Master thesis U.S.E.

Are finfluencers the new experts in the field of investment advice?

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Abstract

The objective of this paper is to research to what extent finfluencers could be regarded as experts fulfilling the role of information intermediaries that contribute to an efficient market. To test this, a hand-collected dataset consisting of finfluencer recommendations was used to conduct an event study in the short and long-run. A distinction was also made between stocks and crypto's. The results show that, on average, all stocks within the event window [-10, +10] yield a significant CAAR of -3.291%, implying that finfluencers cannot be regarded as experts in the short-run. The long-run BHAR was negative, however, insignificant. Based upon this and the fact that finfluencers often do not possess a license to give financial advice and recommend risky investments, we urge the AFM to regulate more rigorously so that inexperienced investors are protected from taking excessive risks.

JEL Classifications: G14, G18
Keywords: Finfluencers, experts, market efficiency, event study

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1. Introduction

The notorious cryptocoin Xpose served as a prelude to the start of the finfluencer era in the Netherlands. The firm Xpose Protocol attracted many investors through prime marketing campaigns, causing the market cap of the coin to soar up to $125 million (Radar, 2021). After reaching its peak, the value of the coin plummeted just as quickly; today, Xpose protocol is worth $0 (Binance, 2022). Many saw their investments disappear, among which many youngsters. They were encouraged by influencers on Social Media, promising mountaintops and miracles but in reality, only a few people got very rich and many were left penniless.

The Dutch supervisor of financial markets, AFM, received dozens of reports about people losing a vast amount of money after taking the advice of these self-proclaimed financial gurus (NOS, 2021). Finfluencers, short for financial influencers, is a relatively new concept as it made its first media debut in the Netherlands in February 2021. The Volkskrant defined the concept as 'financial influencers who sell the fairy tale world of the stock market on Social Media' (De Waard, 2021). The description has a negative connotation and indicates that the finfluencers mostly show the positive sides of investing but do not discuss the risks that are involved with it as much. Consequently, many watch this contemporary phenomenon with suspicion (Tabarki, 2021). Yet, others rather embrace this new trend as it raises awareness on how to manage your money well. The difference in opinion is mainly due to the wide diversity in types of finfluencers. The AFM makes a distinction in terms of professionalism as well as number of followers (NOS, 2021). Tabarki (2021) goes even further by claiming that some finfluencers are more focused on motivating and advising people to save money whereas others are especially keen on presenting their followers investment opportunities. With respect to this, they may not always be transparent and sincere; they often endorse certain brokers or platforms whilst receiving compensation in return (NOS, 2021).

Furthermore, the AFM states that one is not allowed to give investment advice without a license. The law defines investment advice as 'a recommendation for a specific financial product from a specific provider to a specific customer' (AFM, 2022). Despite the fact that many finfluencers apply the disclaimer 'this is not financial advice' in their videos, posts or blogs, they still do; especially during exclusive events and meetings (AFM, 2021). Up until now, there has been no active enforcement of these rules; many loopholes and grey areas can be found with the existing laws. Also, no specific regulation regarding finfluencers has been designed yet as it is a relatively new phenomenon. It should be noted, however, that the finfluencer trend is increasing rapidly. In only two years time, half a million people have become investors in the Netherlands of which 10% have started investing thanks to recommendations or advice on Social Media (RTL Nieuws, 2021). Moreover, this problem is urgent because a large share of the people that listen to finfluencers are youngsters (Fit & Basir, 2021). These youngsters are inexperienced and naive about the dangers of investing; they regard the finfluencers as financial experts despite the fact that most of them do not have relevant financial education or work experience (AFM, 2021).

The aim of this paper is to present empirical knowledge of the extent to which finfluencers could be regarded as experts fulfilling the role of information intermediaries that contribute to an efficient market. This paper only includes finfluencers that encourage their followers to start investing and focus on the public investment recommendations they make. Subsequently, the extent to which these recommendations deliver positive abnormal returns will be measured by means of an event study. In this way, this paper will evaluate whether finfluencers have stock and other asset picking skills and could therefore be regarded as 'experts' that contribute to an efficient market. Accordingly, the research question of this paper is:

To what extent do finfluencers contribute to an efficient financial market?

Once this has been answered, I will evaluate whether immediate action in terms of regulation is necessary which is based on the sub-question 'to what extent do finfluencers engage in advising high risk and complex financial investments?'. Due to the fact that finfluencers are new and have not been researched extensively yet, this research paper is highly topical and scientifically relevant. It is also socially relevant; awareness should be raised about the risks that are involved with this new trend so that new and inexperienced investors can be guarded.

This remainder of this paper is organized as follows; section 2, literature review, provides an overview of the existing literature concerning financial intermediation theory, the Efficient Market Hypothesis (EMH) and (financial) experts. In this section, I also intend to clarify the way that finfluencers approach their audience by introducing the finfluencer decision journey. In section 3, methodology, I explain the methods used to conduct the research. In section 4, data collection and description, I elaborate on the data collection and selection procedure and provide descriptive statistics of the sample used for this study. In section 5, the results of this study will be provided. Finally, section 6 will summarize the paper and present a brief conclusion and the limitations. Also, policy recommendations based on the results of the event study will be provided.

2. Theoretical framework

2.1 Finfluencer trend

According to the Cambridge Dictionary (2022), an 'influencer' is 'someone who affects or changes the way that other people behave'. Using influencers for promoting products is prominent in the field of marketing. Social Media has facilitated and fastened the process of promoting products which is why it made way for the term 'Social Media influencer'. This is 'someone who has built a reputation based on their knowledge and expertise with the ability to influence others in the society.' (Kiss & Bichler, 2008). Given the fact that investing has become an evident trend in recent years, popular demand introduced a new subtype of Social Media influencers; that is, finfluencers. The trend in investing could be attributed to, among others, the low interest rate (Ma & Zijlstra, 2018), the pandemic (Domm, 2020) and the drive to make a change in the world by investing in sustainable companies (Choi, 2018). The popularity in investing goes hand in hand with the increased interest in finfluencers; they augment this investment trend as they encourage people to start thinking about building their wealth as well. Another new trend called 'social trading', enhances the interest in finfluencers as well (Robertson, 2021). The idea is that people share their trades on their profiles so that other people can interact with them and copy. The aim of this is to encourage people to start investing despite having little or no knowledge about financial markets. The World Economic Forum (2015) applauded social trading for being a low-cost and highly sophisticated alternative that empowers customers to have more control over their wealth management. Despite these benefits, there are also serious consequences to this trend as it could lead to fire sales and scams. Lastly, another reason why investing has become so popular is due to the Financial Independence Retire Early (FIRE) trend. It refers to an economical lifestyle where the goal is to achieve enough self-generated passive income to finance life choices and dreams. Once achieved, the passively generated income provides individuals freedom and flexibility as they do not have to adhere to mandatory workdays and could instead pursue their true calling (Siru, 2021; Rieckens, 2019). Correspondingly, generating a passive income by investing corresponds to the topics being discussed by these finfluencers.

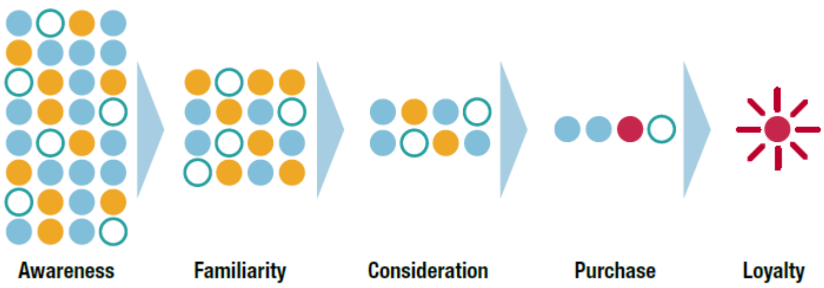
In the Netherlands, the prime reason to invest is to build wealth (Prins, Groen & Bos, 2021). This urge is fortified among the younger generation. Looking ahead, they notice the need for being financially self-reliant (Vogels, 2021). As a consequence, a large share of the younger generation is familiar with following the advice of finfluencers. In fact, 1 in every 5 youngsters get their financial knowledge from finfluencers (Oepkes, 2021). More than 19% of the so-called ‘Generation Z’, or those born between 1997 and 2010, indicates watching YouTube or reading blogs of finfluencers who explain and discuss financial matters. This, in comparison to 5% of ‘Generation X’ and ‘Baby Boomers’. Hence, one of the reasons why finfluencers are being viewed with suspicion is because they encourage certain investment opportunities despite the fact that a large proportion of their followers are youngsters who are uninformed and naive about the dangers of investing. Additionally, de Jong (2021) claims that finfluencers harm the craft that is called financial advice. According to him, financial advice plays a crucial role in solving large social issues such as sustainability, societal welfare, the housing market and financial resilience. Correspondingly, this large responsibility goes hand in hand with strict requirements before being able to provide financial advice. For example, one must be licensed by the AFM and be in possession of a diploma which one ought to keep up to date by taking an examination every three years. Further requirements are set in the areas of reward, transparency and duty of care. Most finfluencers do not have a license, which means that their financial knowledge and intentions cannot be tested nor supervised. Thus, their actions could have a lot of impact on society.

