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Abstract

We investigate the effect of social media adoption on stock market participation in the United States. Using plausibly exogenous variation in the early adoption of Twitter across counties, we show that a 10% increase in social media usage is associated with a 2.5% higher rate of stock ownership and an overall increase in stock market wealth. Consistent with the idea that social media can lower the cost of accessing information, we find that Twitter adoption is associated with a decline in the number of financial advisors and has larger effects on stock ownership in counties with lower levels of pre-existing stock market knowledge. Twitter adoption also fuels interest in “meme stocks,” which tend to be more volatile and owned by retail investors. Overall, our results suggest a distinct impact of social media platforms on household portfolio choices that differs from that of other modern information technologies.

Keywords: Social Media, Stock Market Participation, Household Finance, Participation Puzzle

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1 Introduction

The rapid rise of social media is transforming the way people interact and gather information. In the United States, more than 300 million people use at least one social media platform, and around 35% use them to get news.¹ Social media is also increasingly used to inform investment decisions. It is the most popular source of investment advice among 18-to-34-year-olds (CNBC, 2021), and almost 80% of institutional investors use social media as part of their regular workflow (Coalition Greenwich, 2015, 2019).² However, there is only limited evidence on whether and how social media adoption affects households' personal finance decisions and portfolio choices.

In this paper, we study the effect of Twitter on stock market participation and investor beliefs in the United States. Whether and how social media should affect stock ownership is ex-ante ambiguous. Existing research has highlighted that acquiring information about the stock market is costly (e.g. Haliassos & Bertaut, 1995; Vissing-Jørgensen, 2002), and that these costs play an important role in explaining the “stock market participation puzzle” in household finance (e.g. Campbell, 2006; Grinblatt, Keloharju, & Linnainmaa, 2011; Guiso & Sodini, 2012). As such, if social media platforms reduce information costs by providing retail investors with easier access to information, especially those who may not regularly engage with traditional media, social media could increase stock market participation. On the other hand, social media could also increase the cost of accessing *accurate* information by generating an information overload (e.g., Bernales, Valenzuela, & Zer, 2023), propagating misinformation (e.g., DeMarzo, Vayanos, & Zwiebel, 2003; Han, Hirshleifer, & Walden, 2022), or amplifying behavioral biases (e.g., Barber et al., 2022). In this case, exposure to social media could also lower stock market participation.

To study the aggregate effects of social media use, we combine data on the geographical location of Twitter users with information on stock ownership from the Internal Revenue Service (IRS), survey data from Gallup, and tweets containing the hashtag “#FinTwit.” “FinTwit”—short for “financial Twitter”—is a popular online community where investors exchange information and advice related to investing. Twitter has become the go-to platform for hedge fund professionals, top bankers, and entrepreneurs—such as Bridgewater Associates

¹Based on data from Statista (Statista, 2022). Finding news is one of the main reasons for people to use social media across all generations (Global Web Index, 2022).

²Coalition Greenwich (2015) surveyed 265 corporate and public pension funds, insurance companies, endowments, and foundations across U.S., Europe, and Asia. They find that over 80% of institutional investors use social media as part of their work, and around 30% of them report that information obtained from social media directly influences their investment decisions. Coalition Greenwich (2019) report that social media is now a more important source of information for institutional investors than finance-specific trade publications.

founder Ray Dalio, former PIMCO CEO Mohamed El-Erian, or Tesla and Twitter CEO Elon Musk—to share information and views about financial markets (CNBC, 2019). Compared to other social media platforms such as “StockTwits”, which mainly focuses on stock-picking, “FinTwit” covers a broad set of financial topics ranging from traditional financial advice to recent topics like cryptocurrencies.³

Estimating the effect of Twitter on stock market participation is challenging because the adoption of Twitter is endogenous. Hence, a naive regression of Twitter usage on stock market participation would likely be biased. Building on Müller and Schwarz (2023), we propose an identification strategy that creates plausibly exogenous variation in the usage of Twitter across counties. In particular, we exploit a shock during Twitter’s early years that put the platform on an explosive growth trajectory and affected local adoption rates by making use of Twitter’s surprise popularity at the South by Southwest (SXSW) Interactive Festival in March 2007. Although Twitter was founded in 2006, it only rose to prominence when it was showcased at the 2007 edition of SXSW Interactive, an annual event held in Austin, Texas. Following a spike in sign-ups by SXSW attendees during the festival, the attendees told their friends and families about the platform, leading to a rapid adoption of Twitter in their home counties. SXSW 2007 is widely considered as the “tipping point” for Twitter to reach a critical mass of users, which helped it to become the major social network it is today (TechCrunch, 2011).⁴

