The Effects of Social Interaction and Internet Usage on Stock Market Participation: Evidence from Europe.

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Abstract

Based on data from the Survey of Health, Ageing and Retirement in Europe, this paper analyses the impacts of social interaction and internet usage on stock market participation using a probit model. Consistent with prior literature, the results show that both greater social interaction and internet usage increase the probability of holding stock. Since both act as information channels, they provide the opportunity to gain insight on, for example, how to invest and the returns offered by the market. However, in contrast to previous research I also find that sociability and internet usage do not act as substitutes, rather they reinforce each other's effects. In line with social network theory, I find that weak-tie social engagement has a greater impact on participation compared to strong-tie social engagement. Finally, this paper also provides novel insights into social and internet multiplier effects, which demonstrate that the impact of social interaction and internet usage are significantly higher in countries with relatively high levels of stock ownership.

[1] including tables and footnotes.

Contents

1 Introduction

Although stock market participation rates are increasing in the long-run, they still remain notably low given the high returns offered by the market (Mankiw and Zeldes (1991)). Therefore, finding key drivers of participation can help explain why some people do not own stocks and shed further light on this puzzle. Previous literature examines various drivers of stock ownership; well-established ones include age (Fagereng et al. (2013); Guiso et al. (2000)), wealth (Vissing-Jorgensen (2004)) and education (Bayer et al. (1996)). However, literature analysing the roles of information channels is relatively nascent. The policy implications of this research are important. Cocco et al. (2005) find that limited stock ownership results in significant welfare losses as some households miss out on the higher premium which can be earned from the stock market. If lack of information acts a significant barrier to stock ownership, this finding can aid policy makers in terms of addressing social welfare and reducing information frictions.

The sociability effect on stock ownership is particularly significant as information gained through this channel is likely to be biased (Shiller (1984)). Consequently, this could cause herd behaviour, creating large fluctuations in asset prices and the formation of asset bubbles which in turn create financial instability. Hence, if sociability significantly influences stock ownership, policies should be implemented to enforce greater transparency and accuracy of information and improve financial literacy.

Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), this paper aims to establish whether information channels, namely social interaction and internet usage, play a key role in stock market participation. It examines whether the results and hypotheses in previous literature and theory are corroborated, as well as weak-tie and strong-tie effects, not only in relation to the distinction between internet usage and sociability but also across different degrees of sociability (such as talking to friends versus attending community organisations).

This research contributes to literature in different ways. Firstly, little analysis exists on the impact of internet usage and especially on the relationship between sociability and internet usage (i.e. if they are substitutes or reinforce each other's effects). Moreover, the data is more up-to-date and includes various European countries, as opposed to only the UK or USA. This also allows for extended analysis of the social multiplier effect, by comparing the marginal effects of sociability and internet usage across countries which differ significantly in terms of their social and economic institutions. This is a further contribution as previous analysis by Hong et al. (2004) is restricted to a country-wide level, whereby US states are more similar in these characteristics.

2 Literature Review

Previous literature finds that both internet usage and social interaction increase stock market participation as they reduce information costs by facilitating the dissemination of information about the stock market. In particular, I focus on work by Hong et al. (2004), Changwony et al. (2015), and Bogan (2008).

Hong et al. (2004) were the first to investigate the effect of sociability on stock ownership. Using data from the Health and Retirement Survey (HRS), they find that greater sociability significantly increases the probability of holding stock, all else equal. They conclude that "socials" (households who interact with their neighbours or attend church) are 4% more likely to hold stock compared to "non-socials". Another important conclusion is the "social multiplier effect"; the social interaction effect is higher in regions where stock ownership rates are already relatively high.

One advantage of the paper is that it controls for the endogeneity of sociability to an extent. Sociability, in addition to its role as an information channel, may also reflect personality traits that are themselves important drivers of participation. For example, they argue that sociable people are more likely to be bold and thus less risk averse. To resolve this issue, they add proxies for risk aversion and optimism to their model. Nevertheless, the social interaction effect could be two-fold. On one hand, "socials" may be more likely to participate due to access to information networks which enable them to learn about stock market returns and how to trade ("information-sharing"). On the other hand, participants may just enjoy talking about the stock market with friends who also hold stocks ("enjoyment-from-talking-about-the-market"). However, the paper does not distinguish between these two channels.

Changwony et al. (2015) further investigate the effect of sociability on stock market participation. Their findings, based on BHPS data, are consistent with prior literature but, more importantly, address the two-fold effect by examining weak-tie engagement, defined by "social group engagement", and strong-tie engagement, defined by "frequency of talking to neighbours." They conclude that weak-tie engagement, which is associated with the "information-sharing" case, has a significant, positive impact on participation. However, strong-tie engagement, which is associated with the "enjoyment-from-talking-about-the-market" case, has no effect. This contrasts with the results of Hong et al. (2004), who find that strong-tie engagement (talking to neighbours) significantly increases the probability of participation. The findings of Changwony et al. (2015) are consistent with the notion that weak-tie engagement transmits more novel information compared to strong-tie engagement because we usually interact with people who share similar interests (Granovetter (2005)). Similarly, I examine this two-fold effect, not only across different forms of social interaction, but also because internet usage is a form of weak-tie engagement.

