Media Exposure and Stock Market Participation^{*}

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Abstract

We show that financial media exposure from cable television increases stock market participation by increasing awareness of and familiarity with the stock market for first-time investors which, in turn, lowers the psychological fixed-costs that normally prohibit participation. We use a novel instrument-the local lineup position of business channels-to break the simultaneity between participation and viewership and identify causal effects. Economically, a one-standard deviation reduction in the lineup position of business channels (approximately 18) increases viewership by 3.8% (Or 8.8 minutes more per week). Subsequently, the propensity to invest in the stock market increases by 8.1% for first-time investors induced into watching by variation in channel position.

Keywords: media exposure, television, awareness, stock market participation. JEL Classification: G11, G14.

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1 Introduction

A significant fraction of the United States (US) population do not own any stock. Recent analysis from the Federal Reserve Bank of St. Louis shows that after reaching an all-time high of 62% in 2007, the financial crises saw participation rates drop back to 57% by 2010.¹ Since then, participation rates have still yet to recover back to pre-crisis levels. Because stock market participation has been argued to have an impact on economic variables like the equity premium (e.g. Mankiw and Zeldes (1991); Heaton and Lucas (1999); Vissing-Jørgensen (2002); Brav, Constantinides and Geczy (2002); Guvenen (2009)), welfare (e.g. Cocco, Gomes and Maenhout (2005)) and inequality (e.g. Favilukis (2013)) understanding its drivers is of significant importance.

In this paper we study how financial media exposure affects stock market participation. A large literature shows that the media plays an important role in shaping investor behavior and explaining financial market movements.² Our paper departs from the literature in two important ways. First, the current debate centers on the role of the media holding investors' participation decisions fixed. In contrast, we are interested in whether and how media exposure impacts the participation decision. Second, we examine exposure to financial news through television (TV), whereas the existing literature focuses on print media.

TV remains the primary source of news for the majority of people. For example, according to the Pew Research Center, in 2016, 57% of adults in the U.S. get their news from TV compared to only 20% for print media.³ We argue that since potential investors have no current vested interest in the stock market they are less likely to consume print media, like say, the Wall Street Journal's "Abreast of the Market" column used in Tetlock (2007)'s seminal work. However, it is possible for potential investors to gain incidental exposure to financial media from TV channels like CNBC simply by "channel surfing". Indeed, incidental

¹These numbers are for households headed by individuals aged 41-60 and based on data from the Survey of Consumer Finances. See "How Has Stock Ownership Trended in the Past Few Decades?" By B. Ravikuma, April 9, 2018, available at: https://www.stlouisfed.org/on-the-economy/2018/april/stock-ownership-trended-past-few-decades (accessed: January 14, 2018).

²See Section 1.1 for a review of this literature.

³See "Americans' online news use is closing in on TV news use", by Jeffrey Gottfried an Elisa Shearer, September 7, 2017, Pew Research Center, available at: http://www.pewresearch.org/fact-tank/2017/09/07/americans-online-news-use-vs-tv-news-use/ (accessed January 1, 2019).

exposure to financial media has been argued to have an important influence on the decision to invest in the stock market (see Bonaparte and Kumar (2013)).⁴

To operationalize our idea, we link cable TV viewership data for business channels (i.e. CNBC, Bloomberg TV and Fox Business) from AC Neilsen with stock market participation data from the Panel Study of Income Dynamics (PSID). A key empirical challenge is the simultaneity of financial news exposure and stock market participation. That is, there could be omitted factors that drive the decisions to participate in the stock market as well as to consume financial news. Or it could be that individuals whom participate in the stock market find it beneficial to watch financial media (i.e. reverse causality). To break the simultaneity, we use a novel instrument similar to Martin and Yurukoglu (2017) for exposure to the financial media: the channel positions of business news channels in cable TV lineups.⁵

The channel lineup, or the numerical ordering of channels, that cable subscribers encounter varies by local cable system. The channel lineup is, in turn, the ordinal position assigned to a given channel in the cable lineup. The assertion is that a business news channel, say CNBC, will be watched more when its channel position is 10 instead of 55. As discussed in detail later, institutional factors imply that the positioning of a given channel in a local cable channel lineup is largely determined by the timing of system upgrades to a digital format, the timing of channel entry and the number of competiting channels. These institutional factors generated large and persistent differences in the positioning of a given channel across geographic locations. Crucially, the local channel lineups of each of the business channels do not correlate systematically with local stock market participation, nor are they correlated with local demographics or economic conditions, alleviating concerns that channel lineups are allocated according to local demand.

We show that a one-standard-deviation decrease in channel position for business channels (approximately 18) is associated with an increase in the fraction of households whom watch a business channel by 3.8%, i.e., approximately 8.8 minutes more per week. Next, for the full sample, we estimate that this increase in business news viewership increases the likelihood of

⁴Bonaparte and Kumar (2013) argue that politically active individuals follow the news more closely and so are also more likely to consume politically related business news.

⁵Martin and Yurukoglu (2017) study the influence of partial bias introduced by Fox News on political outcomes.

participation by 0.6% or 4.2% relative to the unconditional sample average. The economic magnitude is large and comparable to what is reported in recent studies (e.g. Guiso, Sapienza and Zingales (2008); Giannetti and Wang (2016)).

We conduct several tests to investigate the potential mechanisms behind this media exposure effect. First, we find that the effect is stronger for households with a male head, lower financial income or lower wealth. Second, the effect weakens for counties with greater stock market awareness (i.e. counties that have more listed companies or are closer to a financial center). Third, the effect strengthens in periods with positive investor sentiment. Finally, we conduct analysis similar to Brunnermeier and Nagel (2008) and Giannetti and Wang (2016) by considering entry and exit from participation separately. We show that the media effect operates only on the entry margin but not exit margin (i.e. encourages entry but does not discourages exit). Importantly, we find that the media exposure effect is concentrated in households *without* prior investment experience. That is, media exposure induces new entry into the stock market. Economically, greater financial media exposure– from the same one-standard-deviation decrease in channel position for business channels– results in an 8.1% increase in the likelihood of entry into the stock market for first-time investors.

Putting it all together, our results are consistent with the notion that media exposure increases awareness of (Merton (1987); Guiso and Jappelli (2005)) and familiarity with the stock market thereby lowering the psychological fixed-costs that prohibit participation (Vissing-Jørgensen (2003); Brown et al. (2008)) for first-time investors.

1.1 Related Literature

Media and financial markets. Our paper contributes to the literature studying the influence of the media on investor behaviors and financial market outcomes. The most relevant paper is by Engelberg and Parsons (2011), who study how media exposure influences investors' trading behavior conditional on participation. They use individual trading records to study the way local investors respond to coverage of earnings announcements in local newspapers and find that a company whose earnings news is covered in the newspaper experiences significantly higher local trading in the three days around the announcement.

A similar paper by Barber and Odean (2007) studies how attention-grabbing events affect individual and institutional investors' trading behavior.

The rest of the literature largely focuses on the role of media in explaining overall market movements rather than individual investor behavior. Some papers argue that media coverage increases news supply about firms and thus reduces information asymmetry between firms and investors (e.g., Tetlock (2010); Peress (2014); Fang and Peress (2009)). Others argue that media coverage may shift investor attention away from fundamentals and thus bias investor investment strategies (e.g., Daniel, Hirshleifer and Subrahmanyam (1998); Hong and Stein (1999); Engelberg, Sasseville and Williams (2012); Solomon, Soltes and Sosyura (2014)).

Our paper differs from the existing work on two dimensions. First, while the existing literature examines the influence of the media on investor behavior (and the asset pricing implications) conditional on investor participation, we are examining the participation margin itself. Second, unlike prior studies which focus on the impact of the print media on financial markets, we examine media exposure from TV. This difference is important not only because TV is a significantly more important source of news for the average American compared to the print media but also because although potential investors in the stock market are unlikely to consume financial print media we argue they may still be exposed to incidental financial media through TV channel surfing. This is especially important given our findings are concentrated in first-time investors.

Stock market participation. We document a new and important factor explaining the participation puzzle: Media exposure increases investor awareness and so reduces the psychological fixed-costs associated with participation.⁶ The literature studying the participation puzzle can be grouped broadly into two categories. First, there is general acceptance that participation costs (Vissing-Jørgensen (2002)) can explain the lack of participation. A general theme is that information related costs are important (e.g. Bonaparte and Kumar (2013); Guiso and Jappelli (2005)) and so factors that can reduce information based costs

⁶The participation puzzle refers to the prevalence of non-participation observed in data which cannot be explained by the standard models in financial economics (Mankiw and Zeldes (1991); Haliassos and Bertaut (1995)).

such as IQ (Grinblatt, Keloharju and Linnainmaa (2011)), education (Cole, Paulson and Shastry (2014)) and financial literacy (van Rooij, Lusardi and Alessie (2011)) can improve participation rates.