We show that a 10% higher number of SXSW attendees is associated with a 2% increase in the number of tweets sent in a county following SXSW 2007.⁵ Importantly, these counties were on the same trajectory of Twitter adoption before the event, consistent with the parallel trends assumption. This finding suggests that SXSW led to network effects, making it more attractive for people to join the platform in the home counties of attendees. We document that these county-level network effects persist in the long run. A higher number of SXSW 2007 attendees in a county is associated with a higher level of Twitter usage in 2015, even after controlling for a county’s pre-existing interest in SXSW and a host of geographical and

³In previous studies, Twitter data has been widely used to predict stock price movements (e.g. Bollen, Mao, & Zeng, 2011), firm performance (e.g. Bartov, Faurel, & Mohanram, 2018), or trust in CEOs (Elliott, Grant, & Hodge, 2018).

⁴In response to a question on the online messaging board Quora, Twitter co-founder Evan Williams wrote about the role of SXSW in the platform’s success: “I don’t know what was the most important factor, but networks are all about critical mass ... And something clicked.”

⁵This identification strategy is similar to Enikolopov, Makarin, and Petrova (2020), who use the number of students from each town in the cohort of the founder of the social network *Vkontakte* (VK) as an instrument for social media adoption in Russia. Following their paper, we use the term SXSW “attendees” here and throughout the paper for brevity, even though we do not perfectly observe attendance; we discuss this issue in the data section.

socioeconomic variables.⁶

Our identification strategy exploits this plausibly exogenous residual geographic variation in the attendance of SXSW 2007 as an instrument for social media adoption across counties in an event study design. In these event studies, the year before Twitter’s launch (2005) serves as the pre-period. For our main results, we relate changes in stock market participation since 2005 to a county-level measure of Twitter usage (measured as of 2015), instrumented with the number of SXSW 2007 attendees. As such, we exploit within-county variation over time, similar to a difference-in-differences estimator with an (instrumented) continuous treatment variable. This approach holds constant any time-invariant county characteristics, such as whether or not people are generally more interested in adopting new technologies. It also allows us to show that counties more exposed to social media adoption did *not* differ in stock ownership rates going back all the way to 1990, which further alleviates concerns that residual variation in SXSW attendance may pick up unobserved differences across counties correlated with other aggregate shocks.

We find that exposure to social media leads to an economically meaningful increase in stock market participation. We estimate that a 10% higher Twitter adoption increases stock ownership per capita by around 2.5% and the share of income from stock market investments by 2.2%. This effect size is somewhat smaller than that of broadband internet studied by Hvide et al. (2022). Importantly, counties with higher SXSW attendance were on parallel trends with other counties in their stock market participation rates before Twitter’s launch. These parallel trends also hold for the period of the internet bubble and crash of the late 1990s and early 2000s, suggesting that “treated” counties do not simply pick up interest in new technologies more generally. We find a swift and permanent positive effect on stock ownership only once Twitter reached around 15 million people after a wave of new registrations during 2009-10. A range of robustness exercises suggests that our results are also not driven by exposure to the 2000s housing boom and 2007-08 Great Recession.

We provide evidence for two mechanisms through which social media use could affect stock market investments. First, social media could be interpreted as a shock to the costs of acquiring information. Similar to word-of-mouth or observational learning (Bikhchandani, Hirshleifer, & Welch, 1992; Hong, Kubik, & Stein, 2004), social media could lead to an increase in social connections that enable information sharing independent of geographical distance. Consistent with this channel, we find larger effects of social media adoption in

⁶Existing work has used SXSW as an instrument for Twitter usage to study the effect of social media on changes in hate crime around Donald Trump’s presidential campaign (Müller & Schwarz, 2023) and election outcomes (Fujiwara, Müller, & Schwarz, 2021).

counties that had fewer sources of information about the stock market before the launch of Twitter. This finding holds for several proxies for access to information, such as the density of financial advisors or bank branches, knowledge about stock market investments based on survey data, and the share of the population with a bachelor's degree.

We also find evidence that Twitter adoption reduced the number of financial advisors in a county. Our estimates show that a 10% increase in Twitter usage is associated with a 1% drop in financial advisors in the long run. This result is important for two reasons. First, it suggests that digital technologies can displace white-collar jobs that have traditionally been thought of as more resilient to the adoption of new technologies. Second, it supports the idea that social media can act as a substitute to traditional financial advice by reducing the costs of information acquisition about financial topics.

