

Stock Market Participation Puzzle: Social Engagement on Social Media Platforms

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Abstract

This study attempts to unravel the stock market participation puzzle. It approaches the puzzle with the idea that access to information reduces entry costs and, hence, encourages stock market participation. The literature suggests that information dissemination occurs through social interaction. Therefore, higher social engagement increases the odds of stock market participation. This study questions the established relationship due to the increased usage of social media, which has altered traditional forms of interaction. The findings fail to recognize a statistically significant impact of social media on stock market participation or the strength of social ties. The study is based on data from the UK Household Longitudinal Study (UKHLS). The analysis is conducted using fixed-effect logistic regression and simple logistic regression. Proxies for measuring social interaction include the frequency of engagement with neighbors and the number of social groups in which the observed individual actively participates. According to the findings traditional forms of interaction remine as important channels for information dissemination, nonetheless of social usage rate.

Key Words: Stock market participation, social media, social engagement, strong and weak ties, financial decision making, equity premium puzzle.

Popular Science Summary

The recent study tries to answer the question, what make people invest in stock market? Paper explors how different factors influence people's decisions to participate in the stock market. Traditionally, researchers believed that access to information plays a crucial role in encouraging stock market investments. The idea is that the more people engage with others, the more they learn about investing, which leads to the increased stock market participation.

However, with the rise of social media and digital technologies, the ways in which people interact and share information have changed. Consequently, this study is aimed to see if social media impacts stock market participation.

Using data from the UK Household Longitudinal Study (UKHLS), paper analyzed how different types of social engagement influence stock market investments. Close attention has been devoted to two key indicators: how often people engage with their neighbors and the number of social groups they actively participate in.

By using sophisticated statistical models, paper concludes that increased use of social media does not significantly affect people's decisions to invest in the stock market. And furthermore, the face-to-face interaction remain a good predictor for someone's stock market participation in UK.

Table of Contents

Chapter 1: Introduction	<i>6</i>
Chapter 2: Literature Review	
2.1. Reasons for Studying Stock Market Participation:	9
2.2. Socio-Economic and Demographic Predictors:	
2.3. Preferences and Beliefs	12
2.4. Social Interaction/Sociability	14
2.5. Social Media as Medium	16
2.6. Alternative Predictors	17
Chapter 3: Theoretical Framework	
3.1. Stock Market Participation Puzzle	
3.2. Sociability/Social Engagement/Social Interaction	19
3.3. Social Capital	20
3.4. Theory of Social Networks	20
3.5. Social Media Participation	21
Chapter 4: Methodology	
4.1. Data Source	23
4.2. Ethical Considerations	25
4.3. Stock Market Participation	
4.4. Social Networks	27
4.5. Social Media Activity	29
4.6. Additional Control Variables	
4.7. Descriptive statistics	
4.8. Methods	
4.8.1. Fixed Effects Model:	
4.8.2. Logistic Regression Base Model	
Chapter 5: Results	
5.1. Overview of bivariate results	41
5.2. Multivariate Analysis	43
5.2.1. Fixed Effects Logistic Regression	
4.2.2. Simple Logistic Regression	
4.2.3. Logistic Regression with Interaction Terms	
1.2. 1. Sheeking jor hoonshess	

Conclusion	60
Discussion:	58
Limitations and Future Research:	59
References:	63

Chapter 1: Introduction

Financial markets have become as accessible as ordering food online. There is no observable difference between the number of clicks it takes for someone to purchase financial securities compared to buying goods from "Amazon." Platforms like "Robinhood" have been accused of gamifying the financial markets (Van der Heide & Želinský, 2021). This process has been further amplified through the online reckless financial movements (Lyócsa, Baumöhl, & Výrost, 2022). As a result, more and more content has started to be generated on social media channels dedicated to financial markets and their potential gains.

Word of mouth has always been a great catalyst for stock market participation (Hong, Kubik & Stein, 2004), but have social media channels replaced them? This has been the core question upon which the paper has been developed. A large chunk of literature is dedicated to studying the impact of social media on the prices of financial securities (Khan et al., 2022). Social media sentiment has become one of the commonly used indicators for algorithmic traders (Nguyen, Shirai, & Velcin, 2015). However, comparatively less attention has been devoted to understanding how social media alters financial behavior. This paper positions within that space, as it studies the change of formerly established relationships of social engagement and stock market participation in the light of social media.

Social engagement has been a well-studied predictor of stock market participation (Hong, Kubik & Stein, 2004; Changwony, Campbell, & Tabner, 2015). It has been confirmed that different types of social interaction yield different results. A distinction between the forms of interaction has been made based on Granovetter's (1983) definition of strong and weak ties. Based on the equity premium puzzle, information gained through interaction with people reduces the cost of entry into the stock market. This logic, along with its concepts, has been used by the study and extended into the online space.

Findings of the research demonstrate that the impact of social engagement is not moderated by social media, assuming that the value of face-to-face interaction in the exchange of information still remains strong. Furthermore, social media has not been statistically significant in influencing stock market participation across most sets of models. In the ones where social media usage has been observed as statistically significant, it has shown a negative correlation with stock market participation, leading to the assumption that mechanisms employed to explain the interaction fail to grasp the full picture.

The study has been conducted using the United Kingdom's Household Longitudinal Survey (UKHLS) which provides proxy questions suitable for measuring social engagement through weak and strong ties. Weak ties are expressed as the active engagement with social groups, such as religious, political, and/or other interest groups. The proxy for the strong tie is the frequency of talking with neighbors. Stock market participation has been studied in two alternative ways—general/total stock market participation when the observed respondent holds any forms of financial securities, and direct stock market participation for when the respondent holds directly managed stocks (such as company stocks). These variables have been observed through three waves. However, the proxy measure for social media usage has only been introduced lately, hence it has been studied for the single wave data. Social media usage has been measured through two proxies: frequency of scrolling/browsing and frequency of posting. Along with the key predictors, alternative measures have been used as controls in the models.

An inductive analytical strategy has been used in the paper, meaning that the set of hypotheses has been developed and tested. To test the hypotheses, two distinct statistical approaches have been used. Panel data has been analyzed using the fixed-effect logistic regression, and data with social media usage has been analyzed through simple logistic regression. The fixed effects model allows observing the influence changing variables has on the individuals' odds of participation in the stock market.

The paper has been structured in the following way. Chapter two introduces the literature and previous research. It provides an overview of the studies on financial behavior and stock market participation. It provides an insight into the research theme and identifies the gap where the paper is positioned. Chapter three outlines the

theoretical framework and logic of how the interaction works between the predictors and outcome variables. The chapter provides conceptualization of the variables and offers sets of hypotheses which have been tested in the later parts of the paper. Chapter four is dedicated to methodology. It presents data and provides descriptive measures. It introduces the analytical strategy and statistical models used in the analysis, as well as addresses potential ethical considerations. Chapter 5 presents the results of the statistical modeling and analyses those against the hypotheses. Chapter 6 offers concluding remarks along with connecting findings to the bigger picture discussion. The chapter offers a thorough overview of the limitations and potential practical implications.

Chapter 2: Literature Review

Introduced by Mehr and Prescott (1985), the equity premium puzzle has remained as one of the primary questions for scholars interested with the topic of financial decision making. Haliassos and Michaelides (2003) have revisited the puzzle, outlining the illogical nature, that despite the higher expected returns of stocks over risk-free assets, a majority of households abstain from investing in the stock market. This phenomenon raises a set of questions about the factors that influence and/or encourage market participation. These sets of questions have created the space for research within which this paper positions.

Over the past three decades, scholars have thoroughly investigated and extensively documented the interplay between socio-demographic and behavioral characteristics and individuals' willingness to participate in the stock market. These studies have revealed a complex list of factors, from cognitive and psychological attributes to socio-economic characteristics, that influence financial decision-making. The following section provides a brief overview of the literature on the topic of stock market participation. This literature review aims to dissect the dynamics and influences that determine stock market participation by exploring how various elements from the broader ecosystem either enable or deter individuals from participating in the stock

market. This review seeks to unravel the layers of this enduring puzzle and identify the gaps that could serve as missing pieces in the quest to solve the outlined puzzle.

2.1. Reasons for Studying Stock Market Participation:

In one the earlier studies on the stock market participation and social interaction Hong and colleagues (2004, p. 137-138) argue for the importance of studying household stock market participation. According to the main argument offered by them, there might be two reasons why households would abstain from participation. One, the premiums for stock market participation not being appealing enough and second lack of knowledge/information which would enable them to participate. Once answer for the question "What are the underlying determinants of the stock-market participation rate?" (Hong, Kubik, & Stein, 2004 p. 137) is found it would become easier for the policies to be tailored and directly targeted at the problem. While the logic is loud and clear, I find that the purpose of understanding what makes people invest goes well beyond the interests of the policy designers. Understanding what are the social determinants leading to one's participation on the stock market holds the keys to broader understanding on matters of information dissemination and social networks as found in Changowany and colleagues' work (2015). In other words, studying the outlined phenomenon creates not only empirical evidence for policy adaptation but contributes to theoretical knowledge and helps to better understand the fabric of society.

Understanding the influence of socio-economic and demographic predeterminants on the choice to participate in financial markets has been studied from a variety of perspectives. According to Liu and colleagues (2014, p. 1) there are three major factors that affect people's stock market participation - personal and family background, wealth and income, and education and cognitive skills coupled with the attitude towards risk. While proposed mapping of the influential determinants is true, it is primitive, leaving some of the well-studied determinants out of the picture. Meanwhile, the "conceptual hierarchical model of stock market participation" developed by Kaustia and colleagues (2023, p. 2) captures a more nuanced overview of predeterminants for the stock market participation. According to the model (see Figure 1) factors are layered hierarchical and for one to be influential, the factors below should be met at first (Kaustia, Conlin, & Luotonen, 2023, p. 14). To simplify, the hierarchical model argues for the sequenced relationship between the covariates. The influence of wealth, income, and health are primary factors; once these are established, the effects of education, BMI, cognitive skills, and sociability come into play. Understanding this sequence allows for a more structured approach to the exploration of the phenomenon and leaves room for further investigation.

2.2. Socio-Economic and Demographic Predictors:

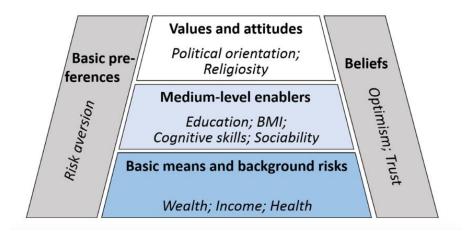
Early research on financial market participation has been mostly concentrated on the set of variables that would fit within the foundational level of the hierarchical model. For example, wealth has continuously been found to have positive impact on the stock market participation (Campbell & Viceira, 2002; Hong, Kubik, & Stein, 2004; Calvet, Campbell & Sodini, 2007; Böckerman, Conlin & Svento, 2021) following the common logic that wealth and stock market participation are strongly correlated as one enables the other. The effect of wealth not only positively influences the household stock market participation but also changes the structure of the portfolio household holds (Calvet, Campbell & Sodini, 2007, p. 709-710, 719, 740-743). Similar findings have been made on income (Brown & Taylor, 2010; Kaustia, Conlin, & Luotonen, 2023), which fits the same logic. Higher the income, the bigger the chance for the household to participate on the stock market.

Campbell and Viceira (2002) have identified that behavior changes among the investors based on their age. However, these findings do not hold to be consistent over the literature. While interaction between age and stock market participation is consistent it is not always straightforward. Campbell (2006) finds that age has a slightly negative effect on stock market participation, meaning that older participants are less likely to participate in the stock market. However, even he recognizes that the

phenomenon might be connected with the 1990s stock market boom and data being controlled for income and wealth (Campbell, 2006, p. 1566). Study of the Japanese household survey data reveals weak correlation between age and stock market participation, but unlike Campbell's findings it is positively correlated (Fujiki, Hirakata & Shioji, 2012, p. 12). In other words, older participants are more likely to own a stock or alternative financial instruments. Similar findings can be observed in recent research papers based on European survey data as well (Changwony, Campbell, & Tabner, 2015).

Age remains as the control variable all across the literature but rarely is used as a primary predictor for stock market participation. Similarly, sex is considered as one of the demographic control variables, which is constant in literature. The evidence found throughout the literature suggest, that men are more active on the stock market than women, even when controlled for income, wealth and education (general characteristics which also tend to contribute to the gender gap). Almenberg and Dreber (2015, p. 7-11) find this phenomenon to be connected with women's tendency of being more risk averse although not fully explained by it. According to them women tend to abstain from stock market participation, as they are less willing to take on the risks associated with financial securities ownership. Barasinska and Schäfer (2018, p. 11-14) find that risk aversion is an important factor explaining the gender-based gap in stock market participation. However, gender role asymmetry is what plays a major part in reducing women's willingness to participate in the financial market. Findings are based on the difference in gender gap in different countries. Such distinction is explained with the difference based on collective norms and values.

Figure 1. Conceptual hierarchical model of stock market participation (Kaustia, Conlin, and Luotonen, 2023, p. 2)



2.3. Preferences and Beliefs

Risk aversion on its own is one of the frequently used predictors when studying the stock market participation. Kaustia and colleagues treat it as an overarching predeterminant (2023). Generally, risk aversion is found to be negatively correlated with stock market participation (Lee et. al, 2015, p. 14-15). Higher the tendency to avoid risk, less likely it is that the person will participate in the stock market. Furthermore, fixed costs of participation suggest that investors who are more tolerant of risk are more inclined to engage in the market. This is because they are open to allocate a larger proportion of their financial wealth to risky assets, thus increasing the returns that could potentially offset the initial entry costs (Guiso and Sodini, 2013, p. 1453-1454). Additionally, investors' attitude towards risk, not only dictates their participation but also guides the structure of their investment portfolio. Meanwhile, one of the key challenges associated with the strand of research on the topic of risk aversion/risk tolerance is difficulties associated with operationalization. Common proxy used to measure risk aversion is the self-assessment question asked directly in a survey (Laudenbach, Malmendier, & Niessen-Ruenzi, 2020, p. 21). Alternative approach is to use questions related to the frequency and/or willingness to participate in alternative risk prone activities such as gambling for example (Guiso, Sapienza, & Zingales, 2008, p. 2574 - 2575; Hong, Kubik and Stein, 2004, p. 17; Addoum, Korniotis and Kumar, 2017). However, none of these approaches can make an absolute claim that one's willingness to participate in something risky is transferable to other scenarios as well.