2.2 Finfluencer decision journey

Marketeers use the consumer decision journey by McKinsey (Court, Elzinga, Mulder & Vetvik, 2009) to better grasp how the consumer mind works. This framework is based on the traditional funnel metaphor, which is shown in figure 1.

Figure 1. The traditional funnel (Court et al., 2009)

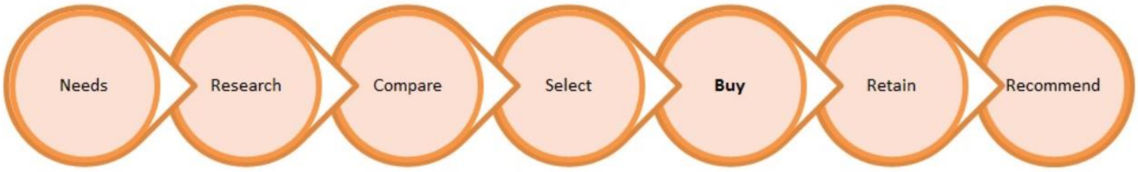
This figure presents the traditional funnel metaphor graphically, which specifies how a consumer starts with a large set of potential brands and gradually eliminates or chooses brands until eventually being left with one.



IRM (2016) built upon this framework by designing the investor decision journey. Companies should be aware of this process to be better able to retain their shareholders.

Figure 2. The Investor Journey (IRM, 2016)

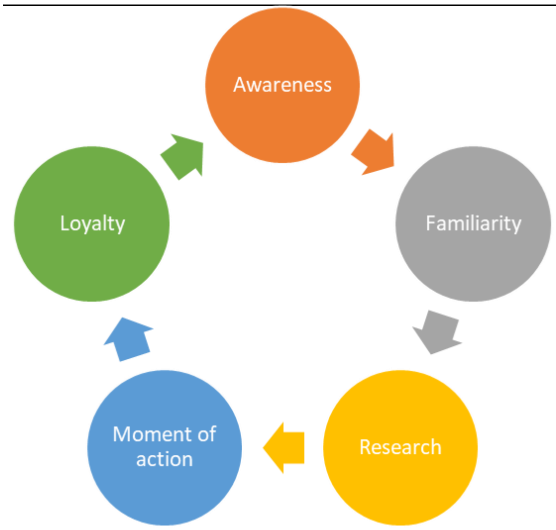
This figure shows the Investor Journey which depicts how an investor goes through various stages before making an investment decision.



In order to fully understand why someone would trust a finfluencer's investment recommendations and comprehend how finfluencers are able to get so many followers, these decision journeys need to be analysed. However, the existing frameworks cannot be applied to the finfluencers as the potential investors do not seek investment products that suit their needs themselves but are rather presented with opportunities. Hence, by combining these two frameworks and tailoring it to the Social Media environment, the following model is created to give further insight in the journey of a finfluencer follower before he or she makes an investment decision.

Figure 3. The finfluencer decision journey

This figure represents the finfluencer decision journey which consists of 5 phases and indicates a vicious cycle.



In the first stage, ‘awareness’, the potential investor is triggered and made aware of a need or problem (Kietzmann, Paschen & Treen, 2018). Investment opportunities are presented in this stage as well. As finfluencers mainly operate via Social Media, the trigger could be conveyed through a post, video or blog. Attention-grabbing visuals are often used as it triggers the potential investor (Milosavljevic, Navalpakkam, Koch & Rangel, 2012).

During the second stage, ‘familiarity’, the credibility of the finfluencer is assessed. The degree of credibility depends on whether the finfluencers could create a relationship with their followers; this bond is stronger if it is based on trust and high affinity (Noort, Voorveld & Van Reijmersdal, 2012). Interactivity and engagement are essential in building this bond and could be measured by analysing the number of followers, followings, shares, likes and comments.

In the third stage, ‘research’, information is gathered online or the opinions of peers are assembled. Although research suggests that celebrities and Social Media influencers can positively impact the effort to raise awareness about a product, it is necessary to point out that people still trust endorsements from people they know personally above all else (Cooley & Parks-Yancy, 2019). According to Virlics (2013), an investment decision is based on two factors: the investor’s past profit experiences and his guesses about future profit opportunities. Since a large component of the finfluencer audience is either young or inexperienced, the latter factor has a higher weight in the decision-making process. Peer pressure and the Fear Of Missing Out (FOMO) makes way for risky investments (Carrick, 2021).

In the fourth stage, ‘moment of action’, the investor has made up his mind to invest. Depending on how much they trust the finfluencer and the degree to which they expect the investment to be fruitful, they invest a specific amount of money. Another decision that could be made during this stage is joining the community of this particular finfluencer. In order to become a member, they either need to pay a subscription fee or purchase a package deal. Once you have become a member, many finfluencers are willing to provide more information and give further insight in their trading portfolio.

Finally, if the first investment leads to positive returns, the credibility of the finfluencer will increase and the investor will become a loyal follower, instigating a vicious cycle. Online word of mouth may be the next step as this investor will share his or her positive experience with other people (Moran, Muzellec & Nolan, 2014), increasing the following base of the finfluencer. Those with negative returns will lose confidence in the finfluencer and ‘unfollow’. Consequently, the following base will resemble an echo chamber where positive experiences are shared, convincing potential new investors to join the finfluencer journey as well.

2.3 Financial intermediation theory and EMH

Financial intermediaries, such as banks and mutual funds, serve as middlemen in financial transactions between two parties (Bethune, Sultanum & Trachter, 2021). Information intermediaries go one step further; these are individuals or groups who obtain, analyse, and interpret information with the aim of communicating their findings to others (Law, 2010).

Financial intermediation theory explains that intermediaries are valuable and necessary in financial markets because they reduce transaction costs and informational asymmetries (Benston & Smith, 1976). Despite the fact that this theory was able to prove the existence of intermediaries in the past, the literature is conflicted about whether it is still able to do so nowadays. Due to, among others, the advancement in technology that fastens the process of information circulation and the increasing provision of financial services, transactions costs and information asymmetries have been declining substantially, however, intermediation has been increasing (Scholtens & Wensveen, 2003). Whereas Allen and Santomero (1997) explain that intermediaries are needed because they reduce participation costs, Lee and Cho (2005) indicate that the increased demand for information intermediaries could be attributed to the information overload that consumers are experiencing; consumers need to carefully distribute their limited time and attention to a wide range of information sources. Thus, the progress in information technology has enhanced the need for information intermediaries. With respect to this, extensive literature can be found about experts (financial analysts) fulfilling the role of information intermediaries that discover, use and interpret the wide range of financial information and fluctuations in the stock market (Clement, 1999; Ramnath, Rock & Shane, 2008). As explained by Huang, Lehavy, Zang and Zheng (2017), analysts perform an interpretation role by clarifying the publicly available information, offering their opinions and comparing the performance of the firm to a benchmark. In this way, analysts contribute to the efficiency and well-functioning of capital markets (Bradshaw, Ertimur & O'Brien, 2017; Davies & Canes, 1978).

In contrast to the financial intermediation theory, the Efficient Market Hypothesis (EMH) states that financial intermediaries do not contribute to market efficiency because the market is already efficient (Arffa, 2001). This theory suggests that information is quickly absorbed by the market and reflected in the stock prices which is why individuals are not able to consistently outperform the market (Levmore, 1984). Accordingly, many studies indicate that investment managers are not able to outperform index funds that resemble the market (Jensen, 1968; Malkiel, 2003). There are three forms of EMH (Downey, 2021): the strong form states that all public and private information are known by the market and reflected in the share prices. The semi-strong form states that only public information is known and the weak form claims that past shares prices do not affect today's stock price and cannot be used to forecast the course of future prices (Smith, 2021). Thus, assuming that finfluencers have no access to private firm information and that the semi-strong form of the EMH holds, neither technical nor fundamental analysis would help finfluencers outperform the market as the share prices will resemble a random walk (Titan, 2015).