Second, a number of papers highlight how investors perceive the benefits of investing in the stock market as an important determinant. For example, researchers have argued factors such as social interaction and peer-effects (Hong, Kubik and Stein (2004); Brown et al. (2008)), trust in the stock market (Guiso, Sapienza and Zingales (2008); Georgarakos and Pasini (2011); Giannetti and Wang (2016)), personal values (Kaustia and Torstila (2011)) and investor sentiment or beliefs (Kaustia and Knüpfer (2012)) as all potential mechanisms for explaining participation.⁷

2 Background

During our sample period 2005-2017, TV remains the most preferred platform for news in the US.⁸ Most households in the US have three options for television service: a wire-based cable package, a satellite package, or over-the-air broadcast signals.⁹ Each of the two nationwide satellite providers, DirecTV and the Dish Network, have their own packages and lineups that are common to all locations nationwide. The set of channels on cable varies across providers as well as geographical locations for the same provider. Cable content is produced by media conglomerates such as Viacom, News Corporation, ABC-Disney, or NBC Universal. The cable companies contract with these firms to offer their content to subscribers.

The focus of this study is on business news delivered through cable television. Cable television subscriptions in the US peaked around the year 2000. Since then cable subscriptions have been in slow decline, but in 2017, the cable providers still had more than half

⁷Some authors argue nontraditional preferences can also help explain the participation puzzle (e.g, Ang, Bekaert and Liu (2005); Barberis, Huang and Thaler (2006).

⁸See "Americans Still Prefer Watching to Reading the News-and Mostly Still Through Television", by Amy Mitchell, December 3, 2018, Pew Research Center, available at: https://www.journalism.org/2018/12/03/americans-still-prefer-watching-to-reading-the-news-and-mostly-still-through-television/pj_2018-12-03_read-watch-listen_0-01/ (accessed July 9, 2019).

⁹Some households, for example households in remote rural areas, did not have a cable option whereas other households, mostly in urban areas, have two cable operators. And some households which do not have a direct line of sight due to physical obstructions like tall buildings, trees, or steep slopes, do not have a satellite option.

of the market share in paid TV. As of December 2016, there are 53.2 million cable TV subscribers in the US.¹⁰ The major business channels during our sample period are CNBC, Bloomberg and Fox Business. Launched in 1989, CNBC was the first and only channel devoted to business news. As such, its availability was almost universal at the beginning of our sample period. CNBC gained a competitor in the financial news genre with Bloomberg TV, which was created in 1994 by Bloomberg L.P., led by former New York City Mayor Michael Bloomberg. The final entrant onto the business news market was Fox Business News which launched in 2007. Fox Business News' ratings were initially very low but have increased steadily and now has overtaken CNBC as the leading business news provider.¹¹

The channel lineup, or the numerical ordering of channels, that cable subscribers encounter varies by local cable system. The first set of channel positions are generally allocated to over-the-air broadcast affiliates, after which the cable channels begin. We argue that the ordering of a channel in the lineup can have significant effects on viewership.

Our rationale is as follows. American households have no shortage of options for TV channels. For example, in 2014, Neilsen reported that the average US household receives over 189 channels.¹² With so many channels to choose from, "channel surfing"(i.e. sequentially flipping through channels in search of something to watch) has become an American pastime. A 2016 report by the Ericsson Consumer Lab on the habits of American television viewers found that while the average person spends about two hours a day watching TV, one-fifth of that time is used for channel surfing. According to the report, about 44% of Americans spend an average of 23 minutes a day trying to pick something to watch.

Despite the tendency for channel surfing, the 2014 Nielsen report also points out that that many channels simply get overlooked, with only 17 of the 189 channels being viewed consistently. This fact is consistent with evidence documented in Lohse (1997), Galesic et al. (2008) and Feenberg et al. (2017) that people tend to bias toward the top of a list or default option when searching information from the yellow pages, responding to surveys or reading

¹⁰See "Annual Assessment of the Status of Competition in the Market for the Delivery of Video Programming", Federal Communications Commission, 2017.

¹¹See for example "Fox Business beats CNBC in total viewers for 4th straight month", by Joe Concha, February 1, 2017, The Hill.

¹²See "Changing channels: Americans view just 17 channels despite a record number to choose from", June 5, 2014 by Nielsen Media.

scientific publications, respectively.¹³ Similarly, a channel with a lower channel position has a greater chance of being viewed given the tendency for channel surfing. Accordingly, investors in places where business channels have lower positions are more likely to be exposed to financial news. We argue that this type of incidental exposure to financial news is sufficient to encourage participation.

Figure 1 depicts the relationship between viewership and channel lineup for all three business channels. We can see a clear negative relationship: channels with lower positions are significantly more likely to be viewed. Moreover, Martin and Yurukoglu (2017) show that the pattern is not limited to business channels or news channels but holds for all channels.¹⁴

Figure 2 plots the distribution of channel lineups for the three business channels across geographic locations. We can see that there is substantial variation in the lineup of these channels. In order to capture the exogenous component of exposure to financial news from all business channels (i.e. total exposure), we use the lowest position across these channels lineup as the instrument.

One possible concern with the instrument is that business channels might have lower position in places with greater demand for business news. We investigate and reject this concern through several empirical tests in Section 4.2. Meanwhile Martin and Yurukoglu (2017) discusses how historical factors generate persistent cross-sectional variation in channel lineups, which also lends support to the validity of the instrument. Briefly, the mid-1990s saw cable systems upgrade from analogue to digital equipment which dramatically expanded the number of new channels offered by operators. New channels were often added sequentially to local lineup, in the order in which they joined a system. As a result, the position of any channel in a given local system depended on the timing of that system's upgrade to digital as well as the process of bilateral negotiations with the multiple new channels entering the market. Combined with the desire to limit changes in positions so as to not confuse customers, these factors generated persistent cross-system variation in channel lineups.

 $^{^{13}\}mathrm{A}$ theoretical literature models such behavior (see, e.g., Rubinstein and Salant (2006), Horan (2010) and Masatlioglu and Nakajima (2013).)

¹⁴See Figure 1 and Table A1 in Online Appendix G in Martin and Yurukoglu (2017).

3 Data

We discuss the data sources for our analysis in this section. Our source of stock market participation information is the Panel Study of Income Dynamics (PSID). This database is produced from a survey of 9,000 U.S. households and is maintained by the University of Michigan's Institute for Social Research. In addition to information regarding stock market participation, this database contains a wealth of demographic and economic information. During our sample period, data on household financial wealth and equity holdings are available every other year. We follow the literature (e.g., Guiso, Sapienza and Zingales (2008); Giannetti and Wang (2016)) and construct a proxy for household equity market participation, *Participation*, as an indicator variable that equals one if and only if the household holds any stocks in publicly held corporations, mutual funds, or investment trusts in a given year. The survey years used in our regression are 2005, 2007, 2009, 2011, 2013, 2015 and 2017.¹⁵

For media exposure, we use two proprietary datasets from The Nielsen Company (Nielsen): Nielsen Local Television View (NLTV) and Nielsen FOCUS. The NLTV dataset measures television viewership from a rotating panel of households. Since our focus is on business news, we acquired county level ratings for CNBC, Fox Business News, and Bloomberg TV for the period of 2005 till 2017. The measurements come in the units of rating points which indicate what fraction of households that were tuned into each channel in a given time period. The Nielsen FOCUS dataset consists of annual observations of cable systems (*device*). At the channel level, it provides information about the availability of cable channels, channel names and lineups. At the device level, it also provides information about device specification and geographic coverage of the system. We further aggregate cable system channel lineups to county level. Since we do not have subscription data across different cable systems, we first compute the county level minimum positions for each financial channel across devices, and then compute the minimum position across the three financial channels. To this end, we merge household level economic and demographic data with county level business channels viewership and lineup to obtain our sample.

Summary statistics are presented in Table 1. We can see that direct equity participation

 $^{^{15}\}mathrm{We}$ also use early years (1984-2003) of the survey to identify entry and repeated entry into the stock market.

in our sample is low: only 14% of households report having direct investments in the stock market.¹⁶ The average natural logarithm of age, household size, income and wealth are 3.76, 0.79, 10.68, and 8.01 respectively (i.e. approximately 42 years, 2.2 persons, \$42,000 per annum and \$2,939 thousands—or \$2.939 million—respectively). Further, 47% of household heads are married, 26% have college education, 68% are male and 58% are white. The mean of the natural logarithm of business channel position is 3.48 and 16% of households are viewing a business channel at a given point in time over the course of a year.

4 Empirical Analysis

We estimate the effects of media exposure on stock market participation following Giannetti and Wang (2016)'s linear specification:

$$Participation_{h,c,t} = \alpha_h + \alpha_t + \eta Viewership_{h,c,t} + \beta' \boldsymbol{X}_{h,c,t} + \varepsilon_{h,c,t}$$
(1)

where Participation_{*h,c,t*} is an indicator that equals one if and only if household *h* in county *c* holds any stocks in publicly held corporations, mutual funds, or investment trusts in year *t*; Viewership_{*h,c,t*} is the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^{*b*}_{*h,c,t*} where *b* indexes each of the business channels) by household *h* in county *c* and year *t*, expressed as the average fraction of households in county *c* that were tuned into each of the business channels in year *t*; α_h is a household fixed effect and α_t is a time fixed effect which varies by year or state-by-year depending on the specification.