One's decision to invest goes well beyond the openness towards risk taking. Having trust/faith in the system, data, analysis, sources of information, or any other factors involved in the decision-making is essential (Guiso, Sapienza, & Zingales, 2008, p. 2557). Kaustia and colleagues (2023. p. 2), treat trust as another overarching explanatory variable which does not particularly belong to any hierarchical layer. Guiso, Sapienza, and Zingales (2008, p. 2577 - 2583) identify that trust significantly influences both the decision to buy stocks and the volume of stocks purchased. They found that individuals with higher levels of trust are more likely to participate in the stock market and invest a greater portion of their assets. They highlight the perception of risk and potential for cheating as a pivotal component of trust (2008, p. 2557-2558), noting that those with lower trust perceive a higher risk of fraud, which in turn deters their market participation.

Impact of fraud as the condition for reduced trust has been further explored in the literature. Giannetti and Wang (2016, p 2592) have studied the impact of corporate fraud, which according to their findings leads to the decreased household stock market participation. In other words, trust is a finite resource which can be lost due to the external actors' behavior, which ultimately leads to the decreased willingness among people to take the risk of part-taking in ownership of risky assets. Notably this phenomenon can be reversed. External factors such as increased CSR score of the local companies, could lead to the increased trust, resulting in higher stock market participation, which would ultimately lead to the increased willingness to own the company shares (Tsang & Yu, 2023, p. 6). Impact of trust is increasingly strong in the countries where the stock market participation rate is low. Thus, demonstrating that countries where the financial equity ownership is less frequent need to be more trusting to participate on the stock market (Georgarakos & Pasini, 2011, p. 696).

Contrary, to trust the impact of sociability is more profound in societies where the rate of social market participation is higher. As Georgarakos and Pasini outline the channels of impact for these two covariates is different, first (lack of trust) reduces expected returns on investment, based on the idea that the involved actors in the transaction/contract will not keep up to their side of the bargain. While the second (sociability) reduces the cost of participation through information dissemination (2011, p. 694).

2.4. Social Interaction/Sociability

Sociability and/or social interaction have been exercised as means to understand the stock market participation puzzle, potentially reducing fixed costs through information sharing (Hong, Kubik, & Stein, 2004; Changowany, Campbell, & Tabner, 2015; Brown et. al 2008; Brown and Taylor 2010; Kaustia and Knüpfer 2012). Social interaction leads to increased stock market participation in two major ways. One it provides participants with the opportunity to collect the information which will enable them to invest on the stock market, information which might be related to the process itself or about the premium gains (Changowany, Campbell, & Tabner, 2015). On the other hand, it motivates participation through peer effect (Hong, Kubik, & Stein, 2004). Outlined two possible ways of influence can be understood through the lens of social network theory (explained further in the consequent chapter) as influence of strong and weak ties.

One should note that the sociability as the concept is not uniform and consequently the proxies used to measure the concept are different from each other, with the intention to cover the different types of social interaction. For example, Hong and colleagues (2004) confirmed that social interaction influences stock-market participation. According to them, individuals who are socially active, engaging with neighbors and attending church, are more likely to invest in the stock market. This correlation holds even after controlling for other influential factors such as wealth, race, education, and risk tolerance. Hong et. al(2004) explain this relationship through the peer-effect model. According to their model, social investors perceive the market as more

attractive when they see higher participation rates among their peers. This is created by the combination of observational learning (Individuals learning from the actions and experiences of their peers) and a shared enthusiasm for investment activities that further encourage participation. In support of their logical framework, Hong and colleagues (2004) find that the effect of social interaction is stronger in the area with overall higher market participation.

Brown and colleagues (2008) further extend the argument in support for the peer-effect on stock market participation. They propose that social interactions reduce the barriers to stock market entry by enhancing individuals' knowledge and comfort level with investing. However, they utilize geographical units as proxies for communities with the assumption of active interaction among the people belonging to the communities (2008, p. 515-516, 520-521). Similar findings have been made by (Kaustia & Knüpfer, 2012) that local peers' recent stock returns significantly affect an individual's decision to invest in stocks. Additionally, study has revealed that individuals are more likely to enter the stock market once the high returns are experienced by their peers, and this effect is not reduced even when returns fall below zero, suggesting that people generally do not discuss poor investment outcomes (2012, p. 332-333). However, as study is using individual transaction data it is rather hard to argue in regards to forms of social interaction.

On the other hand, Changowany et. al's (2015) study on sociability and stock market participation tests the different forms of social interaction. Their findings are consistent with the theory that social interactions, which provide access to information and networks, lower the barriers to stock market entry. Specifically, the study distinguishes between 'strong ties' (interactions with neighbors) and 'weak ties' (involvement in social groups). It finds that while strong ties do not significantly affect stock market participation, weak ties have a positive impact, likely due to their role in spreading unique and valuable information across social networks. Proxies used for strong ties are frequency and quality of interaction with neighbors. While, weak ties are expressed through the active participation in the social groups. According to the study other

factors such as risk aversion and religiousness also play a role in a decision to participate in financial markets.

Recent studies, including those by Kaustia et. al (2023, p. 14), affirm the positive influence of social interaction on stock market participation. However, the existing literature primarily focuses on direct, face-to-face interactions. Commonly used proxies for sociability, such as the frequency of conversations with neighbors or participation in physically-oriented social groups like churches or political organizations, predominantly measure in-person engagement. This approach overlooks the role of online social interactions, which are increasingly relevant. This oversight represents a gap in the literature on sociability's impact on stock market participation. This project aims to address this gap by exploring the effects of digital social interactions on investment behaviors.

2.5. Social Media as Medium

The logic used to explain the interaction between the stock market engagement and sociability can be extended to the online space as it is not limited to just face-to face interaction. In other terms both proposed explanations of reducing the fixed cost of participation through acquiring the information and/or the peer pressure can be experienced through the digital channels. Consequently, it could lead to the same results - increased stock market participation. Social media, online news platforms and internet sentiments have already been harnessed for predicting the stock market developments (Jiao, Veiga, & Walther, 2020; Khan et al. 2022; Sul, Dennis, & Yuan, 2017). Müller, Pan, and Schwarz (2024) have also identified the influence of twitter on increased stock market participation. According to their findings, adoption of Twitter has been shown to correlate with increased stock market engagement. It was found that a 10% increase in Twitter usage though the information dissemination, reduces the information gap that traditionally hinders wider stock market participation

The shift captured in the article exposes the evolving nature of how financial information is spread/consumed, and the growing relevance of social media as a source of financial guidance (Müller, Pan, & Schwarz, 2023). Meanwhile, media has been found to be the primary learning channel that increases the likelihood of stock ownership compared to alternative channels like private networks and/or financial advisors (Hermansson, Jonsson, & Liu, 2022, p.). The impact of the media on financial decision making is not limited to the stock market. Hu and colleagues (2023) have found the positive correlation between the exposure to business TV and increased the likelihood of households to refinance their mortgages when interest rates drop, suggesting that media can play a crucial role in enhancing financial literacy and decision-making among viewers. These findings support the idea that any analysis of stock market participation that fails to consider the oversight of digital and media platforms may lack comprehensive understanding of the puzzle. Therefore, a nuanced examination of this ecosystem is crucial for a coherent analysis of the factors influencing stock market engagement.

2.6. Alternative Predictors

Alternative, but a large strand of research pays close attention to financial literacy in fostering stock market participation. According to them, financial literacy equips individuals with the necessary skills and confidence to make informed financial decisions, which is crucial for navigating the complexities of financial markets (Lusardi & Mitchell, 2011; Lusardi & Mitchell, 2014; Nyakurukwa & Seetharam, 2024). Studies have continuously found the positive correlation between financial literacy and stock market participation. However, financial literacy does not necessarily moderate the impact of new information channels on the contrary. Specifically, Hermansson and colleagues (2022, p. 12-13) find that higher financial literacy enhances the effectiveness of media as a learning tool for stock market engagement.

Research on stock market participation has also explored various unconventional determinants beyond mere behavioral or socio-demographic characteristics, shedding

light on how individual circumstances and traits impact financial decision making. For instance, the impact of health on financial decisions has been a significant focus, with studies like Böckerman et al. (2021) demonstrating that early health conditions such as birth weight can influence risk aversion and, subsequently, stock market participation. Moreover, the investigation into how political engagement relates to financial decisions reveals that higher information costs can deter stock market participation among politically active individuals, as shown by Bonaparte et al. (2022).

Cognitive abilities also play a role, with Christelis et al. (2013) correlating higher cognitive skills with more sophisticated portfolio choices. This relationship is echoed in studies by Grinblatt et al. (2011), which connect higher IQ levels to increased likelihood of stock market activity. Furthermore, perceived health risks have been explored as potential influencer over the financial behavior, with Addoum et al. (2017) suggesting that personal traits such as obesity might impact investment choices due to associated health risks influencing risk preferences.

These studies highlight the complexity of factors influencing stock market participation, suggesting that both inherent traits and external circumstances shape financial decisions. To continue and uncover the ways in which individual differences impact economic behavior, study will employ the wide variety of covariants borrowed for the pre-existing literature on stock market participation.

Chapter 3: Theoretical Framework

Research project takes a theory testing approach (Gerring & Christenson, 2017, p. 194-196), with limited ambition to create new theoretical input in the field of household finance. The project undertakes the challenge of testing existing empirical findings and re-evaluating them under new conditions. The study's value for theoretical advancement lies in its effort to confirm the validity of previous empirical evidence that supports the theoretical framework explaining household stock market participation. The chapter discusses the mechanisms and concepts utilized in the study, and presents a list of hypotheses that have been tested throughout the research.

3.1. Stock Market Participation Puzzle

The research builds up on the long-standing issue of the stock market participation puzzle. According to the theory, decision on stock market participation is taken with the consideration of fixed cost (Vissing-Jørgensen, 2003). Meanwhile the fixed cost can be associated with monetary expenses along with information cost (Guiso & Sodini, 2013, p. 1453). To simplify, the households might abstain from participation not because the equity premium is not attractive or lucrative, but because the participation is associated with fixed cost, which would require extra investment. As discussed above, a number of factors from socio-demographic characteristics to behavioral patterns might influence the decision in regards to entering the financial market. In line with the stock market participation puzzle, for these conditionalities to increase the chances of stock market participation they should reduce the cost of entry. Literature supports this argument as findings from different studies offer the clear connection between the stock market participation and one's financial assets, wealth or income (Campbell & Viceira, 2002; Brown & Taylor, 2010; Hong, Kubik, & Stein, 2004; Calvet, Campbell & Sodini, 2007; Böckerman, Conlin & Svento, 2021; Kaustia, Conlin, & Luotonen, 2023). Even the literature on the demographic such as age and sex relies on the idea of reduced entry cost for explaining how the mechanisms of interaction(influence) work (Almenberg & Dreber, 2015; Campbell, 2006; Fujiki, Hirakata & Shioji, 2012).

3.2. Sociability/Social Engagement/Social Interaction

Social interaction and engagement have been identified as predictors of stock market participation, primarily because they are thought to lower the fixed costs associated with entering the market. This reduction in costs is believed to stem from the acquisition of new information through social interactions. However, social engagement manifests in various forms and degrees, raising the question of whether all forms of social engagement yield similar outcomes. Prior research has differentiated between these forms, revealing that while some types of social interactions significantly influence stock market participation, others do not. The concept frequently employed in the literature to describe an active predisposition towards social engagement is "sociability." Although previous studies have mostly focused on sociability in offline contexts, this study expands the concept to include digital interactions as well. Thus, in this article, sociability includes an individual's willingness and desire to engage socially, regardless of whether the interaction occurs online or offline.

3.3. Social Capital

Social engagement, and by extension sociability, is closely associated with the broader concept of social capital. Changwony et al. (2015, p. 321) argue that social capital is accumulated through ongoing social engagement. Although conceptualizations of social capital vary, one of the seminal definitions originates from Putnam's early work (1993, p. 167), which identifies trust, norms, and networks as core elements of social capital. However, the concept is broad, and Robinson et al. (2002, p. 2) later would suggest that to effectively consider it as capital, it must be reduced to those social interactions that most closely resemble capital-like qualities. The primary characteristics of physical capital, such as "transformation capacity, durability, flexibility, substitutability, decay, reliability, and the ability to generate one form of capital from another, as well as opportunities for investment and divestment, and alienation" (Robison, Schmid, & Siles, 2002, p. 9), should also apply to social engagement. When social engagement is evaluated against these criteria, it becomes plausible to consider it a form of social capital. This understanding clarifies how social capital contributes to reducing the fixed costs of participation, alongside other forms of capital, thereby reinforcing the theoretical framework of this research.

3.4. Theory of Social Networks

Literature on social interaction makes distinction based on the forms of social engagement. To justify this distinction study uses the theory of social networks, developed by Granovetter (1973, 1983, 2005). Similar approach has already been used by Changwony et. al (2015) to make distinction between the forms of social engagement through strong and weak ties. One of the objectives of the research paper is to test the formerly found relationships between the social engagement and the stock

market participation, study builds up on the similar theoretical logic. In line with the theory of social networks, by making the distinction between weak and strong ties.

The primary distinction between weak and strong ties lies in the proximity of the social groups with which interaction occurs. Strong ties typically involve close-knit groups such as family, friends, and neighbors, whereas weak ties extend to broader social networks, including professional associations, religious, and/or social/political groups. Granovetter (2005, p. 36) states that "Because all social interaction unavoidably transmits information," each type of tie contributes to the acquisition of information that can influence the fixed cost of participation in the stock market. According to the theory, information gained from interactions outside one's close circle often provides access to unique, economically valuable insights.

However, as discussed in the previous sections, literature suggests that not only weak ties but also engagement with strong ties can enhance stock market participation. This study adopts a set of hypotheses from Changwony and colleagues (2015, p. 322) and tests them using up-to-date data. These hypotheses are designed to assess the impact of strong and weak ties on an individual's decision to participate in the stock market.

Hypothesis 1. "Individuals who talk more frequently with their neighbors are more likely to participate in the stock market".

Hypothesis 2. "Individuals who are active in social groups are more likely to participate in the stock market".

3.5. Social Media Participation

Muller and colleagues (2023, p. 3-4) present a compelling argument about the role of social media in reducing information costs, thus adding a new dimension to the stock market participation puzzle. Their findings suggest that as modes of information dissemination evolve beyond traditional word-of-mouth, new factors must be considered in analyzing stock market engagement.

Williams (2006) was among the first to explore how social capital transitions into the digital realm. He integrates Putnam's (2000, seen at Williams, 2006, p. 597) concepts of bonding and bridging social capital with Granovetter's (1983, 2003) framework of weak and strong ties, applying these ideas within online spaces. Williams develops tools to measure these types of social capital, which have become essential for understanding online social dynamics.