Nevertheless, despite this theory, there is a growing demand for financial advice and advisors (Harrison, 2021). To grasp why this is the case, we need to dive in the literature to research to what extent these experts could be considered as valuable. As the primary role of experts is delivering accurate forecasts (Tyszka and Zielonka, 2002), we can measure the extent to which they are valuable by analysing to what degree they make accurate forecasts. Studies show that this varies per industry; Tetlock (1999) notes that political experts are only slightly better in predicting political events than chance. Shanteau (1995) evaluated the accuracy of expert judgments by measuring the internal consistency among experts within a domain and found that whereas internal consistency was highest among weather forecasters, it was the lowest among stockbrokers. Tyszka and Zielonka (2002) found similar results: according to their study, a third of the financial analysts were correct in their forecasts whereas this corresponded to two-thirds of the weather forecasters. This illustrates the complexity in financial markets. Nonetheless, predictions made by experts within the financial domain in the fields of stocks (Ramnath et al., 2008), commodities (Fritsche, Pierdzioch, Rülke & Stadtman, 2013), exchange rates (Pierdzioch & Rülke, 2015) and Bitcoin (Gerritsen, Lugtigheid & Walther, 2021) have proven to be valuable as they correctly define the course of future price movements.

Contrary to what these studies claim, however, Metcalf and Malkiel (2010) argue that financial experts perform no better than chance. The study compared the returns of stocks that were recommended by four expert portfolio managers and the returns of stocks that were randomly selected by four darts. Besides picking riskier stocks, the experts were not able to perform better than the darts after controlling for risk. In fact, investors who bought the stocks that were recommended by these experts achieved lower returns because the publicity associated with the experts eliminated most of the abnormal returns. Corresponding to this, Tetlock (1999) showed that, despite the fact that experts rarely exceed chance, they are overconfident in their abilities; experts assigned confidence estimates of 80% or higher were only right in 45% of the cases. Overconfidence is particularly common among financial experts (Tyszka & Zielonka, 2002; Korn & Laid, 1999). More specifically, they are drawn towards an illusion of control, timing optimism, desirability effect, in which they overestimate the odds of something happening because the outcome is desirable, and over ranking, in which they rate their own personal performance as higher than actually is and compared to others (CFI, 2022). In addition to this, investors are prone to suffer from behavioural biases such as loss aversion, herd behaviour and FOMO (Gupta & Shrivastava, 2021; Hershfield, 2020). For this reason and given that most finfluencers have no financial background that they can rely on, they will likely be drawn faster towards heuristics and cognitive biases influencing their perception of risk and decision-making (Kahneman, 2011; Pachur, Hertwig & Steinman, 2012; Shanteau, 1992). This could distort their accuracy in delivering forecasts.

Hence, given the complexity of the financial markets, the fact that most finfluencers do not have relevant financial experience and the presence of cognitive biases, I hypothesize that the finfluencers are not able to correctly forecast the course of the security prices. In order to give a more detailed analysis, this hypothesis will be stated for the short-term and long-term:

H1: Finfluencers are not able to achieve positive abnormal returns in the short-term.

H2: Finfluencers are not able to achieve positive abnormal returns in the long-term.

There are various methodologies that test the ability of experts within the financial field, however, this paper will define the experts by their ability to correctly pick stocks (Bodnadruk & Simonov, 2015). Accuracy will be measured by the extent to which the recommendations have led to positive abnormal returns.

2.4 Local vs. Foreign analysts

To further draw attention to the performance of financial analysts, various studies have researched whether distance affected the quality of information investors have. The literature is conflicted with regards to this topic; whereas some studies find that local analysts have a significant information advantage compared to foreign analysts (Malloy, 2005; Bae, Stulz & Tan, 2008), other studies claim that foreign investors generate a superior performance compared to local investors (Bachmann & Bolliger, 2003; Grinblatt & Keloharju, 2000). What is more, Farooq (2013) finds that neither group had an information advantage over the other. However, this study was conducted during an economic crisis; the uncertainty that goes hand in hand with this might have affected the results.

There are two conflicting theories with regards to the role of distance. According to the literature, local analysts could be more exposed to home bias, which is the tendency to stick with what feels familiar such as domestic stocks. International barriers such as transactions costs and currency risk explain this phenomenon (Chan, Covrig & Ng, 2005). Home bias could cause the portfolios of the local analysts to be less diversified which could affect the returns. On the other hand, local analysts could have an information advantage because they have a better understanding of the local market or the firm. Home bias could then be accounted for by this information advantage (Bae, Stulz & Tan, 2008). Malloy (2005) finds that the information advantage even applies in the case that analysts live closer to the headquarters of a firm.

Given this extensive body of literature, this paper will test whether the information advantage applies to finfluencers as well. The finfluencers gathered in this research will all be based in the Netherlands, making it feasible to compare the performance of the recommended Dutch stocks to the recommended foreign stocks. Hence, the following hypothesis is stated:

H3: Finfluencers are better able to achieve positive returns in domestic markets than in foreign markets.

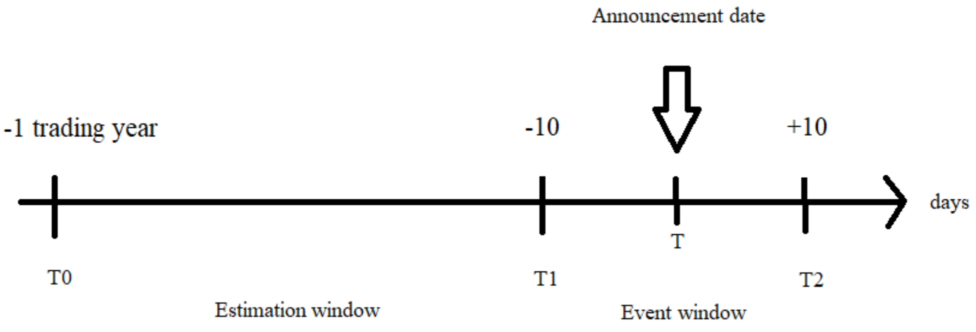
3. Methodology

Besides performing exploratory research and descriptive statistics to evaluate, for example, how many finfluencers have a financial background, the objective of this paper is to find out to what extent finfluencers could be regarded as experts fulfilling the role of information intermediaries. As mentioned in the theoretical framework, this paper defines the experts by their ability to correctly pick stocks and other assets. Despite the fact that having a financial background or experience in the field could be regarded as a factor that increases one's affinity with selecting assets, it does not function as a determinant for measuring one's ability to do so. Hence, this study assesses this asset-picking ability by analysing whether the recommended stocks and cryptocurrencies (crypto's) have outperformed the market. An event study will be the most appropriate method in testing this.

The performance of the recommended assets were tested in the short and long-run. The short-term event window consists of 10 days prior to the event and 10 days after the event. The estimation window is 260 trading days prior to the start of the first event window. Below, a visualization of the event window for the CAAR is presented:

Figure 4. Short-term event window CAAR

This figure shows that the event window is 10 days before and 10 days after the announcement date which is the date that a certain recommendation was made. The estimation window is 1 trading year or 260 trading days prior to the start of the event window.



Finfluencers often give an indication of whether the recommended asset should be hold for a short or long period. Besides having analysed the short-term event window [-10,+10] for all assets, I therefore also tested the short-term event window for only the short-term recommended assets.

Furthermore, whereas the AEX substituted the market for the Dutch stocks, the S&P 500 suited the American stocks. The 10-year Dutch Treasury bonds served as a proxy for the risk-free rate for the Dutch stocks but it was the 3-month US Treasury bonds for the American stocks. Both indices and bonds were adjusted for daily returns. As no consistent benchmark for the crypto's exists yet, the literature uses the mean-adjusted return model instead (Joo, Nishikawa & Dandapani, 2020; Ante, 2022).