The vector of household and county demographic control variables, $X_{h,c,t}$, includes: (i) Age, the natural logarithm of the age of the household head; (ii) Married, an indicator that equals one if and only if the household head is married; (iii) Size, the natural logarithm of the number of people living in the household; (iv) Income, the natural logarithm of the household income; (v) Wealth, the natural logarithm of household wealth; (vi) College, an indicator that equals one if and only if the household head has college education; (vii) Male, an indicator that equals one if and only if the household head is male; (viii) White, an indi-

¹⁶This number is 27% if we include indirect investments via individual retirement accounts (IRAs).

cator that equals one if and only if the household head is white; (ix) *Middle Age*, an indicator that equals one if and only if the household head is middle aged, i.e, between 31 and 60; (x) *Risk Tolerance*, an indicator that equals one if and only if the household head has risk tolerance above median;¹⁷ (xi) *Participation*_{h,c,t-1}, an indicator that equals one if and only if the household owned stocks in the prior year; and several county-level social and economic control variables such as population, unemployment rate and income. The detailed list is in Table ??. The error term ε captures other sources of heterogeneity in participation decisions. These may include investment mistakes (Odean (1999), Calvet, Campbell, and Sodini (2007)), time-varying heterogeneity in risk aversion (Vestman (2012)), or measurement error in income (Cocco (2005)).

We conduct empirical analysis in three steps. First, we estimate Equation (1) using ordinary least squares (OLS). Second, we use an instrumental variable approach to identify the causal impact of media exposure on stock market participation. Finally, to shed light on the potential economic channels at play, we examine how prior investment experience, stock market awareness, investor sentiment and households demographics affect the media exposure-stock market participation relation.

4.1 OLS Estimation

We report the OLS estimates of Equation (1) in Table 2. Column 1 of Table 2 reports OLS estimates of a univariate regression of the stock market participation on viewership. We find that an increase in viewership is positively associated with the stock market participation.

In order to account for variation in participation decisions induced by household and county characteristics, in Column 2 we include controls for household age, size, income, wealth, education level, ethnicity, risk tolerance, past participation, county level factors (i.e. population, income and unemployment) as well as household and year fixed effects. The inclusion of these covariates reduces the coefficient on viewership by approximately 85% and renders it insignificant, though still positive. This is likely because households with higher

¹⁷The survey conducted in 1996 includes questions which allow researchers to calculate the degree of risk aversion or tolerance of the head of household. These survey questions have not been repeated so we only have a single observation for this variable for each household. Please refer to Kimball, Sahm and Shapiro (2009) for detailed information.

demand for financial channels tend to be wealthier or face less background risk and these omitted factors also induce them to participate in the stock market.

In Column 3, we add state fixed effects to tease out any unobservable but time-invariant state-level determinants of stock market participation. This further reduces the magnitude of the coefficient. Finally, in Column 4 we adopt state-by-year fixed effect instead of state and year fixed effects to account for unobserved local time-varying factors, such as state corporate scandals(Giannetti and Wang (2016)). This further reduces the coefficient of interest but the sign remains positive and insignificant.

The instability of the OLS estimates demonstrate that the effect of viewership on stock market participation is likely biased by endogeneity between the two variables. These findings motivate our focus on formulating a research design that isolates exogenous variation in viewership that is plausibly orthogonal to other unobserved determinants of stock market participation.

Table 2 is here.

4.2 Instrumental Variable Approach

In general, isolating the causal effect of viewership on participation is difficult because of omitted variables and reverse causality. The latter is especially important: households who have already participated in stock market might have higher viewership for financial channels. As a result, participation may be correlated with viewership even if media exposure has no direct effect on household stock market participation decisions. To address this concern, we use the lowest position of financial channels to instrument viewership in estimating Equation (1), because channel positions only affect stock market participation through viewership.

Specification. Our first stage regression relates business channel viewership to the lineup positions of the business channels. The estimating regression takes the form

$$Viewership_{h,c,t} = \alpha_h + \alpha_t + \gamma p_{h,c,t} + \beta' \boldsymbol{X}_{h,c,t} + \epsilon_{h,c,t}$$
(2)

where $p_{h,c,t}$ is the natural logarithm of the lowest lineup position of the three business channels in county c and time t, i.e., $p_{h,c,t} = \ln [\min (p_{h,c,t}^b)]$ for $b \in \{\text{CNBC}, \text{Bloomberg}, \text{FBN}\}$, and $p_{h,c,t}^b$ is the line up position of channel b.¹⁸ Following our discussion in Section 2, channels with lower lineup positions are associated with higher viewership, implying that $\gamma < 0$.

Using the predicted values from Equation (2) we then estimate second stage regressions of the form

$$Participation_{h,c,t} = \alpha_h + \alpha_t + \eta \text{Viewership}_{h,c,t} + \beta' \boldsymbol{X}_{h,c,t} + \varepsilon_{h,c,t}$$
(3)

We estimate this system of equations using ordinary least squares thus the second stage is a linear probability model (LPM). This approach allows us to control directly for household time-invariant heterogeneity by including α_h in the regressions.

First stage estimation results. We have presented graphical evidence of a strong negative relation between lineup position and viewership in Section 3. Here, we provide further evidence to validate our instrument. We begin by presenting the results from estimating equation (2) in Table 3 under various specifications.

Column 1 reports the univariate correlation between viewership and lineup position. Column 2 includes control variables and household as well as year fixed effects in the regression, whereas Column 3 additionally includes state fixed effects to the specification. The most restrictive specification is Column 4, which includes household as well as state-by-year fixed effects and an extensive set of covariates.

The results show a negative and significant relation between the lineup position and viewership. The point estimate in our most conservative model (Column 4) is -0.016 which implies that a standard deviation fall (approximately 18 channels) in the position of business news channels increases the fraction of households who view business news by about 0.6%, i.e., approximately a 3.8% increase relative to the sample mean. An alternative interpretation of the impact of channel lineup on viewership is to multiply the coefficient by 1440 (the

¹⁸Since some counties are served by more than one cable system, we use the minimum $p_{h,c,t}$ across systems within a given county in these instances. Our Internet Appendix provides more detail regarding the construction of the instrument.

number of minutes per day) such that a standard deviation fall in the position increases business news viewership by approximately 8.8 minutes per day per household.

We compare the cluster-robust F-statistics from the first stage to the rule of thumb level in testing weak instruments (i.e. $F \ge 10$)).¹⁹ We can see that as our model specification becomes more and more restrictive, the F statistics are declining but all remain above 10, which reduces the concern that weak instruments may contaminate our inference.

Table 3 is here.

IV Validation. There are two natural concerns which arise in our setting. First, that local economic and demographic factors simultaneously determine channel lineup as well as the propensity to invest in the stock market thus violating the exclusion restriction condition. That is, cable companies may cater to local demand for business news by placing business channels in low positions in areas where participation and/or viewership of business news is expected to be higher.

To further strengthen our argument on the quasi-experimental nature of the channel position we formally address this concern by asking: (i) whether financial channels have lower channel positions in counties whose economic and demographic characteristics predict that the viewership of financial channels or stock market participation is high; (ii) whether nearby counties' channel positions predict local viewership or participation decisions; and (iii) whether future channel positions predict current viewership or participation decisions conditional on the current positions. In short, the answers to these questions are all negative suggesting that the exclusion restriction condition is not violated in our setting. We present the results from this analysis in Table 4 and elaborate below.

Column 1 in Table 4 shows the relationship between business channel position and *observ-able* economic and demographic characteristics. We first construct the predicted viewership of financial channels from the regression of actual viewership on economic and demographic characteristics. The characteristics we use include the vector of household and county demographic control variables $X_{h,c,t}$ from Equation (1) plus the following additional variables:

¹⁹Note that there is only one instrument and the system is exactly identified. In this case, we report the Kleibergen-Paap F statistic, which is equivalent to Montiel Olea-Pflueger effective first-stage F statistic. See Kleibergen and Paap (2006) and Olea and Pflueger (2013) for detailed discussion.

(i) an indicator for whether the county is urban or rural; (ii) the physical distance of the county to the nearest financial center (i.e. New York City, New York; San Francisco, California; Charlotte, North Carolina, Minneapolis/St. Paul, Minnesota; and Chicago, Illinois); and (iii) the voting share for the Democratic party in the county.²⁰

We then regress predicted viewership on our instrument, channel position along with household and state-by-year fixed effects and the set of control variables $X_{h,c,t}$ from Equation (1). If cable companies are catering to local demand then we expect this relation to be negative. That is, cable companies will placing the positions of business channels lower for viewers in counties where business news viewership is expected to be high. However, we find the relationship to be positive which is inconsistent with the view that channel positioning is a result of local demand.

Cable companies may instead cater to local demand by placing business channels in lower positions in counties where stock market participation is expected to be high-assuming that stock market investors are more inclined to watch business news. We explore this possibility in Column 2 by replacing the dependent variable in Column 1–predicted viewership–with the predicted propensity to invest in the stock market. To generate the predicted participation propensities we regress actual participation on the same set of economic and demographic characteristics used above. We show that the predicted propensity of stock market participation has a positive but insignificant correlation with local channel position. In other words, the channel position in counties associated with higher predicted propensity of stock market participant is, if anything, slightly *higher* than the average. The combined results of Columns 1 and 2 suggest that places associated with higher predicted viewership of financial channels or higher predicted propensity for stock market participation are *not* associated with business channels with lower positions.