Building on Williams' groundwork, Vitak (2014) finds that weak ties particularly benefit from platforms like Facebook, leveraging these connections for broader information reach. However, contrary to traditional theories that emphasize the informational advantage of weak ties, Krämer et al. (2014) observe that strong ties play a more significant role in disseminating information online, suggesting a shift in the dynamics of social interactions in digital spaces.

Given this theoretical foundation and recent empirical insights from scholars examining social capital in the digital arena, the study develops setsof hypotheses to test the mechanics of information dissemination within the complex environment of social media. This research aims to further test how these dynamics influence stock market participation among social media users. An alternative hypothesis has also been developed to scrutinize the relative strength and impact of weak versus strong ties among these users.

Hypothesis 3: Individuals who scroll social media frequently are more likely to participate in the stock market.

Hypothesis 4: Active social media users who frequently talk with their neighbors are more likely to participate in the stock market.

Hypothesis 5: Active social media users who are active in social groups are more likely to engage in the stock market.

Chapter 4: Methodology

The study design is shaped by the goal to explore how social engagement, both offline and online, influences stock market participation. It follows deductive study design, as outlined by (Aneshensel, 2013, p. 39-40; Greener, 2011, p. 4-5), using a robust theoretical framework to examine and possibly challenge the empirically observable aspects of social interaction and stock market participation. For the study, data from the United Kingdom has been chosen.

The selection of the United Kingdom as the study location is strategic, due to its moderately high stock market participation rates, which makes it an ideal context for investigating the patterns of stock market participation. The UK's robust financial market infrastructure and the widespread acceptance of investment practices among the general population provide a fertile ground for testing how different types and modes of social engagement influence individual decisions to participate in the stock market. It allows us to comprehensively analyze the interaction between social dynamics and financial activity, offering insights that might be less pronounced in regions with lower levels of market participation. Although, potentially generalizable to the rest of the world with similar socio-cultural structures and level of economic development.

4.1. Data Source

The database used for this study comes from Understanding Society, a longitudinal UK household survey (UKHLS) initiated in 2009. Understanding Society succeeded the British Household Panel Survey (BHPS), which was established in 1991. UKHLS inherited much of its survey architecture and the sample from BHPS. The survey covers approximately 40,000 households across the United Kingdom and employs face-to-face and phone interviews along with self-completed online surveys. It gathers information at both the household and individual levels. The survey is composed of permanent and rotating questionnaires that vary from wave to wave. As of 2023, there have been 13 waves of data collection, with each wave's fieldwork spanning approximately two years, starting in January and concluding in May of the following year.

Decision to use UKHLS as the primary data source has been made for a number of reasons. UKHLS offers the most comprehensive data for the UK, alternatives either cover different sets of countries and/or are limited with the number of observations. Meanwhile, UKHLS provides information both on investment decisions as well as in regards to socio-demographic and behavioral patterns. UKHLS' newest waves observe respondents' digital behavior, providing an opportunity to test the outlined hypothesis. Furthermore, compared to the alternative data sources, it provides more questions suited to conceptualize the list of predictor and control variables. Additionally, the longitudinal data allowed the study to observe phenomena through the time, and by doing so, bringing an added value to the research.

Lastly, as discussed previously, the research project draws significant inspiration from the work of Changwony and colleagues (2015). And adopts a comparable methodological approach to assess the impact of social engagement on stock market participation. Furthermore, the study not only adopts the set of hypotheses developed by Changwony et al. (2015, p. 322) but also strives for continuity and comparability in data usage. Changwony and colleagues (2015, pp. 325-326) conducted their analysis using data from the British Household Panel Survey (BHPS), which, as mentioned already, has since been replaced by the Understanding Society: UK Household Longitudinal Study (UKHLS). Therefore, using UKHLS data not only ensures consistency with previous research but also allows for the application of similar proxies to measure variables in the analysis.

This study primarily utilizes data from three survey waves: Wave 4 (2012-2014), Wave 8 (2016-2018), and Wave 13 (2021-2023). Additionally, observations from alternative waves are incorporated as needed. The primary outcome variable, stock market participation, is derived from questions asked during these specific waves. For proxies missing from selected three waves, study uses data from the nearest available wave. This approach is based on two assumptions: One, that the observations do not vary significantly from wave to wave. And second, the impact of the predictors is mostly lagged as the acquisition of information does not immediately lead to the stock

ownership, it takes time for the information to be distilled and transformed into tangible actions (in other word into market participation).

Study is based on the analysis of 137 485 unique observations. Observations coming from three different waves are divided according to waves in the following way: Wave 4 - 54 690, Wave 8 - 50 353, and Wave 13 - 32 442. Notably, the sample for analysis varies based on the hypothesis. Hypothesis 1 and 2 are tested on the whole sample, while Hypothesis 3, 4, 5 are tested only with the observations from the Wave 13. The reason behind this decision is lack of online activity questions, which are essential proxies for measuring social media activity. Hence the data from Wave 4 and 8 is not suitable for testing the hypotheses on the social media activity and its implications on the stock market participation.

Table 1 provides detailed information on the specific survey wave from which each question originated. It's crucial to note that although the analysis incorporates both individual and household survey data, behavioral measures are evaluated at the individual level.

4.2. Ethical Considerations

Keeping the scientific rigor within the ethical standards is essential. Consequently, this study comprehensively assessed the potential ethical considerations, and approached the process with full compliance to the conditions of ethical research.

Survey data, used in the research is open and available for everyone's use. Ethical approval is provided on the UKHLS web-page. Link to the web page as well as the body of the text of "Ethical Approval Statement" can be seen in the footnote.¹

https://www.understandingsociety.ac.uk/documentation/mainstage/user-guides/main-survey-user-guide/ethics/

Body of Text: Ethical approval statement

¹ Link to the UKHLS' Ethical Approval Statement:

The University of Essex Ethics Committee has approved all data collection on Understanding Society main study and innovation panel waves, including asking consent for all data linkages except to health records. Requesting consent for health record linkage was approved at Wave 1 by the National Research Ethics Service (NRES) Oxfordshire REC A (08/H0604/124), at BHPS Wave 18 by the NRES Royal Free Hospital & Medical School (08/H0720/60) and at Wave 4 by NRES Southampton REC A (11/SC/0274). Approval for the collection of biosocial data by trained nurses in Waves 2 and 3 of the

4.3. Stock Market Participation

The outcome variable - "stock market participation" has been understood as an act of holding the financial securities. In other words, it means the passive action of buying and holding rather than active trading. This definition is cohesive with the wide spectrum of literature (Bonaparte & Kumar, 2013, p. 763; Changowany, Campbell, & Tabner, 2015, p. 326; Brown & Taylor, 2010, p. 4-5)

To measure stock market participation, we employ a specific question from the UKHLS questionnaire that inquires: "Which, if any, of these types of investments are held by you or anyone in your household?" Respondents are provided with the following options: "National Savings and Investment (NS&I) Certificates or Bonds (Capital, Income, or Deposit); Unit Trusts / Investment Trusts (excluding ISAs/PEPs); Company stocks or shares, UK or foreign (excluding ISAs/PEPs); Other investments (e.g., gilts, government or company bonds or securities, stock options)." These options allow study to assess the type of investment holdings among survey participants, which helps to maintain the detailed analysis of stock market participation.

Notably, these options are not mutually exclusive and the same individual can invest in each of them, however it still provides us with an opportunity to make a distinction based on the choice of investment. Consequently, two outcome variables have been created. SMP_total - if an individual owns any of the up mentioned securities. SMP_direct - for the cases when an individual owns "Company stocks or shares, UK or foreign (excluding ISAs/PEPs)". Second option helps us identify investors who participate in the stock market directly, meaning that these participants have no investments in mutual funds and/or in other passively managed securities. While the total stock market participation is the primary outcome variable, creating the alternative

main survey was obtained from the National Research Ethics Service (Understanding Society – UK Household Longitudinal Study: A Biosocial Component, Oxfordshire A REC, Reference: 10/H0604/2).

measure for the direct stock market participation has been a suggested pattern in literature (Changwony, Campbell & Tabner, 2015, p. 326; Kaustia, Conlin & Luotonen, 2023, p. 5).

4.4. Social Networks

The primary predictor used in the study is social engagement. Study treats social engagement as the means of information dissemination/consumption leading to increased stock market participation. Furthermore, based on the theoretical framework distinction is made between strong and weak ties, when studying social engagement. Similarly, to the rest of the literature (Hong et al. 2004, Georgarakos & Pasini 2011, Liu et al. 2014; Changwony, Campbell & Tabner, 2015) study uses questions related with social interaction as the proxy for measuring the sociability of an individual and its degree of social engagement.

Two questions from the survey have been used as proxy measures for social engagement. Each of them represents the interaction with the group of people with different proximity of closeness. In other words, weak and strong ties. Such approach is cohesive with the previous work done on the topic of social engagement and stock market participation (). Consequently, enabling study to engage in discussion with previous literature.

Question used as the proxy measure for strong ties is Likert scale question where the statement ("I regularly stop and talk with people in my neighborhood") is provided and the respondent should choose if they agree or disagree with it. Response choices start at "Strongly agree" and end with "Strongly disagree". Question has been recoded into binary variable ("talks_with_neighbors") which is equal to 1 if respondent chose that they either "Strongly agree" or "Agree" with the statement and 0 if they chose "Neither agree/disagree", "Disagree", "Strongly disagree".

Question used for the proxy measure of engagement with weak ties is active participation with the social groups. Literature has been split on the choice of the proxy measure for social engagement through weak ties. While some use social group membership and others active participation in social groups, study uses later as the measure. Two simple arguments can be made in favor of this decision. Firstly, membership does not guarantee any form of engagement or participation, for example a person might belong to a religious group but not attend the service. Secondly, people can participate and be actively involved in activities of the social group even if they are not members. For example, attend the gathering and events of the local interest group or a political party, without actual membership. To sum up, interaction is essential for the information transition, and study assumes that active participation is a better measure than membership. Hence, the question used for measuring is - "Whether you are a member or not, do you join in the activities of any of these organisations on a regular basis?", question is asked for a set of different organizations and respondents can either confirm or deny. Responses have been re-coded into categorical variable (org_activity) with three levels, where the 0 is equal to no engagement with any of the organizations, while 1 is engagement with the one to three organizations, and 2 if participation is active with more than three organizations. Such an approach leaves space to look more in depth into the influence weak ties have on the stock market participation.

While two primary predictions serve as proxies for weak and strong ties, they must be controlled for potential confounders. Based on the survey questionnaire, data availability, theoretical framework, and previous research, a set of control variables has been identified. Engagement with neighbors can be influenced by one's sense of belonging to the neighborhood. A lack of belonging or distrust among neighbors could lead to a misinterpretation of the neighborhood as a space for strong ties. Consequently, variables such as trust in and belonging to the neighborhood, along with the willingness to seek advice from the local community, have been studied and included in the analysis (a detailed description is available in Table 1).

Additionally, social behavioral controls, including religiousness, have been incorporated into the analysis. The literature shows mixed findings regarding the impact of religiousness on stock market participation (Hong, Kubik & Stein, 2004; Georgarakos & Pasini, 2011; Changwony, Campbell & Tabner, 2015), yet it is consistently used to account for behavioral patterns. Therefore, our study also utilizes

this control, measuring it with a specific question: "Does religion make a difference to your life?" Responses are re-coded into a binary variable ("religiousness"), where values of 0 correspond to "A little difference" and "No difference," and values of 1 are assigned to "A great difference" and "Some difference."

4.5. Social Media Activity

As discussed in previous chapters, study expands on the established relationship between sociability and stock market engagement by testing them in an online environment. To achieve this, the paper identifies social media as the space for engagement and then operationalizes what it means to be active on social media. Operationalization is done by using a specific question from the most recent wave of the UKHLS. Due to the limited overlap between observations on social media activity and stock market participation within a single wave, the analysis is conducted on a restricted number of observations. Consequently, hypotheses 3, 4, and 5, which incorporate the concept of social media engagement, are tested using data from the most recent survey wave (13).

The primary question used to measure social media activity is: "How often do you use the internet for personal use in the following activities? Looking at content on social media/websites and apps (e.g., looking at text, images, videos on Facebook, Twitter, Instagram)." Responses to this question have been re-coded into a binary variable "active_soc_media," which assigns a value of 1 if the respondent selects "Every day" or "Several times a week." The variable takes a value of 0 if the respondent selects "Several times a month", "Once a month", "Less than once a month", or "Never".

While social media has been perceived as the new medium of information dissemination, study finds it essential to control the variable with other proxies dedicated at observing the alternate social media activity (beyond scrolling) and general online behavior. Previous research suggests that access computer literacy (Changwony, Campbell, & Tabner, 2015, p. 360) have positively influenced stock market participation. To avoid overstretching the potential influence of social media engagement on the outcome variable, there is an essential need to control for the

variables which enable a person to engage with social media. Variables such as browsing the internet have been used to moderate the effects of social media engagement on the stock market participation (Liu, Zhang, & Yang, 2014). As an alternative proxy for social media engagement, frequency of posting on social media has been adapted. These steps have been taken to eliminate the unseen effects of potential confounding variables, and allows the interpretation of the interaction between the stock market participation and activity on the social media to remain controlled for the influences of moderating and confounding variables.

4.6. Additional Control Variables

As already discussed in the literature review, research on stock market participation has touched different angles and perspectives. Consequently, the list of the variables which have been observed to influence one's decision in regards to holding the financial securities is broad. Demographic conditions along with socioeconomic characteristics dictate the decision to enter the market. Study is using inclusive strategy consequently most of the accessible control variables from the literature have been added to the analytical models. Full list of the variables can be found below in table 1. Table is composed with the name of the variable; description - which contains the question and or description from the UKHLS survey; Value - recoded values for the variables; Wave - from which survey wave does the observations come (notably H and I are the indicators for if the response is on Household or Individual level).