Although Hong et al. (2004) state that technology lowers participation costs they focus solely on social interaction. Bogan (2008) takes previous research to another direction by investigating the effect of internet usage. She estimates that the positive impact of computer/internet usage on stock ownership is equivalent to having over $27,000 more of household income. This is because it reduces information and transaction costs and thus encourages greater stock market participation. One downside to Bogan's finding is that she mainly focusses on computer usage and takes it as a proxy for internet usage as it is based on a larger sample. Furthermore, HRS data consists of older individuals, hence the findings of Bogan (2008) and Hong et al. (2004) are not truly representative; their results are skewed as older people are less likely to own stock, especially through the use of new technology (Barber and Odean (2002)). Bogan herself notes that her results represent a "lower bound" and the impact of internet usage is expected to be higher. In contrast, data used by Changwony et al. (2015) reports stock ownership across different age groups.

All papers reported use probit methodology. Bogan (2008) constructs a probit model looking at two waves of data and controls for omitted variables that may reflect the "financial sophistication" of a household which is likely to increase the probability of holding stock. She does this by including "stock ownership in 1992" as an independent variable in her 2002 regression. In this way, her results are more robust compared to Hong et al. (2004), who use only wave 1 of cross-sectional data, as she partially controls for unobserved heterogeneity. In contrast, Changwony et al. (2015) use a pooled probit model which best controls for endogeneity as they are able to properly disaggregate the influence of social engagement from other variables. This, combined with their more representative data, means that Changwony et al. (2015) present the strongest results, establishing the clearest relationship between stock market participation and social interaction.

I apply the same probit methodology approach as previous literature, but also incorporate the effects of both sociability and internet usage into the model. There is a gap in current literature as there is little analysis which investigates both variables simultaneously. Liang and Guo (2015), using data from China, find that internet usage and sociability have significant, positive impacts on stock ownership, but are substitutes for each other as they are both information channels. However, their results are subject to endogeneity issues. In contrast, Hong et al. (2004) claim that the social multiplier effect causes internet usage to reinforce the positive impact of sociability, but they do not analyse this hypothesis further. Hence, investigating this interaction could determine whether the different conclusions can be reconciled.

3 Theory and Hypotheses

The theoretical framework below adapts and combines elements of the portfolio models used by Georgarakos and Pasini (2011), Guiso et al. (2008) and Bogan (2008). An investor can invest part of his wealth in a risk-free asset, yielding a riskless return r_f, and the remaining share in a risky portfolio, yielding an uncertain return $\tilde{r}$, where $E[\tilde{r}] > r_f$. Hence, he aims to maximise the following expected utility function:

$$\max_{\alpha_i} EU[\alpha_i \tilde{r}(W_i - I_i) + (1 - \alpha_i) r_f (W_i - I_i)] \tag{a}$$

α_i represents the fraction of net wealth invested in risky stocks. $W_i - I_i$ represents the investor's wealth (W_i) net of stock market participation costs (I_i). This includes transaction and information costs, such as buying investment guides, broker advice and the opportunity cost of time spent on research. According to the Consumption Capital Asset Pricing Model, investing in risky stocks creates uncertainty in the investor's wealth and, in turn, his consumption (Breeden (1979)). Consequently, the investor will participate in the stock market if:

$$EU[\alpha_i \tilde{r}(W_i - I_i) + (1 - \alpha_i) r_f (W_i - I_i)] \geq U[r_f W_i] \tag{b}$$

Therefore, if participation costs are sufficiently high to remove the expected utility gain of owning risky stocks, an individual will not participate.

Hypothesis 1: according to theory and literature, people who socialise and use the internet frequently are more likely to own stock due to lower information costs (I_i falls); they face a greater possibility of obtaining information about how to invest and the returns that could be earned. Hence, with low enough participation costs, the expected utility gain of owning stock is likely to outweigh the costs.

Hypothesis 2: weak-tie engagement (i.e. internet usage) is expected to have a greater impact on participation than strong-tie engagement (i.e. sociability) as it coveys more unknown and newer information (Granovetter (2005)).

Hypothesis 3: the effect of sociability is likely to be greater in countries with relatively high levels of stock ownership due to the social multiplier effect (Hong et al. (2004)); in regions with low participation rates, it is unlikely that social interaction will transmit relevant information and induce people to hold stock. I hypothesise that the same logic is unlikely to hold for internet usage, as the internet contains the same information on stock markets regardless of where one lives.

4 Data

This research uses data from SHARE, a biennial cross-national panel survey containing information on health, financial holdings and demographics. It contains data across different age groups (from 24 years old) but focusses mainly on individuals aged 50 years or over. There are 7 waves in total; wave 1 was conducted in 2004 and wave 7 (published in April 2019) was conducted in 2017. The average stock ownership rate across waves is very low, demonstrated by Figure 1[2], which is consistent with the stock market participation puzzle. Moreover, stock ownership levels have remained relatively constant over time in the data. Although aggregate worldwide data suggests that participation rates are steadily increasing in the long run (Mankiw and Zeldes (1991)), given that SHARE does not have a very long time series, it is difficult to establish any meaningful trend. However, there is a notable drop in stock ownership after wave 2. Data collected after this wave was during the Global Financial Crisis, which affected Europe significantly, and the subsequent recovery from it. Hence, a possible explanation for this decline is that, having suffered financially during the recession, individuals were relatively more risk averse and thus less willing to hold risky stocks.

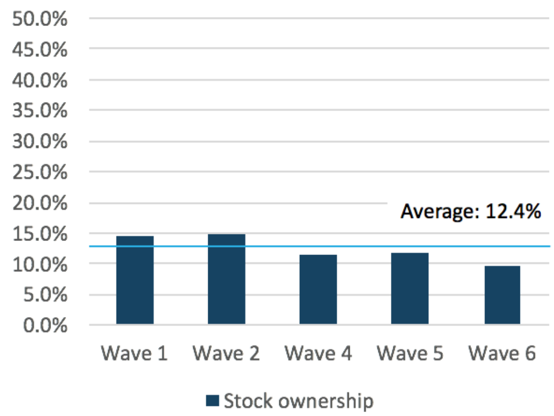


Figure 1: Stock market participation across waves.