For all stocks, the CAPM model was used. This means that the abnormal return for each recommendation was calculated using the following formula:

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

$R_{i,t}$ is the excess realized return of asset i and time t, which is the return on a stock minus the risk-free interest rate. $E(R_{i,t})$ is the expected return of asset i at time t. This was calculated as follows:

$$E\left(R_{i,t}\right) = \alpha + \beta(R_{m,t})$$

The alpha and beta were computed using the estimation window of 260 trading days. $R_{m,t}$ is the return of the market at time t minus the risk-free interest rate. In order to compute the cumulative abnormal return (CAR), the sum of the abnormal returns during the event window was taken:

$$\widehat{CAR}_{i,t}(T1, T2) = \sum_{t=T1}^{T2} \widehat{AR}_{i,t}$$

Ultimately, the cumulative average abnormal return (CAAR) was calculated using the CAR of all recommendations within a certain event window. The CAAR could be expressed as:

$$\overline{CAAR}_{i,t} = \frac{1}{N} \sum_{i=1}^{N} CAR_{i,t}$$

As the mean-adjusted return model was applied to the crypto's, the following formula was used to calculate the abnormal returns:

$$AR_{i,t} = R_{i,t} - \bar{R}_i$$

where $R_{i,t}$ is the excess realized return of asset i at time t and $\bar{R}_i$ is the mean of the asset's realized returns during the estimation window, which is 260 trading days prior to the event window. Subsequently, the CAR and CAAR were computed using the same formulas as presented above.

With regards to the long-term event window, the BHAR is often used instead of the CAAR as it is more competent (Khotari & Warner, 2006). Hence, this paper estimates the BHAR on a month-to-month basis for 12 months after the announcement date for all assets as well as only those assets that were recommended for the long-term. The following formula was used:

$$BHAR_{i,h} = \prod_{t=1}^{h}\left(1 + R_{i,t}\right) - \prod_{t=1}^{h}(1 + R_{m,t})$$

where $BHAR_{i,h}$ is the abnormal return of a stock i over period h. $1 + R_{i,t}$ is the simple rate of return in the month t and for asset i. $1 + R_{m,t}$ is the simple rate of return in month t of the benchmark m, which is the AEX for the Dutch stocks and the S&P 500 for the US stocks. The S&P 500 was also used as a benchmark for the crypto's due to a lack of consistent benchmark and the fact that this conforms with the literature (Jain & Jain, 2019). The benchmarks were adjusted for monthly returns.

Finally, a t-test was conducted to test the second hypothesis. For this, the difference in means was taken from the US and Dutch stocks. Given the difference in sample size, a t-test assuming unequal variances was conducted and applied twice as both the CAAR and BHAR were checked.

4. Data selection and description

Currently, there is no database available that covers the recommendations of the finfluencers. Thus, the data were collected manually from Instagram, YouTube, Discord and personal websites because these platforms were marketed the most by the finfluencers. It should be noted that most personal recommendations take place in private channels or events, often for which you have to pay. Due to the time and budget limit of this study, this paper therefore only included public recommendations which are not directed at individuals but intended for a public audience. Criteria for gathering the data were the following; the finfluencer had to be Dutch, have a minimum of 1000 followers and the stocks should be recommended in a convincing way. A recommendation was convincing if the finfluencer explained that the particular stock would deliver high returns in a particular time frame, if it was called an interesting stock with good prospects for a specific month or in general, or if it was presented as a good example within a sector which they believed would become very profitable or indispensable in the future. The personal belief that a share price would increase in value was avouched by providing subjective analysis of the firm expectations and/or business model. Another way of making the recommendation sound convincing was if the finfluencer made clear that they bought the recommended stock themselves. The latter could be done by stating it verbally or by sharing a picture of their portfolio, which corresponds with the 'social trading' trend. Some finfluencers also informed their audience about stocks that, according to their own analysis, would not yield high returns. Oftentimes, this was because they believed the share price was inflated and would be corrected soon. Another reason was that they were convinced of better alternatives. These stocks were not included in the analysis; only recommendations that they believed would yield positive returns were incorporated. Despite the fact that many finfluencers provided the disclaimer 'this is no financial advice', their recommendations were still included in this analysis. The finfluencers often provided proof of having bought the recommended stock; this, in combination with a high level of enthusiasm displayed could increase the level of perceived credibility, leading to many people listening and buying the asset. Even if people conduct their own research, as is emphasized by most finfluencers, their analysis will be biased, especially if these people do not have a financial background. The recommendations gathered stem from January 2018 to May 2022. Ultimately, 748 asset recommendations were gathered from the 22 most famous and/or interactive finfluencers in the Netherlands. This dataset includes recommendations of financial products that were recommended more than once by one finfluencer, however, in order to prevent the inclusion of the same results in the analysis, the event study only incorporated the first time a certain asset was recommended by one finfluencer. Also, due to the fact that some data were either missing or lacking, not all recommendations could be included in the analysis. Finally, this study only anlysed American and Dutch stocks because these were largest in sample size. A list of recommended stocks that are exchanged on other stock markets is presented in table 1 in the appendix. Due to these deductions, the number of recommendations used was smaller. Whereas 289 US stocks and 79 Dutch stocks were analysed for the CAAR calculation, 250 US stocks and 69 Dutch stocks were analysed for the BHAR calculation. The difference in number of observations is due to the fact that some stocks were recommended in, for example, May 2022; the long-term event window of one year cannot be applied to these assets. This also applies to the crypto's where 92 recommendations were used for the CAAR calculation and 86 for the BHAR calculation. Table 2 below shows how many observations were used for each calculation.

The stock data was amassed from Factset and Yahoo Finance. Crypto data was collected from CoinGecko. As it is difficult to compare stocks to crypto's, they were differentiated in the study.

Table 2. Number of observations per calculation

This table presents how many observations were included in the different event study calculations in the short and long-term window and with regards to the stocks and crypto's.

Asset	Calculation	Number of observations
Stocks	All stocks in short-term window	368
	Short-term recommended stocks in short-term window	110
	All stocks in long-term window	319
	Long-term recommended stocks in long-term window	273
Crypto	All crypto's in short-term window	92
	Short-term recommended crypto's in short-term window	44
	All crypto's in long-term window	86
	Long-term recommended crypto's in long-term window	37

5. Results

5.1 Summary statistics

First, a general overview of the findings will be given. The recommendations were labelled in terms of financial asset to examine whether finfluencers recommend risky financial products. The following results were found:

Table 3. Asset summary

This table shows how many observations were found per type of financial asset.

Financial asset	Number of observations	Percentage
Individual stocks	480	64.17%
Crypto’s	187	25%
ETF’s	68	9.09%
SPAC	6	0.80%
Commodities	3	0.40%
Equity fund	2	0.27%
ETN’s	2	0.27%
Total	**748**	**100%**

The table shows that the majority of the recommendations are individual stocks. These stocks vary in terms of risk as it includes blue-chip stocks, dividend stocks, growth stocks, value stocks and penny stocks. Since the categorization of the 480 stocks into one of the aforementioned categories is rather subjective, they are placed under the same label. The finfluencers explained that they were looking for growth stocks with the aim of gaining high yields. Accordingly, the majority of the recommendations concern individual stocks because diversified funds, such as ETF’s, do not yield exceedingly high returns. However, investors should be aware that a downside of investing in individual stocks is that unsystematic risk is not accounted for. To eliminate unsystematic risk, investors should diversify their portfolio themselves but presuming that many finfluencer followers are youngsters that are inexperienced, this could be a difficult task. Some finfluencers share their ‘diversified’ portfolio with the aim of inspiring others and increasing their credibility. Despite the ‘do not copy’ disclaimers, many could still choose to copy the portfolio. The urge to do so is only fortified if portfolios with high returns are shown. Nevertheless, this act is risky as well because many finfluencers have no license to legally advise others, which means that their financial knowledge has not been examined by an authorized institution.

The second most recommended assets were crypto's. These digital assets are oftentimes not backed up by physical assets and extremely volatile which is why they could be seen as high-risk investments (ESMA, 2022). Also, many finfluencers stated that they were trying to find cryptocoins that were not popular or worth much yet so that they would be in the game when the price skyrockets; a case similar to Bitcoin. This is very risky because experts predict that up to 90% of all cryptocoins will not survive in the coming years and that the crypto market is comparable to the early dotcom days (Kharpal, 2022). Finally, approximately 9% of the recommendations were about particular ETF's. These funds are well-diversified and therefore less risky investments. This would be safer options for inexperienced investors.

It should be noted that the event study incorporated the individual stocks, ETF's and SPAC's but refers to them as 'stocks'. Only crypto's were distinguished explicitly in this study. The ETN's, Equity funds and commodities were not incorporated due to a lack of data.

Moreover, the recommendations were labelled in terms of ESG risk. This was done with the intention of finding out whether finfluencers care for the non-financial factors as well. The ESG risks associated with a particular stock were gathered from Sustainalytics.