Variable	Description	Value	Wave	
Outcome Variable				
Total Stock Market Participation _ SMP_total (holds any form of the financial securities)	Which, if any, of these types of investments are held by you or anyone in your household?	National Savings and Investment (NS&I) Certificates or Bonds (Capital, Income or Deposit)"; "Unit Trusts / Investment Trusts (excluding ISAs/PEPs)"; "Company stocks or shares, UK or foreign (excluding ISAs/PEPs)" and/or "Other investments (e.g. gilts, government or company bonds or securities, stock options)"- 1;	4, 8, 13 H	

Table 1. List of Variables

		Other or none - 0	
Stock Market Participation _ SMP_direct (holds directly managed financial securities)	Which, if any, of these types of investments are held by you or anyone in your household?	"Company stocks or shares, UK or foreign (excluding ISAs/PEPs)" - 1; Other or none - 0	4, 8, 13 H
	Social Engagement 1	Measures	
talks_with_neighbors (tendency of individual to engage in communication with neighbors)	I regularly stop and talk with people in my neighborhood	"Strongly agree" or "Agree" - 1; "Neither agree/disagree", "Disagree", "Strongly disagree" - 0	3, 6, 9, 12 I
org_activity (active participation in social groups)	Whether you are a member or not, do you join in the activities of any of these organizations on a regular basis?	If more than 3 organization has been mentioned - 2; If 1-3 organization has been mentioned - 1; None - 0	3, 6, 9, 12 I
	Social Engagement	Controls	
local_advice (willingness to seek advice from neighbors)	If I needed advice about something I could go to someone in my neighborhood.	"Strongly agree" or "Agree" - 1; "Neither agree/disagree", "Disagree", "Strongly disagree" - 0	3, 6, 9, 12 I
belong_neighborhoob (feeling of belonging individual hold towards neighborhood)	I feel like I belong to this neighborhood.	Strongly agree" or "Agree" - 1; "Neither agree/disagree", "Disagree", "Strongly disagree" - 0	3, 6, 9, 12 I
Trust_neighborhood (feeling of trust individual holds for neighbors)	people in this neighborhood can be trusted	Strongly agree" or "Agree" - 1; "Neither agree/disagree", "Disagree", "Strongly disagree" - 0	3, 6, 9, 12 I
	Social Media Activity	Measures	<u></u>
active_soc_media (frequency of browsing social media)	(How often do you use the internet for personal use in the following activities?) Looking at content on social media/websites and apps (e.g., looking at text, images, videos on Facebook, Twitter, Instagram)	"Every day", "Several times a week" - 1; "Several times a month", "Once a month", "Less than once a month", "Never" - 0	12, 13 I
	Social Media and Inter	net Controls	

post_soc_media (frequency of posting on social media)	(How often do you use the internet for personal use in the following activities?) Posting content on social media/websites and apps (e.g., posting text, images, videos on Facebook, Twitter, Instagram)	"Every day", "Several times a week" - 1; "Several times a month", "Once a month", "Less than once a month", "Never" - 0	12, 13 I
browse_internet (frequency of browsing the internet)	How often do you use the internet for personal use in the following activities? Browsing websites	Every day", "Several times a week" - 1; "Several times a month", "Once a month", "Less than once a month", "Never" - 0	12, 13 I
has_internet (household access to internet)	Does your household have access to the internet from home?	Yes - 1; No - 0	4, 8, 13 H
has_pc (personal computer phone ownership)	Does your household have PC (question is not consistent though survey waves but by re-coding similar question we get the similar information)	Yes - 1; No - 0	4, 8, 13 H
has_mobile_phone (mobile phone ownership)	Does household have mobile phone	Yes - 1; No - 0	4, 8, 13 H
	Additional Con	trols	L
total_hh_income (household income before taxes and deductions)	Total household net income – no deductions. It is the sum of monthly total net personal income – no deductions received by all household members.	Recoded into factor variable: 5 quantile	4, 8, 13 H
age (age at the moment of interview)	Age of the respondent at the moment of the interview. All respondents are older than 16.	Recoded into following groups: "16-25", "26-35", "36-45", "46-55", "56-65", "65+"	4, 8, 13 I
sex (binary variable)	Self-identified sex of the respondent	Female - 0; Male - 1	4, 8, 13 I
employment (form of employment)	Which one best describes your current employment situation?	Unemployed, maternity leave, family care, full- time student, sick, disabled, government training scheme, or other -0; retired -1; self-employed - 2; and employed - 3	
health (if individual has any long standing health issues)	Do you have any long-standing physical or mental impairment, illness or disability? By 'long-standing' I mean anything that has troubled you over a period of at least 12 months or that is likely to trouble you over a period of at least 12 months.	Yes - 1; No - 0	4, 8, 13 I

religiousness (general perception on religion, not controlled for denomination)	religion makes a difference to life	"A great difference", "Some difference" - 1; "A little difference", "No difference" - 0	4, 8, 12 I
Education (level of academic education individual has)	Current status highest educational or vocational qualification.	Re-ordered for easier understanding "Degree" - 5 "Other higher degree" - 4 "A-level etc" - 3 "GCSE etc" - 2 "Other qualification" - 1 "No qualification" - 0	4, 8, 13 I

4.7. Descriptive statistics

Survey data used in the paper counts 137 485 observations. However, it should be noted that not all variables are observed for every entry. Consequently, fixed effects models analyze approximately 20% of all observations for testing hypothesis 1 and 2. Such a drastic reduction in the number of observations happens because fixed effects need entry to be consistently present thought the waves. The model used to test the hypothesis 3, 4 and 5 analyzed the sample is approximately 26 000 observations as is uses only data from the third wave.

Primary outcome variables have been observed in 110 358 cases. Data indicates that it is more likely for the people to own some form of financial securities (36%) than own directly managed company stocks (21%). It is logical and expected observation, both of the outcome variables have high standard deviation, indicating considerable variability among the respondents.

Social engagement predictors demonstrate a high level of participation among the respondents. 67% of the respondents frequently talk with their neighbors, while 40% of them are actively engaged in the activities of social groups. Respondents are more likely to trust their neighbors (68%), feel belonging towards their neighbors (66%) and seek advice from their neighbors (54%) than not.

Observation on the proxies used to measure social media activity are considerably less than the rest of the observation. Approximately, 26 000 observations have been collected through the last wave of the survey. Limited information on the matter of social media engagement has been already mentioned, and has been addressed in the analytical part of the chapter as well. 78% of the respondents, state that they are actively engaged with social media, through scrolling. While, only 28% of the respondents post actively on social media channels.

The data indicates widespread adoption of alternative internet resources among the respondents, with 90% regularly browsing the internet and 87% using email. This trend underscores a broader shift toward a heightened online presence in society. Such a shift is facilitated by widespread accessibility to technological resources: 95% of the surveyed population has access to the internet, 90% own personal computers, and 97% possess mobile phones. Notably, sample maintains gender balance, with a slight majority in favor of women (54%).

Variable Description	Number of Observations	Mean	Standard Deviation	Min	Max
Total ownership of any financial securities	110358	0.36	0.48	0	1
Ownership of directly managed financial securities	110358	0.21	0.40	0	1
Frequency of talking with neighbors	105049	0.67	0.47	0	1
Active participation in social groups (factor)	124155	1.42	0.54	1	3
Openness to seek advice among neighbors	105042	0.52	0.50	0	1
Belonging to the neighborhood	105083	0.66	0.47	0	1
Trust in neighbors	110285	0.68	0.47	0	1
Perceives religion important	109334	0.37	0.48	0	1
Actively engages with social media	26406	0.78	0.42	0	1
Frequently post on social media	26394	0.28	0.45	0	1

Table 2. Descriptive Statistics for All Variables Used In the Analysis

Frequently uses email	26413	0.87	0.34	0	1
Frequently browses internet	26434	0.90	0.30	0	1
Has access to internet	106302	0.95	0.21	0	1
Owns personal computer	112185	0.90	0.30	0	1
Owns mobile phone	109473	0.97	0.18	0	1
Household Income (factor of five quantiles)	112665	3.01	1.41	1	5
Age groups (factor)	114352	3.73	1.71	1	6
Sex (Factor, 1 is male)	114363	0.46	0.50	0	1
Type of employment (factor)	113709	2.82	1.22	1	4
Has any long-standing health issues	114108	0.34	0.47	0	1
Education (factor)	112840	2.92	1.65	0	5
Wave (to which wave of survey it belongs)	137485	1.84	0.78	1	3

4.8. Methods

Two distinct regression models have been used to test the set of hypotheses introduced in the earlier part of the paper. The outcome variable as already stated is dichotomous, hence for its analysis study uses the logistic regressions, which have been considered to be the most conventional approach (Aneshensel, 2013, p. 363-364). While the decision to have two different regression models makes the analytical process more complicated, it was dictated by the data. As mentioned already, social media participation is only observed in the later waves of the survey. Consequently, the first two hypotheses are analyzed by using the three-panel data and fixed effects logistic regression. The rest of the hypotheses (3, 4, 5) are analyzed based on the third wave data and by using simple logistic regression.

Key differences between the fixed and random regression models can be understood how the regression model treats unobserved differences. In random regression such variables are treated as random variables, while fixed effects regression treats the differences as fixed parameters (Wilson & Lorenz, 2015, p. 226). In other words, in fixed effect regression "unobserved variables are allowed to have any association with observed variables" (Allison, 2009, p. 3). The main advantage of the fixed effect model, especially with the panel data, is that it can control for omitted variable bias, as each observation is its own control (Wilson & Lorenz, 2015, p. 228). However, for the data to be suitable for the fixed effect model, it should adhere to two conditions: outcome variable should be measured at least on two occasions, within the same population and metrics. And the predictor should vary in values across multiple observations for a significant portion of the sample (Allison, 2009, p. 1-2). UKHLS' three panel data used in the study fulfills these requirements and consequently allows paper to use fixed effects logistic regression for analysis. Meanwhile, observation from a single wave of the study fails to adhere to conditions required for a fixed effects model, consequently more traditional ordinary logistic regression has been used for testing social media engagement hypothesis.

Both of the models used in analysis follow a sequential logic. Initially, a basic model is presented that examines the straightforward relationship between the outcome and the predictor variables. Later, the model is expanded step-by-step to include potential confounding and mediating variables. This methodical approach ensures a thorough analysis, progressively building complexity to capture the nuanced relationships between the variables.

4.8.1. Fixed Effects Model

Baseline model for the fixed effects logistic regression includes two sets of predictor variables, proxies for the social engagement. Control variables are introduced to the model step by step. Initially the general control variables are introduced to the model, and lastly the predictor affiliated controls. As there are two types of outcome variable (*total* and *direct*), each formula is presented twofold. Notably, primary interest for the research is *total* participation and more attention will be paid to it in the results parts, than to *direct* participation. Pairs of formulas are different only with the outcome variable.

$$log\left(\frac{P(Y_{total,it} = 1)}{1 - P(Y_{total,it} = 1)}\right)$$
$$= \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_2 X_{org_active,it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

$$log\left(\frac{P(Y_{direct,it} = 1)}{1 - P(Y_{direct,it} = 1)}\right)$$
$$= \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_2 X_{org_active,it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

Study uses two proxies to measure the stock market participation " Y_{total} " and " Y_{direct} ". Total participation is understood as holding of any forms of financial securities, while direct participation is limited to only directly managed financial securities. " $P(Y_{it} =$ 1)" is the probability of stock market participation for individual "*i*" at the time of "*t*". " β_0 " is an intercept. " $X_{talk_neighbor}$ " is a predictor from social engagement (frequency of engagement with neighbors) and " β_1 " express its coefficient. Similarly, " X_{org_avtive} " is social engagement proxy variable for weak ties (active participation in social groups) and " β_2 " consequently its coefficient. " α_i " is the individual-specific effect (fixed effect) for individual "*i*" that captures all unobservable individual-specific influences that do not vary over time. " γ_t " is the fixed effect for the wave of the survey. " ε_{it} " is an error term.

4.8.1.2. Introducing Controls

$$log\left(\frac{P(Y_{total,it} = 1)}{1 - P(Y_{total,it} = 1)}\right) = \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_2 X_{org_active,it} + \beta_3 X_{control,it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

$$log\left(\frac{P(Y_{direct,it} = 1)}{1 - P(Y_{direct,it} = 1)}\right)$$

= $\beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_2 X_{org_active,it} + \beta_3 X_{control,it} + \alpha_i$
+ $\gamma_t + \varepsilon_{it}$

First step to refining the model is to introduce additional controls into the equation. In fixed effects logistic regression variables that don't vary and are not time sensitive, generally are not effective. Consequently, the controls added to the model are ones which change over the time: age, income, health conditions, employment. Each of this variable will have its own " β_n " for an individual "*i*" at a time of "*t*". However, for the sake of simplicity of the formula they are expressed as joint " $X_{control}$ ".

4.8.1.3. Introducing Social Engagement Controls

$$log\left(\frac{P(Y_{total,it} = 1)}{1 - P(Y_{total,it} = 1)}\right)$$
$$= \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_2 X_{org_active,it} + \beta_3 X_{control,it}$$
$$+ \beta_4 X_{sociability_conrol,it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

$$log\left(\frac{P(Y_{direct,it} = 1)}{1 - P(Y_{direct,it} = 1)}\right)$$

= $\beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_2 X_{org_active,it} + \beta_3 X_{control,it}$
+ $\beta_4 X_{sociability_conrol,it} + \alpha_i + \gamma_t + \varepsilon_{it}$

Last step of the model specification is introduction of the social interaction control variables. As discussed in the previous parts of the paper, social interaction should be controlled for the confounding and mediating variables such as trust and belonging to the neighborhood and/or willingness to seek advice from the local community. Each of these variables are expected to change over time, and consequently can be used in the fixed effects model. As other controls introduced in the previous step, control variables for social engagement are presented as one variable in the formula.

4.8.2. Logistic Regression Base Model

Similar to the fixed effects model, logistic regression model also follows the sequential logic, hence initially the baseline model is presented and step by step the additional controls are introduced.

4.8.2.1. Baseline Model

$$log\left(\frac{P(Y_{total,it}=1)}{1-P(Y_{total,it}=1)}\right) = \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_2 X_{org_active,it} + \beta_3 X_{soc_media_active,it} + \varepsilon_i$$

$$log\left(\frac{P(Y_{direct,it}=1)}{1-P(Y_{direct,it}=1)}\right) = \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_2 X_{org_active,it} + \beta_3 X_{soc_media_active,it} + \varepsilon_i + \varepsilon_$$

The outcome variable is presented as log odd. In other terms the logarithm of the ratio of probability of the event to occur - " $P(Y_{it} = 1)$ ", to the probability of the event not occurring - " $1 - P(Y_{it} = 1)$ ", where " Y_k " is the outcome variable. Independent variables are presented as " X_k " along with their " β_k " - coefficient. " β_0 " is the intercept and " ε_i " is an error term for observation "i". Additional explanatory variable of social media engagement has been added to the logistic regression model, which allows to observe the influence of social media activity on the stock market participation.

