the low (high) portfolio 47.06% (35.29%) of the time. The evidence above suggests that these coins face large changes in their usage over time. In Panel B, we see that the largest and generally earliest and more mature cryptocurrencies, such as Bitcoin (BTC) and Ethereum (ETH), are in the low α portfolio most of the time; ETH (BTC) is in the low α portfolio 77.50% (70%) of the time. The latter evidence is consistent with Cong et al. (2021) and Sockin and Wei (2023) who show that in equilibrium the convenience yield (capital gain) of the larger and more mature cryptocurrencies is higher (lower). Conversely, younger and more speculative cryptocurrencies, such as GNO and VGX, are found consistently in the high α portfolio. In Panel C, we document that no cryptocurrency is in the low β portfolio more than 40% of the time, indicating the large variation in the composition of the portfolios over time. For the high portfolio, we find that Ethereum (ETH) is in the high portfolio 33% of the time, which is probably due to the smart contract capabilities of the Ethereum blockchain and the many other layer 2 cryptocurrencies that use the Ethereum blockchain to run on. Therefore the constituents of each portfolio make theoretical sense and support our earlier arguments.

We conclude our analysis by examining the cross-sectional predictability of total adoption, innovators' adoption α and imitators' adoption β on the cryptocurrency returns, by extending the holding period from 1 month analysed in Table 2, to 3, 6, 9 and 12 months ahead.[16] Panels A, B and C of Table I1 of Online Appendix present the performance of the low, medium, high and long–short (high-low) total adoption, innovators' adoption α and imitators' adoption β portfolios, respectively. Two important points stand out. First, we document that total adoption premia render negative from the 3-month holding period onwards (apart from the 9-month period), while imitators' adoption premia remain negative across all holding periods. Second, we find that innovators' adoption effect fades away in the more extended holding periods. In particular, the effect is concentrated in short and medium term holding periods, namely 1, 3, 6 and 9 months, with innovators' adoption premia be statistically and economically significant in the 1- and 3-month holding periods, equal to 18.20% and 15.33%, respectively. In the 6- and 9-month holding periods, the premia are equal to 10.68% and 4.32%, albeit statistically insignificant. In the 12-month period innovators' adoption premia fade away.

To explain this result, consider two cryptocurrencies: A and B. At a given point in time, cryptocurrency A has a high level of innovation adoption, while cryptocurrency B has a low level. Our findings indicate that an investor who takes a long position in A and a short position in B can earn a statistically and economically significant profit over the subsequent three months. However, this profit opportunity dissipates after the three-month period. This observation is plausible due to the

[16] Thanks to the anonymous referee for this suggestion.

diminishing difference in innovation adoption between A and B over time. More specifically, as cryptocurrency A initiates the process with a high level of innovation, the magnitude of its innovation adoption decelerates. Conversely, cryptocurrency B commences with a low level of innovation, leading to an increasing number of innovators adopting it, thus accelerating the magnitude of its innovation adoption. This process gradually reduces the disparity in innovation adoption between A and B. Consequently, while the long position in A and short position in B generate a significant difference in the dynamics of innovation adoption between the two cryptocurrencies at the beginning of the process, this difference diminishes over time, resulting in a corresponding decrease in the returns generated by the long–short position. A similar pattern is observed in stocks, with Ang and Bekaert (2007) showing that return predictability is concentrated at short horizons.

5. Market microstructure implications of the adoption model

Thus far, we have investigated and tested the impact of innovators' and imitators' adoption on cryptocurrency pricing. Our results show that early adopters significantly contribute to explaining cross-sectional variations in cryptocurrency prices. In this section, we turn our attention to applying the adoption model within the context of market microstructure. The discussion in this section focuses on the informational differences between innovators and imitators, with a particular focus on the premise that innovators are generally more informed traders than imitators.