Table 4. ESG risk summary

This table summarizes how many observations were found per ESG risk category.

ESG risk	Number of observations	Percentage
Severe	21	2.81%
High	83	11.10%
Medium	198	26.47%
Low	177	23.66%
Negligible	4	0.53%
Not known	187	25%
Total	**748**	**100%**

The data shows us that most stocks recommended currently score 'medium' for ESG risk. The ESG risk is unknown for the majority of the recommendations; this is because the ESG risks of crypto's are not clear.

Moreover, it was difficult to determine the financial background of the finfluencers as many of them were anonymous and did not disclose this information. This is striking as it is required by the law to reveal your identity when providing financial advice or recommendations. Approximately 9 finfluencers did have some form of financial background; they finished an economic bachelor, claimed to be a financial or insurance consultant or stated to be a 'professional trader' for a long time. Unfortunately, no proof was found to substantiate these claims. The other finfluencers either did not have a relevant background or did not disclose this information. Almost all of them did not possess a financial license to give recommendations.

When gathering the data, not all famous finfluencers could be included. This is because many did not give insights or recommendations to the public but rather asked for a compensation before passing on any information. They do this by offering classes on how to become financially independent or to learn day trading. Some even encourage their audience to become part of their community. In exchange for money, you are then able to gain access to private channels such as WhatsApp or Discord. Prices asked range between a few hundred Euros to a few thousand Euros.

5.2 Stocks in the short-term event window

For this paper, several event studies were carried out. The first hypothesis tested whether the recommendations yielded positive abnormal returns in the short-run. Table 5 on the following page summarizes the average abnormal returns (AARs) and cumulative average abnormal returns (CAARs) for all stocks and the short-term recommended stocks within the short event window [-10, +10]. In addition to this, a pre-event window [-10, -1], event day window [0], and two post-event windows [+1, +5] [+1, +10] were constructed. These serve as more thorough analyses of the effect of the recommendations in a certain timeframe. The post-event window [+1, +5] intends to research the effect after a recommendation was made more narrowly as compared to the other post-event window [+1, +10]. Table 5 shows that all stocks yield a CAAR of -3.291% within the short-term event window of [-10, +10]. This is significant at the 1% level. Additionally, the post-event windows of [+1, +5] and [+1, +10] give a significant average return of -1.842% and -2.561%, respectively. The pre-event window of [-10, -1] and event day itself [0] provide negative returns as well but are insignificant. As the CAAR is significant and shows a negative return, this paper rejects the first hypothesis with regards to all stocks, meaning that we can accept the alternative hypothesis that finfluencers are not able to predict a positive abnormal return on average in the short term. When only taking into account the short-term recommended stocks, the CAAR is slightly positive (0.993%) but this could be attributed to the fact the pre-event window [-10, -1] yields a CAAR of 2.005%. The event day [0] and both post-event windows [+1, +5] [+1, +10] are negative. Nonetheless, these results are insignificant. Thus, the first null hypothesis cannot be rejected when only considering short-term recommended stocks within the short-event window.

Table 5. Stocks within short-term event window [-10,+10]

This table reports the Average Abnormal Returns (AARs) for all stocks (Panel A) and the short-term recommended stocks (Panel B). The Cumulative Average Abnormal Returns (CAARs) for all stocks (Panel C) and the short-term recommended stocks (Panel D) are presented as well. The asterisks * and ** report the significance levels of 5% and 1%, respectively. S.E. is short for Standard Error.

	Panel A: Average Abnormal Returns (AARs) all stocks		**Panel B: Average Abnormal Returns (AARs) short-term recommended stocks**	
Relative day	AAR (%) (S.E.)	t-statistic	AAR (%) (S.E.)	t-statistic
-10	-0.325	-1.538	0.098	0.228
	(0.212)		(0.429)	
-9	-0.014	-0.07	-0.453	-1.316
	(0.201)		(0.342)	
-8	0.225	0.791	0.156	0.436
	(0.285)		(0.357)	
-7	-0.122	-0.604	-0.085	-0.213
	(0.202)		(0.399)	
-6	0.033	0.127	0.423	0.566
	(0.262)		(0.744)	
-5	-0.132	-0.607	0.497	1.025
	(0.218)		(0.483)	
-4	0.052	0.252	0.012	0.035
	(0.207)		(0.360)	
-3	-0.311	-1.76	0.161	0.429
	(0.177)		(0.374)	
-2	0.025	0.073	1.085	1.066
	(0.347)		(1.013)	
-1	-0.046	-0.243	0.103	0.4
	(0.190)		(0.256)	
0	-0.291	-1.522	-0.101	-0.271
	(0.191)		(0.370)	
1	**-0.499****	**-2.898**	-0.371	-0.98
	(0.172)		(0.377)	
2	-0.332	-1.469	-0.037	-0.089

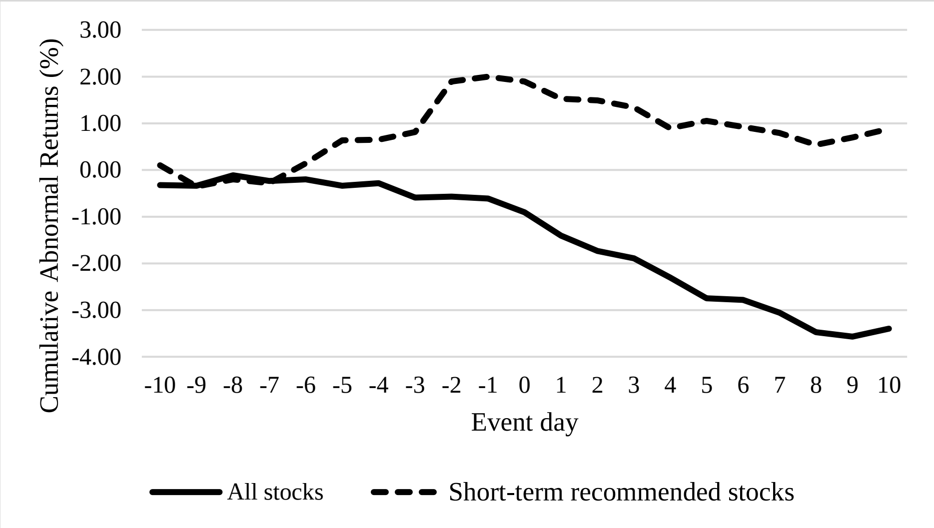
	(0.226)		(0.416)	
3	-0.157	-0.938	-0.146	-0.432
	(0.168)		(0.337)	
4	**-0.409***	**-2.267**	-0.450	-1.259
	(0.180)		(0.356)	
5	**-0.455***	**-2.353**	0.158	0.414
	(0.189)		(0.379)	
6	-0.034	-0.19	-0.128	-0.535
	(0.180)		(0.239)	
7	-0.271	-1.733	-0.132	-0.418
	(0.157)		(0.313)	
8	**-0.423***	**-2.24**	-0.252	-0.633
	(0.189)		(0.397)	
9	-0.092	-0.619	0.162	0.639
	(0.149)		(0.252)	
10	0.173	0.969	0.183	0.527
	(0.179)		(0.345)	
N	368		110	

	Panel C: Cumulative Average Abnormal Returns (CAARs) all stocks		**Panel D: Cumulative Average Abnormal Returns (CAARs) short-term recommended stocks**	
Event window	CAAR (%) (S.E.)	T-statistic	CAAR (%) (S.E.)	T-statistic
[-10,-1]	-0.615	-0.767	2.005	1.068
	(0.802)		(1.869)	
[0]	-0.291	-1.522	-0.101	-0.271
	(0.191)		(0.370)	
[+1, +10]	**-2.490****	**-3.977**	-1.015	-0.895
	(0.626)		(1.128)	
[+1, +5]	**-1.842****	**-3.935**	-0.451	
	(0.468)		(0.740)	
[-10,+10]	**-3.291****	**-3.183**	0.993	0.465
	(1.034)		(2.133)	
N	368		110	

Graph 1 visualizes the results of table 5. As a robustness check, the cumulative raw returns were calculated. This means that the market and risk-free rate are not considered. Panel A and B in table 6 in the appendix presents these results. The cumulative raw returns are positive and significant, which accentuates the fact that, in comparison with the market and risk-free rate, the returns become negative (or almost negative) and not as notable.