4.8.2.2. Introducing Controls

$$log\left(\frac{P(Y_{total,it} = 1)}{1 - P(Y_{total,it} = 1)}\right)$$
$$= \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_1 X_{org_active,it}$$
$$+ \beta_3 X_{soc_media_active,it} + \beta_4 X_{controls,it} + \varepsilon_i$$

$$log\left(\frac{P(Y_{direct,it} = 1)}{1 - P(Y_{direct,it} = 1)}\right)$$
$$= \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_1 X_{org_active,it}$$
$$+ \beta_3 X_{soc_media_active,it} + \beta_4 X_{controls,it} + \varepsilon_i$$

Initial controls have been added to the equation. While in fixed effects model controls which were prone to stay stagnant through time have been omitted, in case of regression models these variables have been added to the equation. Consequently, in addition to the controls used in the fixed effect model, sex and education have been added to the equation.

4.8.2.3. Introducing Predictor Centered Controls

$$log\left(\frac{P(Y_{total,it}=1)}{1-P(Y_{total,it}=1)}\right) = \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_1 X_{org_active,it} + \beta_3 X_{soc_media_active,it} + \beta_4 X_{sociability_control,it} + \beta_5 X_{soc_media_control,it} + \beta_6 X_{controls,it} + \varepsilon_i$$

$$log\left(\frac{P(Y_{direct,it}=1)}{1-P(Y_{direct,it}=1)}\right) = \beta_{0} + \beta_{1}X_{talk_neighbor,it} + \beta_{1}X_{org_active,it} + \beta_{3}X_{soc_media_active,it} + \beta_{4}X_{sociability_control,it} + \beta_{5}X_{soc_media_control,it} + \beta_{6}X_{controls,it} + \varepsilon_{i}$$

Additional controls have been added to the equation, designed to control the effects predictors might have on the stock market participation. Different controls are used for social engagement and social media activity, however notably these are set of different variables - " X_k " with their own coefficients " β_k ".

4.8.2.4. Introducing Interaction Terms

 $log\left(\frac{P(Y_{total,it}=1)}{1-P(Y_{total,it}=1)}\right) = \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_1 X_{org_active,it} + \beta_3 X_{soc_media_active,it} + \beta_4 X_{sociability_control,it} + \beta_5 X_{soc_media_control,it} + \beta_6 X_{controls,it} + \beta_7 (X_{soc_media_active,it} \times X_{talk_neighbor,it}) + \beta_8 (X_{soc_media_active,it} \times X_{org_active,it}) + \varepsilon_i$

$$log\left(\frac{P(Y_{direct,it}=1)}{1-P(Y_{direct,it}=1)}\right) = \beta_0 + \beta_1 X_{talk_neighbor,it} + \beta_1 X_{org_active,it} + \beta_3 X_{soc_media_active,it} + \beta_4 X_{sociability_control,it} + \beta_5 X_{soc_media_control,it} + \beta_4 X_{sociability_control,it} + \beta_5 X_{soc_media_control,it} + \beta_5 X_{so$$

 $\beta_{6}X_{controls,it} + \beta_{7}(X_{soc_media_active,it} \times X_{talk_neighbor,it}) + \beta_{8}(X_{soc_media_active,it} \times X_{org_active,it}) + \varepsilon_{i}$

Final step of testing the proposed hypothesis is to introduce the interaction terms within the equation. As the hypothesis assumes that the hierarchy and strength of social ties is challenged in the social media environment, the need to introduce the interaction terms within the equation emerges. When observed, interaction terms imply that the social interaction variables (talking with neighbors and active engagement with the social groups) influence the outcome variable depending on the social media activity.

Chapter 5: Results

Paper has tested interaction between the social engagement measures in the online and offline world and their impact on stock market participation. Findings have been presented in the following chapter. Results of the analysis are split into two based on the two alternated samples of observations used in the study.

5.1. Overview of bivariate results

When exploring stock market participation, identifying the correct variables is a critical yet challenging task, especially in contexts where proxy measures are used. Study positions in the complex environment of varied predictors. While, proxies used in the analysis further increase the risk of incorporating overlapping variables into explanatory models. Which would potentially alter and skew the results, leading to biased outcomes. Overlap between the independent variables might indicate that the variables are measuring similar or identical constructs, a potential shortcoming that requires careful attention.

One effective strategy to mitigate this issue is to examine potential multicollinearity among the independent variables. Multicollinearity occurs when two or more independent variables are strongly correlated, typically exceeding a bivariate correlation coefficient threshold of |0.70| (Pearson, 2010, p. 289). Observing such high

correlations suggests that the variables may not be providing unique information, and might be overleaping, leading to the distorted outcomes of regression analyses.

In case, when strong correlations are identified, it is suggested to either remove these variables from the regression model or conduct further investigations to understand the underlying causes of these interdependency. Another approach to managing multicollinearity involves creating an index from the strongly correlated variables, thereby merging them into a single predictor. This technique not only simplifies the model but also retains the essential information, potentially enhancing the model's interpretability and accuracy.

The correlation matrix of the variables used in the study is presented in Figure 2. Analysis of the matrix reveals that there is no strong correlation among predictors, indicating no need to exclude any of selected predictors from the analysis due to concerns of multicollinearity. The matrix confirms that the risk of multicollinearity is minimal across most variables.

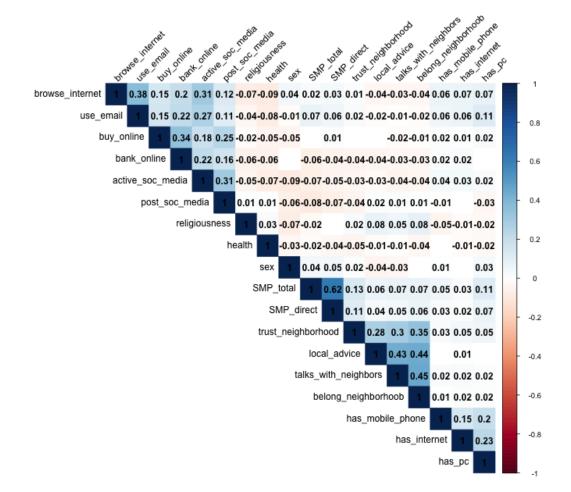
However, a moderate level of correlation is observed among the social engagement indicators and its controls: frequency of talking with neighbors (talks_with_neighbors), feelings of belonging within the neighborhood (belong_neighborhood), seeking advice from the local community or neighbors (local_advice), and trust in neighbors (trust_neighborhood). The correlations among these variables are arrangeed from 0.28 to 0.45, which is lower the generally accepted threshold.

The only bivariate relationship approaching the correlation threshold is between the outcome variables, total (SMP_total) and direct (SMP_direct) stock market participation, with a correlation coefficient of 0.63. This correlation is not considered a threat to the analysis as both are outcome variables, hence not particularly interacting with each other. Furthermore, such an interaction between them is expected as one variable represents a subset of the other.

Figure 2: Correlation Matrix.

This table presents a Pearson correlation matrix, which displays the interactions between pairs of variables. In this matrix, a red color denotes a negative correlation, indicating a negative relationship

between variable pairs. Conversely, a blue color signifies a positive correlation, highlighting a direct relationship between the variables. It is generally accepted that a Pearson correlation coefficient greater than 0.7 or less than -0.7 suggests a strong linear relationship (Pearson, 2010, p. 289). Such high correlations warrant careful consideration, as they may imply redundancy; the variables involved could potentially be measuring the same underlying attribute or phenomenon. This understanding is crucial for ensuring the validity and reliability of any further analysis, as highly correlated variables may affect the outcomes of predictive models or multivariate analyses.



5.2. Multivariate Analysis

Understanding the factors that influence an individual's decision to participate in the stock market requires a comprehensive analytical approach. While bivariate analyses, such as correlation matrix, offer initial insights into the interaction between variable pairs, they fall short in several critical areas. Most notably, they cannot account for the complex interdependencies and multivariate influences that characterize financial decision-making processes. Consequently, to better understand the dynamics guiding

the stock market participation it is essential to introduce analytical tools designed to handle complex puzzles. As described in the methodology chapter study is using fixed effects logistic regression for analysis of survey panel data. As panel data is not available for all the observed variables, regular logistic regression is used to study social media activity and its impact on financial market participation.

5.2.1. Fixed Effects Logistic Regression

Fixed effects model allows a more nuanced understanding of the interaction between the studies outcome variable and its predictors, by eliminating the noise. Model ensures that observations are made across time for the same individuals. By doing so, it becomes possible to study the direct effect of the predictors in the environment of fixed unobserved conditions.

According to the coefficients from Table 3, derived from a fixed effects logistic regression model, indicators of social engagement consistently show a significant influence on market participation. The findings remain robust from the base model (F_1) to the model with the highest number of specifications (F_3) . Notably, the introduction of additional specifications improves the model's reliability, as shown by the increased difference between the null deviance and residual deviance when control variables are introduced.

The data indicates that individuals who frequently interact with their neighbors are more likely to own financial securities. This observation is significant, and transforming the log odds of 0.14 to a probability reveals approximately a 53% increase in the likelihood of owning financial securities. In simpler terms, individuals who frequently engage with their neighbors are about 53% more likely to participate in the financial market by owning some form of financial securities. This trend also holds for direct stock market participation, and there is about a 55% increase (corresponding to 0.20 log odds) in the probability that individuals who frequently interact with neighbors will own directly managed company stocks.

A similar pattern emerges with the proxy measure for weak ties, indicating that participation in social groups leads to an increased probability of stock ownership. The

data suggests that the probability of owning any financial securities, as well as directly managed company stocks, increases with active participation in social group activities. This effect is moderately statistically significant for general stock market participation and statistically significant for direct stock market participants. Specifically, the chances of owning any financial securities increase by approximately 52% (0.10 log odds) when individuals engage with one to three interest groups, compared to those who do not actively engage with any social groups. However, no statistical significance was found between general stock market participation and active involvement in more than three social groups. The influence of weak ties on direct stock market participation is evident in both scenarios (one to three groups, and more than three groups), with the probability of owning directly managed stocks being even higher—approximately 58% (0.34 log odds)—when an individual engages with more than three social groups.

Table 3: Fixed Effect Logistic Regression:

This table provides the output from a fixed effects logistic regression analysis, coefficients are presented in log odds, positive numbers are indicating the positive interaction and vice versa. The model is designed to control for inherent characteristics that do not vary across the observed period by incorporating two fixed effects: individual identifier (id) and time. Id represents unique individuals within the dataset, allowing the model to adjust for any unobserved heterogeneity that could bias the results if individuals were significantly different from each other. Time, on the other hand, accounts for the panel structure of the dataset, enabling the model to differentiate changes that occur due to temporal dynamics rather than across individuals. This approach significantly enhances analytical robustness as it evaluates how the outcome variable—stock market participation—varies over time for the same individuals, rather than aggregating data across different individuals who may have not been observed consistently over time. By focusing on within-individual changes, the fixed effects model provides insights that are more precise about the effects of variables that change over time.

Fixed Effects Logistic Regression Models						
Dependent variable:						
	SMP_total		:	SMP_direc	t	
(F_1)	(F_2)	(F_3)	(F_4)	(F_5)	(F_6)	
0.14^{*}	0.14^{*}	0.14^{*}	0.21**	0.23**	0.20^{*}	
(0.06)	(0.06)	(0.06)	(0.08)	(0.08)	(0.08)	
0.10^{*}	0.10^{*}	0.10^{*}	0.11	0.14^{*}	0.14^{*}	
(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)	
0.14	0.17	0.15	0.33**	0.36*	0.35*	
(0.15)	(0.15)	(0.16)	(0.17)	(0.17)	(0.18)	
	(F_1) 0.14* (0.06) 0.10* (0.05) 0.14	SMP_total (F_1) (F_2) 0.14* 0.14* (0.06) (0.06) 0.10* 0.10* (0.05) (0.05) 0.14 0.17	$\begin{array}{c c} & & & & \\ & & & \\ \hline \\ Dependen \\ \hline \\ SMP_total \\ \hline \\ (F_1) & (F_2) & (F_3) \\ 0.14^* & 0.14^* & 0.14^* \\ (0.06) & (0.06) & (0.06) \\ 0.10^* & 0.10^* & 0.10^* \\ (0.05) & (0.05) & (0.05) \\ 0.14 & 0.17 & 0.15 \\ \end{array}$	Dependent variable: SMP_total SMP_total (F_1) (F_2) (F_3) (F_4) 0.14* 0.14* 0.14* 0.21** (0.06) (0.06) (0.06) (0.08) 0.10* 0.10* 0.10* 0.11 (0.05) (0.05) (0.05) (0.06) 0.14 0.17 0.15 0.33**	Dependent variable: Dependent variable: SMP_total SMP_direc (F_1) (F_2) (F_3) (F_4) (F_5) 0.14* 0.14* 0.21** 0.23** (0.06) (0.06) (0.08) (0.08) 0.10* 0.10* 0.11 0.14* (0.05) (0.05) (0.05) (0.06) (0.07) 0.14 0.17 0.15 0.33** 0.36*	

local_advice		-0.02		-0.06
		(0.06)		(0.042)
belong_neighborhoob		0.07		0.15^{*}
		0.07		(0.08)
trust_neighborhood		0.02		0.10
-		(0.06)		(0.08)
religiousness	0.10	0.12	0.08	0.10
rengiousiess	(0.08)	(0.08)	(0.10)	(0.10)
health	0.17*	0.17*	0.10	0.12
	(0.06)	(0.07)	(0.08)	(0.08)
employment2	0.18	0.20	0.11	0.15
	(0.14)	(0.14)	(0.17)	(0.17)
employment3	-0.06	-0.08	0.10	0.13
	(0.15)	(0.15)	(0.19)	(0.19)
employment4	-0.16	-0.16	0.04	0.08
	(0.10)	(0.10)	(0.13)	(0.14)
Age 26-35	0.25	0.23	0.68***	0.61*
	(0.15)	(0.16)	(0.20)	(0.20)
Age 36-45	0.55**	0.53*	1.26***	1.20***
	(0.21)	(0.21)	(0.27)	(0.28)
Age 46-55	0.83**	0.80^{**}	1.65***	1.57***
	(0.25)	(0.26)	(0.33)	(0.33)
Age 56-65	0.90**	0.87**	1.85***	1.76***
	(0.30)	(0.30)	(0.38)	(0.38)
Age 65+	0.94	0.93**	1.67***	1.52***
	(0.35)	(0.36)	(0.43)	(0.44)
total_hh_income2	0.36***	0.36***	0.25^{*}	0.24^{*}
	(0.09)	(0.09)	(0.12)	(0.12)
total_hh_income3	0.63***	0.63***	0.47***	0.46***
	(0.10)	(0.10)	(0.13)	(0.13)
total_hh_income4	0.75***	0.76***	0.61***	0.60***
	(0.10)	(0.10)	(0.13)	(0.13)
total_hh_income5	1.04***	1.06***	0.99***	0.97***
	(0.11)	(0.11)	(0.13)	(0.14)

Observations	23,292	22,650	22,109	15,774	15,340	15,040
Residual Deviance	30,361.77	29,348.56	28,661.93	20,084.21	19,372.42	18,997.50
Null Deviance	32,285.23	31.396.11	30,647.25	21,838.43	21,239.87	20,826.24
Note:			*p**p***	p<0.01		

4.2.1.1. Connecting findings to Hypothesis:

One of the core ideas for the paper has been re-evaluation of the findings from the literature with the newer data, assuming that some of the former interaction might have been lost and or altered due to the technological changes. In line with this pathos two hypotheses have been borrowed from Changwony et. al (2015, p. 322). These hypotheses offer an insight into the interaction between social engagement and stock market participation. Findings of the fixed effects logistic regression model have offered empirical evidence explaining the outline interaction.