This is plausible because, as discussed in Section 2.1, the key distinction between innovators and late adopters is that innovators' adoption decisions are based on superior information, while late adopters are followers who rely on information sourced from innovators (Bass, 1969). Interestingly, these characteristics align innovators and late adopters with informed and uninformed traders, respectively. However, it is important to note that cryptocurrency markets lack private information, so this analogy should be interpreted with caution. Specifically, in the standard market microstructure literature (Glosten & Milgrom, 1985; Kyle, 1985), informed traders possess superior *private* information about firms' fundamentals, which is not applicable in the context of cryptocurrency markets. Instead, in these markets, traders with a deeper understanding of the underlying technology may have more *public* information than those without this expertise. Therefore, our information analogy here is more akin to high-frequency trading (HFT) in financial markets. The relevant literature suggests that HFTs typically trade less on private information and instead leverage their skills to interpret public information more effectively and quickly than slower traders, often engaging in "latency arbitrage" (Aquilina et al., 2022; Nimalendran et al., 2024; Rzayev & Ibikunle, 2019). Hence, our definition of informed trading aligns more closely with traders who possess superior skills in interpreting public information, while uninformed traders are those who derive less benefit from public information due to their technological disadvantages.

The results provided in Section 4.1 offer us initial insights about the plausibility of relating the innovators and late adopters coefficients to informed and uninformed traders. Thus, we first want to briefly discuss the findings described in Section 4.1 in the market microstructure context. According to Kyle (1985), stock prices reflect information gradually due to informed traders' strategic behaviour. The study shows that informed traders tend to hide their private information and trade in such a way that their private information is not incorporated into prices very quickly. This allows them to maximize their profit. Glosten and Milgrom (1985) also show that it takes time for private information to be revealed after the trade. This strategic behaviour of informed traders allows them to predict the direction of future price changes. Interestingly, Brogaard et al. (2014) and Hirschey (2021) show that while HFTs primarily trade on public information, their technological advantages allow them to predict order flows and, consequently, future price changes, much like the informed traders described in Glosten and Milgrom (1985) and Kyle (1985).

The main implication of the above discussion for our study is that if innovators coefficient estimated by using Eq. (2) indeed related to informed trading, then it should be significantly associated with the future return. Consistent with this, the results depicted in Table 1 document a statistically significant association between innovators adoption and future return. On the other hand, the effect of late adopters on future return is not statistically significant, which also confirms our argumentation.

While these initial findings offer valuable insights, they are not conclusive. To further explore the potential correlation between innovators and informed traders, as well as imitators and uninformed traders, we conduct an additional, more direct test. Specifically, we study the relationship between innovators/late adopters and volatility. Stock return volatility (price discovery) is driven by two factors: information and noise (Brogaard et al., 2014). Hellwig (1980) and Wang (1993) show that informed trading is significantly related to future return volatility. This is because stock price reflects the information content of informed traders' order flow. Additionally, Collin-Dufresne and Fos (2016) and Daigler and Wiley (1999) find that uninformed traders also increase volatility by inducing noise in the price discovery process. Consistent with this, Brogaard et al. (2014) demonstrate that traders with superior technological capabilities, such as HFTs, increase information-driven price discovery even when trading on public information, whereas traders with less technological capacity tend to introduce noise into prices. This implies we can directly test the empirical relevance of the adoption model to decompose the adoption process into informed and uninformed users by investigating the association between innovators/late adopters coefficients and information/noise components of volatility. We expect to see the positive effects of innovators' (imitators) adoption on the information (noise) component of price discovery. We estimate the following three models to test this prediction:

$$\sigma_{i,m+1} = \theta_i + \mu_m + \gamma_1\alpha_{i,m} + \gamma_2\beta_{i,m} + \gamma_3 OIB_{i,m} + \gamma_4 Amihud_{i,m} + \gamma_5 Volume_{i,m} + \gamma_6 Return_{i,m} + \gamma_7\phi_{i,m} + \varepsilon_{i,m+1} \quad (6)$$

$$\sigma^{EPD}_{i,m+1} = \theta_i + \mu_m + \gamma_1\alpha_{i,m} + \gamma_2\beta_{i,m} + \gamma_3 OIB_{i,m} + \gamma_4 Amihud_{i,m} + \gamma_5 Volume_{i,m} + \gamma_6 Return_{i,m} + \gamma_7\phi_{i,m} + \varepsilon_{i,m+1} \quad (7)$$

$$\sigma^{NPD}_{i,m+1} = \theta_i + \mu_m + \gamma_1\alpha_{i,m} + \gamma_2\beta_{i,m} + \gamma_3 OIB_{i,m} + \gamma_4 Amihud_{i,m} + \gamma_5 Volume_{i,m} + \gamma_6 Return_{i,m} + \gamma_7\phi_{i,m} + \varepsilon_{i,m+1} \quad (8)$$

where $\sigma_{i,m+1}$ is the standard deviation of cryptocurrency returns and our measure of volatility, $\sigma^{EPD}_{i,m+1}$ and $\sigma^{NPD}_{i,m+1}$ are information- (efficient price discovery) and noise-driven (noise price discovery) components of volatility estimated by using the state-space modelling approach described in Hendershott and Menkveld (2014) and Menkveld et al. (2007).[17] All other variables are as defined previously.