Consistent with an information channel, we find that Twitter adoption is associated with a change in retail investor beliefs that suggests an improved understanding of financial markets. Using survey data from Gallup, we show that Twitter usage is associated with an increased likelihood to believe stocks are the best long-term investment and a matching decrease for gold and real estate. Given that limited stock market participation is a puzzle (Campbell, 2006; Grinblatt, Keloharju, & Linnainmaa, 2011; Guiso & Sodini, 2012), and that the historical risk-adjusted returns of stocks are clearly much higher for stocks relative to gold, an increase in the belief that stocks are a good investment relative to other asset classes suggests that social media can lower the cost of information acquisition. The survey data also allow us to confirm that an exogenous increase in Twitter use in a county increases the probability of owning stocks, even after controlling for a host of individual characteristics that are known to affect stock market participation.

The second mechanism we consider is that social media platforms could lead to a reinforcement of similar views in “echo chambers” (Cookson, Engelberg, & Mullins, 2022), which in turn could amplify behavioral biases (Heimer, 2016) and lead to trading frenzies (Tengulov et al., 2021). Consistent with the idea that social media can facilitate risky investments in lottery-type assets (Pedersen, 2022), we provide evidence that social media increases the likelihood of investing in “meme stocks.” In particular, counties with higher Twitter adoption due to SXSU saw a spike in Google searches for GameStop, AMC, and other meme stocks following the short squeeze episode in early 2021. Importantly, these counties were on parallel trends to others before, which suggests a causal effect of exposure to social media on the likelihood of participating in the trading craze.

To understand the differences between social media and traditional media, we also investigate the frequency of stock mentions on Twitter relative to financial news outlets. The

most overrepresented stocks on Twitter are more volatile and more likely to be owned by retail investors, which is also consistent with a role of social media in contributing to risky investments by relatively inexperienced investors. As such, one interpretation of our findings is that social media may be a “double-edged sword” for financial decision-making: while it can spur stock market participation, it may also encourage investments in volatile and risky assets. While we provide evidence that Twitter adoption increases total stock market wealth and the returns on initial wealth, presumably driven by its effect on information provision, our data do not allow us to measure portfolio volatility. The welfare implications of higher social media use on investor decisions in our setting are thus ambiguous.

Our paper contributes to a growing literature on the effects of information technology on financial markets. Existing work has studied the effect of internet and smartphone usage (e.g. Barber & Odean, 2002; Bogan, 2008; Choi, Laibson, & Metrick, 2002; Kalda et al., 2021). Other work has linked various measures of social media sentiment to stock returns (e.g. Bartov, Faurel, & Mohanram, 2018; Bollen, Mao, & Zeng, 2011; Chen et al., 2014; Cookson et al., 2022; Luo, Zhang, & Duan, 2013). Cookson and Niessner (2020) and Cookson, Engelberg, and Mullins (2022) study disagreement and selective exposure on investor social media. Heimer, 2016 studies the effect of social networks on the disposition effect. Hirshleifer, Peng, and Wang (2021) show a link between the centrality of a firm’s location on social media and stock reactions to earnings surprises. Tengulov et al. (2021) analyze social media activity around the short squeeze events in the U.S. stock market in early 2021. Dessaint, Foucault, and Frésard (2021) show that exposure to social media content changes the informativeness of analysts’ long-term compared to short-term forecasts. Cookson, Niessner, and Schiller (2022) show that negative social media sentiment is associated with a higher probability of merger withdrawals. Farrell et al., 2022 suggest that posts on the crowd-sourced investment platform SeekingAlpha make trades by retail investors better informed. Kuchler et al., 2021 use Facebook data to show that institutional investors are more likely to invest where they have more social ties.

To the best of our knowledge, our paper is the first to estimate the causal effect of social media adoption per se on household financial decisions. A related paper by Hvide et al. (2022) studies the causal effect of broadband internet rollout on the investment decisions of individual investors in Norway. Their central finding is that broadband spurs a “democratization of finance” by increasing stock market participation for poorer and less-educated individuals. We find some complementary evidence that counties with less information about financial markets and a higher share of minorities benefit from social media adoption. However, we also show that within a given county, stock ownership particularly increases among people

with the highest incomes, who are more likely to own stocks in the first place. One potential reason for this difference relative to the results in Hvide et al. (2022) could be that, while social media provides information, it does not fundamentally alter the infrastructure of accessing investment accounts.