Graph 1. Stocks within the short-term event window [-10, +10]

This graph represents the abnormal returns of the stocks each day cumulatively and distinguishes between all stocks and the short-term recommended stocks



5.3 Crypto's in the short-term event window

With regards to the crypto's, the mean-adjusted return model was used. This model was applied within the short-term event window [-10, +10]. Table 7 showcases the results. Concerning all crypto recommendations, the total CAAR [-10, +10] is slightly positive (1.935%), however, insignificant. The positive return could mainly be attributed to the period before and during the announcement day. The CAAR for the event window [+1, +5] is -4.363% and significant. This means that within 5 days after a recommendation was made, the crypto's yield a significant negative return. Moreover, if short-term recommended crypto's are considered only, the CAAR for the window [-10, +10] is slightly negative (-0.062%) but insignificant. Only the window [+1, +5] yields a significant CAAR of -5.957%. The insignificance of the total CAAR could be explained by the fact that the sample size is rather small, making it more difficult to determine significant results. However, because the CAAR for the period after the announcement date is significant, we are able to partly reject the first null hypothesis with regards to the crypto's. This implies that finfluencers are unable to predict positive abnormal returns for crypto's in the short period after a recommendation was made.

Table 7. Crypto's within short-term event window [-10,+10]

This table reports the Average Abnormal Returns (AARs) for all crypto's (Panel A) and the short-term recommended crypto's (Panel B). The Cumulative Average Abnormal Returns (CAARs) for all crypto's (Panel C) and the short-term recommended crypto's (Panel D) are presented as well. The asterisks * and ** report the significance levels of 5% and 1%, respectively. S.E. is short for Standard Error.

	Panel A: Average Abnormal Returns (AARs) all crypto's		**Panel B: Average Abnormal Returns (AARs) short-term recommended crypto's**	
Relative day	AAR (%) (S.E.)	t-statistic	AAR (%) (S.E.)	t-statistic
-10	**2.738***	**2.103**	1.314	0.918
	(1.302)		(1.432)	
-9	2.013	1.33	3.145	1.093
	(1.513)		(2.879)	
-8	0.479	0.419	0.737	0.395
	(1.143)		(1.863)	
-7	0.138	0.15	-0.425	-0.39
	(0.921)		(1.091)	
-6	1.1	0.699	0.413	0.258
	(1.574)		(1.600)	
-5	-0.099	-0.1	2.771	1.583
	(0.987)		(1.750)	
-4	1.627	1.149	2.795	1.022
	(1.416)		(2.736)	
-3	-0.651	-0.708	**-3.129****	**-2.568**
	(0.920)		**(1.218)**	
-2	-1.258	-1.497	-1.813	-1.895
	-0.84		(0.956)	
-1	-0.629	-0.692	-1.71	-1.501
	(0.909)		(1.139)	
0	0.772	0.977	-0.306	-0.364
	(0.790)		(0.841)	
1	**-1.921***	**-2.233**	**-3.071****	**-3.102**
	(0.860)		**(0.990)**	
2	**-2.020****	**-2.682**	**-3.100****	**-4.366**

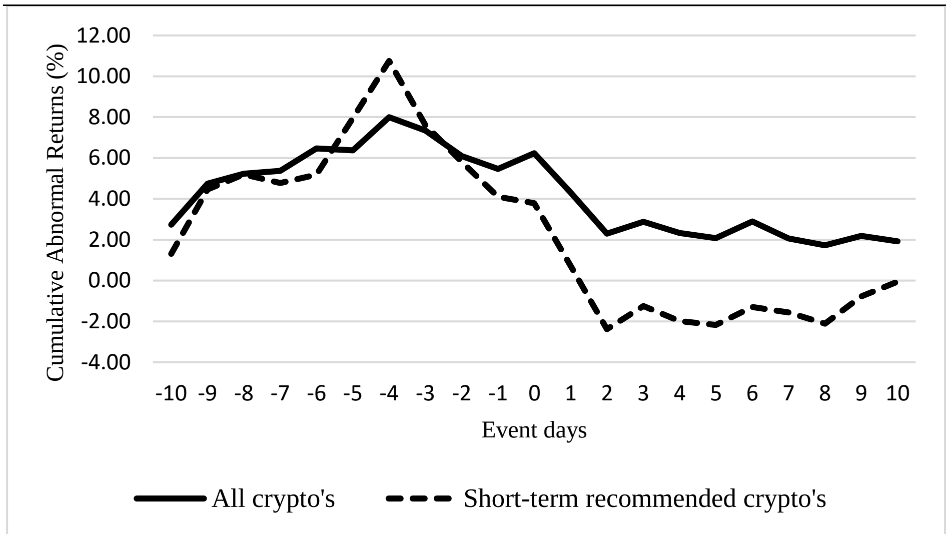
	(0.753)		(0.710)	
3	0.583	0.817	1.126	0.959
	(0.714)		(1.175)	
4	-0.545	-0.683	-0.729	-0.792
	(0.798)		(0.921)	
5	-0.252	-0.375	-0.183	-0.159
	(0.671)		(1.152)	
6	0.822	1.103	0.876	1.058
	(0.746)		(0.828)	
7	-0.829	-1.458	-0.267	-0.273
	(0.569)		(0.977)	
8	-0.342	-0.373	-0.546	-0.579
	(0.917)		(0.943)	
9	0.459	0.456	1.324	0.927
	(1.007)		(1.429)	
10	-0.272	-0.359	0.716	0.593
	(0.757)		(1.208)	
N	92		44	

	Panel C: Cumulative Average Abnormal Returns (CAARs) all crypto's		**Panel D: Cumulative Average Abnormal Returns (CAARs) short-term recommended crypto's**	
Event window	CAAR (%) (S.E.)	T-statistic	CAAR (%) (S.E.)	t-statistic
[-10,-1]	6.115	1.313	4.097	0.562
	(4.656)		(7.290)	
[0]	0.781	0.982	-0.306	-0.364
	(0.795)		(-0.364)	
[+1, +10]	-4.961	-1.743	-3.854	-1.004
	(2.846)		(-1.004)	
[+1, +5]	**-4.363****	**-2.678**	**-5.957****	**-2.786**
	(1.629)		**(2.138)**	
[-10, +10]	1.935	0.338	-0.062	-0.007
	(5.725)		(-0.007)	
N	92		44	

To illustrate the findings depicted in table 7, graph 2 below is presented. As can be seen from the graph, the short-term recommended crypto's yield a lower cumulative abnormal return compared to all recommended crypto's. This could suggest that finfluencers are not able to pick the right crypto's for the very short-term despite their recommendations and beliefs. A robustness test was carried out that did not account for the mean-adjusted return model and only incorporated the realized returns of the crypto's. The cumulative raw results, presented in panel A and B of table 8 in the appendix, are positive and significant. This indicates that, when compared to the mean of the crypto's, the digital assets have underperformed. During the post-event window [+1, +5], this underperformance was even negative and significant.

Graph 2. Crypto's in the short-term event window [-10, +10]

This graph represents the abnormal returns of the crypto's each day cumulatively and shows the difference between the short-term recommend crypto's and all crypto's.



5.4 Stocks in the long-term event window

The second hypothesis was tested using the BHAR method. Again, two analyses were carried out: all stocks in the long-term event window and only the long-term recommended stocks in the long-term event window. The American stocks were compared to the S&P 500 and the Dutch stocks were compared to the AEX. The results of holding the recommended stock on a month-to-month basis for 12 months consecutively can be found in table 9.

With respect to all stocks, the buy and hold abnormal return is -0.910% after 12 months. Only accounting for the long-term recommended stocks yields an abnormal return of -2.068%, which is ever more negative. The returns are negative but due to the insignificance, the second null hypothesis cannot be rejected with regards to stocks.