This paper focusses on wave 6 due to the recency of data and availability of relevant variables (prior waves lack data on internet usage, stock ownership and/or sociability). Unfortunately, wave 7's release came too late, having already conducted the majority of my analysis. However, future research can implement this latest data to generate more robust results. The merged dataset contains 7,607 observations, but after dropping missing values and incorporating variables into one model it falls to 4,641. Risk aversion has the lowest number of observations but given the importance of this variable in previous literature it is necessary to include it. Adding too many controls will make results skewed through reduced observations, thus a parsimonious model is preferable. Table 6 reports the summary statistics and descriptions, corresponding to wave 6, for variables used in this analysis. The unit of analysis is respondent level. Respondents are randomly selected using probability-based sampling, hence there is no issue of self selection bias. Countries included in wave 6 are Austria, Germany, Sweden, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Israel, the Czech Republic, Poland, Luxembourg, Portugal, Slovenia, Estonia and Croatia. Figure 2 demonstrates how stock market participation varies across countries in SHARE, which is useful for later analysis of the multiplier effect.

The average age in wave 6 is 62 years, thus there is some bias in my results as they are skewed towards older individuals. However, applying the same argument highlighted in Section 2, this does not make my results redundant, rather they represent a lower bound.

[2]wave 3 does not contain data on stock ownership.

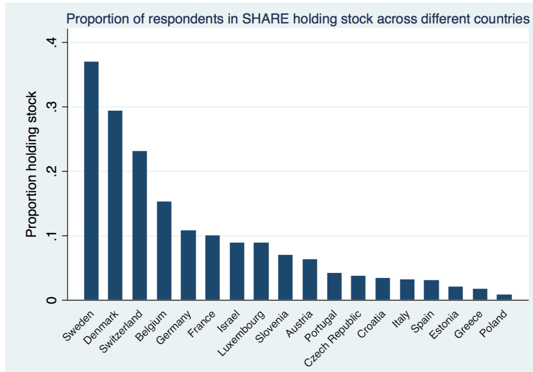


Figure 2: Proportion of respondents in SHARE holding stock across different European countries.

5 Empirical Analysis

5.1 Methodology

Model 1 represents the baseline probit model which includes social interaction, internet usage and their interaction term as the key explanatory variables. The control variables are age, sex, ln(income), ln(wealth), age, risk aversion and years of education. Column A in Table 1 shows the results from model 1.

$$Pr(stock_i = 1) = \Phi(\beta_1 social_i + \beta_2 internet_i + \sum_{k=3}^{K} \beta_k x_{ik}) \tag{1}$$

- $stock_i$ is a binary dependent variable (=1 if the individual holds stock, 0 otherwise).
- $social_i$ is a binary variable (=1 if the individual has participated in any social activities in the past month: charity/voluntary work, attended a community organisation, gone to a sports/social club or attended a training course).
- $internet_i$ is a binary variable (=1 if the individual has used the internet in the past week).
- x_{ik} is the set of control variables.

5.2 Baseline Model Results

Consistent with Bogan's (2008) results, the marginal effect of internet usage is positive and significant. Internet using respondents have a 2.22% higher probability of holding stock compared to non-internet using respondents, all else equal and given average characteristics. Socials have a significantly 2.44% higher probability of holding stock compared to non-socials, given average characteristics and holding all else equal. This corroborates previous literature; Hong et al. (2004) report a marginal effect of sociability between 0.0245 and 0.0474. Thus, respondents who socialise and use the internet frequently are more likely to participate in the stock market, supporting hypothesis 1. According to the model, sociability has a bigger impact on stock ownership compared to internet usage. This is a contradiction to hypothesis 2 since, as a form of weak-tie engagement, internet usage is expected to have a greater effect. A possible explanation for this is that my social interaction variable is itself a form of weak-tie social engagement compared to other forms of sociability, such as talking to friends (Changwony et al. (2015)). Hence, the conclusion of this theory does not necessarily hold in this case. Further analysis is required to check if this theory holds under strong-tie social engagement, in which case the marginal effect is expected to be lower than those of the initial sociability variable and internet usage. I test this hypothesis in Section 5.4.

The interaction term between sociability and internet usage determines whether the information channels are substitutes or reinforce each other. The marginal effect of social interaction for an internet using respondent is 0.038, compared to only 0.019 for a non-internet using respondent. This implies that both information channels reinforce each other's effects, which confirms the hypothesis presented by Hong et al. (2004), rather than the results of Liang and Guo (2015). Figure 3 demonstrates this effect. Hong et al. (2004) argue that an exogenous change in an outside parameter will cause the marginal effect of sociability to change. With the case of the internet this effect is positive; some people may initially gain information from the internet and pass this information onto others when socialising.

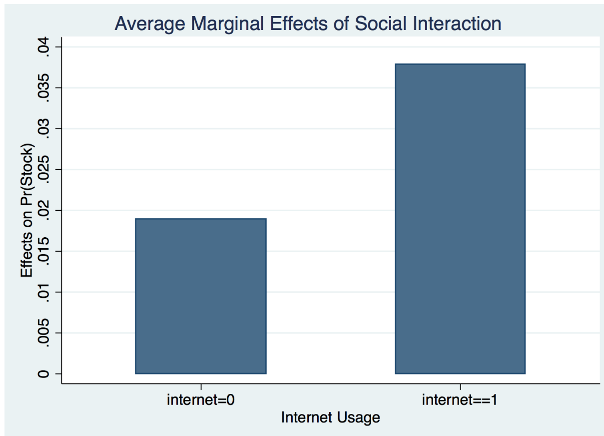


Figure 3: The average marginal effect of social interaction for internet versus non-internet using respondents.