In Columns 3 and 4 we take an alternative approach to examine whether channel positions are determined by local demand. Specifically, we ask whether channel positions in nearby counties predict local viewership and participation. The idea is that if local economic and demographic factors are correlated with those of nearby counties, then catering to demand

²⁰We find very similar results if we repeat this analysis using just the characteristics in $X_{h,c,t}$ from Equation (1).

implies that the channel positions of nearby counties should also be correlated and thus predict local viewership and participation. However, if unobserved tastes are uncorrelated with local positions, as we claim, they should also be uncorrelated with nearby positions. To support this argument, we regress local viewership and participation on channel positions in nearby counties. In particular, for each county in each year, we construct a variable *Nearby Lineup Position* by taking the average of the channel positions of that county's adjacent counties that are not in the same cable system.²¹ We do not see a significant correlation between nearby channel position and local viewership or participation, only local channel position is significantly related to viewership and participation.

Finally, Columns 5 and 6 check whether *future* local channel position predicts current viewership and participation, conditional on the current local position. If tastes are shifting over time and channel positions are endogenous but sticky, future channel position should predict current viewership and participation. Our results suggest that the future channel position does not predict viewership and participation, conditional on current position. Taken all together, the results from Table 4 suggest that business channel positions are unlikely to be determined by local demand which reassures us that the exclusion restriction condition is satisfied in our setting.

The second set of concerns arise from saturating our regression with fixed effects. Our preferred model includes household as well as state-by-year fixed effects which allow us to control for all time-invariant household heterogeneity as well as time-varying state level factors that may be corrected with participation, such as state corporate scandals (Giannetti and Wang (2016)). Under this specification, our estimate is identified by tracking the business news viewership response of household h to a change the cable lineup induced by moving from county c to c' within the same state and same year t. The first concern is that there may not be very instances where households move county in our sample. This concern is unwarranted as 95% of the households in our sample move at least once.

Second, households moving decisions do not correlate with business channel positions. In particular, we calculate the change in the business channel position for household h induced by moving from county c to c' and plot the density in Figure 3. The red vertical line centers

 $^{^{21}}$ We find similar results if we use the mode or minimum value.

at zero (i.e. no change in *LineupPosition*) and the green solid line plots the density. Values to the left of the red vertical line represent a fall in *LineupPosition* (i.e. households have moved to a county where business news has a lower channel number or appears higher in the lineup) whereas values to the right represent an increase in *LineupPosition*. We can see even though some households do not face changing channel lineups a significant number of households in fact do (approximately 20% of the moves in our sample are associated with a change in *LineupPosition*).

Third, readers may argue that latent variables may explain both the decision to move as well as to invest in the stock market. Precisely, it may be the case that households move to higher income areas as their income increase which is also correlated with the participation decision. The problem arises if *LineupPosition* is also correlated with local income therefore violating the exclusion restriction condition. Although we have already demonstrated that *LineupPosition* is not determined by local preferences we take the following additional steps to address this concern directly. Re-examining Figure 3 we can see that the change in business channel position household h faces after moving from county c to c' looks just as likely to be positive or negative. A formal t-test confirms that there is no statistical difference in the likelihood that households experience a decrease or increase in *LineupPosition* following a move.

Additionally, Figure 3 also plots the distributions of LineupPosition for all households who move between two surveys at two points in time: after their move (i.e. current geographic locations represented with the dashed-blue line) and prior to their move (i.e. geographic locations two-years ago represented with a dashed-red line). It can be seen that the two distributions are almost identical, suggesting that, on average, households are just as likely to move to places where business news channels have higher channel positions as to move to places where business news channels have lower channel positions. Figure 3 therefore demonstrates the near randomness of our identification strategy and should alleviate concerns regarding violating the exclusion restriction condition. Lastly, in Online Appendix table 12 and 13, we expand the regressors in our set of control variables to also include all county-level factors for both household h's current as well as previous county to rule out that differences in county factors may be driving the result. Our results-both first and second stages (discussed below)–are robust to this test.

Table 4 is here.

Second stage estimation results. Having demonstrated the validity of our instrument, we now estimate Equation (3) and present our key finding in Table 5. Column 1 reports the univariate regression result. The null hypothesis that business news viewership does not have an effect on stock market participation is rejected with p < 0.01 with a point estimate on Viewership_{h.c.t} of 0.992.

Column 2 further includes household and time fixed effects, as well as additional economic and demographic controls, whereas Column 3 adds state fixed effects to the specification in Column 2. Column 4 is the most restrictive specification: It includes economic and demographic controls, household fixed effects and state-by-year fixed effects. This captures many time-varying local factors that might affect stock market participation, such as corporate fraud Giannetti and Wang (2016). In each of these three models, Viewership_{c,t} remains positive and statistically significant at 5% level. Notably, the point estimate on Viewership_{c,t} in the most restrictive model, Column 4, is 1.011 which is very close to the point estimate in the univariate regression.

Table 5 is here.

Thus, across all four specifications, the effect of Viewership_{c,t} on stock market participation is positive and significant, suggesting that exposure to financial media increases stock market participation. Economically, a standard deviation reduction in channel lineup position (which, from our first stage regression, increases viewership by 4%) leads to a 0.6% rise in the likelihood of participation. This 0.6% increase translates to a 4.2% increase in the participation rate relative to the unconditional sample average (14.6%). The size of this effect is inside the range of those reported recent studies, for example, Guiso, Sapienza and Zingales (2008) report that trusting others increases the probability of buying stock by 50% whereas Giannetti and Wang (2016) report that exposure to corporate fraud reduces the likelihood of participation by about 4%. Our controls have the expected signs.²² Household heads that are married, have a college education, higher income and higher wealth are more likely to participate, whereas larger families are less likely to participate. Interestingly, our indicator Participation_{h,c,t-2} is negative and significant. This is due to the fact that most of our sample is during the post 2007-2008 financial crisis period, which saw significant exit from the stock market.

Robustness. Following prior work (e.g. Giannetti and Wang (2016)), our main results are obtained using the linear probability model (LPM). Although the LPM model benefits from being simple as well as allowing for easier interpretation of interaction effects compared to non-linear models (Ai and Norton (2003)), it can be problematic since the error term of an LPM has a binomial distribution instead of a normal distribution, which implies that the traditional t-tests for individual significance and F-tests for overall significance are invalid. Moreover, predictions from a LPM are not bound between zero and one.

Thus, as a robustness test, we adopt an alternative approach by using a non-linear model in the second stage. Specifically, we estimate Equation (3) using a Probit model. However, estimating α_h in non-linear models leads to the incidental variables problem resulting in a biased estimate of η (see e.g. Chamberlain (1982), Chamberlain (1984); Lancaster (2000)). We therefore account for cross-sectional heterogeneity by estimating a Probit model allowing for correlated random effect rather than estimating α_h directly (see Chamberlain (1982), Chamberlain (1984); Mundlak (1978); and Wooldridge (2018)). This approach yields a consistent within-estimate of η .

The results are presented in Table 6. Since this exercise essentially shares the same first stage results with LPM, we only present the second stage results. As in the LPM model, we estimate four alternative specifications: Column 1, a simple univariate regression; Column 2, a multivariate regression which includes economic and demographic controls as well as year fixed effect and correlated random effect; Column 3, a regression which further includes state fixed effects to the specification in Column 2. Finally, Column 4, our most restrictive specification, which replaces the fixed effects in Columns 2 and 3 with the state-by-year fixed effects.

²²The coefficients of control variables are reported in Online Appendix Table 14.

We find similar results using this alternative approach. We find a strong positive and significant relation between $\widehat{\text{Viewership}}_{h,c,t}$ and participation across all specifications. From Column 4, the coefficient estimate of 4.982 implies that the 0.6% increase in viewership induced by a standard deviation fall in channel position, in turn, leads to a 2.99% increase in the probability of participation. Compared to the sample participation rate, this increase is equal to a 21% rise in the probability of investing in the stock market.

Therefore, we find consistent evidence as reported earlier. Although the magnitude of the effect is larger using a Probit model with CRE compared to the LPM model, it still falls well inside the range of effects reported on prior studies (e.g. Guiso, Sapienza and Zingales (2008); Giannetti and Wang (2016)).

4.3 Economic Channels

There are several channels through which the media might influence participation decisions. For example, media exposure might reduce the cost of information acquisition (Grossman and Stiglitz (1980); Verrecchia (1982)) or simply increase investors' awareness of financial assets (Merton (1987); Guiso and Jappelli (2005)). In this section, we perform several additional analyses to understand the economic mechanisms behind our main finding that exposure to the financial media increases the propensity to invest in the stock market.