We also contribute to the broader literature on the stock market “participation puzzle” in household finance (e.g. Campbell, 2006; Guiso & Sodini, 2012; Haliassos & Bertaut, 1995). This literature has identified many correlates of stock market participation. Existing work would suggest that factors reducing the cost of acquiring information about financial topics could increase stock market participation (Vissing-Jørgensen, 2002). For example, there is evidence that higher levels of education (Bernheim & Garrett, 2003; Cole, Paulson, & Shastry, 2014), cognitive ability (Grinblatt, Keloharju, & Linnainmaa, 2011), and financial literacy (Van Rooij, Lusardi, & Alessie, 2011) are positively associated with stock market participation rates. These findings suggest that individuals who possess greater financial knowledge and better information processing skills are more likely to invest in the stock market. Another line of research has focused on how investor beliefs and psychological biases affect decision-making about households’ financial decision-making. (e.g., Briggs et al., 2021; Guiso, Sapienza, & Zingales, 2008). Social interactions and the influence of peers have also been found to matter (e.g., Brown et al., 2008; Hong, Kubik, & Stein, 2004; Kaustia & Knüpfer, 2012). Against this backdrop, our study presents evidence for social influence on households’ financial decisions in the context of social media, where we observe how individuals communicate and exchange information in a dynamic and interactive way, which in turn may shape household beliefs and behaviors.

The remainder of this paper is organized as follows. Section 2 describes the data sources used in the paper. Section 3 introduces our empirical strategy. Section 4 presents the main results. Section 5 analyzes potential mechanisms. Section 6 concludes.

2 Data

We combine several data sources for our analysis: (1) county-level data on stock market participation based on IRS individual income tax returns, (2) county-level data on Twitter usage, (3) county-level data on the number of people attending the SXSW festival in 2007, (4) individual-level survey data from Gallup, (5) DMA-level data on Google search interest in meme stocks, (6) additional county-level variables mostly used as controls, and (7) the

frequency stocks are mentioned on Twitter and in traditional media. We describe these datasets in turn.

2.1 County-level stock market participation

The IRS Statistics of Income (SOI) provide aggregated individual income tax data at the county level. These data are publicly available from 1989 to 2019 and provide, among others, information about adjusted gross income (AGI) and dividend income. If someone receives any income from dividends, they must own stocks. Therefore, we follow the existing literature (e.g., Brown et al., 2008; Chodorow-Reich, Nenov, & Simsek, 2021) and construct measures of stock ownership using this information on dividends. Our main variables are the ratio of total dividend income to population or the ratio of total dividend income over total AGI. Because these ratios are highly skewed, we take their log transformation in our baseline analysis. We consider other measures and transformations for robustness.

While dividend income from tax returns has been widely used as a proxy for stock ownership, it likely contains measurement error for two reasons. First, we do not observe ownership of stocks that do not pay dividends. Second, we do not observe indirectly held stocks in retirement accounts or other non-taxable entities. We therefore validate our baseline measure using survey data from Gallup that asks individuals whether they directly or indirectly own stocks. Figure A.3 plots a county's dividend income per capita against the share of households reporting they own stocks in the Gallup data, which we describe in 2.4 below. We find a strong positive correlation. Measures based on dividend income thus appear to be reasonable proxies for actual stock market participation as reported in individual-level surveys.

We also use two proxies for the total wealth earned by stock market investors. First, we take the measure of total stock market wealth from Chodorow-Reich, Nenov, and Simsek (2021). They capitalize the IRS SOI taxable dividend income data using a county-level age-specific CRSP price-dividend ratio and then adjust for stock wealth held in nontaxable accounts.⁷ Second, we construct a proxy for the returns stock market investors earn on their wealth. We start with data on the total capital gains from the sale of assets that are available

⁷The capitalization process begins by deriving the price-dividend ratio for the value-weighted CRSP portfolio, with further adjustments that allow for variations in dividend yields across age groups. In order to calculate age-specific dividend yields, the authors use a sample of account-level portfolio holdings and combine it with CRSP stock and mutual fund data, and then compute average dividend yields for five age groups within each county. The resulting capitalization factor is obtained by taking age-wealth-weighted averages of age-specific dividend yields within each county based on data from the Survey of Consumer Finances (SCF). The adjustment for nontaxable stock market wealth considers the relationship between taxable dividend income and total stock wealth with demographics, also from the SCF.

from the IRS SOI from 2010 to 2019. To create our proxy for county-level portfolio returns, we then scale capital gains by the total stock market wealth in the previous year, again from Chodorow-Reich, Nenov, and Simsek (2021).