The signs of the control variables' marginal effects are as expected and in line with previous literature. For example, $ln(wealth)$ has a positive marginal effect, which corroborates the finding of Vissing-Jorgensen (2004); wealthier individuals face lower "fixed costs" because minimum investment requirements and transaction costs become less of an issue, and consequently are more likely to hold stock. Moreover, education has a positive effect, which is consistent with analysis by Bayer et al. (1996), who conclude that people with more education are more likely to know about and grasp basic investment terminology as well as concepts like risk tolerance and risk-return trade-offs. Interestingly age, age^2 and $ln(income)$ are insignificant. age^2 is included in model 1 to capture the inverted U-shape relationship between age and stock ownership found in the raw data (Figure 6) and literature (Fagereng et al. (2013)). This relationship is explained by the life cycle, whereby younger individuals invest money to save for retirement, then reduce their exposure to the stock market when they are older. However, after cleaning the data the minimum age corresponding to the model is now 36 and, given that SHARE mainly consists of those aged 50 years and over, this relationship is not properly captured. Hence, in this restricted dataset, age and stock ownership should largely follow a negative linear relationship. Model 2 drops age^2 from model 1; age still remains insignificant (mainly because there is still not a large variation in age) and the marginal effects of sociability and internet usage remain almost unchanged and significant. The results of this model are reported in column B in Table 1.

5.3 Robustness Checks

5.3.1 Omitted Variables

I added further controls to address omitted variable bias and check the sensitivity of my baseline model. Overall, I found that these robustness checks do not drastically affect the significance or magnitudes, both relative and absolute, of the marginal effects for internet usage and sociability, as well as the control variables, suggesting sufficient model robustness.

Job Search: $lookjob$ takes a value of 1 if the respondent is actively looking for a job. This variable addresses omitted variable bias as it captures the effect of leisure time; individuals searching for a job have less time to not only research about the stock market and but also socialise, implying a negative bias on sociability when $lookjob$ is not included in the model. The results of model 3 are reported in column C in Table 1.

The marginal effect of $lookjob$ is negative, as expected, yet insignificant at the 10% level. Furthermore, although the marginal effect of sociability rises, confirming the negative bias, this increase is only very small,

Table 1: Results of Models 1-4

	A n=4,641	B n=4,641	C n=4,641	D n=4,629
Social	0.0244 (**) (0.010)	0.0248 (**) (0.010)	0.0251 (**) (0.010)	0.0219 (**) (0.010)
Internet	0.0222 (**) (0.009)	0.0223 (**) (0.009)	0.0222 (**) (0.009)	0.0193 (**) (0.009)
Age	0.0038 (0.004)	0.0005 (0.0004)	0.0005 (0.0004)	0.0004 (0.0004)
Age^2	-0.00003 (0.00003)	–	–	–
$ln(Income)$	0.0016 (0.002)	0.0016 (0.002)	0.0016 (0.002)	0.0014 (0.001)
$ln(Wealth)$	0.0054 (***) (0.001)	0.0053 (***) (0.001)	0.0053 (***) (0.001)	0.0049 (***) (0.001)
Risk aversion	-0.0777 (***) (0.011)	-0.0780 (***) (0.011)	-0.0778 (***) (0.011)	-0.0743 (***) (0.010)
Education	0.0039 (***) (0.001)	0.0039 (***) (0.001)	0.0039 (***) (0.001)	0.0039 (***) (0.001)
Male	0.0121 (*) (0.007)	0.0125 (*) (0.007)	0.0127 (*) (0.007)	0.0124 (*) (0.007)
Look job	–	–	-0.0276 (0.017)	–
Life satisfaction	–	–	–	0.0067 (***) (0.002)

MEs at average characteristics reported, with robust SEs in brackets. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

from 0.0248 to 0.0251.

Life Satisfaction: $lifesat$ is measured on a scale of 0 to 10 (the more satisfied with life you are, the higher the number). This variable addresses omitted variable bias as it captures the effect of optimism. People who socialise more are more likely to be optimistic or find meaning with life (Hong et al. (2004)), implying a positive bias on sociability. The results of model 4 are reported in column D in Table 1.

The marginal effect of $lifesat$ is positive and significant at the 1% level. This makes sense because people with higher life satisfaction might view stock market participation more positively, finding it beneficial to invest in stocks and reap the benefits later in life. Moreover, the marginal effect of social interaction falls to 0.0219, confirming the positive bias on social. It also falls for internet usage, implying a positive bias on internet too. However, their relative marginal effects remain similar to those corresponding to model 2.

The marginal effects of the control variables remain largely similar, except for that of risk aversion, which increases from -0.0780 to -0.0743. This implies a negative bias on risk aversion; people with higher life satisfaction are more likely to have a positive outlook about stock returns and hence less likely to be risk averse.

5.3.2 Endogeneity

To formally test the endogeneity of my main explanatory variables I undertook the IV 2SLS method (see Appendix B.2).

The instruments used for internet usage are computer skills and the number of respondent's children in their network. *compskills* is positively correlated with internet usage as those with better computer skills are better equipped to use the internet. *childnet* is negatively related to internet usage; people with more children in their network are less dependent on using the internet as they are more likely to rely on their children. These instruments should also be exogenous (i.e. independent of unobservable traits and stock ownership over and above their influence on internet usage). For computer skills, this is harder to argue if some respondents use technology for stock market trading. However, as Barber and Odean (2002) argue, older people are less likely to own stock through this channel. Thus, it is likely that computer skills is independent of stock ownership.