The estimated coefficients are reported in Table 4. Two results stand out. First, we find that both innovator and late adopter components are positively and statistically significantly (1% and 5% levels, respectively) related to volatility. This result is consistent with our argument

[17] We employ the state-space modelling approach because it is a more efficient way of variable decomposition due to two reasons. First, the mechanism behind the state-space modelling approach, Kalman filtering, allows for dealing with missing values. Second, Kalman smoother updates estimations based on every additional observation. Further details of the state-space modelling approach are discussed in Menkveld et al. (2007).

that volatility is driven by both groups of adopters. Second, we document that innovators' adoption coefficient is positively and statistically significantly related (at 1% level) to efficient price discovery, while late adopters offer no explanatory power for this component of the price discovery. Moreover, we detect that the late adopters' adoption process significantly determines future noise price discovery at 10% level. These results imply that stock prices reflect information brought by innovators; this indicates that the innovators component of our adoption model captures information trading activity. Furthermore, our findings suggest that late adopters induce noise into the price discovery process, which is in line with the effects of uninformed trading on price discovery. Thus, these findings validates our argument that our adoption model may indeed also be used to decompose total cryptocurrency adoption into informed and uninformed components.

This result has important academic and practical implications. The most important implication of the findings discussed in this section is that the impact of users' adoption on cryptocurrency asset pricing may be explained by the fact that innovators' adoption has higher information content. Investigating this question further may be useful in linking the cryptocurrency pricing factors to the information risk factor offered in the market microstructure literature (Easley et al., 2002; Easley & O'Hara, 2004). Moreover, our results suggest that investigating the association between adoption and price volatility using generic measures of total adoption (such as trading volume) and total volatility (such as standard deviation of stock returns) is a limited approach in a cryptocurrency setting. A more comprehensive approach is decomposing volatility info efficient and noise price discoveries and the adoption into innovators' and late adopters' adoption dynamics.

The practical implication of this result is that it highlights the importance of understanding technological updates. The introduction of more investors with the capacity to follow, understand and use technological updates in their adoption decisions may make cryptocurrency markets more efficient. Institutional investors are traders with this capacity. Hence, recent interests of institutional traders in these markets may increase price efficiency and may have long-term positive effects on cryptocurrency markets.[18] From an academic perspective, the results described in this section suggest that the implications of using the formal product adoption model, such as described in Eq. (2), are not limited to the asset pricing context only. It offers us significant insights into informed and uninformed users' adoption and hence, also has market microstructure implications.

Table 4
The impact of innovators and late adopters on volatility and price discovery.

Variable	$\sigma_{i,m+1}$	$\sigma^{EPD}_{i,m+1}$	$\sigma^{NPD}_{i,m+1}$
$\alpha_{i,m}$	0.079***	0.084***	−0.004
	(3.57)	(3.53)	(−0.21)
$\beta_{i,m}$	0.035**	0.009	0.039*
	(2.03)	(0.51)	(1.92)
$OIB_{i,m}$	0.132**	0.156***	−0.017
	(7.86)	(8.50)	(−0.87)
$Volume_{i,m}$	−0.055**	−0.061**	0.035
	(−2.35)	(−2.40)	(1.31)
$Amihud_{i,m}$	0.111***	0.040*	0.081***
	(5.93)	(1.92)	(3.69)
$Return_{i,m}$	0.124***	0.114***	0.061***
	(7.10)	(5.94)	(3.02)
$\phi_{i,m}$	0.059***	0.064***	−0.031**
	(4.46)	(4.44)	(−2.02)
Crypto FEs	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes
R^2	56.86%	48.29%	41.63%
N	3008	3008	3008

This table reports the results for the estimation of the impacts of innovators and late adopters on aggregate volatility and the efficient and noise components of price discovery where the sample comprises 77 cryptocurrencies (see Table A1) and spans the period January 1, 2014, to July 31, 2022. All variables are defined in Table A2. All variables are standardized and the standard errors used to compute the t-statistics (in brackets) are double clustered by cryptocurrency and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively.