2.2 County-level Twitter adoption

We measure social media adoption across counties using Twitter data. Twitter was launched in 2006 by Jack Dorsey, Noah Glass, Biz Stone, and Evan Williams. Today, Twitter has around 230 million “monetizable” daily active users. To measure how Twitter usage differs across counties, we start with a large dataset of almost 500 million geo-located tweets collected between June and November in 2014 and 2015 by Kinder-Kurlanda et al. (2017). We collected profile information for the users in this dataset and assign each user to the county they tweet from most frequently. In total, we can geo-locate around 3.7 million profiles, covering approximately 7% of all US Twitter users as of 2015. These data also allow us to create measures of Twitter usage over time. Our baseline measure of Twitter usage is the natural logarithm of Twitter users in a county in 2015. Figure A.1b shows that there is substantial geographical variation in Twitter usage.

2.3 County-level number of SXSW 2007 attendees

We build on Müller and Schwarz (2023) in exploiting the SXSW Interactive Festival in March 2007 as an exogenous shock to Twitter adoption. Ideally, we would like to measure the number of attendees coming from each county directly from the billing addresses used for SXSW ticket sales. Such data are unfortunately unavailable. To proxy for SXSW attendance, we follow Enikolopov, Makarin, and Petrova (2020) and use social media data for measurement. In particular, we proxy for the number of attendees coming from a particular county based on the number of Twitter followers of the SXSW account who signed up in March 2007. As we will discuss below, Twitter was widely adopted at SXSW 2007, which means our data likely cover a substantial fraction of actual attendees, and an even larger fraction of SXSW attendees that signed up to Twitter due to the festival. For the sake of brevity, we follow Enikolopov, Makarin, and Petrova (2020) and refer to our proxy for attendance as “SXSW attendees” for the remainder of the paper.

The data on the followers of the SXSW account are taken from Müller and Schwarz, 2023, who collected them using the Twitter API. User profiles are assigned to counties based on location strings mentioned in the user profiles. The profiles also allow us to measure when

a particular user joined Twitter. While Twitter does not provide information on when a user started following a specific account, it is reasonable to assume that SXSW followers who signed up at the exact time of the festival in 2007 likely also attended it.

Using social media data to measure SXSW attendance could introduce measurement error. However, such potential measurement error is unlikely to affect our findings for three reasons. First, there is no obvious reason why measurement error in the attendance of SXSW 2007 should be correlated with changes in stock market participation. If such measurement error is random, it would simply bias our results towards zero. Second, we focus on *within*-county changes in stock market participation over time. By definition, this means we abstract from any county-specific selection bias arising from measurement error. Suppose our proxy “overstates” SXSW attendance in county A and “understates” it in county B. Further suppose this bias is systematically correlated with the *level* of stock ownership, but not changes in stock ownership over time. Because we look at changes in stock market participation in our empirical design, such bias would be differenced out and thus no concern for our estimates. Third, as we will discuss below, we use an event study design to link changes in stock ownership to SXSW attendance. As such, changes in the relation between stock ownership and measurement error in who attended SXSW would have to coincide precisely with the time when Twitter’s popularity saw a sudden increase around 2009-10, and there would have to be no such link going back all the way to 1990. It seems unlikely that any potential measurement error in measuring SXSW attendance should give rise to such a distinct and sharp event study pattern.

2.4 Individual-level survey data

To analyze the mechanisms through which social media could spur stock market participation, we use individual-level survey data from the Gallup Social Survey covering the period 2006–2021. Every April, this survey asks around 1,000 respondents aged 18 and older living in all 50 states and the District of Columbia about their personal financial situation and a host of additional information. The dataset has a broad geographical coverage of around 600 counties every year, representing two thirds of the US population.

To construct a measure of stock market participation, we focus on the question “*Do you personally or jointly with a spouse, have any money invested in the stock market right now – either in an individual stock, a stock mutual fund, or in a self-directed 401-K or IRA?*.” We code responses into an indicator variable equal to 1 if an individual answers “Yes”, and 0 if they answer “No.” As discussed in Section 2.1, the share of respondents owning stocks in the

Gallup data is highly correlated with our baseline measure of stock market participation based on IRS data.

The Gallup Social Survey also allows us to infer people’s opinion about different types of investments. In particular, we use the question “*Which of the following do you think is the best long-term investment – Bonds, real estate, savings accounts or CDs, stocks or mutual funds, or gold?*” Similar to the stock ownership question, we code the responses into indicator variables equal to 1 if an individual mentioned a particular investment to be the best, and 0 otherwise. Appendix Table A.1 provides summary statistics for the individual-level survey data from Gallup.

Stock ownership in the Gallup data is similar to that reported in the Survey of Consumer Finance (SCF).⁸ Figure A.4 shows that around 53% of families owned stocks directly or indirectly as of 2019 in the SCF data, a slight upwards trend from 2013. Similarly, the Gallup data in Figure A.4 reports 55% of households in the U.S. own stocks as of 2019.