Effects of household demographics We begin by examining how the media-participation relation varies with household characteristics. To this end, we include an additional interaction term between $\widehat{\text{Viewership}}_{h,c,t}$ and various household characteristics in equation 1. In order to identify the coefficients using instrumental variable approach, we adopt the interaction between lineup positions $p_{c,t}$ and household characteristics as additional instrument in estimation. We focus on the specification in Column (4) from Table 5, which includes economic and demographic controls, household as well as state-by-year fixed effects. The results are presented in Table 7, with each Column corresponding to a different household demographic characteristic. Column 1 reports interaction result with household age. The coefficient of viewership is positive and significant, and has similar magnitude when compared to our benchmark case. However, the interaction term between viewership and household age is positive but insignificant, suggesting that the influence of media exposure on stock market participation is similar for young and older household heads. We find similar insignificant results from Column 2 to 6 for household head marital status, household size, household head college education, household race, and household head risk tolerance: the media exposure-participation relation does not vary with these household characteristics.²³

Column 7 reports interaction results for household head gender. Households with a male head tend to be more influenced by media exposure. Column 8 and 9 report interaction results for household income and household wealth. The coefficients on viewership are positive and significant, and largely comparable to our benchmark specification. The level effects from household financial income and wealth are positive and significant, i.e., higher financial income and household wealth are correlated with stock market participation. However, the coefficients of interaction terms are both negative and significant, implying that the media exposure effect is weaker for households with higher income and higher wealth.

The results for income and wealth are particularly interesting. Prior studies (as do our estimates here) show that income and wealth are positively correlated with participation. However, we find that the media exposure effect on participation weakens with higher income/wealth.

Since higher income/wealth households are much more likely to participate in the stock market, they are also more likely to have stock market awareness, investment experience and thus face the ongoing information costs associated with investing. But the fact that the media exposure-participation relation is weaker for higher income/wealth household seems to suggest that the channel through which the effect operates is *less* likely to be about the media reducing ongoing information acquisition costs for investors and more likely to be related the media's potential role in increasing awareness, especially for inexperienced investors. In what follows, we provide more direct evidence to corroborate the suggestive

 $^{^{23}}$ Note that household risk tolerance is only observed for a single survey and so the level effect is subsumed by the household fixed effects.

evidence presented here.

Investor awareness. It is possible that the media exposure increases awareness of (Merton (1987); Guiso and Jappelli (2005)) and familiarity with the stock market thereby lowering the psychological fixed-costs that prohibit participation (Vissing-Jørgensen (2003); Brown et al. (2008)). This channel predicts that the media exposure effect on participation will weaken with stock market familiarity. Accordingly, we construct two proxies for investor awareness to test this prediction.

Our first proxy is the geographic distance of the county the household is located in to the nearest financial center (i.e. New York City, New York; San Francisco, California; Charlotte, North Carolina, Minneapolis/St. Paul, Minnesota; and Chicago, Illinois). The idea here is that households located closer to financial centers will have greater stock market awareness. For ease of interpretation, we multiply this variable by -1 such that higher values correspond to greater investor awareness. Our second proxy is the number of publicly listed companies headquartered locally. We expect that the larger the number of public companies located in the county a household lives in increases their stock market awareness.

We introduce each of these awareness variables (one at a time) along with their interaction term with viewership into our regression model. The results of the second stage regressions are presented in Table 8.

Table 8 is here.

We can see that the interaction term between awareness and viewership is negative and significant in both models, implying that the media exposure effect weakens with investor awareness. In the case of our second proxy–number of listed companies–we also find that awareness significantly increases likelihood of participation.

Taken together, we find that while media exposure increases participation, this effect is weaker for household whom have greater stock market awareness. The evidence is thus consistent with the notion that media exposure can increase participation by raising awareness.

Investor sentiment. Prior research (e.g. Kaustia and Knüpfer (2012)) documents that asset price bubbles are associated with sharp increases in participation rates from *new* entry.

Put another way, first time investors are much more likely to enter the stock market during periods of positive investor sentiment and vice versa. One interpretation of this phenomenon is that the psychological fixed-costs associated with participation (Vissing-Jørgensen (2003) also vary with investor sentiment: periods of positive sentiment are associated with lower psychological fixed-costs.²⁴

Under this view, the media exposure effect should also vary with investor sentiment if the media is increasing awareness and lowering psychological fixed-costs as indicated by our results above. We argue that during periods of positive sentiment, investors' participation decisions are more likely to be influenced by media exposure. To test this idea, we use two proxies for investor sentiment. First, we use the Volatility Index (VIX) as a proxy for negative sentiment, the VIX is widely viewed by investors as a market gauge of investor fear (Whaley (2000)) and so higher values correspond to more negative sentiment. Second, we use the investor sentiment index from Baker and Wurgler (2006, 2007) where higher values are associated with periods of more positive sentiment. We introduce these variables one at a time into our regression along with their interaction with viewership. The results of the second stage regressions are presented in Table $9.^{25}$

Table 9 is here.

We can see that although media exposure is positively related to participation, this relation weakens during periods of negative sentiment (i.e. negative and significant coefficient on the interaction between VIX and viewership) and strengthens in positive sentiment periods (i.e. positive and significant coefficient on the interaction between investor sentiment and viewership).

Entry, exit and prior investment experience. The results in this section so far points toward that the typical investor who is induced to participate by media exposure is lacking

²⁴Since peer-effects (e.g. Hong, Kubik and Stein (2004); Brown et al. (2008)) has been argued to reduce the psychological fixed costs associated with participation (Brown et al. (2008)), one reason for the psychological fixed-costs to vary with investor sentiment is that it has been shown that peer-effects also vary with investor sentiment. For example, Kaustia and Knüpfer (2012) find that high neighbourhood returns are associated with an increase in the number of new investors entering the stock market in the same neighbourhood the following month.

²⁵Note that since these proxies are aggregate sentiment measures with no cross-sectional variation, we drop our state-by-year fixed effects and include state fixed effects instead.

awareness and prior experience in the stock market. To further confirm this, we conduct analysis similar to Brunnermeier and Nagel (2008) and Giannetti and Wang (2016) by considering entry into and exit from the stock market separately. We also examine the role that individuals' prior investment experience has in altering the media exposure effect.

We introduce three additional variables that relate to a household's participation decisions. First, we define $\operatorname{Entry}_{h,c,t}$ as an indicator variable that equals one if household h in county c participates in the stock market in year t but not in year t-2 (i.e. the prior survey); zero if household h in county c does not participate in year t or in year t-2; otherwise, it is recorded as missing. This allows us to investigate the effect from media exposure on the entry margin.

Second, we define $\operatorname{Exit}_{h,c,t}$ as an indicator variable that equals one if household h in county c participates in year t-2 but not in year t; zero if household h in county c does not participate in year t nor in year t-2. This allows us to investigate the effect from media exposure to the exit margin.

Third, we define Inexperience_{*i*,*c*,*t*} as an indicator variable that equals to one if household h in county c does *not* participate at or any point before year t - 4; and zero otherwise. This differentiates our sample further: on the entry margin we are able to differentiate effects for new entrants and re-entrants; on the exit margin we can differentiate effects for first-time exiters and investors who have exited previously.

Table 10 reports our results. The dependent variable in Column 1 and 2 is $\operatorname{Entry}_{h,c,t}$ and the dependent variable in Column 3 and 4 is $\operatorname{Exit}_{h,c,t}$. Column 1 reports our benchmark result for the effect of viewership on entry behavior. The coefficient is positive and statistically insignificant.

Column 2 reports the impact of media exposure on entry behavior for households with and without prior investment experience respectively. In particular, the estimated coefficient on viewership represents the effect for households with prior investment experience: It is positive and statistically insignificant, which suggests that media exposure does not materially affect the entry decision for experienced investors. On the contrary, the estimated coefficient on the interaction term between viewership and the inexperience dummy is positive and significant. This term captures the effect of media exposure on the entry decisions made by the households *without* prior investment experience (i.e. new entrants). The point estimate on the interaction term implies that a standard deviation drop in the lineup position of business channels results in an 8.1% increase in the likelihood of entry for first-time investors.

Finally, Columns 3 and 4 report the results for exit. We find that media exposure will reduce the likelihood of exit. This finding is similar for both experienced and inexperienced investors. However, these results are statistically significant.

The message is clear: the media exposure effect is concentrated on households without prior investment experience. The implication is that the marginal benefit from media exposure for first-time participants is particularly high relative to experienced investors. Since first-time investors need to pay an extra fixed psychological cost to participate in the stock market as suggested in Vissing-Jørgensen (2002), these results add weight to our interpretation that media exposure increases awareness of and familiarity with the stock market thereby lowering the psychological costs that inhibit participation.

4.4 Discussion and additional tests

The typical investor who is induced to participate in the stock market by media exposure is male, with lower income and wealth (although having sufficient surplus to invest), and lacking in stock market awareness and prior investment experience. Moreover, positive investor sentiment increases the likelihood that media exposure will influence him to participate. While this description does not necessarily paint a pretty picture, we want to make two points clear here.

First, we are not making any normative statements regarding the role of the media. Second, although some may interpret our results as being consistent with the salient view in the literature: that media coverage is biased and so creates incentives for manipulation or exacerbates investor biases (e.g. Solomon, Soltes and Sosyura (2014); Daniel, Hirshleifer and Subrahmanyam (1998); Hong and Stein (1999)), we emphasize that our results hold even if with unbiased media reporting–where the media acts purely as an intermediary.

We round out the paper with additional corroborating evidence. In particular, we examine whether media exposure influences indirect stock market participation, whether general news has any impact on the participation decision, as well as whether the estimated effect operates through particular business channels. We report our results in detail in the Online Appendix 9.