6. Conclusion

Business studies and OR literature document that, in addition to the magnitude of users' adoption, the timing of the adoption matters for the success of innovations. Given that cryptocurrencies are highly innovative products in the financial ecosystem, we examine whether the timing of adoption matters in the effects of users' adoption in cryptocurrency markets. By decomposing the total users' adoption into innovators (early adopters) and imitators (late adopters) components using the product adoption model developed in the business studies literature, we first show that the adoption mechanism of cryptocurrencies is consistent with other innovative products' adoptions.

In the second test, we examine the link between total, innovators', and imitators' adoption and cryptocurrency prices. Our results show that only innovators' adoption is associated with future realized and expected returns. A long–short portfolio with exposure to innovators' adoption earns a positive and sizable risk premium, aligning with Cong et al. (2021), who find that adoption affects prices most in early stages. We also find that the innovators' adoption premium is positively associated with the cryptocurrency size premium. This is in line with the empirical evidence in Liu et al. (2022) that small and less mature cryptocurrencies exhibit higher returns when transactional demand is high since our proposed high (low) innovators' adoption portfolio is associated with increased (decreased) demand from transactions.

We also test the market microstructure implications of the adoption model. Drawing from innovation adoption literature, we argue that innovators' adoption is linked to informed traders who better utilize public information due to their understanding of the technology, while late adopters are associated with uninformed traders. To test this, we examine the relationship between innovators' and imitators' adoption and market volatility. Using state-space modelling, we decompose volatility into information- and noise-driven components, showing that innovators improve price efficiency, while late adopters add to price noise. These results, while warranting cautious interpretation due to the differences between informed trading in equity and cryptocurrency markets, align with our expectations and suggest that product adoption models can be meaningfully explored within the market microstructure context.

Our study provides important insights into cryptocurrency markets, with significant implications for both finance and OR literature. First, we demonstrate that adoption models capture key phenomena such as price information and herding behaviour more effectively than traditional methods, suggesting their valuable use in investment decisions and portfolio optimization. We provide a detailed example in Online Appendix J that demonstrates the development of trading strategies based on early versus late adoption patterns. Second, we highlight the critical role of innovators' adoption in determining cryptocurrency prices, underscoring its importance for the success of new cryptocurrencies—particularly relevant given the high failure rate of many, which represents a loss of global welfare. Third, our findings suggest that adoption by technologically advanced traders, like institutional investors, can enhance market efficiency, offering guidance to cryptocurrency developers and market participants on attracting sophisticated traders. Fourth, we show that innovators' adoption provides a more accurate measure of transactional demand than total adoption, improving the precision of price prediction models. Finally, our insights on the roles of early and late adopters in market efficiency and operational success can inform the design and management of decentralized

[18] https://www.forbes.com/sites/ninabambysheva/2022/05/25/jpmorgan-says-bitcoin-is-undervalued-by-28-says-cryptocurrencies-are-now-its-preferred-alternative-asset/.

systems, such as blockchain-based supply chains and peer-to-peer energy markets, where operational researchers can develop strategies to optimize system performance and resilience.

CRediT authorship contribution statement

Khaladdin Rzayev: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Athanasios Sakkas:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Andrew Urquhart:** Writing – review & editing, Writing – original draft, Data curation, Conceptualization.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ejor.2024.11.024.

References

Abrahamson, E., & Bartner, L. R. (1990). When do bandwagon diffusions roll? How far do they go? and When do they roll backwards?: A computer simulation. *Vol. 1990*, In *Academy of management proceedings* (pp. 155–159). Academy of Management Briarcliff Manor, NY 10510.

Adkins, L. C. (2022). Weak identification in nonlinear econometric models. *Southern University College of Business E-Journal*, *17*(3), 2.

Adkins, L. C., Waters, M. S., & Hill, R. C. (2015). Collinearity diagnostics in gretl. *Economics Working Paper Series*, *1506*, 1–28.

Akhavein, J., Frame, W. S., & White, L. J. (2005). The diffusion of financial innovations: An examination of the adoption of small business credit scoring by large banking organizations. *Journal of Business*, *78*(2), 577–596.

Akyildirim, E., Cepni, O., Corbet, S., & Uddin, G. S. (2023). Forecasting mid-price movement of bitcoin futures using machine learning. *Annals of Operations Research*, *330*(1), 553–584.

Alexander, C., & Heck, D. F. (2020). Price discovery in bitcoin: The impact of unregulated markets. *Journal of Financial Stability*, *50*, Article 100776.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56.