2.5 Google search interest data

We test the link between social media adoption and interest in meme stocks using data from Google Trends. Da, Engelberg, and Gao (2011), for example, suggest that Google Search Volume Index (SVI) data can be used as a direct measure of retail investor attention. Data on the frequency of different search terms is available back to January 2004 on the level of 210 designated market areas (DMAs), which are largely defined based on metropolitan areas. We thus obtain measures of search interest for the tickers of several “meme stocks” (e.g., “GME” for GameStop Corporation).⁹ We use tickers because, as pointed out by Da, Engelberg, and Gao (2011), using searches for company names could be problematic if investors search for companies for reasons unrelated to investing or if they use different versions of a company’s name. Searches for ticker symbols, instead, are unambiguously motivated by an investment motive.

⁸The SCF data is widely used to study stock market participation (Campbell, 2006; Hong, Kubik, & Stein, 2004), but it does not provide identifiers about the location of the survey participants.

⁹We construct an average SVI based on a list of keywords for “meme” stocks, including “GME” (“GameStop Corp.”), “AMC” (“AMC Entertainment Holdings Inc”), “UPST” (“Upstart Holdings Inc”), “BBBY” (“Bed Bath & Beyond Inc.”), “BBIG” (“Vincovest Ventures Inc”), “BB” (“BlackBerry Ltd.”), “NOK” (“Nokia Corp.”), “SAVA” (“Cassava Sciences, Inc”), “CLOV” (“Clover Health Investments Corp”), “PLTR” (“Palantir Technologies.”), “SPCE” (“Virgin Galactic Holdings”), and “LCID” (“Lucid Group, Inc. ”). We construct this list of meme stocks based on articles published on the articles Investopedia and Yahoo Finance. We also collect data on Google searches for “crypto,” given the importance of social media for “pump and dump” schemes (Li, Shin, & Wang, 2021).

The Google SVI measures how frequently a given search term is entered into Google’s search engine relative to the site’s total search volume over a given period of time. In order to build a panel of SVI data that compares each DMA region and point in time, we follow the existing literature and normalize the data using a two-step process. First, each data point is divided by the total searches in a DMA and time period to measure relative popularity. Second, the resulting numbers are then scaled to range between 0 and 100. See Appendix A.1 in the online appendix for details.

2.6 Additional county-level variables

We obtain control variables to measure county-level differences in socioeconomic factors, demographics, geography, and media usage. Demographic and socioeconomic conditions are taken from the United States Census and the American Community Survey. County-level unemployment rates and industry-level employment shares are from the Bureau of Labor Statistics. The number of bank branches is taken from the FDIC’s Summary of Deposits (SOD). We take county-level data on financial advisors from Charoenwong, Kwan, and Umar (2019). We also construct a measure of knowledge of financial markets based on the National Financial Capability Study (NFCS), a large survey on various aspects of personal finance and financial literacy. In particular, we calculate the share of respondents in a state that say they have very high overall financial knowledge (7 on a scale of 1 to 7) on the state-level. Information on TV viewership patterns was collected from Simply Analytics and the Facebook Social-connectedness Index (SCI) is from the Meta Humanitarian Data Exchange.

We also use several variables to measure county exposure to the housing boom of the 2000s. Data on changes in house prices are based on the House Price Index (HPI) published by the FHFA.¹⁰ Growth in mortgage credit is measured by aggregating loan-level data published as part of the Home Mortgage Disclosure Act (HMDA). County-level debt to income ratios are calculated using data from the Federal Reserve Bank of New York data and IRS, taken from Mian, Rao, and Sufi (2013). Table 1 presents summary statistics for the county-level dataset.

¹⁰We assign changes in the state-level house price index to counties where the FHFA does not publish county-level data, but this does not make any difference for our results.

2.7 #FinTwit and Factiva data

To shed light on the extent of stock market-related topics on Twitter, we collect data using the Twitter Academic API. More specifically, we scraped all tweets that contain the hashtag “#FinTwit.” This allows us to analyse the volume as well as the content of these tweets over time. Additionally, we used the Twitter count API to obtain the number of tweets containing the ticker of any stock listed on the NASDAQ or the New York Stock Exchange (NYSE) for each day in our observation period.

We explore the content and topics discussed on “financial Twitter” by visualizing a “FinTwit” word cloud. Figure A.2, based on textual tweets with the hashtag “#FinTwit” posted between December 2010 and December 2020, shows that “stock”, “market”, “trading”, “buy” and “sell” appear as frequent words. The prevalence of words such as “learn” and “community” suggest a potential role of social media in reducing the cost of acquiring information about stock markets.