Direct v.s. indirect participation. Up to this point, we have followed prior literature and examined direct stock market participation. However, the PSID data allow us to also examine indirect participation via individual retirement accounts (IRAs). Traditional IRAs let individuals contribute pre-tax dollars to a retirement investment account, which can grow tax-deferred until withdrawals occur at retirement. Custodians hold traditional IRAs and based on the offerings available, place the invested funds into different investment vehicles per the account holder's instruction. Individuals can typically open an IRA through a broker or financial advisor.

According to the Tax Policy Center, ownership of IRAs increases with income and age. For example, only 16% of tax payers with annual gross income below 50,000 hold an IRA whereas this number is 73% for those earning 500,000 or more a year. Further, men and women are about as equally likely to own an IRA.²⁶ The profile of the typical IRA holder is thus very different to that of our typical media-induced investor described above. Accordingly, we do not expect that media exposure will significantly impact the decision to open an IRA.

To test this, we define an indicator variable, $IRA_{h,c,t}$, equal to one if and only if a household h in county c holds an IRA in year t. We replace our main dependent variable, Participation_{h,c,t} with $IRA_{h,c,t}$ and reestimate our system of Equations (3) and (5) using our instrument. We find that the estimated coefficient on viewership in the second stage is positive but insignificant, as expected.

Business news v.s. general news. Some may argue that incidental exposure to financial news when watching general news might be enough to encourage participation. We find this unlikely given the business segment in a general news broadcast is generally very short. Nevertheless, we investigate the possibility by reestimating our main models, Equations (3) and (5), replacing viewership of business news with viewership of general news (i.e. Fox

 $^{^{26}}$ See https://www.taxpolicycenter.org/briefing-book/who-uses-individual-retirement-accounts.

News, MSNBC and CNN). We find that general news does not have significant influence on the participation decision (the coefficient estimate is positive though). As an alternative robustness test, we include general news viewership as an additional control variable in our main model and find that our results are robust.

Individual channels Our empirical specification implicitly assumes that financial channels are substitutes. We repeat our exercise in two alternative settings. First, we re-estimate the relationship between participation and media exposure, channel by channel. We obtain similar results in this case: Viewership increases stock market participation, and the effect is more significant for CNBC and Fox Business. Second, instead of using total viewership across three different channels, we use the viewership from the channel that has the lowest position (i.e. used in our instrument). We obtain similar results in this specification as well. All in all, though we make a strong assumption that business channels are substitutes in order to capture the effect of total media exposure, our results using individual channels are largely consistent.

5 Conclusion

In this paper we investigate the influence of financial media exposure on the propensity to invest in the stock market. We use a novel instrument: the local lineup position of business channels to break the simultaneity between participation and business channel viewership. We find that reduction in the channel position (i.e. the channel appears higher in the lineup) of business channels increases viewership, which in turn increases the likelihood of participation.

The effect is stronger for households with a male head, lower financial income or lower wealth and during periods of positive investor sentiment. Importantly, we find that the media exposure effect weakens for counties with greater stock market awareness and is concentrated in households *without* prior investment experience. That is, media exposure induces entry into the stock market by first-time investors with low stock market awareness.

Our results are thus consistent with the notion that media exposure increases awareness

of and familiarity with the stock market which in turn lowers the psychological fixed-costs that prohibit participation for inexperienced investors.

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6 Figures



Figure 1: Scatter plot of ratings (viewership) against Lineup $\mathsf{Position}_{h,c,t}$



Figure 2: Distribution of channel positions for each business channel



Figure 3: The distributions of Lineup $\mathrm{Position}_{h,c,t}$ before and after a household moves as well as the difference in Lineup $\mathrm{Position}_{h,c,t}$ before and after moving

7 Tables

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
Family ID	47441	3991.84	2312.74	1988	3992	5976
Survey Year	47441	2011.02	4	2007	2011	2015
Equity participation	47441	.14	.35	0	0	0
Equity participation (including IRA)	47328	.27	.45	0	0	1
Entry	39654	.14	.35	0	0	0
Exit	7449	.85	.36	1	1	1
Viewership	47441	.16	.14	.1	.1	.2
Lineup Position	47441	3.48	.38	3.26	3.5	3.71
Log of HH head age	47437	3.76	.36	3.47	3.78	4.04
Married	47441	.47	.5	0	0	1
Log of HH size	47441	.79	.57	0	.69	1.39
Log of HH financial income	47015	10.68	.95	10.1	10.78	11.35
Log of HH wealth	27348	8.01	2.1	6.8	8.11	9.39
College Education	46291	.26	.44	0	0	1
Male HH head	47441	.68	.47	0	1	1
White HH head	47441	.58	.49	0	1	1
Middle age HH head	47437	.59	.49	0	1	1
Above average risk tolerance	47313	.19	.19	0	.15	.28
Log county median income	47441	10.82	.25	10.64	10.81	10.97
Log county population	47113	5.75	1.57	4.59	5.89	6.86
County unemployment rate	47441	6.74	2.66	4.7	6.1	8.4
County median house price	45810	140.6	31.56	119.27	132.38	157.74
Percent of people in poverty	47441	15.51	5.54	11.2	15.1	19
County number of establishments	41913	29.55	61.82	2.16	9.25	29.62
County per capita income	47166	41.34	11.23	33.38	39.26	46.81
Lagged equity participation	47103	.16	.36	0	0	0
Distance to Financial Centers	47441	5.81	1.12	5.49	5.91	6.58
Number of listed companies	47441	1.69	1.64	0	1.1	2.85
Investor Sentiment	40623	.05	.35	01	.04	.21
VIX	47441	18.29	6.66	12.81	16.67	24.2

 Table 1: Summary Statistics

This table presents the summary statistics for the variables used in our analysis. Variable definitions are contained in Appendix.

Table 2: Media exposure and stock market participation: OLS estimates

This table presents the results from OLS regressions for equation 1. The dependent variable is $Participation_{h,c,t}$ is an indicator that equals one if and only if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is $Viewership_{h,c,t}$ the total viewership of business news (i.e. $\sum_{b=1}^{3} Viewership_{h,c,t}^{b}$ where b indexes each of the business channels) by household h in county c and year t, expressed as the average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Depender	nt Variab	le: Parti	cipation
	(1)	(2)	(3)	(4)
Viewership	0.095***	0.016	0.011	0.009
	(2.76)	(1.12)	(0.80)	(0.69)
Control	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
State FE	No	No	Yes	No
State \times Year FE	No	No	No	Yes
Household FE	No	Yes	Yes	Yes
Observation	$54,\!119$	$24,\!428$	$24,\!410$	$24,\!395$
R^2	0.001	0.358	0.363	0.374

Table 3: Media exposure and stock market participation: First Stage This table presents the results from our first stage regression, (i.e. equation 2). The dependent variable is Viewership_{h,c,t} is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is Lineup Position_{h,c,t}, the natural logarithm of the lowest lineup position of the three business channels in county c and time t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dep	pendent Varia	able: Viewers	hip
	(1)	(2)	(3)	(4)
Lineup Position	-0.020 $(0.005)^{***}$	-0.029 $(0.005)^{***}$	-0.019 $(0.006)^{***}$	-0.016 $(0.006)^{***}$
Control	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
State FE	No	No	Yes	No
State \times Year FE	No	No	No	Yes
Household FE	No	Yes	Yes	Yes
N. of clusters: Households	7812	6630	6623	6623
N. of clusters: Years	7	7	7	7
Robust F -Stat	16.403	27.772	11.329	10.414
Observation	47441	20958	20936	20936

This table presents the results support on Lineup Position _{h,c,t} . Column (3) Lineup Position _{h,c,t} . Column (5) and tered by household and by year are in p	tring the validity of the and (4) regresses actual (6) regresses actual View arentheses. Significance le	Viewership _{h,c,t} and Partic ership _{h,c,t} and Partic ership _{h,c,t} and Partic ership _{t,c,t} and Participation evels of 10, 5, and 1 percent i	and (2) regress j ipation _{h,c,t} , respectively, $_{h,c,t}$, respectively, are represented by	predicted Viewershi ectively, on financie , on future Lineup I , *, **, and ***.	$p_{h,c,t}$ and Partis 1 Lineup Position Position _{h,c,t} . Rol	$a_{h,c,t}$ respective $a_{h,c,t}$ and nearby council to the standard errors of oust standard errors of the standard errors erro	lly, ity is-
	Pred. Viewership	Pred. Participation	Viewership	Participation	Viewership	Participation	
	(1)	(2)	(3)	(4)	(5)	(9)	
Lineup Position	0.006^{***}	0.003	-0.014^{**}	-0.015^{*}	-0.011^{*}	-0.019^{**}	
	(4.32)	(1.94)	(-2.74)	(-2.14)	(-2.08)	(-3.12)	
Nearby Lineup Position			-0.000	0.005			
			(-0.02)	(0.86)			
Future Lineup Position					0.000	-0.003	
					(0.0)	(-0.45)	
Control	Yes	Yes	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	
State \times Year FE	Yes	Yes	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	\mathbf{Yes}	
Household FE	Yes	Yes	\mathbf{Yes}	\mathbf{Yes}	${ m Yes}$	\mathbf{Yes}	
Observation	20,902	20,902	20,768	20,697	16,763	16,704	
R^{2}	0.557	0.378	0.491	0.405	0.485	0.433	