Ang, A., & Bekaert, G. (2007). Stock return predictability: Is it there? *The Review of Financial Studies*, *20*(3), 651–707.

Aquilina, M., Budish, E., & O'neill, P. (2022). Quantifying the high-frequency trading "arms race". *Quarterly Journal of Economics*, *137*(1), 493–564.

Atsalakis, G. S., Atsalaki, I. G., Pasiouras, F., & Zopounidis, C. (2019). Bitcoin price forecasting with neuro-fuzzy techniques. *European Journal of Operational Research*, *276*(2), 770–780.

Ballis, A., & Drakos, K. (2020). Testing for herding in the cryptocurrency market. *Finance Research Letters*, *33*, Article 101210.

Barucci, E., Giuffra Moncayo, G., & Marazzina, D. (2023). Market impact and efficiency in cryptoassets markets. *Digital Finance*, *5*(3), 519–562.

Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science*, *15*(5), 215–227.

Belsley, D. A., Kuh, E., & Welsch, R. E. (2005). *Regression diagnostics: Identifying influential data and sources of collinearity*. John Wiley & Sons.

Bhambhwani, S. M., Delikouras, S., & Korniotis, G. M. (2023). Blockchain characteristics and cryptocurrency returns. *Journal of International Financial Markets, Institutions and Money*, *86*, Article 101788, URL https://www.sciencedirect.com/science/article/pii/S1042443123000562.

Bhimani, A., Hausken, K., & Arif, S. (2022). Do national development factors affect cryptocurrency adoption? *Technological Forecasting and Social Change*, *181*, Article 121739, URL https://www.sciencedirect.com/science/article/pii/S0040162522002657.

Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., & Menkveld, A. J. (2023). Equilibrium bitcoin pricing. *The Journal of Finance*, *78*(2), 967–1014.

Bianchi, D., & Babiak, M. (2022). On the performance of cryptocurrency funds. *Journal of Banking & Finance*, *138*, Article 106467.

Bianchi, D., Babiak, M., & Dickerson, A. (2022). Trading volume and liquidity provision in cryptocurrency markets. *Journal of Banking & Finance*, *142*, Article 106547.

Brandt, M. W., & Kang, Q. (2004). On the relationship between the conditional mean and volatility of stock returns: A latent VAR approach. *Journal of Financial Economics*, *72*(2), 217–257.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *The Review of Financial Studies*, *27*(8), 2267–2306.

Chau, P. Y., & Hui, K. L. (1998). Identifying early adopters of new IT products: A case of windows 95. *Information and Management*, *33*(5), 225–230.

Chordia, T., Roll, R., & Subrahmanyam, A. (2002). Order imbalance, liquidity, and market returns. *Journal of Financial Economics*, *65*(1), 111–130.

Collin-Dufresne, P., & Fos, V. (2016). Insider trading, stochastic liquidity, and equilibrium prices. *Econometrica*, *84*(4), 1441–1475.

Cong, L., Karolyi, G. A., Tang, K., & Zhao, W. (2022). Value premium, network adoption, and factor pricing of crypto assets. Available at SSRN: https://ssrn.com/abstract=3985631.

Cong, L. W., Li, Y., & Wang, N. (2021). Tokenomics: Dynamic adoption and valuation. *The Review of Financial Studies*, *34*, 1105–1155.

Daigler, R. T., & Wiley, M. K. (1999). The impact of trader type on the futures volatility-volume relation. *The Journal of Finance*, *54*(6), 2297–2316.

de Bondt, G., & Ibáñez, D. M. (2005). High-yield bond diffusion in the United States, the United Kingdom, and the euro area. *Journal of Financial Services Research*, *27*(2), 163–181.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703–738.

Dionysopoulos, L., Marra, M., & Urquhart, A. (2024). What drives stablecoin growth? Available at SSRN: https://ssrn.com/abstract=4791530.

Dobrynskaya, V. (2023). Cryptocurrency momentum and reversal. *The Journal of Alternative Investments, Summer*, *26*(1), 65–76.

Easingwood, C. J., Mahajan, V., & Muller, E. (1983). A nonuniform influence innovation diffusion model of new product acceptance. *Marketing Science*, *2*(3), 273–295.

Easley, D., Hvidkjaer, S., & O'hara, M. (2002). Is information risk a determinant of asset returns? *The Journal of Finance*, *57*(5), 2185–2221.