The relevance and exogeneity tests for the internet usage instruments give an F value of 925.87 and J statistic of 1.76 ($< \chi^2_{1,10\%}$=2.71), respectively. Therefore, the instruments are relevant and exogenous. The results of these regressions are reported in Table 7.

Unfortunately, I was unable to find instruments for sociability that fulfilled both the relevance and exogeneity criteria. However, according to Georgarakos and Pasini (2011), it is safe to assume that the sociability measure is exogenous to stock ownership; it is unlikely that respondents solely participate in these types of social activities to gain information on the stock market. Nevertheless, sociable people might have certain personality traits which influence the likelihood of stock ownership. I have extracted the influence of some observable traits, such as optimism and risk tolerance, but not unobservable ones, such as making efficient use of time. Hong et al. (2004) argue that if sociability mostly reflects the influence of unobservable traits, there is no a priori reason to expect a differential effect of this indicator across areas with different levels of stockholding. However, this effect is observed, implying that sociability is exogenous. The same reasoning can also be applied to internet usage, for which this differential effect is also observed (Section 5.5).

The Wu-Hausman test gives a p-value of 0.75, thus internet usage is exogenous, and given the argument above, the probit models used in this paper are fairly robust to endogeneity concerns. However, unlike Georgarakos and Pasini (2011), who use the Rivers-Vuong method (Rivers and Vuong (1988)), I only tested endogeneity using the IV method and only for internet usage. Although my baseline model is a probit model, Wooldridge (2001) shows that the 2SLS standard errors remain valid even for binary dependent models. Moreover, the marginal effects estimated by LPM and probit endogeneity techniques are indistinguishable (Angrist and Pischke (2009)). The IV method is also more efficient than other techniques and can test for endogenous instruments, given over-identification, unlike the Rivers-Vuong method. Despite these arguments, IV is still not the best way to test for endogeneity in a probit model; the predicted probability from a LPM is not bound between 0 and 1 and is unlikely to be linearly related to the independent variables for all their possible values (Wooldridge (2012)). To better test for endogeneity, other techniques should be used, including a panel data analysis approach adopted by Changwony et al. (2015). Given the lack of relevant variables in prior waves I am unable to carry out panel data analysis and due to time constraints I have not yet incorporated wave 7 data. Further endogeneity testing is left for future research.

5.4 Strong-Tie Social Engagement

To further test hypothesis 2, I added the variable $friend$ (=1 if the respondents talk to their friends at least once a month) to model 4. According to Changwony et al. (2015), frequently talking to friends is a form of strong-tie social engagement. The results of model 5 are reported in Table 2.

The relative and absolute magnitudes of the marginal effects for the initial sociability variable and internet usage remain very similar to before and still significant. Moreover, the marginal effect of $friend$ is smaller and insignificant, suggesting that strong-tie social engagement has no effect on stock ownership. This supports hypothesis 2 and the findings of Changwony et al. (2015), who also find that strong-tie social engagement, measured by frequency of talking to neighbours, has no effect.

5.5 Multiplier Effects

Hong et al. (2004) find that the sociability effect is higher in regions with already relatively high stock ownership rates. To test this effect I added a categorical variable for country participation as well as interaction terms with both sociability and internet usage. *countryparticip* takes a value of 0, 1 or 2 if the respondent is from a country with a low, medium or high stock ownership level, respectively. Results of this model and construction of the *countryparticip* variable are reported in Tables 3 and 8, respectively.

The marginal effects, at average characteristics, for internet usage and sociability are lower once *countryparticip* is added, but their relative magnitudes remain intact. Moreover, their significance levels fall to 10%. This is because country participation controls, to an extent, the institutional differences between countries with different levels of stock ownership; countries with relatively high participation rates, such as those in central Europe, differ significantly to countries with relatively lower rates, such as those in southern Europe, in terms of their social and economic environments. For instance, the Global Financial and Eurozone Debt Crises threatened countries disproportionately more in southern Europe, particularly Greece, Italy, Portugal and Spain, compared to other European countries. In contrast, countries in northern and central Europe, in particular Germany, experienced steady economic growth in the mid-2010s. Moreover, Zurich in Switzerland, home to the SIX Swiss Exchange, and Frankfurt in Germany, home to the ECB and Frankfurt Stock Exchange, are considered as leading global financial centres. Thus, it is no surprise that stock ownership varies widely within Europe.

The model confirms the social multiplier effect across countries; the marginal effects of sociability are 0.014, 0.017 and 0.028 for low, medium and high country participation, respectively. Figure 4 demonstrates this effect. The multiplier effect also seems to somewhat hold for internet usage. This is a further contribution to literature as an internet multiplier effect has not been previously investigated. Although the marginal effect of internet usage is lower for medium country participation than low country participation (0.002 versus 0.009), the marginal effect corresponding to high country participation is considerably higher than both medium and low country participation (0.059). Figure 5 demonstrates this effect. This is a contradiction to hypothesis 3 which argues that since the internet contains the same information on the stock market regardless of where one lives, a differential effect should not be observed. A possible explanation for this finding is location based targeting on the internet (Goldfarb (2014)). For example, adverts on Google regarding stock market trading are likely to be more prominent in regions with already high stock ownership levels.