To study differences between social media and traditional media sources, we calculate the number of times a stock is mentioned in the Wall Street Journal or Dow Jones Institutional News relative to Twitter between 2006 and 2020. The traditional news counts are taken from the Factiva database, where we focus on the 120 most frequently mentioned US stocks on Twitter. To study the correlates of over-representation on social media, we also use data on stock returns from the Yahoo Finance API and the retail ownership share inferred from institutional investors’ holding share available in 13F filings.

3 Empirical Strategy

To estimate the causal effect of social media usage on stock market participation, we use the SXSW Festival in 2007 as an exogenous shock to the adoption of Twitter across US counties in an IV strategy. Section 3.1 provides some historical background on SXSW and Twitter adoption. Section 3.2 discusses the first stage results. Section 3.3 describes our IV model and the identifying assumptions.

3.1 South by Southwest and Twitter Adoption

Our identification strategy exploits plausibly exogenous variation in Twitter adoption across counties based on the platform’s popularity at the South by Southwest Festival (SXSW) in March 2007. First held in 1987, SXSW is an annual event in Austin, Texas, combining media,

music, and film festivals and conferences. One part of the event, SXSW Interactive, focuses on new technologies.

Originally launched in March 2006, Twitter had few users before SXSW 2007. At the event, Twitter put up large displays in the hallways of SXSW Interactive that showed tweets sent by the participants. The company also provided a festival-specific feature that allowed attendees to create a Twitter account by sending a simple text message.

These incentives motivated many of the around 8,000 SXSW attendees to sign up, which massively increased Twitter activity. The daily volume of tweets tripled from 20,000 to 60,000 during SXSW during the festival (Gawker, 2007), as bloggers and other attendees broadcasted the platform to the outside world, urging their friends, families, and colleagues to sign up. Today, SXSW is widely considered the “tipping point” in Twitter’s popularity that put the platform on a rapid growth trajectory.

3.2 First stage results

Müller and Schwarz (2023) and Fujiwara, Müller, and Schwarz (2021) show that SXSW had large effects on Twitter adoption in the United States. Immediately after the festival, the home counties of SXSW attendees signed up to Twitter at much higher rates than other counties. As a result, around 60% of Twitter’s early adopters likely joined during SXSW 2007 or were directly connected to someone who did.

We summarize this evidence here by plotting event study estimates relating cumulative Twitter users per capita x_{it} in county i in half-year t to SXSW 2007 attendance z_i interacted with half-year dummies:

$$x_{it} = \sum_{w \neq 2006h2} \gamma_t z_i \cdot \mathbb{1}\{T_t = t\} + \theta_i + \theta_t + \nu_{it}, \quad (1)$$

where z_i is defined as counts in natural logarithm (with one added inside). The estimates for γ_t measure the change in Twitter users per capita relative to the period before SXSW 2007, depending on the number of festival attendees in a county. Standard errors are clustered by state, and we plot 95% confidence intervals.

Figure 1 plots the point estimates of γ_t . These estimates suggest no pre-existing trends before SXSW 2007. After the festival, the adoption effect of SXSW on Twitter usage shows an S-shaped pattern commonly found for the adoption of new technologies. This S-curved adoption effect moves hand in hand with the overall adoption of Twitter, proxied here by search interest for the word “Twitter” on Google.

This evidence for the effect of SXSW 2007 on Twitter adoption motivates the following first stage regression model:

$$x_i = \theta + \lambda z_i + \mathbf{X}_i' \phi + v_i \quad (2)$$

where x_i is the number of Twitter users in county i (in natural logarithm). z_i is our instrument: the number of SXSW 2007 attendees in natural logarithm (with one added inside). \mathbf{X}_i' is a vector of control variables, which we describe in more detail in Section 3.3.

The results are reported in Appendix Table A.2. Consistent with previous evidence in Müller and Schwarz (2023) and Fujiwara, Müller, and Schwarz (2021), we find that SXSW 2007 had a permanent effect on the intensity of Twitter adoption across counties. The estimate of 0.256 in column (5) suggests that a 10% increase in SXSW attendance is associated with a 2.6% increase in Twitter usage. The next section outlines how we use this variation to identify the causal effect of social media on stock market participation.