Easley, D., López de Prado, M. M., & O'Hara, M. (2012). Flow toxicity and liquidity in a high-frequency world. *The Review of Financial Studies*, *25*(5), 1457–1493.

Easley, D., & O'Hara, M. (2004). Information and the cost of capital. *The Journal of Finance*, *59*(4), 1553–1583.

Entrop, O., Frijns, B., & Seruset, M. (2020). The determinants of price discovery on bitcoin markets. *Journal of Futures Markets*, *40*(5), 816–837.

Farrell, J., & Saloner, G. (1985). Standardization, compatibility, and innovation. *The RAND Journal of Economics*, 70–83.

Fieberg, C., Liedtke, G., Poddig, T., Walker, T., & Zaremba, A. (2024). A trend factor for the cross-section of cryptocurrency returns. *Journal of Financial and Quantitative Analysis*, forthcoming.

Filippou, I., Rapach, D., & Thimsen, C. (2022). Cryptocurrency return prediction: A machine-learning analysis. Available at SSRN: https://ssrn.com/abstract=3914414.

Frame, W. S., & White, L. J. (2004). Empirical studies of financial innovation: lots of talk, little action? *Journal of Economic Literature*, *42*(1), 116–144.

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, *14*(1), 71–100.

Hackethal, A., Hanspal, T., Lammer, D. M., & Rink, K. (2022). The characteristics and portfolio behavior of bitcoin investors: evidence from indirect cryptocurrency investments. *Review of Finance*, *26*(4), 855–898.

Hellwig, M. F. (1980). On the aggregation of information in competitive markets. *Journal of Economic Theory*, *22*(3), 477–498.

Hendershott, T., & Menkveld, A. J. (2014). Price pressures. *Journal of Financial Economics*, *114*(3), 405–423.

Hirschey, N. (2021). Do high-frequency traders anticipate buying and selling pressure? *Management Science*, *67*(6), 3321–3345.

Hung, J.-C., Liu, H.-C., & Yang, J. J. (2021). Trading activity and price discovery in bitcoin futures markets. *Journal of Empirical Finance*, *62*, 107–120.

Ibikunle, G. (2018). Trading places: Price leadership and the competition for order flow. *Journal of Empirical Finance*, *49*, 178–200.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53–74.

Jain, D. C., & Rao, R. C. (1990). Effect of price on the demand for durables: Modeling, estimation, and findings. *Journal of Business & Economic Statistics*, *8*(2), 163–170.

Jiang, S., Li, Y., wang, S., & Zhao, L. (2022). Blockchain competition: The tradeoff between platform stability and efficiency. *European Journal of Operational Research*, *296*, 1084–1097.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, *75*(3), 424–440.

King, T., & Koutmos, D. (2021). Herding and feedback trading in cryptocurrency markets. *Annals of Operations Research*, *300*, 79–96.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, 1315–1335.

Lewellen, J. (2002). Momentum and autocorrelation in stock returns. *The Review of Financial Studies*, *15*(2), 533–564.

Lindner, T., Puck, J., & Verbeke, A. (2020). Misconceptions about multicollinearity in international business research: Identification, consequences, and remedies. *Journal of International Business Studies*, *51*, 283–298.

Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, *34*, 2689–2727.

Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, *77*, 1133–1177.

Lynn, T., Muzellec, L., Caemmerer, B., & Turley, D. (2017). Social network sites: early adopters' personality and influence. *Journal of Product & Brand Management*, *26*, 42–51.

Mahajan, V., Muller, E., & Bass, F. M. (1990). New product diffusion models in marketing: A review and directions for research. *Journal of Marketing*, *54*(1), 1–26.

Mahajan, V., & Sharma, S. (1986). A simple algebraic estimation procedure for innovation diffusion models of new product acceptance. *Technological Forecasting and Social Change*, *30*(4), 331–345.

Mansfield, E. (1961). Technical change and the rate of imitation. *Econometrica*, *29*, 741–766.

Meade, N., & Islam, T. (1995). Forecasting with growth curves: An empirical comparison. *International Journal of Forecasting*, *11*(2), 199–215.

Menkveld, A. J., Koopman, S. J., & Lucas, A. (2007). Modeling around-the-clock price discovery for cross-listed stocks using state space methods. *Journal of Business & Economic Statistics*, *25*(2), 213–225.

Molyneux, P., & Shamroukh, N. (1996). Diffusion of financial innovations: The case of junk bonds and note issuance facilities. *Journal of Money, Credit and Banking*, *28*(3), 502–522.