Table 9. Stocks in the long-term event window

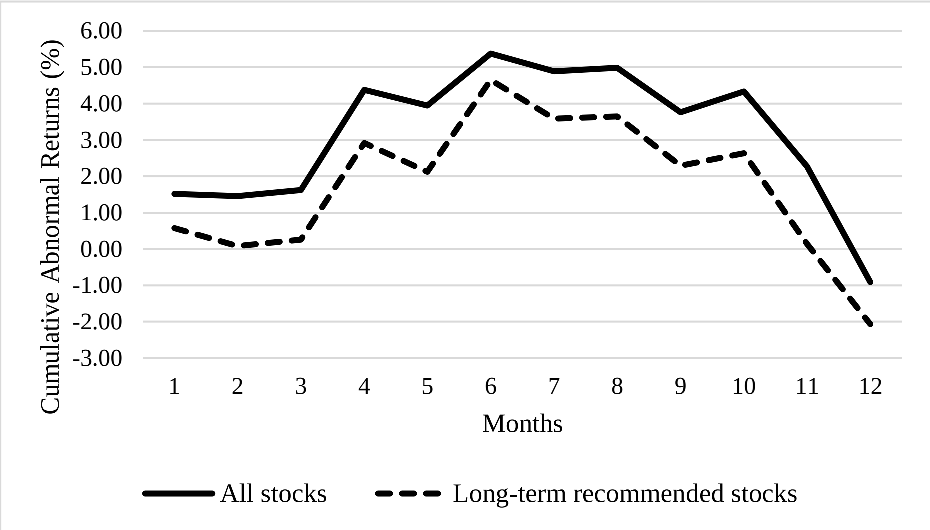
This table showcases the results of the Buy and Hold Abnormal Return (BHAR) calculation method to all stocks (Panel A) and the long-term recommended stocks (Panel B). The asterisks * and ** report the significance levels of 5% and 1%, respectively. S.E. is short for Standard Error.

	Panel A: BHAR all stocks		**Panel B: BHAR long-term recommended stocks**	
Months cumulatively	BHAR (%) (S.E.)	t-statistic	BHAR (%) (S.E.)	t-statistic
1	1.512 (0.010)	1.478	0.577 (0.012)	0.478
2	1.457 (0.012)	1.168	0.083 (0.014)	0.058
3	1.623 (0.022)	0.751	0.257 (0.025)	0.102
4	4.377 (0.027)	1.621	2.919 (0.031)	0.942
5	3.946 (0.026)	1.533	2.124 (0.029)	0.722
6	5.375 (0.028)	1.905	4.649 (0.032)	1.433
7	4.890 (0.031)	1.575	3.586 (0.035)	1.024
8	4.989 (0.034)	1.487	3.650 (0.037)	0.974
9	3.764 (0.037)	1.011	2.292 (0.042)	0.552
10	4.336 (0.046)	0.935	2.637 (0.053)	0.500
11	2.276 (0.046)	0.498	0.142 (0.051)	0.028
12	-0.910 (0.049)	-0.184	-2.068 (0.056)	-0.369
N	319		273	

Graph 3 illustrates the findings of table 9 graphically. It should be noted that the long-term recommended stocks have underperformed in comparison with all recommended stocks, implying that finfluencers are not able to pick the right stocks for the long-term despite their recommendations and beliefs.

Graph 3. Stocks in the long-term event window

This graph represents the abnormal returns of the stocks each month cumulatively and shows the difference between the long-term recommended stocks and all stocks.



Additionally, a robustness check was carried out in which the realized returns of the stocks were shown and not compared to the benchmark. The cumulative raw returns are presented in panel C and D in table 6 in the appendix. The returns are positive and significant. This is in contrast with the results shown in table 9 and indicates that the picked stocks were, on average, able to yield positive significant results in the long-run. However, when compared to the benchmark (S&P 500 and AEX), they are negative and insignificant. In essence, this implies that investing in an index fund generates higher returns.

5.5 Crypto's in the long-term event window

The same two analyses were carried out for the crypto's. The results are presented in table 10. Taking into account all crypto's, holding them 12 months consecutively yields an insignificant positive return of 3.271%. With regards to the long-term recommended crypto's, the BHAR after 12 months was high (19.625%) but insignificant as well. The insignificance could be attributed to the low sample size. Hence, the second null hypothesis cannot be rejected with regards to the crypto's.

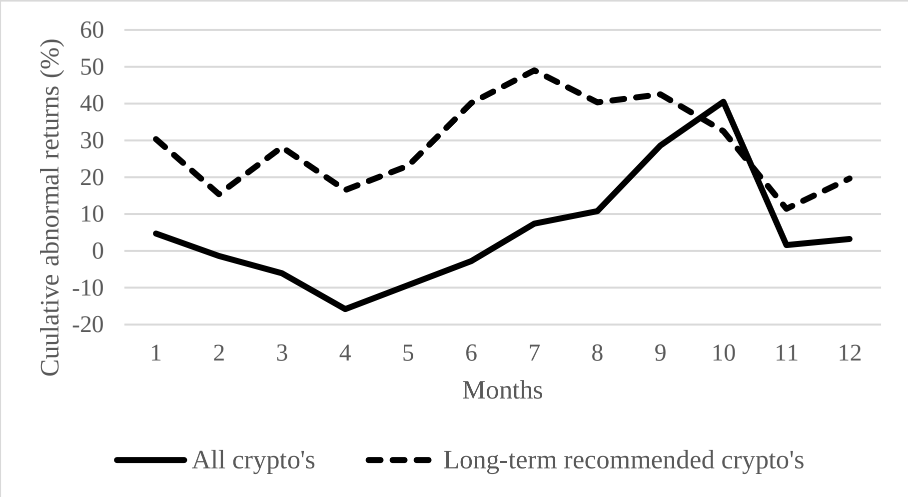
Table 10. Crypto's within long-term event window

This table showcases the results of the Buy and Hold Abnormal Return (BHAR) calculation method to all crypto's (Panel A) and the long-term recommended crypto's (Panel B). The asterisks * and ** report the significance levels of 5% and 1%, respectively. S.E. is short for Standard Error.

	Panel A: BHAR all crypto's		**Panel B: BHAR long-term recommended crypto's**	
Months cumulatively	BHAR (%) (S.E.)	t-statistic	BHAR (%) (S.E.)	t-statistic
1	4.681	0.537	30.376	1.650
	(0.087)		(0.184)	
2	-1.384	-0.143	15.399	0.891
	(0.097)		(0.173)	
3	-6.079	-0.533	28.155	1.239
	(0.114)		(0.227)	
4	-15.795	-1.552	16.551	0.805
	(0.102)		(0.205)	
5	-9.313	-0.808	23.097	1.165
	(0.115)		(0.198)	
6	-2.731	-0.201	40.158	1.537
	(0.136)		(0.261)	
7	7.450	0.501	49.019	1.705
	(0.149)		(0.287)	
8	10.770	0.642	40.322	1.606
	(0.168)		(0.251)	
9	28.577	1.111	42.538	1.543
	(0.257)		(0.276)	
10	40.495	1.189	32.522	1.171
	(0.341)		(0.278)	
11	1.565	0.079	11.437	0.486
	(0.198)		(0.235)	
12	3.271	0.150	19.625	0.623
	(0.218)		(0.315)	
N	86		37	

Graph 4. Crypto's within the long-term event window

This graph represents the abnormal returns of the crypto's each month cumulatively and shows the difference between the long-term recommended crypto's and all crypto's.



Graph 4 shows the abnormal returns of each month cumulatively. An additional robustness test was carried out that did not account for a comparison with the S&P 500. The results of this test are presented in panel C and D of table 8 in the appendix. Similar to the results presented in table 10, the BHAR of all crypto's and the long-term recommended crypto's is positive, however, insignificant. This supports the robustness of the study.

5.6 T-test comparison Dutch vs. US stocks

The third and final hypothesis was tested by means of a t-test assuming unequal variances. Both the CAAR and the BHAR of the Dutch and US stocks were compared. Table 11 shows the results.

The T-test comparison of the CAAR calculations between US and Dutch stocks shows that the mean is significantly different at the 5% level for both a one-tailed and two-tailed test. The mean of the US stocks is -4.124% whereas the mean of Dutch stocks is -0.628%. Although the means are both negative, the Dutch stocks are 'less negative' and closer to zero. This means that we can reject the third null hypothesis if we consider the short-term; finfluencers are better able in predicting accurate forecasts for Dutch stocks compared to US stocks. With regards to the BHAR calculation, the means are not significantly different. However, it should still be noted that the mean of the Dutch stocks is slightly positive whereas the mean of US stocks is slightly negative. Nonetheless, the third null hypothesis cannot be rejected considering the long-term abnormal returns. This implies that we are only partly able to reject the third null-hypothesis.

Table 11. T-test comparison Dutch vs. US stocks

This table presents the results of the t-test assuming unequal variances. The asterisks * reports the significance levels of 5%.