Multiplier effects demonstrate the importance of greater information access (i.e. in regions with high stock ownership levels there is greater exposure to stock market information, hence the social interaction and internet usage effects are much stronger). Consequently, as mentioned in Section 5.3.2, evidence of multiplier

Table 2: Effect of Strong-Tie Social Engagement

	Model 5 n=4,629
Social	0.0214 (**) (0.010)
Friend	0.0121 (0.011)
Internet	0.0192 (**) (0.009)
Age	0.0004 (0.0004)
$ln(Income)$	0.0014 (0.001)
$ln(Wealth)$	0.0049 (***) (0.001)
Risk Aversion	-0.0743 (***) (0.010)
Education	0.0039 (***) (0.001)
Male	0.0129 (**) (0.007)
Life Satisfaction	0.0066 (***) (0.002)

MEs at average characteristics reported, with robust SEs in brackets. * p<0.1, ** p<0.05, *** p<0.01.

effects suggest that the roles of sociability and internet usage on stock ownership predominantly embody information effects, rather than unobserved ability and/or personality traits.

Table 3: Multiplier Effects

		Model 6 n=4,629
Social		0.0148 (*) (0.008)
Internet		0.0125 (*) (0.008)
Age		0.0003 (0.0004)
ln(Income)		-0.0003 (0.001)
ln(Wealth)		0.0031 (***) (0.001)
Risk Aversion		-0.0746 (***) (0.010)
Education		0.0041 (***) (0.001)
Male		0.0121 (*) (0.006)
Life Satisfaction		0.0059 (***) (0.002)
Country Participation	*Medium*	0.0373 (***) (0.009)
	High	0.0635 (***) (0.016)

MEs at average characteristics reported, with robust SEs in brackets. * p<0.1, ** p<0.05, *** p<0.01.

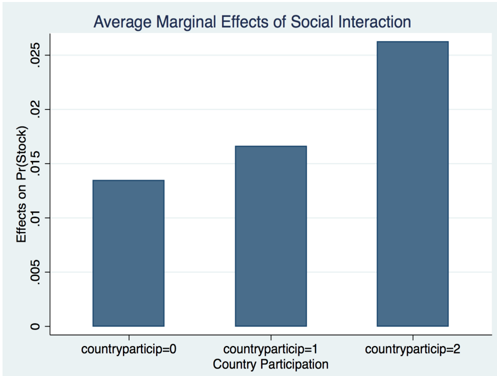


Figure 4: Social Multiplier Effect: the average marginal effect of social interaction across countries with different participation rates.

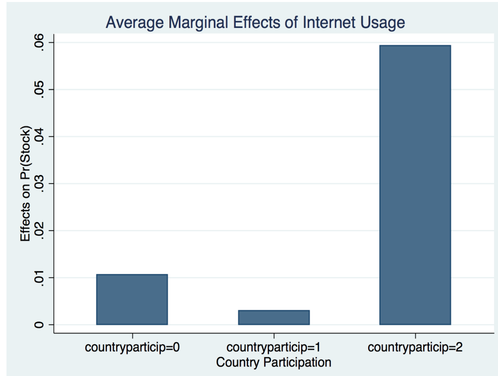


Figure 5: Internet Multiplier Effect: the average marginal effect of internet usage across countries with different participation rates.

6 Conclusion

To conclude, both weak-tie social interaction and internet usage increase the probability of stock market participation. To my knowledge, this is the first paper to acknowledge a gap in previous literature by addressing two contrasting hypotheses that the two information channels either act as substitutes or reinforce each other's effect. In contrast to the results of Liang and Guo (2015), I find that sociability and internet usage reinforce each other's effects, which corroborates the theory proposed by Hong et al. (2004). Moreover, the effects of sociability and internet usage are stronger in countries where participation rates are already relatively high. Therefore, this paper also provides novel insights into the multiplier effects of sociability and internet usage using European data. Finally, strong-tie social engagement, measured by frequent contact of friends, has no effect on stock ownership. This, combined with evidence of multiplier effects and the results of the endogeneity test, also suggest that sociability and internet usage primarily reflect information effects rather than unobservable traits, which may make someone better equipped to do investment. In other words, sociable and internet-using people are more likely to own stock primarily because of better information access.

Despite undertaking robustness checks, my results are still subject to limitations. Firstly, they are skewed as SHARE data is based mainly on an older sample. These results are not redundant but should be taken as a lower bound, given that older individuals are less likely to own stock, especially through the use of new technology. Therefore, further analysis should test these effects using data from a range of age groups. Due to time constraints I was unable to fully address endogeneity concerns beyond the IV method. Panel data analysis with wave 7 will help address this issue. Incorporating wave 7 will also create more robust results, through a richer dataset, and potentially exploit temporal variation, such as cross-sectional differences that may have occurred due to, for example, the effect of the 2016 Brexit referendum on risk aversion levels prevailing in Europe.

Further extensions to this research include analysing the effects of other information channels and breaking down the broad effect of internet usage into different components, such as social media, to determine which channels have the greatest influence on stock ownership. Moreover, incorporating trust into the model will shed further light on the sociability and internet usage effects, especially in light of media bias and "fake news".

Despite the aforementioned limitations, these conclusions still indicate important policy implications. Having shown that information acts as a significant barrier to holding stock, and given that limited stock market participation causes welfare losses (Cocco et al. (2005)), these findings highlight the importance of addressing social welfare by reducing information frictions. Furthermore, information gained through social interaction is likely to be biased compared to other information channels (Shiller (1984)), which in turn can cause herd behaviour. Consequently, since (weak-tie) sociability has a greater impact on stock ownership than internet usage, it is also important to increase the transparency and accuracy of information related to the stock market, as well as promote greater financial literacy.

References

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Number 8769 in Economics Books. Princeton University Press.

Barber, B. M. and Odean, T. (2002). Online Investors: Do the Slow Die First? *Review of Financial Studies*, 15(2):455–488.