"Hypothesis 1. Individuals who talk more frequently with their neighbors are more likely to participate in the stock market."

"Hypothesis 2. Individuals who are active in social groups are more likely to participate in the stock market"

According to the findings from the model individuals who frequently talk with their neighbors have higher chances of stock market participation. This observation is true both for the generally owned financial securities as well as directly managed company stocks. Taking into account these findings it is possible to argue that hypothesis 1 is true and can be confirmed based on the findings from the fixed effects regression.

Furthermore, findings are not as consistent in regards to weak ties. There is statistically marginally evidence of significance in support that social group participation leads to the increased odds of security ownership. This is true especially for the general stock market participation. With directly managed stocks it is clear that increased interaction with the social groups outside of the ones direct circle leads to the increased odds of financial market participation.

To sum up hypothesis 2 can be confirmed especially when looking at the direct stock market participation. But with a potential question mark which addresses the lack of statistical evidence to support the relationship between the active participation with more than three social groups and the general stock market participation.

5.2.2. Simple Logistic Regression

Table 4 presents the results from logistic regression analyses that examine the impact of social media activity on stock market participation. As outlined in the methodology section, the models introduce control variables step by step, following the sequential pattern. The table shows outputs of six models, with the first three focusing on total stock market participation (SMP_total) and the subsequent three targeting direct stock market participation (SMP_direct). The number of observations decreases from 22,046 in the simplest model to 19,684 in the most comprehensive model, which incorporates all controls. This reduction reflects the exclusion of cases due to the missing data on the control variables introduced as a part of model specification. However, the number of observations remains a significant part of the full sample. The Akaike Information Criterion (AIC) scores decrease with the introduction of additional controls, suggesting that the more complex models provide a better fit for the data. This improvement is confirmed by the increase in the Log Likelihood values as well, which indicates an enhanced model accuracy with the introduction of new controls.

The analysis reveals that the odds of participating in the stock market are consistently below one (see constant) when all predictors are at their baseline levels, suggesting an inherent reluctance towards stock market participation under standard conditions. On the other hand, most of the predictors and controls introduced in the models hold significant and frequently positive effects on the odds of stock market participation.

The variables measuring social engagement are not similarly treated by the model. Weak ties (such as talks with neighbors) remain as a significant predictor across all models. While strong ties (such as organizational activity), is a significant predictor only within the baseline model for both total and direct stock market participation. The impact of active engagement in social group activities is expressed using a factor variable that distinguishes between the number of social groups an individual is involved with. Notably, the odds ratio for "org_activity3" is higher than for "org_activity2," indicating that for individuals who engage with more than three organizations the chances of stock market participation is larger compared to those who engage with one to three organizations. The reference category for both variables is no participation in any organization at all. Findings demonstrate that nonetheless of the number of organizations, odds of stock market entry increase along with the choice to engage with social groups.

The interaction of strong social ties, measured through the frequent engagement with neighbors, varies model to model. However, in both cases, general and direct stock market participation, the models with most specifications treat it as an insignificant predictor. These findings align with existing literature on social engagement and stock market participation (Changwony, Campbell & Tabner, 2015).

The primary objective of this paper is to explore the impact of social media on individuals' decisions to engage in stock market activities. Contrary to the initial hypothesis that social media usage would positively correlate with stock market participation, the findings consistently reveal a negative association (further discussed later). Frequent use of social media demonstrably decreases the likelihood of engaging in stock market activities. This effect remains insignificant across all models.

However, the use of an alternative proxy for social media engagement, "post_soc_media," which assesses whether individuals frequently post on social platforms or not, also shows a negative correlation with stock market participation and is a significant predictor. This further confirms the observed pattern that active social media engagement may deter rather than encourage stock market activity.

Furthermore, digital behavior controls such as internet usage (odds ratio of 1.156), email usage (odds ratio of 1.393), and access to personal technology like computers (odds ratio of 3.012) exhibit a positive influence on the likelihood of participating in the stock market and are significant. These findings hold true for both general stock ownership and direct stockholding, suggesting that while active social media usage

may have a deterrent effect, broader digital engagement enhances the probability to invest in the stock market.

Furthermore, analysis did not reveal any deviations from existing literature regarding the control variables. Consistent with previous studies, both income and education levels exhibit positive effects on stock market participation across all models. On the other hand, health-related issues consistently deter individuals from engaging with the stock market, indicating that better health correlates with increased investment activity.

Employment status also plays a significant role, with any form of employment showing a considerable positive correlation with stock market participation compared to unemployment. This observation remains as a significant explanatory variable across the general stock market participation models. However, does not hold to be true with direct stock ownership.

Notably, a gender-based gap in stock market participation does not hold to be present in the general stock market participation model. On the other hand, it is present in the direct stock market participation model. Such disparity can be explained by the men's willingness to take risk compared to women as direct stock ownership is associated with higher risk and reward. Model does not include any variables for measuring social openness towards risk taking, hence gender serves as the proxy measure in line with literature (Kaustia & Torstila, 2011).

Table 4: Odds Ratio from Logistic Regression Models

This table presents the odds ratios derived from logistic regression analyses, which evaluate the effects of various predictors on both total and direct stock market participation. Odds ratios offer a straightforward interpretation of logistic regression outputs, particularly for categorical variables. An odds ratio quantifies the factor by which the odds of the outcome variable are multiplied for each one-unit increase of a predictor (Menard, 2010, pp. 93-96). An odds ratio below 1 indicates a negative association between the predictor and the outcome, signifying a decrease in the odds of the outcome occurring. Conversely, an odds ratio greater than 1 suggests a positive association, indicating an increase in the odds of the outcome occurring. This metric is particularly useful in clarifying the impact of each variable on stock market participation, providing a clear, interpretable measure of effect size and direction.

Odds Ratios from Logistic Regression Models						
Dependent variable:						
Total Sto	ck Market Pa	rticipation	Direct Stor	ck Market Pa	rticipation	
(1)	(2)	(3)	(4)	(5)	(6)	