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Table 5: Media exposure and stock market participation: Second Stage This table presents the results from our second stage regression (i.e. equation 3). The dependent variable is Participation_{h,c,t} is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^b_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Deper	ndent Variab	ole: Particip	ation
	(1)	(2)	(3)	(4)
Viewership	$\begin{array}{c} 0.992 \\ (0.148)^{***} \end{array}$	0.440 (0.216)**	0.675 (0.331)**	1.011 (0.331)**
Control	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
State FE	No	No	Yes	No
State \times Year FE	No	No	No	Yes
Household FE	No	Yes	Yes	Yes
N. of clusters: Households	7812	6630	6623	6623
N. of clusters: Years	7	7	7	7
Observation	47441	20958	20936	20936

Table 6: Media exposure and stock market participation: Robustness

This table presents the results from our second stage regression (i.e. equation 3) when running a probit model instead of linear probablity model. The dependent variable is Participation_{h,c,t} is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^b_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Deper	ident Varia	ble: Partici	pation
	(1)	(2)	(3)	(4)
Viewership	3.789***	2.535^{*}	3.352^{*}	4.982***
	(6.07)	(1.86)	(1.69)	(2.86)
Control	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
State \times Year FE	No	No	No	Yes
Correlated RE	No	Yes	Yes	Yes
Observation	47,444	$21,\!954$	$21,\!880$	$21,\!237$
Log Likelihood	5819.499	7874.823	8409.821	9322.660

This table presents the results from our second stage regress characteristics. Each column corresponds to a different ho levels of $10, 5$, and 1 percent are represented by $*, **$, and	Table ' sion (i.e. equat ousehold charac l ***.	/: HOUSEL ion 3) investig teristic. Rob	oust standard						
				Dependent	Variable: P	articipation	_		
	(1)	(2)	(3)	(4)	(2)	(9)	(2)	(8)	(6)
Viewership	1.045^{**}	0.780^{*}	0.962^{**}	0.791	-0.017	0.734^{*}	0.136	1.090^{***}	1.014^{**}
Viewership \times Log of HH head age	(2.41) -0.075 (-1.58)	(1.93)	(2.27)	(1.56)	(-0.02)	(1.72)	(0.24)	(2.67)	(2.44)
Viewership \times Married	~	0.456 (0.57)							
Viewership \times Log of HH size			0.004 (0.05)						
Viewership \times College Education				0.263					
Viewership \times White HH head				(0.43)	1.607				
Viewership \times Above average risk to lerance					(00.0)	0.543			
Viewership \times Male HH head						(00.1)	0.875^{*}		
Viewership \times Log of HH financial income							(0,1,1)	-0.170***	
Viewership \times Log of HH wealth								(00.0-)	
Corresponding Level Effect	0.015	-0.058	-0.010	0.018	-0.235		-0.158^{*}	0.035^{***}	(12.29) (10.019^{***})
Control	Yes	Yes	Yes	Yes	Y_{es}	\mathbf{Yes}	Yes	Yes	Yes
State × Year FE	Yes	$\mathbf{Y}_{\mathbf{es}}$	Yes	Yes	Yes	Yes	${ m Yes}$	Yes	Yes
Household FE Observation Likelihood	$^{\mathrm{YeS}}_{20,936}$ 1345.394	${}^{ m Yes}_{ m 20,936}$ 413.142	$_{ m Yes}^{ m Yes}$ 20,936 1463.210	${}^{ m Yes}_{ m 20,936}$ 1685.735	$^{\mathrm{Yes}}_{20,936}$ -4475.526	$^{\mathrm{YeS}}_{20,879}$ 1167.544	${ m Yes}$ 20,936 130.610	$^{ m YeS}_{ m 20,936}$ 1441.632	${}^{ m YeS}_{ m 20,936}$ 1529.912

Table 8: Investor Awareness

This table presents the results from our second stage regression (i.e. equation 3) investigating how the media exposure effect varies with proxies for stock market awareness. The two proxies for awareness are distance to finance centers (column 1) and number of listed firms locally (column 2). Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent V	Variable: Participation
	(1)	(2)
Viewership	1.126^{***}	1.332***
	(2.71)	(2.58)
Viewership \times Negative Distance to Financial Centers	-0.145^{*}	
	(-1.93)	
Viewership \times Number of Listed Firms		-0.194***
		(-2.62)
Corresponding Level Effect	-0.002	0.022^{***}
	(-0.29)	(3.22)
Control	Yes	Yes
State \times Year FE	Yes	Yes
Household FE	Yes	Yes
Observation	20,936	20,936
Likelihood	1144.469	135.107

 Table 9: Investor Sentiment

 This table presents the results from our second stage regression (i.e. equation 3) investigating how the media exposure effect
 varies with proxies for investor sentiment. The two proxies for sentiment are investor sentiment index from Baker and Wurgler (2006) and Baker and Wurgler (2007) (column 1) and the Volatility Index (VIX) as a proxy for negative sentiment (column 2). Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent	Variable: Participation
	(1)	(2)
Viewership	0.854^{**}	0.998**
	(2.44)	(2.17)
Viewership \times VIX	-0.138^{*}	
	(-1.83)	
Viewership \times Investor Sentiment		0.234^{***}
		(4.30)
Corresponding Level Effect	0.002	-0.044***
	(1.06)	(-2.60)
Control	Yes	Yes
State FE	Yes	Yes
Household FE	Yes	Yes
Observation	$20,\!958$	19,934
Likelihood	1884.287	150.445

Table 10: Entry, Exit and Investment Experience

This table presents the results for the entry and exit margin. The dependent variable for columns 1 and 2 is $Entry_{i,c,t}$ which is an indicator variable that equals one if household h in county c participates in the stock market in year t but not in year t-2(i.e. the prior survey); zero if household h in county c does not participate in year t or in year t-2; otherwise, it is recorded as missing. The dependent variable for columns 3 and 4 is $Exit_{i,c,t}$ which is an indicator variable that equals one if household h in county c participates in year t-2 but not in year t; zero if household h in county c does not participate in year t nor in year t-2. Inexperience_{*i*,*c*,*t*} as an indicator variable that equals to one if household h in county c does not participate at or any point before year t-4; and zero otherwise. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^b_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	En	try	E	xit
	(1)	(2)	(3)	(4)
Viewership	0.625	0.233	-3.439	-3.324
	(1.35)	(0.49)	(-1.06)	(-1.04)
Viewership \times In experience		1.893^{***}		-1.148
		(4.52)		(-1.58)
Control	Yes	Yes	Yes	Yes
State \times Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Observation	16,722	16,722	1,029	1,029
Log Likelihood	2832.210	1026.518	-183.472	-173.771

8 Appendix

8.1 Variable Definitions

8.2 The Nielsen FOCUS dataset

The source of cable system channel lineups comes from the Nielsen FOCUS dataset. These data are provided in two files. The first file contains information about channels lineup and the second file contains information about cable systems and geocode information.

An observation in the first file is a cable system-year-channel. We dropped any system type not labelled as "Cable". We than include the following channel names in our construction of the instrument.

Fox: Fox Business HD, Fox Business Network, Fox Business Network HD, Fox Business NT Bloomberg: Bloomberg TV, Bloomberg TV HD

CNBC: CNBC, CNBC HD

We further drop any system labelled "CMTY" or "UNIQ". And when there are both "DIG" and "REG" format for one particular channel in a given system, we keep the "DIG" format. Otherwise, we keep the "REG" one. If a given channel shows up in two different channel positions within a system, we keep the minimum position. We thus reduce the data to a DMA (designated market area)-system-channel-year level. The second file provides a link between DMA-system to counties and zip codes annually. We use 2017-2018 DMA shapefile provided by Nielsen to further remove those device-county links that do not appear in the shapefiles. By merging these system -county links with system -channel-lineup data, we finally obtain a county-year lineup database for these financial channels by keeping the minimum position across different devices.