Bayer, P. J., Bernheim, B. D., and Scholz, J. K. (1996). The Effects of Financial Education in the Workplace: Evidence from a Survey of Employers. NBER Working Papers 5655, National Bureau of Economic Research, Inc.

Bogan, V. (2008). Stock market participation and the internet. *Journal of Financial and Quantitative Analysis*, 43(01):191–211.

Breeden, D. T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, 7(3):265–296.

Changwony, F., Campbell, K., and Tabner, I. (2015). Social engagement and stock market participation. *Review of Finance*, 19(1):317–366.

Cocco, J. F., Gomes, F., and Maenhout, P. (2005). Consumption and Portfolio Choice over the Life Cycle. *Review of Financial Studies*, 18(2):491–533.

Fagereng, A., Gottlieb, C., and Guiso, L. (2013). Asset market participation and portfolio choice over the life-cycle. Discussion Papers 758, Statistics Norway, Research Department.

Georgarakos, D. and Pasini, G. (2011). Trust, Sociability, and Stock Market Participation. *Review of Finance*, 15(4):693–725.

Goldfarb, A. (2014). What is different about online advertising? *Review of Industrial Organization*, 44(2):115–129.

Granovetter, M. (2005). The impact of social structure on economic outcomes. *Journal of Economic Perspectives*, 19(1):33–50.

Guiso, L., Haliassos, M., and Jappelli, T. (2000). Household Portfolios: An International Comparison. CSEF Working Papers 48, Centre for Studies in Economics and Finance (CSEF), University of Naples, Italy.

Guiso, L., Sapienza, P., and Zingales, L. (2008). Trusting the Stock Market. *Journal of Finance*, 63(6):2557–2600.

Hong, H., Kubik, J. D., and Stein, J. C. (2004). Social Interaction and Stock-Market Participation. *Journal of Finance*, 59(1):137–163.

Liang, P. and Guo, S. (2015). Social interaction, Internet access and stock market participation—An empirical study in China. *Journal of Comparative Economics*, 43(4):883–901.

Mankiw, N. G. and Zeldes, S. (1991). The consumption of stockholders and nonstockholders. *Journal of Financial Economics*, 29(1):97–112.

Rivers, D. and Vuong, Q. H. (1988). Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics*, 39(3):347–366.

Shiller, R. (1984). Stock prices and social dynamics. Cowles Foundation Discussion Papers 719R, Cowles Foundation for Research in Economics, Yale University.

Vissing-Jorgensen, A. (2004). Perspectives on behavioral finance: Does "irrationality" disappear with wealth? evidence from expectations and actions. In *NBER Macroeconomics Annual 2003, Volume 18*, pages 139–208. National Bureau of Economic Research, Inc.

Wooldridge, J. M. (2001). *Econometric Analysis of Cross Section and Panel Data*, volume 1 of *MIT Press Books*. The MIT Press.

Wooldridge, J. M. (2012). *Introductory Economics: A Modern Approach*. South-Western Cengage Learning, 5th edition.

Appendices

A Data and Preliminary Analysis

Table 4: Correlation Matrix

	Stock	Social	Internet	Age	Wealth	Income	Risk Aversion	Education	Male
Stock	1								
Social	0.186	1							
Internet	0.211	0.328	1						
Age	-0.030	-0.118	-0.417	1					
Wealth	0.181	0.201	0.241	-0.050	1				
Income	0.127	0.143	0.187	-0.051	0.170	1			
Risk Aversion	-0.224	-0.206	-0.241	0.156	-0.070	-0.201	1		
Education	0.170	0.248	0.468	-0.331	0.101	0.197	-0.239	1	
Male	0.110	0.020	0.058	0.029	0.046	0.035	-0.107	0.076	1

Figure 6: Stock market participation over age (raw data).

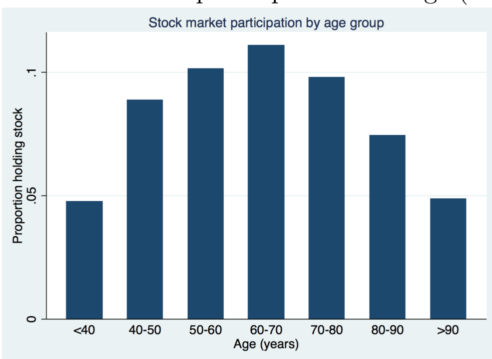


Table 5: Difference in means tests for social interaction and internet usage across different countries.

Country	Difference in means (social interaction)	Difference in means (internet usage)
Sweden	0.094 (*)	0.155 (*)
Denmark	0.077 (*)	0.117 (*)
Germany	0.074 (*)	0.085 (*)
Poland	0.025 (*)	0.016 (*)
Greece	0.002	0.024 (*)
Estonia	0.021 (*)	0.029 (*)

Preliminary analysis of the multiplier effects. Green represents countries with above average participation. Red represents countries with below average participation. (*) represents rejection of the null hypothesis of no difference in means at the 1% level. The magnitudes of the difference in means for both social interaction and internet usage are higher for countries with above average participation than those with below average participation.