(0.03)(0.107)(0.25)(0.044)(0.142)(0.147)1alks_with_neighbon1.177"1.078"1.0230.0300.0300.0390.039org_activity21.985"1.521"*1.450"*1.832"*1.414"*1.366"*0.0290.0320.0340.0340.0370.0370.037org_activity32.625"*1.726"*1.618"*2.483"*1.645"*1.581"*0.01070.0100.0100.0120.01200.0280.0440.0380.041active_soc_media0.891"*0.9960.9240.841"*0.9730.94310030.0330.0340.0440.0390.0440.039local_advice1.0561.0410.0410.0410.041trus_neighborhood11.387"*1.0410.043trus_neighborhood11.387"*1.441"*1.491"*post_soc_media10.800"*1.0410.041trus_neighborhood11.387"*1.441"*1.491"*post_soc_media11.56"1.242"*0.0451trus_neighborhood11.363"*1.242"*0.04110.0411post_soc_media11.56"1.242"*0.04110.0411post_soc_media11.56"1.242"*0.04110.0411post_soc_media11.36"*1.393"*1.242"*0.0411post_soc_media11.36"*1.36"*1.242"*0.0411 <td< th=""><th>Constant</th><th>0.549***</th><th>0.073***</th><th>0.027***</th><th>0.217***</th><th>0.033***</th><th>0.019***</th></td<>	Constant	0.549***	0.073***	0.027***	0.217***	0.033***	0.019***
(0.030) (0.033) (0.039) (0.036) (0.039) (0.037) (0.037) $org_activity2$ 1.985^{***} 1.726^{***} 1.618^{***} 2.483^{***} 1.645^{***} 1.581^{***} $org_activity3$ 2.625^{***} 1.726^{***} 1.618^{***} 2.483^{***} 0.645^{***} 1.581^{***} $org_activity3$ 2.625^{***} 1.726^{***} 1.618^{***} 0.120 0.120 0.120 0.120 0.120 $active_soc_media$ 0.801^{***} 0.996 0.924 0.841^{***} 0.973 0.943 0.033 0.038 0.044 0.038 0.044 0.038 0.044 0.049 $10cal_advice$ 0.801^{***} 0.973 0.441 0.0493 0.044 $10cas_neighborhoob$ 1.878^{***} 0.037 1.044 0.0451 pts_soc_media 1.878^{***} 0.037 1.044 0.0451 pts_soc_media 1.387^{***} 1.663^{***} 0.0451 0.0451 pts_soc_media 1.867^{***} 0.637 1.249^{**} 0.0451 pts_soc_media 1.581^{***} 0.663^{**} 0.0751^{**} 0.0751^{**} pts_soc_media 1.581^{***} 0.663^{**} 0.621^{**} 0.0751^{**} pts_soc_media 1.581^{***} 0.663^{**} 0.621^{**} 0.021^{**} pts_soc_media 1.581^{***} 0.629^{**} 0.621^{**} 0.621^{**} pts_soc_media 0.719^{**} 0.0351^{**} 0.0351^{*		(0.036)	(0.107)	(0.256)	(0.044)	(0.142)	(0.317)
org_activity21,985***1,521***1,450***1,832***1,414***1,366*** (0.029) (0.032) (0.034) (0.034) (0.037) (0.037) (0.037) $org_activity3$ $2,625**$ $1,726**$ $1,618**$ $2,483**$ $1,645**$ $1,581**$ (0.107) (0.116) (0.120) (0.120) (0.120) (0.120) (0.120) $active_soc_media$ $0.801***$ 0.996 0.924 $0.841***$ 0.973 0.943 $10cal_advice$ $1.0560.037blog_neighborhood$	talks_with_neighbors	1.177***	1.078^{*}	1.012	1.122**	1.062	0.974
(0.029) (0.032) (0.034) (0.037) (0.037) (0.037) $org_activity3$ 2.625^{**} 1.726^{**} 1.618^{**} 2.483^{**} 1.645^{**} 1.581^{**} (0.017) (0.116) (0.121) (0.120) (0.120) (0.120) (0.120) $active_soc_media$ 0.801^{**} 0.996 0.924 0.841^{**} 0.973 0.943 (0.033) (0.038) (0.044) (0.038) (0.044) (0.049) $local_advice$ 1.056 0.973 1.044 $belong_neighborhoob$ 1.387^{**} (0.037) (0.045) $trust_neighborhood$ 1.387^{**} (0.037) (0.045) $post_soc_media$ 0.973 1.387^{**} (0.037) (0.045) $post_soc_media$ 1.387^{**} (0.037) (0.045) $post_soc_media$ 1.387^{**} (0.037) (0.045) $post_soc_media$ 1.156^{*} (0.037) (0.045) $post_soc_media$ 1.393^{**} (0.037) (0.076) us_email 1.393^{**} (0.037) (0.076) us_email 1.993^{**} (0.134) $(0.171)^{*}$ $hs_spic(0.161)^{*}(0.128)^{*}(0.128)^{*}has_mobile_phone1.222^{*}(0.629^{*})^{*}ucation20.719^{**}0.752^{**}0.825^{**}(0.033)(0.035)(0.039)(0.116)^{*}us_spicenes0.719^{**}0.752^{**}0.825^{**}$		(0.030)	(0.033)	(0.039)	(0.036)	(0.039)	(0.046)
org_activity3 2.625^{**} 1.726^{**} 1.618^{**} 2.483^{***} 1.645^{***} 1.581^{***} (0.107) (0.110) (0.112) (0.120) (0.123) (0.144) (0.049) lcal_advice 1.056 1.056 (0.047) (0.047) (0.047) (0.047) belong_neighborhood 1.887^{***} (0.037) (0.047) (0.047) trus_neighborhood 1.387^{***} (0.037) (0.047) post_soc_media 0.800^{***} (0.037) (0.047) post_soc_media 1.56^{**} (0.037) (0.047) use_email 1.156^{*} (0.037) (0.047) hs_piternet 0.629^{*} (0.031) (0.073) hs_pic 1.393^{***} (0.059) (0.23) has_mobile_phone 1.222 (0.131) (0.131) religiousness 0.719^{***} 0.625^{**} 0.825^{***} (0.033) (0.035) (0.039) (0.049) (0.131) education2 1.679^{***} 1.608^{***} 1.494^{**} (0.033) (0.030) (0.030) (0.116) (0.131)	org_activity2	1.985***	1.521***	1.450***	1.832***	1.414***	1.366***
$ \begin{array}{ccccc} & (0.107) & (0.116) & (0.121) & (0.120) & (0.120) & (0.123) \\ (0.031) & (0.038) & (0.044) & (0.038) & (0.044) & (0.049) \\ (0.038) & (0.038) & (0.041) & (0.038) & (0.044) & (0.049) \\ (0.038) & (0.036) & (0.043) & (0.042) \\ (0.036) & (0.042) & (0.042) \\ (0.036) & (0.043) & (0.044) & (0.041) \\ (0.039) & (0.041) & (0.045) \\ (0.041) & (0.037) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.037) & (0.045) & (0.045) \\ (0.037) & (0.045) & (0.045) \\ (0.037) & (0.045) & (0.045) \\ (0.037) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.045) & (0.045) \\ (0.045) & (0.059) & (0.045) & (0.073) \\ (0.045) & (0.073) & (0.073) \\ (0.045) & (0.059) & (0.073) & (0.073) \\ (0.045) & (0.073) & (0.073) \\ (0.045) & (0.059) & (0.073) & (0.073) \\ (0.045) & (0.073) & (0.073) & (0.073) \\ (0.045) & (0.059) & (0.073) & (0.073) \\ (0.045) & (0.073) & (0.073) & (0.073) \\ (0.045) & (0.059) & (0.073) & (0.073) \\ (0.045) & (0.073) & (0.073) & (0.073) \\ (0.045) & (0.075) & (0.075) & (0.075) \\ (0.128) & (0.052) & (0.052) & (0.152) \\ (0.152) & (0.052) & (0.053) & (0.059) & (0.041) \\ (0.04) & (0.00) & (0.131) & (0.138) \\ (0.04) & (0.00) & (0.151) & (0.154) \\ (0.04) & (0.00) & (0.151) & (0.154) \\ (0.04) & (0.00) & (0.151) & (0.154) \\ (0.04) & (0.00) & (0.151) & (0.154) \\ (0.04) & (0.00) & (0.151) & (0.154) \\ (0.05) & (0.05) & (0.05) & (0.05) \\ (0.05) & (0.05) & (0.05) & (0.05) \\ (0.05) & (0.05) & (0.05) & (0.05) \\ (0.05) & (0.05) & (0.05) & (0.05) \\ (0.05) & (0.05) & (0.05) & (0.05) \\ (0.05) & (0.05) & (0.05) & (0.05) \\ (0.05) & (0.05) & (0.05) & (0.05) & (0.05) \\ (0.05) & (0.05) & (0.05) & (0.05) & (0.05) \\ (0.05) & (0.05) & (0.05) & (0.05) & (0$		(0.029)	(0.032)	(0.034)	(0.034)	(0.037)	(0.039)
active_soe_media 0.801*** 0.996 0.924 0.841*** 0.973 0.944 lo033 (0.038) (0.044) (0.038) (0.044) (0.038) local_advice 1.056 0.988 belong_neighborhoob 0.973 1.044 (0.039) 0.973 1.044 (0.039) 0.045 1.047 belong_neighborhood 0.973 0.987 0.045 trust_neighborhood 0.973 0.973 0.045 post_soc_media 0.800*** 0.037 0.045 post_soc_media 0.800*** 0.037 0.045 post_soc_media 0.800*** 0.037 0.045 post_soc_media 0.800*** 0.045 0.0451 post_soc_media 1.156* 0.800*** 0.0451 post_soc_media 1.916** 0.800*** 0.021* post_soc_media 0.800*** 0.021* 0.021* post_soc_media 0.914 0.922 0.621* post_soc_media 0.921	org_activity3	2.625***	1.726***	1.618***	2.483***	1.645***	1.581***
(0.033)(0.038)(0.044)(0.038)(0.044)(0.049)loca_advice1.0560.988(0.030)0.0731.044(0.030)0.0731.044(0.037)1.0430.045tust_neighborhood1.387**0.037)pos_soc_media0.800**0.045poswse_internet1.156*0.0475use_email1.393**0.0629*na_pe0.029*0.021*has_pc3.012**0.021*na_posile_phone1.2220.021*na_mobile_phone1.2220.021*religiousness0.719**0.752**0.825***nonsi0.0330.0350.0310education21.679***1.608**1.494**nonsi0.0330.0350.0311education31.679***1.674**1.404**nonsi0.0300.0300.031education30.0350.008**1.636**		(0.107)	(0.116)	(0.121)	(0.112)	(0.120)	(0.123)
local_advice 1.056 0.988 loc36) 0.042) belong_neighborhoob 0.973 1.044 loc39) 0.045) trust_neighborhood 1.387*** 1.439*** loc37) 0.045) post_soc_media 0.800*** 0.787*** loc37) 0.045) browse_internet 1.156* 1.249** loc63) 0.0070) 0.0070) use_email 1.393*** 1.242** loc059) 0.0073) 0.0073) has_internet 0.629* 0.621* loc198) 0.0239) 0.0239 has_pc 3.012*** 2.271*** loc134) 0.1701 0.1701 has_mobile_phone 1.222 0.962 loc133 0.035 0.039 0.0401 education2 0.719*** 0.752*** 0.825*** 0.859*** loc031 0.035 0.039 0.0401 0.131 0.131 education3 2.175*** 1.608*** </td <td>active_soc_media</td> <td>0.801***</td> <td>0.996</td> <td>0.924</td> <td>0.841***</td> <td>0.973</td> <td>0.943</td>	active_soc_media	0.801***	0.996	0.924	0.841***	0.973	0.943
0.036) 0.042) belong_neighborhoob 0.973 1.044 (0.039) 0.045) trust_neighborhood 1.387*** 1.439*** (0.037) 0.045) post_soc_media 0.800*** 0.787*** (0.037) 0.045) browse_internet 1.156* 1.249** (0.063) 0.0761 use_email 1.393*** 1.242** (0.059) 0.0731 has_internet 0.629* 0.621* (0.134) (0.170) 0.621* has_pc 3.012*** 2.271*** (0.134) (0.170) 0.621* trust_nobile_phone 1.222 0.962 religiousness 0.719*** 0.752*** 0.825*** (0.033) 0.035) (0.039) 0.0401 education2 1.679*** 1.608*** 1.494** 1.405* (0.033) 0.035) (0.039) 0.0161 0.131		(0.033)	(0.038)	(0.044)	(0.038)	(0.044)	(0.049)
belong_neighborhood 0.973 0.045 trust_neighborhood 1.387*** 1.439** trust_neighborhood 1.387*** 1.439** (0.037) 0.045 post_soc_media 0.800*** 0.787** (0.037) 0.045 browse_internet 1.156* 1.249** (0.063) 0.076 use_email 1.393*** 1.242** (0.063) 0.079 use_email 1.393*** 1.242** (0.059) 0.021 has_internet 0.629* 0.621* (0.198) 0.239 has_pc 3.012*** 0.629* (0.134) 0.177 has_mobile_phone 1.222 0.962 (0.134) 0.179 tas_mobile_phone 1.222 0.962 (0.128) 0.039 0.0401 education2 0.719*** 0.752*** 0.825*** 0.859** (0.033) 0.035 0.039 0.0401 education3 0.075*** 1.608*** 1.494** 1.405* (0.083) 0.089) 0.116 0.131	local_advice			1.056			0.988
(0.039) (0.045) trust_neighborhood 1.387*** 1.439*** (0.037) (0.045) post_soc_media 0.800*** 0.787*** (0.037) (0.045) post_soc_media 0.800*** 0.045) post_soc_media 0.800*** 0.045) post_soc_media 0.800*** 0.045) browse_internet 1.156* 1.249** (0.063) (0.076) (0.076) use_email 1.393*** 1.242** (0.059) (0.073) (0.073) has_internet 0.629* 0.621* (0.198) (0.239) (0.239) has_pc 3.012*** 2.271*** (0.134) (0.177) (0.177) has_mobile_phone 1.222 0.962 (0.128) (0.033) (0.035) (0.039) religiousness 0.719*** 0.752*** 0.859*** (0.031) (0.033) (0.035) (0.039) (0.040) education2 1.679***				(0.036)			(0.042)
trust_neighborhood 1.387*** 1.439*** (0.037) (0.045) post_soc_media 0.800*** 0.787*** (0.037) (0.045) browse_internet 1.156* 1.249** (0.063) (0.076) use_email 1.393*** 1.242** (0.059) (0.073) has_internet 0.629* 0.621* (0.198) (0.239) has_pc 3.012*** 2.271*** (0.134) (0.137) has_mobile_phone 1.222 0.962 (0.134) (0.152) religiousness 0.719** 0.752*** 0.825*** 0.859*** (0.033) (0.035) (0.039) (0.049) relucation2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.116) (0.116)	belong_neighborhoob			0.973			1.044
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				(0.039)			(0.045)
post_soc_media 0.800*** 0.787*** powse_internet 1.156* 1.249** powse_internet 1.393*** 1.242** powse_internet 1.393*** 1.242** powse_internet 0.629* 0.621* post_soc_mobile_phone 0.629* 0.621* post_soc_mobile_phone 1.222 0.962 religiousness 0.719*** 0.752*** 0.825*** 0.859*** post_soc_mobile_phone 1.222 0.962 0.0143) 0.0150 religiousness 0.719*** 0.752*** 0.825*** 0.859*** post_soc_mobile_phone 1.608*** 1.404** 1.405* religiousness 0.719*** 0.752*** 0.825*** 0.859*** post_soc_mobile_phone 1.608*** 1.404** 1.405* post_soc_mobile_phone 0.719*** 0.603** 0.603** post_soc_mobile_phone 1.608*** 1.404** 1.405** post_soc_mobile_phone 1.679*** 1.608*** 1.404** 1.405** <t< td=""><td>trust_neighborhood</td><td></td><td></td><td>1.387***</td><td></td><td></td><td>1.439***</td></t<>	trust_neighborhood			1.387***			1.439***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$				(0.037)			(0.045)
browse_internet 1.156* 1.249** (0.063) (0.076) use_email 1.393*** 1.242** (0.059) (0.073) has_internet 0.629* 0.621* (0.198) (0.239) has_pc 3.012*** 2.271*** (0.134) (0.177) has_mobile_phone 1.222 0.962 (0.128) (0.152) religiousness 0.719** 0.752*** 0.825*** 0.859*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.16) (0.12)	post_soc_media			0.800^{***}			0.787***
(0.063) (0.076) use_email 1.393*** 1.242** (0.059) (0.073) has_internet 0.629* 0.621* (0.198) (0.239) has_pc 3.012*** 2.271** (0.134) (0.177) has_mobile_phone 1.222 0.962 (0.128) (0.152) (0.152) religiousness 0.719*** 0.752*** 0.825*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.034) (0.100) (0.131) (0.138) (0.138) (0.131) (0.131) education3 2.175*** 1.976*** 2.008*** 1.863***				(0.037)			(0.045)
use_email 1.393*** 1.242** (0.059) (0.073) has_internet 0.629* 0.621* (0.198) (0.239) has_pc 3.012*** 2.271*** (0.134) (0.177) has_mobile_phone 1.222 0.962 (0.128) (0.152) religiousness 0.719*** 0.752*** 0.825*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.116) (0.122)	browse_internet			1.156*			1.249**
(0.059) (0.073) has_internet 0.629* 0.621* (0.198) (0.239) has_pc 3.012*** 2.271** (0.134) (0.177) has_mobile_phone 1.222 0.962 (0.128) (0.152) 0.962 religiousness 0.719*** 0.752*** 0.825*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.116) (0.122)				(0.063)			(0.076)
has_internet 0.629* 0.621* (0.198) (0.239) has_pc 3.012*** 2.271*** (0.134) (0.177) has_mobile_phone 1.222 0.962 (0.128) (0.152) religiousness 0.719*** 0.752*** 0.825*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.116) (0.122)	use_email			1.393***			1.242**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				(0.059)			(0.073)
has_pc 3.012*** 2.271*** (0.134) (0.177) has_mobile_phone 1.222 0.962 (0.128) (0.152) religiousness 0.719*** 0.752*** 0.825*** 0.859*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.116) (0.122)	has_internet			0.629*			0.621*
(0.134) (0.177) has_mobile_phone 1.222 0.962 (0.128) (0.152) religiousness 0.719*** 0.752*** 0.825*** 0.859*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.116) (0.122)				(0.198)			(0.239)
has_mobile_phone 1.222 0.962 (0.128) (0.152) religiousness 0.719*** 0.752*** 0.825*** 0.859*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.116) (0.122)	has_pc			3.012***			2.271***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$				(0.134)			(0.177)
religiousness 0.719*** 0.752*** 0.825*** 0.859*** (0.033) (0.035) (0.039) (0.040) education2 1.679*** 1.608*** 1.494** 1.405* (0.094) (0.100) (0.131) (0.138) education3 2.175*** 1.976*** 2.008*** 1.863*** (0.083) (0.089) (0.116) (0.122)	has_mobile_phone			1.222			0.962
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				(0.128)			(0.152)
education2 1.679^{***} 1.608^{***} 1.494^{**} 1.405^{*} (0.094) (0.100) (0.131) (0.138) education3 2.175^{***} 1.976^{***} 2.008^{***} 1.863^{***} (0.083) (0.089) (0.116) (0.122)	religiousness		0.719***	0.752***		0.825***	0.859***
(0.094)(0.100)(0.131)(0.138)education32.175***1.976***2.008***1.863***(0.083)(0.089)(0.116)(0.122)			(0.033)	(0.035)		(0.039)	(0.040)
education32.175***1.976***2.008***1.863***(0.083)(0.089)(0.116)(0.122)	education2		1.679***	1.608***		1.494**	1.405^{*}
(0.083) (0.089) (0.116) (0.122)			(0.094)	(0.100)		(0.131)	(0.138)
	education3		2.175****	1.976***		2.008****	1.863***
education4 2.530*** 2.197*** 2.522*** 2.202***			(0.083)	(0.089)		(0.116)	(0.122)
	education4		2.530****	2.197***		2.522****	2.202***

		(0.083)	(0.089)		(0.115)	(0.121)
education5		3.085***	2.622***		2.910***	2.543***
		(0.086)	(0.092)		(0.117)	(0.123)
education6		4.041***	3.261***		3.789***	3.166***
		(0.082)	(0.088)		(0.112)	(0.119)
health		0.885***	0.904**		0.813***	0.832***
		(0.034)	(0.036)		(0.040)	(0.042)
employment2		2.818***	2.600***		2.149***	1.973***
		(0.075)	(0.079)		(0.088)	(0.091)
employment3		1.511***	1.442***		1.209*	1.179
		(0.074)	(0.077)		(0.090)	(0.093)
employment4		1.180**	1.136*		1.069	1.033
		(0.052)	(0.054)		(0.066)	(0.068)
sex		1.063*	1.031		1.142***	1.109**
		(0.031)	(0.032)		(0.036)	(0.037)
age2		0.711***	0.686***		0.872	0.858
		(0.071)	(0.074)		(0.087)	(0.091)
age3		0.823***	0.782**		0.881	0.860
		(0.067)	(0.070)		(0.083)	(0.086)
age4		1.040	0.987		1.085	1.055
		(0.064)	(0.067)		(0.078)	(0.082)
age5		1.346***	1.296***		1.484***	1.481***
		(0.066)	(0.069)		(0.080)	(0.084)
age6		1.333***	1.314*		1.204^{*}	1.234*
		(0.086)	(0.090)		(0.100)	(0.104)
total_hh_income2		1.432***	1.405***		1.302***	1.259***
		(0.052)	(0.054)		(0.067)	(0.069)
total_hh_income3		1.777***	1.682***		1.649***	1.544***
		(0.052)	(0.054)		(0.065)	(0.068)
total_hh_income4		2.372***	2.227***		2.191***	2.050***
		(0.052)	(0.054)		(0.064)	(0.067)
total_hh_income5		3.497***	3.171***		3.344***	3.040***
		(0.053)	(0.056)		(0.064)	(0.067)
Observations	22,046	21,224	19,684	22,046	21,224	19,684
Log Likelihood	-14,491.680					

5.2.2.1. Connecting findings to Hypothesis:

Based on previous literature and theoretical frame of the stock market participation puzzle, paper has developed an expectation that social media engagement would encourage stock market participation. This assumption was the basis of one of the hypotheses:

Hypothesis 3: Individuals who frequently engage with social media are more likely to participate in the stock market.