Naoum-Sawaya, J., Elhedhli, S., & De Carvalho, P. (2023). Strategic blockchain adoption to deter deceptive counterfeiters. *European Journal of Operational Research*, *311*, 373–386.

Nepp, A., & Karpeko, F. (2022). Hype as a factor on the global market: The case of bitcoin. *Journal of Behavioral Finance*, 1–14.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*, 703–708.

Nimalendran, M., Rzayev, K., & Sagade, S. (2024). High-frequency trading in the stock market and the costs of options market making. *Journal of Financial Economics*, *159*, Article 103900.

Paç, M. F., Savin, S., & Velu, C. (2018). When to adopt a service innovation: Nash equilibria in a competitive diffusion framework. *European Journal of Operational Research*, *271*(3), 968–984.

Ram, S., & Jung, H.-S. (1994). Innovativeness in product usage: A comparison of early adopters and early majority. *Psychology & Marketing*, *11*(1), 57–67.

Reinganum, J. F. (1981). On the diffusion of new technology: A game theoretic approach. *Review of Economic Studies*, *48*(3), 395–405.

Richins, M. L., & Bloch, P. H. (1986). After the new wears off: The temporal context of product involvement. *Journal of Consumer Research*, *13*(2), 280–285.

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In *An integrated approach to communication theory and research* (pp. 432–448). Routledge.

Rzayev, K., & Ibikunle, G. (2019). A state-space modeling of the information content of trading volume. *Journal of Financial Markets*, *46*, Article 100507.

Sakkas, A., & Urquhart, A. (2024). Blockchain factors. *Journal of International Financial Markets, Institutions and Money*, *94*, Article 102012, URL https://www.sciencedirect.com/science/article/pii/S1042443124000787.

Schmittlein, D. C., & Mahajan, V. (1982). Maximum likelihood estimation for an innovation diffusion model of new product acceptance. *Marketing Science*, *1*(1), 57–78.

Schnaubelt, M. (2022). Deep reinforcement learning for the optimal placement of cryptocurrency limit orders. *European Journal of Operational Research*, *296*(3), 993–1006.

Shahzad, M. F., Xu, S., Lim, W. M., Hasnain, M. F., & Nusrat, S. (2024). Cryptocurrency awareness, acceptance, and adoption: the role of trust as a cornerstone. *Humanities and Social Sciences Communications*, *11*(1), 1–14.

Shams, A. (2020). The structure of cryptocurrency returns. In *Fisher college of business working paper (2020–03)* (p. 011).

Shang, G., Ilk, N., & Fan, S. (2023). Need for speed, but how much does it cost? Unpacking the fee-speed relationship in bitcoin transactions. *Journal of Operations Management*, *69*(1), 102–126.

Sockin, M., & Wei, X. (2023). A model of cryptocurrencies. *Management Science*, *69*, 6417–7150.

Soh, C., Mah, Q. Y., Gan, F. J., Chew, D., & Reid, E. (1997). The use of the internet for business: the experience of early adopters in Singapore. MCB UP Ltd,

Srinivasan, V., & Mason, C. H. (1986). Nonlinear least squares estimation of new product diffusion models. *Marketing Science*, *5*(2), 169–178.

Stummer, C., Kiesling, E., Günther, M., & Vetschera, R. (2015). Innovation diffusion of repeat purchase products in a competitive market: An agent-based simulation approach. *European Journal of Operational Research*, *245*(1), 157–167.

Tadesse, S. (2004). The allocation and monitoring role of capital markets: Theory and international evidence. *Journal of Financial and Quantitative Analysis*, *39*(4), 701–730.

Wang, J. (1993). A model of intertemporal asset prices under asymmetric information. *Review of Economic Studies*, *60*(2), 249–282.

Wei, Y., & Dukes, A. (2021). Cryptocurrency adoption with speculative price bubbles. *Marketing Science*, *40*(2), 241–260.

Wurgler, J. (2000). Financial markets and the allocation of capital. *Journal of Financial Economics*, *58*(1–2), 187–214.

Zhang, Z., Ren, D., Lan, Y., & Yang, S. (2022). Price competition and blockchain adoption in retailing markets. *European Journal of Operational Research*, *300*, 647–660.

Zhang, L., & Zhang, X. (2024). Mispricing and algorithm trading. *Information Systems Research*.