This table presents the definitions for the	variables used in our analysis	
Variable	Description	Source
Participation	an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t .	PSID
Entry	an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t but not in year t -1	PSID
Exit	an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in vear t -1 but not in vear t	PSID
Viewership	the total viewership of business news (i.e. $\sum_{b=1}^{3} Viewership_{h,c,t}^{b}$, where b indexes each of the business channels) by household h in county c and year t , expressed average fraction of households that were tuned in to each of the business channels in year t	Nielsen
Lineup Position	$p_{c,t}$ in equation (2), defined as the natural logarithm of the lowest lineup position of the three business channels in county c and year t , i.e. $p_{c,t} = \ln(\min(p_{c,t}^b))$ where $b = \{1, 2, 3\}$ and $p_{c,t}^b$ is the lineup position of channel b .	Nielsen
Age Married	the natural logarithm of the age of the household head	PSID
Size	the natural logarithm of the number of people living in the household	PSID
Income	the natural logarithm of the household income	PSID
Wealth	natural logarithm of household wealth	PSID
College	an indicator if the household head has college education	PSID
White	an indicator it the nousehold nead is male an indicator equal one if the household head is white	PSID
Middle Aged	an indicator equal one if the household head is middle aged, where middle age is between 31 and 60	PSID
Risk Tolerance	an indicator equal one if the household head has above risk tolerance	PSID
County Income	natural log of median county income	St. Louis Fed
County Population	natural logarithm of the median county population	St. Louis Fed
County Unemployment	natural logarithm of the county unemployment rate	St. Louis Fed
County House Price	county median house price	St. Louis Fed
Poverty Ratio	percent of population in poverty	St. Louis Fed
Establishment	number of county level establishment	St. Louis Fed
Per capita income Distance to Financial Centers	county per capita income physical distance of the county the household is located in to the nearest financial center (i.e. New York City, New York; San Francisco, California; Charlotte, North Carolina, Minneapolis/St. Paul, Minnesota; and Chicago, Illinois)	St. Louis Fed Author calculations
Number of Listed Companies Investor Sentiment Vix	the number of publicly listed companies headquartered locally Baker and Wurgler investor sentiment index Vix implied volatility index	Jeffrey Wurgler's website St Louis Federal Reserve

Table 11: Variable Definitions

9 Online Appendix

Table 12: Media exposure and stock market participation: First Stage

This table presents the results from our first stage regression, (i.e. equation 2) by including households' lagged economic and demographic variables. The dependent variable is $Viewership_{h,c,t}$ is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is Lineup Position_{h,c,t}, the natural logarithm of the lowest lineup position of the three business channels in county c and time t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent Variable: Viewership			
	(1)	(2)	(3)	(4)
Lineup Position	-0.020 $(0.005)^{***}$	-0.030 $(0.006)^{***}$	-0.023 $(0.007)^{***}$	-0.020 $(0.007)^{***}$
Control	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
State FE	No	No	Yes	No
State \times Year FE	No	No	No	Yes
Household FE	No	Yes	Yes	Yes
N. of clusters: Households	7812	5708	5704	5704
N. of clusters: Years	7	6	6	6
Robust F -Stat	16.403	26.158	12.053	9.880
Observation	47441	16108	16093	16093

Table 13: Media exposure and stock market participation: Second Stage This table presents the results from our second stage regression (i.e. equation 3) by including households' lagged economic and demographic variables. The dependent variable is Participation_{h,c,t} is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^b_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent Variable: Participation				
	(1)	(2)	(3)	(4)	
Viewership	$\begin{array}{c} 0.992 \\ (0.148)^{***} \end{array}$	$0.520 \\ (0.257)^{**}$	$0.704 \\ (0.359)^{**}$	$0.900 \\ (0.359)^*$	
Control	No	Yes	Yes	Yes	
Year FE	No	Yes	Yes	No	
State FE	No	No	Yes	No	
State \times Year FE	No	No	No	Yes	
Household FE	No	Yes	Yes	Yes	
N. of clusters: Households	7812	5708	5704	5704	
N. of clusters: Years	7	6	6	6	
Observation	47441	16108	16093	16093	

Table 14: Media exposure and stock market participation: Full Results This table presents the full regression results from our second stage regression (i.e. equation 3). The dependent variable is Participation_{h,c,t} is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^h_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent Variable: Participation				
	(1)	(2)	(3)	(4)	
Viewership	0.992***	0.440**	0.675**	1.011**	
-	(6.68)	(2.04)	(2.04)	(2.38)	
Log of HH head age	· /	-0.002	0.000	-0.002	
0 0		(-0.29)	(0.04)	(-0.27)	
Married		0.019***	0.018***	0.021***	
		(3.10)	(2.88)	(3.36)	
Log of HH size		-0.010***	-0.009***	-0.014***	
		(-3.15)	(-3.12)	(-3.41)	
Log of HH financial income		0.022***	0.022***	0.024***	
		(6.61)	(6.34)	(7.25)	
Log of HH wealth		0.016***	0.016***	0.017***	
		(15.47)	(16.78)	(17.24)	
College Education		0.063***	0.063***	0.066***	
conege Dateation		(11.62)	(11.43)	(10.71)	
Male HH head		-0.010	-0.010	-0.008	
		(-1.55)	(-1.57)	(-1.10)	
White HH head		0.041***	0.046***	(1.10)	
White III head		(8.96)	(9.75)		
Middle age HH head		-0.000	-0.001		
middle age mi neau		(-0.10)	(-0.25)		
Log county median income		0.050	-0.005	-0.012	
Log county median mediae		(1.50)	(-0.12)	(-0.22)	
Log county population		-0.000	(-0.12)	-0.003	
Log county population		(-0.15)	(0.41)	-0.005	
County unomployment rate		0.002	0.003	0.004	
County unemployment fate		(1.52)	(1.43)	(1.12)	
County modian house price		(-1.52)	0.000	(-1.12)	
County median nouse price		(1.85)	(1.58)	(1.07)	
Percent of people in powerty		0.003**	(1.55)	0.003	
referrent of people in poverty		(2.40)	(1.65)	(1.53)	
County number of establishments		(2.40)	0.000	0.000	
County number of establishments		(1, 43)	(0.51)	(0.41)	
County por appite income		(1.43)	0.001	0.002	
County per capita income		(0.86)	(0.001)	(1.48)	
Lagrad aquity participation		(-0.80)	(-0.90)	(-1.40)	
Lagged equity participation		(6.30)	(654)	(6.71)	
Constant	0.017	(-0.50)	(-0.04)	(-0.11)	
Constant	(1.18)				
	(-1.18)				
Control	No	Yes	Yes	Yes	
Year FE	No	Yes	Yes	No	
State FE	No	No	Yes	No	
State \times Year FE	No	No	No	Yes	
Household FE	No	Yes	Yes	Yes	
Observation	47,441	20,958	20,936	20,936	
	/	,	,	,	

Table 15: Media exposure and stock market participation: Indirect participation This table presents the full regression results from our second stage regression (i.e. equation 3). The dependent variable is Participation_{h,c,t} is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^b_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent Variable: Participation			
	(1)	(2)	(3)	(4)
Viewership	$\begin{array}{c} 0.949 \\ (\ 0.239)^{***} \end{array}$	0.568 (0.286)**	0.567 (0.471)	0.528 (0.471)
Control	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
State FE	No	No	Yes	No
State \times Year FE	No	No	No	Yes
Household FE	No	Yes	Yes	Yes
N. of clusters: Households	7812	5254	5249	5249
N. of clusters: Years	7	7	7	7
Observation	40608	15074	15059	15059

Table 16: Media exposure of general news and stock market participation

This table presents the full regression results from our second stage regression (i.e. equation 3). The dependent variable is $Participation_{h,c,t}$ is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent Variable: Participation				
	(1)	(2)	(3)	(4)	
Viewership	$\begin{array}{c} 0.833 \ (\ 9.036) \end{array}$	-0.117 (0.178)	-0.221 (1.007)	0.231 (1.007)	
Control	No	Yes	Yes	Yes	
Year FE	No	Yes	Yes	No	
State FE	No	No	Yes	No	
State \times Year FE	No	No	No	Yes	
Household FE	No	Yes	Yes	Yes	
N. of clusters: Households	7812	6641	6634	6634	
N. of clusters: Years	7	7	7	7	
Observation	47566	21010	20988	20988	

Table 17: Media exposure and stock market participation: Channels This table presents the results from our second stage regression (i.e. equation 3). The dependent variable is Participation_{h,c,t} is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^b_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent Variable: Participation			
	CNBC	BLOOMBERG	FBN	
Viewership	0.932	0.348	1.583	
	$(0.407)^{**}$	(5.463)	(0.846)*	
Control	Yes	Yes	Yes	
State \times Year FE	Yes	Yes	Yes	
Household FE	Yes	Yes	Yes	
N. of clusters: Households	6623	2479	4319	
N. of clusters: Years	7	7	6	
Observation	20930	5685	10635	

Table 18: Media exposure of general news and stock market participation: Min position channel

channel This table presents the full regression results from our second stage regression (i.e. equation 3). The dependent variable is Participation_{h,c,t} is an indicator equal one if household h in county c holds any stocks in publicly held corporations, mutual funds, or investment trusts in year t. The independent variable of interest is the predicted value of Viewership_{h,c,t} instrumented by the natural logarithm of the lowest lineup position of the three business channels in county c and time t, where Viewership_{h,c,t} measures the total viewership of business news (i.e. $\sum_{b=1}^{3}$ Viewership^b_{h,c,t} where b indexes each of the business channels) by household h in county c and year t, expressed average fraction of households that were tuned in to each of the business channels in year t. Other variable definitions are contained in the Appendix. Robust standard errors clustered by household and by year are in parentheses. Significance levels of 10, 5, and 1 percent are represented by *, **, and ***.

	Dependent Variable: Participation				
	(1)	(2)	(3)	(4)	
Viewership	$\frac{1.185}{(0.239)^{***}}$	0.617 (0.324)*	$\frac{1.164}{(0.541)^{**}}$	$\frac{1.462}{(0.541)^{**}}$	
Control	No	Yes	Yes	Yes	
Year FE	No	Yes	Yes	No	
State FE	No	No	Yes	No	
State \times Year FE	No	No	No	Yes	
Household FE	No	Yes	Yes	Yes	
N. of clusters: Households	7812	6582	6575	6575	
N. of clusters: Years	7	7	7	7	
Observation	46578	20655	20633	20633	