However, findings from the logistic regression analysis of the 13th wave of the UK Household Longitudinal Study (UKHLS) indicate that social media usage does not enhance the likelihood of stock market participation; rather, it appears to diminish it. This observation holds consistently across all models and forms of stock market participation, leading us to reject Hypothesis 3. Importantly, the rejection of this hypothesis does not imply that the rationale behind its formulation was flawed. Instead, it emphasizes the complexity of the stock market participation puzzle and signals a need for more in-depth research to uncover the underlying dynamics of this relationship.

Additionally, the analysis reveals that stock market participation is strongly and positively correlated with digital skills that extend beyond mere social media usage. This distinction highlights the potentially different roles that various digital skills may play in financial engagement. The theoretical implications of these findings and potential explanations for these results are further explored in the discussion chapter of the paper.

5.2.3. Logistic Regression with Interaction Terms

Previous parts of the paper have suggested that social media engagement impacts stock market participation by altering the strength of both weak and strong social ties. To examine these proposed behavioral patterns, logistic regression models have been employed, where active social media participation is introduced as an interaction term. This approach enables an exploration of how social media activity modifies the influence of social ties on stock market involvement. Interaction terms are a frequently used method to evaluate how the effect of one variable modifies the effect of another. By applying social media as the interaction term to other social engagement variables, hypothesis 4 and 5 have been tested.

The findings are in line with previous models from Table 5, demonstrating that active engagement with social groups positively affects the odds of stock market participation and that more groups the person engages with higher the chances of stock market participation. Individuals who frequently talk with their neighbors show no significant change in odds of owning any financial securities, but experience a minor decrease in the odds of owning directly managed company stocks. However, the predictor remains statistically non-significant. Moreover, interaction effects remain insignificant for explaining the model along with the social media activity proxy. Indicating to no tangible interaction between the social media activity and stock ownership.

Table 5: Odds Ratio from Logistic Regression Models

This table presents the odds ratios derived from logistic regression analyses, which evaluate the effects of various predictors on both total and direct stock market participation. Models presented in the table offer added value compared to Table X, as they introduce interaction terms between active participation on social media and social engagement proxies.

	Dependen	t variable:
	SMP_total	SMP_direct
	(7)	(8)
Constant	0.027	0.020
	(0.261)	(0.322)
talks_with_neighbors	1.041	0.914
	(0.075)	(0.084)

org_activity2	1.472***	1.386***
	(0.069)	(0.076)
org_activity3	1.908^{*}	1.875**
	(0.258)	(0.240)
active_soc_media	0.957	0.904
	(0.074)	(0.087)
talks_with_neighbors:active_soc_media	0.965	1.086
	(0.081)	(0.093)
org_activity2:active_soc_media	0.980	0.981
	(0.078)	(0.087)
org_activity3:active_soc_media	0.809	0.796
	(0.291)	(0.277)
Controls for Social Engagement	Yes	Yes
Controls for Social Media Usage	Yes	Yes
General Controls	Yes	Yes
Observations	19,684	19,684
Log Likelihood	-11,932.190	-9,463.837
Akaike Inf. Crit.	23,938.390	19,001.670
Note:	 *p**p***p<0.01	

5.2.4. Checking for Robustness

To further explore the impact of active use of social media on the effects of social engagement variables on stock market participation, an alternative analytical approach has been developed. A sub-sample of the observed data was created, focusing exclusively on individuals who are active on social media. Consequently, a logistic regression model was employed to examine the interactions between social engagement variables and stock market participation within this specific group. This method of analysis enables a robustness check of the findings from models "7" and "8",

ensuring that the observed effects are consistent even when the analysis is confined to a subset of the population characterized by active social media usage. This targeted approach helps isolate the influence of social media and assess its interaction with traditional forms of social engagement in impacting financial decision-making.

According to the results observed in the table from the logistic analysis on the subgroup data of active social media users, engaging with neighbors does not enhance the odds of participating in the stock market, with this observation holding true for both direct (odds ratio: 1.006) and general (odds ratio: 1.006) forms of market participation, while remaining statistically insignificant. On the contrary, weak ties continue to be statistically significant predictors that positively influence stock market participation. These findings align with those observed in the full sample, indicating consistency across different subsets of the data.

There is only a marginal difference in the findings from models "3" to "9" and from models "6" to "10" regarding the social engagement proxies. Moreover, the consistency of these observations with the findings from models "7" and "8" emphasizes the limited impact of social media on the variables related to social engagement. Thus, suggesting that while social media usage may not significantly alter the influence of social ties, the established relationships between social engagement and market participation persist even among active social media users.

Table 6: Odds Ratio for Active Social Media Users

This table displays the odds ratios obtained from logistic regression analyses that assess the impact of social engagement predictors on both total and direct stock market participation among active social media users. A sub-sample of the full population has been selectively analyzed using a straightforward logistic regression model. This analysis incorporates control variables for social media usage and social engagement, along with conventional demographic and socio-economic indicators, to provide a comprehensive view of the factors influencing stock market behavior in this specific group.

	Depender	ıt variable:
	SMP_total	SMP_direct
	(9)	(10)
Constant	0.019***	0.017***
	(0.332)	(0.398)
talks_with_neighbors	1.006	1.006
	(0.044)	(0.053)

org_activity2	1.441***	1.370***
	(0.038)	(0.045)
org_activity3	1.534**	1.496**
	(0.137)	(0.144)
Controls for Social Engagement	Yes	Yes
Controls for Social Media Usage	Yes	Yes
General Controls	Yes	Yes
Observations	15,305	15,305
Log Likelihood	-9,264.853	-7,193.993
Akaike Inf. Crit.	18,595.710	14,453.990
Note:	*p	^{**} p ^{***} p<0.01

4.2.4.1. Connecting findings to Hypothesis

The study was designed to explore the dynamics of behavioral factors as they transition into the digital realm, guided by two primary assumptions: firstly, that the digital space alters the structures of information dissemination, which was addressed through Hypothesis 3, and secondly, that it modifies the established effects of social networks by altering the strength of weak and strong ties. These changes were tested through Hypotheses 4 and 5.

Hypothesis 4: Active social media users who frequently converse with their neighbors are more likely to participate in the stock market.

Hypothesis 5: Active social media users who are active in social groups are more likely to engage in the stock market.

Analysis from Tables 5 and 6 indicates that the interaction between social ties and stock market participation among active social media users does not show a significant difference, According to the findings weak ties continue to be an important avenue for information acquisition leading to stock market participation, thus confirming Hypothesis 5 in line with the equity market participation puzzle.

However, the findings for strong ties are more inconsistent. While models "7" and "9" suggest that engagement with neighbors positively influences stock market participation, the effect size is modest and makes only a slight difference. These observations hold true for general stock market participation. However, for direct stock market participants, models "8" and "10" yield divergent results. Furthermore, in none of the described models, the predictor does not remain statistically significant. Consequently, based on these observations, it is challenging, but possible to reject Hypothesis 4.

Discussion

From the first pages, the paper has outlined the influence previous literature had on the study. Furthermore, its findings as well as the assumptions have echoed the work of other authors. Consequently, these findings should not be considered in isolation and require to be studied and understood as a part of a bigger picture. Changwony and colleagues (2015) work has served as the foundation for the study and the first pair of hypotheses comes from their article. However, the findings based on these hypotheses are not similar. On the other hand, findings are consistent with Hong et. al (2004), who also studied interaction and social engagement as the predictor of household stock market participation.

Changwony et. al (2015) has found that strong ties had no statistically significant significance for explaining household stock market participation. However, this study, based on the findings from the fixed effects model, has found that both strong and weak ties are statistically significant and have influence on the probability of stock market participation. Such findings are similar to the work of other scholars (Hong, Kubik & Stein, 2004; Kaustia & Knüpfer, 2012; Brown et. al, 2008). Scholars who have identified the importance of the interaction with people from close proximity circles, build their argument on the alternative set of logical frameworks which encourage stock market participation. According to them, peer pressure might be one of the reasons which nudges others to enter the financial market. The literature explaining interaction between the weak ties and stock market participation, through the lens of

information dissemination, is always studied through the lens of equity premium puzzle. This distinction is important especially because it provides an alternative explanation for the observed occurrence in the study and leaves space for further exploration.

Understanding the role of social media in the process of information dissemination/acquisition has been the new approach tested in the study. Results do not align with the previous research (Müller, Pan & Schwarz 2023) as it indicates no interaction. Müller and colleagues' (2023) follow different approaches when studying the impact of social media on stock market participation. They are studying social media penetration as the predictor for stock holding, while this study uses social media usage frequency as the proxy measure. Distinction leading to the difference in outcomes might lie there. However, it would be hard to make such an assumption based on the limited literature on the topic. These findings are important as they open up space for studying the affects of social media on the stock market participation.

Limitations and Future Research

While the findings presented throughout the study are important and offer valuable insights for future research, it is essential to acknowledge and address the potential limitations associated with the study. Several primary limitations have been identified and are structured in the thematic manner. Putting the comprehensive overview of the study's shortcomings allows the reader not to misinterpret the findings and enables a better understanding of the results.

First set of limitations is associated with the data. While the analytical part of the paper does not mention it frequently, these findings are applicable for the British population, consequently any decision to interpret the data to the wider population should be approached with caution. However, due to the study being limited to a single country it leaves the opportunity to be extended to the wider population. Such an approach will provide more insight into cultural and social factors influencing the stock market participation. While interpreting the findings one should keep in mind that data for social media activity comes only from a single wave of the survey. Analyzing data from a single survey wave is not an issue, but it lacks the ability to observe the phenomenon through time. Hence, the interaction is studied at a fixed moment of time, omitting the potential to analyze the change over the time.

On the other hand the impact of social engagement on stock market participation is examined by studying three wave longitudinal data. There are shortcomings associated with it as well. Fixed effects regression model omits from the analysis the variables which are not time sensitive. Variables which are constant over the time are not included in the model hence no findings can be made on them. Additionally, due the strict requirements of the fixed effects model, the number of observations is drastically reduced and approximately 20% of the observation from the full sample is used for the fixed effect model. This can be a problem reducing the generalisability of the findings, which should be noted for practical implications.

Furthermore, models used in this study have demonstrated a moderately good fit, indicating that while they are effective to a certain extent, they do not capture all the variabilities within the data. Generally, incomplete fit can lead to misinterpretations or oversights regarding the underlying dynamics of the data. However, the findings, even from the models with limited fit, contribute to the exploration of complex behaviors like stock market participation. And they provide a foundation for more detailed studies by narrowing down which variables or interactions need further examination. Furthermore, as the study adds to the existing literature by introducing new variables and testing new relationships, even if the fit is not perfect, the incremental knowledge gained is valuable. Lastly, models used within social science are rarely able to capture and explain the large chunks of the data due to the complex nature of the social environment.

One last limitation, which needs to be addressed is that study is theoretically limited to explain the negative effects of social media on stock market participation. To address the shortcoming, new theoretical frameworks, which hold valid explanatory mechanisms for the unexpected results outlined in the findings.

However, these set of limitations create a fertile ground for the future research project to be cultivated on. Some of the potential suggestions would be to refine the project methodologically and approach same question by observing data from individuals' social media usage along tracking their financial behavior. Such approach will require layers of ethical consideration as well as complicated process of sampling and methodological refinement, but potentially would yield a very interesting finding. Simpler project would be to wait or the new waves of the UKHLS and study the impact of social media usage over the stock market participation through few waves of data, which might unravel the new findings.

Conclusion

In line with the guiding question of the study, the paper has explored the interaction of social engagement and stock market participation. Main contribution of the paper to the field of financial decision-making research comes from integrating social media into the analytical framework. By studying the up-mentioned relationship through the lens of social media as a moderating factor, this study creates new knowledge in understanding how modern forms of interaction influence financial behaviors.

In line with the initial expectations described in the literature review and theoretical framework, the empirical findings confirm that social engagement influences the likelihood of financial security ownership. Analysis of the panel data confirms that the two proxies selected to measure social engagement—frequency of interactions with neighbors and participation in social groups—are statistically significant predictors. And have a positive impact on the probability of potential shareholding.

Moreover, the study's findings challenge the assumption that digital platforms have reduced influence of the traditional avenues of social interaction in financial decisionmaking processes. Instead, they provide evidence that the role of face-to-face interactions in shaping investment behaviors and preferences has not been altered.

One additional observation which comes as a surprise is that on the contrary to the literature there is no significant interaction between social media use and stock market

participation. And even for the scenarios when such interaction is observed it is negative. Which means that the impact of social media usage is repelling households' stock market participation. This observation is especially true for the individuals who actively post on social media. This negative interaction challenges the established understanding embedded within the financial market participation puzzle, which typically anticipates that increased information would increase financial market participation by reducing entry cost. Consequently, to address this shortcoming there is a need to study phenomena from a different angle. One of the ways to explain the results would be to introduce notions of information overload (Lee & Lee, 2004) and choice overload (Scheibehenne, Greifeneder, & Todd, 2010). Both of these concepts are relatable with social media use as both lead to negative outcomes by providing access to too much "good". Similar mechanism could be the reason behind social media's negative effect on stock market participation.

To conclude, the study does not manage to confirm all the assumptions in regards to financial decision making. However, the findings are nonetheless interesting as they provide foundation upon which on one hand further research and/or policies could emerge. The need for social media to be reconsidered as the utopian space of free information has clearly emerged. In the scenario, where information is equated with the financial gains (core ide of equity premium puzzle) social media channels fail to support its users by providing them adequate information. Consequently, these findings can be utilized not only for the advancement of research, but by other stockholders. Such as social media platforms or financial security trading platforms to adjust to the needs of their users.

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Note: In line with the idea of Open Science script used for the analysis is accessible though GitHub repository <u>https://github.com/Gigi4o/SIMZ51-_-Stock-Market-Participation-</u>