	CAAR		BHAR	
	US	Dutch	US	Dutch
Mean (%)	-4.124	-0.628	-0.037	0.090
Variance	472.654	128.461	0.865	0.454
N	289	79	250	69
df	246		147	
T-statistic	-1.936		-1.267	
P-value one-tail	**0.03***		0.10	
P-value two-tail	**0.05***		0.21	

6. Conclusion

This paper intends to find out to what extent finfluencers could be considered as experts fulfilling the role of information intermediaries. The degree of expertise was measured by their stock-picking abilities. In this regard, they should be able to outperform the market. In order to test this, two hypotheses were formulated that tested whether finfluencers were able yield positive abnormal returns in the short and long-term. By means of calculating the cumulative average abnormal return, the short-term event window of [-10, +10] was tested on stocks and crypto's, separately. A distinction was also made between all stocks and crypto's and those that were recommended for the short-term. Considering all stocks within the short-event window [-10, +10] resulted in a significant negative CAAR of -3.291%. When only taking into account the short-term recommended stocks within the [-10, +10] window, the CAAR was 0.993%, but insignificant. The CAAR of the post-event windows [+1, +5] and [+1, +10] were significant and negative for all stocks as well. The same analyses were performed on crypto's; whereas the CAAR for the [-10, +10] event window resulted in insignificant results, the CAAR for the [+1, +5] event window was significant and negative. Therefore, regarding the post-event window [+1, +5] for both short-term recommended stocks and all stocks and the total event window [-10, +10] for all stocks, the first null-hypothesis can be rejected.

The second hypothesis considered the long-term. For this, the BHAR was calculated for all stocks and crypto's as well as those recommended for the long-term. Long-term entails a period of 12 months in this paper. With regards to all stocks, the BHAR were slightly negative (-0.910). Only taking into account the long-term recommended stocks resulted in a negative return of 2.068%, which is even more negative than the first calculation. However, both results were insignificant. With respect to the crypto's, the S&P500 was used as the benchmark. The BHAR for all crypto's was positive (3.271%). Only taking into consideration the long-term recommended crypto's resulted in a positive abnormal return of 19.526%. However, both results were insignificant as well. Hence, we are unable to reject the second null hypothesis.

Finally, the third hypothesis tested whether finfluencers were better able to forecast positive returns for Dutch shares compared to US shares. This hypothesis was tested by means of a t-test assuming unequal variances and applied to both the short and long-term recommendations. The results show that the US mean of -4.124 is significantly different from the Dutch mean of -0.628. As the Dutch mean is less negative, and therefore 'better' than the US mean, we are able to reject the third hypothesis when only taking into consideration the short-term event window of [-10, +10]. As for the long-term, there was no significant difference between both means, however, the Dutch mean was slightly positive in contrast to the US mean. All things considered, we are able to conclude that finfluencers experience a significant information advantage in the short-term.

The first two hypotheses were formulated to test the main research question of this paper: ‘to what extent do finfluencers contribute to an efficient financial market?’. With regards to the short-term, the stocks recommended by the finfluencers yielded a significant negative return, implying that they were not able to outperform the market. The crypto’s also yielded significant negative returns, however, solely for the period after the recommendation was made. Hence, finfluencers cannot be regarded as experts in the short-term. They did not serve as information intermediaries that contributed to market efficiency because their stock-picking abilities were substandard and yielded worse returns than the S&P 500 and AEX. Accordingly, this paper has provided proof that the semi-strong form of the EMH holds. With respect to the sub-question of this paper: ‘to what extent do finfluencers engage in advising high risk and complex financial investments’, summary statistics showed that 64.17% of the recommendations gathered in this paper were individual stocks. As unsystematic risk is unaccounted for with these recommendations and most finfluencer followers are inexperienced and new to investing and diversifying, the recommendations could be considered risky. Also, 25% of the recommendations concerned crypto’s which are volatile and risky investments according to the ESMA (2022). Thus, having established that the stock recommendations yield a lower abnormal return of 3.291% compared to the S&P 500 in the short-run and considering the risk that is involved with these recommendations, it would be more profitable to invest in an index fund that tracks the S&P 500 because it is less risky and provides higher returns. Accordingly, we recommend that the AFM should either enforce the current rules more strictly or draw up new rules that apply to finfluencers specifically. With regards to the latter, the finfluencer decision journey explained in the theoretical framework provides insight in decision journey of people that view the recommendations of the finfluencers. As it represents a vicious cycle in which one gets ‘trapped’, investors could lose a vast amount of money multiple times. It would therefore be worthwhile to assess whether regulation would prevent people from becoming trapped; perhaps showing an official warning banner on platform such as Instagram and YouTube could shield novice investors (especially youngsters) from taking excessive risks.

Finally, the limitations of this paper will be discussed. The recommendations gathered in this study are extracted from the finfluencer’s personal profiles and websites. This means that they are able to delete posts and videos regularly. Correspondingly, this paper might be exposed to survivorship bias as the harmful recommendations could have been deleted already.

In fact, within two months of conducting this study, about 8 of the gathered recommendations have been deleted. As it happens, the share price of all of them but one has declined and most of them are currently below the entry price on the date that the recommendation was made. Furthermore, despite the fact that a relatively large sample of recommendations was gathered, only 92 crypto recommendations could be used for the short-term CAAR calculation and 87 for the long-term BHAR calculation. This has to do with the fact that data was either missing or lacking and because not enough crypto recommendations were gathered in the first place. As a result, it was hard to find significant results. Additionally, only Dutch and US stocks were analysed because stocks that are exchanged on other stock markets (e.g. German, French, English) were small in sample size. Follow-up studies should therefore try to collect more crypto and foreign stock recommendations. Finally, this study only analysed the public recommendations made by the finfluencers, however, in order to fully assess whether finfluencers are engaging in (illegal) risky advice, further studies should examine the recommendations made during exclusive meeting or in private channels. This would support the current findings more extensively.

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1. Appendix

Table 1. Summary of number of stocks exchanged on different stock markets

This table presents the number of recommendations given per stock market

Stock market	**Number**	**Percentage**
US	308	41.18%
No specific exchange market (e.g. crypto and commodities)	192	25.67%
The Netherlands	136	18.18%
UK	25	3.34%
China	22	2.94%
Germany	21	2.81%
France	10	1.34%
Canada	9	1.20%
Belgian	6	0.80%
Switzerland	4	0.53%
Sweden	3	0.40%
Finland	2	0.27%
Norway	2	0.27%
Brasil	2	0.27%
Denmark	1	0.13%
Japan	1	0.13%
Israel	1	0.13%
South Korea	1	0.13%
Hong Kong	1	0.13%
Russia	1	0.13%
Total	748	100%

Table 6. Cumulative raw returns stocks

This table presents the cumulative raw returns for all stocks (Panel A) and the short-term recommended stocks (Panel B) in the short-term event window. The cumulative raw returns for all stocks (C) and the long-term recommended stocks (Panel D) in the long-term event window are presented as well. This table serves as a robustness check. The asterisks * and ** report the significance levels of 5% and 1%, respectively. S.E. is short for Standard Error.

Panel A: Cumulative raw returns of all stocks in short-term event window

CAAR (%) (S.E.)	T-statistic
3.451** (1.044)	3.307

Panel B: Cumulative raw returns of short-term recommended stocks in short-term event window

CAAR (%) (S.E.)	T-statistic
6.428** (2.295)	2.800

Panel C: Cumulative raw returns of all stocks in long-term event window

BHAR (%) (S.E.)	T-statistic
20.279** (0.050)	4.068

Panel D: Cumulative raw returns of all long-term recommended stocks in long-term event window

BHAR (%) (S.E.)	T-statistic
18.692** (0.056)	3.312

Table 8. Cumulative raw returns crypto

This table presents the cumulative raw returns for all crypto's (Panel A) and the short-term recommended crypto's (Panel B) in the short-term event window. The cumulative raw returns for all crypto's (C) and the long-term recommended crypto's (Panel D) in the long-term event window are presented as well. This table serves as a robustness check. The asterisks * and ** report the significance levels of 5% and 1%, respectively. S.E. is short for Standard Error.

Panel A: Cumulative raw returns of all crypto's in short-term event window	
CAAR (%)	T-statistic
(S.E.)	
22.100**	3.855
(5.733)	
Panel B: Cumulative raw returns of short-term recommended crypto's in short-term event window	
CAAR (%)	T-statistic
(S.E.)	
20.656*	2.216
(9.321)	
Panel C: Cumulative raw returns of all crypto's in long-term event window	
BHAR (%)	T-statistic
(S.E.)	
15.014	0.663
(0.227)	
Panel D: Cumulative raw returns of all long-term recommended crypto's in long-term event window	
BHAR (%)	T-statistic
(S.E.)	
34.444	1.047
(0.329)	