Table 6: Variables and Summary Statistics

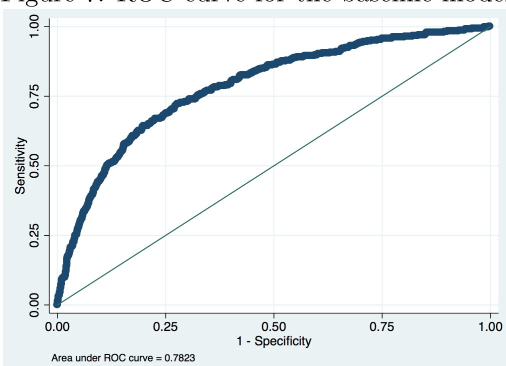
Variable	Description	Mean	SD	Min	Max
Stock	Binary (=1 if direct ownership of stock).	0.10	0.30	0	1
Social Interaction	Binary (=1 if participated in the following social activities in the last month: charity/voluntary work, attended a community organisation, gone to a sports/social club or training course).	0.32	0.46	0	1
Internet Usage	Binary (=1 if used the internet in the past 7 days).	0.49	0.50	0	1
Age	Continuous (years).	62	10.57	36	96
Income	Continuous (net of stockholding);	29,209.26	48,070.65	0	1.42e+07
Wealth	Continuous (net of stockholding);	50,944.97	155,859.2	-534,226.6	5,740,598
Risk Aversion	Binary (=1 if risk averse). Proxy constructed by SHARE (looks at hypothetical situations as to whether the respondent prefers to take on higher levels of financial risks to receive higher returns).	0.76	0.43	0	1
Education	Continuous (years of education).	10.87	4.33	0	26
Male	Binary (=1 if male).	0.44	0.49	0	1
Look Job	Binary (=1 if respondent is actively looking for a job).	0.02	0.13	0	1
Life Satisfaction	Measured on a scale of 0-10. The higher the life satisfaction is, the higher up the scale the respondent is.	7.66	1.79	0	10
Friend	Binary (=1 if respondent talks to friends once a month, once every two weeks, once a week, several times a week or daily, =0 if respondent talks to friends less than once a month or never).	0.25	0.43	0	1
Country Participation	Categorical (=0 if low stock market participation, =1 if medium stock market participation, =2 if high stock market participation).	0.71	0.83	0	2
Computer skills	Binary (=1 if respondent has fair to excellent computer skills, =0 if poor skills)	0.51	0.50	0	1
Child network	Number of respondent's children in their network (respondents can name a maximum of seven persons who they consider confidants).	0.81	0.99	0	7

B Robustness checks

B.1 Predictive power

The predictive power of a probit model can be identified by estimating the area under the ROC curve (an area of 0.5 suggests no predictive power and an area of 1 suggests a perfect model). The graph below shows the ROC curve for the baseline model. The area under the curve is relatively high (0.78), indicating acceptable discrimination for the model (i.e. the model has relatively high predictive power).

Figure 7: ROC curve for the baseline model.



B.2 Endogeneity Test

IV 2SLS Method:

1. Run the instrument relevance test by estimating a LPM for the potentially endogenous variable on the control variables and instruments, then undertake an F-test on the instruments. If F>10, the instruments are relevant.

2. Save the residuals from step 1.

3. Run the instrument exogeneity test by estimating an IV regression of stock ownership on all explanatory variables, including the potentially endogenous variable (which is instrumented), and save the residuals. Then undertake Sargan's J-test (i.e. test the joint significance of the instruments in the regression of the IV residuals on the exogenous variables and instruments). It is necessary to have at least 2 instruments for each potentially endogenous variable to avoid "just-identification". J=m×F, where m is the number of instruments. J $\sim \chi^2_{m-k}$, where k is the number of endogenous variables.

4. Run the Wu-Hausman test for endogeneity for the variable in question by estimating a LPM for stock ownership on all explanatory variables and the residuals obtained in step 2. If the residuals are insignificant, the variable is exogenous. It tests whether β_{OLS}=β_{2SLS}.

NB: an IV probit model is not used as it requires the potentially endogenous regressors to be continuous. Since internet usage is discrete, this method cannot be used.

Table 7: Endogeneity regression results

	Preliminary Regression n=4,640
Internet	0.0244 (***) (0.009)
	Auxiliary Regression n=4,640
Compskills	0.6302 (***) (0.015)
Childnet	-0.0217 (***) (0.006)
	IV Regression n=4,640
Internet	0.0284 (*) (0.016)
Instrument relevance test	F = 925.87
Instrument exogeneity test	F = 0.88
Wu-Hausman test	p = 0.75

Table 7 reports the coefficients for internet usage with standard errors in brackets, from the regressions run for the endogeneity test. Regressions are also controlled for all explanatory variables used in the baseline model. The preliminary regression regresses the stock ownership on all explanatory variables used in the baseline model (OLS model). The auxiliary regression regresses the potentially endogenous variable on its respective instruments and all other control variables (OLS model). The IV regression regresses stock ownership on all explanatory variables used in the baseline model, with internet usage being instrumented. * p<0.1, ** p<0.05, *** p<0.01.

C Multiplier Effect

Table 8: Stock Market Participation across countries in SHARE

Country	Average Stock Market Participation Rate (%)	Country Participation Category (0, 1, 2)
Overall	**10.0**	**1**
Sweden	37.1	2
Denmark	29.3	2
Switzerland	23.0	2
Belgium	15.3	2
Germany	10.8	1
France	10.1	1
Israel	9.0	1
Luxembourg	8.8	1
Slovenia	7.0	1
Austria	6.3	1
Portugal	4.2	0
Czech Republic	3.7	0
Croatia	3.4	0
Italy	3.2	0
Spain	3.2	0
Estonia	2.1	0
Greece	1.7	0
Poland	0.8	0

Table 8 shows how the variable *countryparticip* was constructed from each country's average stock market participation rate in SHARE. NB: Country dummies are not used as they are reported by stata as "not estimable" due to combinations of dummy variables that are not represented in the dataset. Hence, country participation is used to not only test the multiplier effects but also pool together countries with similar levels of participation (and thus partially control for institutional differences). Wave 7, being a richer dataset with more observations, may allow for the incorporation for country dummies though this is left for future research.