3.3 Empirical model

To estimate the causal effect of Twitter adoption, we use the following first-difference IV model:

$$\Delta y_i = \alpha + \beta \hat{x}_i + \mathbf{X}_i' \omega + \varepsilon_i, \quad (3)$$

where Δy_i is the difference in stock market participation between the post-event period (in our baseline, 2015) and the pre-event period (the year before Twitter’s launch, 2005) for each county i . To understand dynamic patterns over time, we vary the post-event period to refer to the years between 1990 and 2019, which gives us year-specific estimates for β akin to an event-study design. \hat{x}_i is the number of Twitter users in county i (measured as of 2015, in natural logarithm) predicted by our instrument, the number of SXSW 2007 attendees in natural logarithm (with one added inside). \mathbf{X}_i' is a vector of control variables, which always includes population decile fixed effects to flexibly control for population size and Census division fixed effects. We also report regressions with more extensive control sets using geographic controls (population density), socioeconomic controls (ethnic composition, educational attainment, age shares, inequality, median household income), controls for other media usage (proxied using the prime-time TV viewership to population ratio and the Facebook Social Connectedness Index), and controls for the 2000s housing boom and bust (changes in house prices, debt-to-

income ratios, and growth in mortgage debt). We weight observations by county population and cluster standard errors by state.

In this specification, β measures changes in the outcome y_i relative to 2005, depending on the number of SXSW 2007 attendees in a county. To interpret the IV estimate β in Equation (3) as the causal effect of Twitter usage requires that, conditional on \mathbf{X}'_i , the instrument z_i in Equation (2) is excludable. In other words, the exclusion restriction requires that the number of SXSW 2007 attendees should only affect changes in stock market participation through its effect on Twitter adoption.¹¹ Because SXSW is mainly a culture, media, and tech event—and financial firms played no role in SXSW 2007—we believe the assumption of excludability is plausible.

By differencing the dependent variable over time, we implicitly control for any time-invariant county-level characteristics that drive stock market participation. As such, the identifying assumption underlying this approach is *not* that SXSW attendance in 2007 was random. Instead, the assumption is that county-level stock market participation would have followed similar trends in the absence of the SXSW adoption shock. Below, we show that there were no pre-existing trends in stock market participation before 2007 depending on the number of SXSW attendees in a county.

A remaining concern could be that selection into SXSW attendance picks up exposure to time-varying aggregate shocks that only affect outcomes after 2007. An obvious candidate would be exposure to the 2000s housing boom and bust. In Section 4.5, we provide extensive evidence that our results cannot be explained by differences in county exposure to the Great Recession and the boom preceding it.

To further address concerns about a selection of particular counties driving our results, we include several control variables in Equation (3): (1) the number of followers of the SXSW account before SXSW 2007, (2) search interest for SXSW on Google before SXSW 2007, and (3) the linear distance from Austin, Texas. Conditional on these controls, the identifying variation comes entirely from the *difference* in SXSW 2007 attendance relative to what one would expect based on pre-existing interest in Twitter and SXSW (and other covariates). To gain intuition, suppose that SXSW 2007 attendance was correlated with an omitted variable, such as a county's overall affinity to new technologies. Any such an omitted variable should also be correlated with interest in Twitter and SXSW *before* 2007, and this pre-existing interest

¹¹The other two assumptions of the IV model are monotonicity and instrument relevance. Figure 2 shows that Twitter usage increases monotonically with the number of SXSW attendees in a county. Table A.2 shows that a regression of Twitter usage on the number of SXSW 2007 attendees is highly statistically significant. In Section 4.2, we show that the corresponding F -statistic is usually in the range of 50; weak instrument bias is thus not a concern in our setting.

should thus also predict changes in stock market participation. As we will show below, the number of Twitter followers of the SXSU account *before* the 2007 festival is uncorrelated with changes in stock market participation. We interpret this as evidence that omitted factors are unlikely to explain the link between SXSU, Twitter adoption, and stock ownership.

4 Results

This section presents the main results on the effect of social media usage on stock market participation. Section 4.1 presents some simple correlations. Section 4.2 describes the baseline regression results. Section 4.3 shows dynamic event study estimates. Section 4.4 differentiates between the intensive and extensive margin of stock ownership. Section 4.5 provides robustness checks and Section 4.6 looks at heterogeneous effects.

4.1 Introductory correlations

Figure 2 shows a binned scatter plot of dividends per capita (our main measure of stock market participation) for the year 2015 as a function of the number of Twitter users in a county. We create 30 bins with approximately 100 counties in each and control for a county's population. The binscatter shows that social media usage and stock ownership are highly correlated. The magnitude of this correlation is substantial. The linear regression underlying the linear fit line in the binscatter suggests that a 10% higher adoption of Twitter is associated with a 2.7% higher stock market participation.

Of course, it is not possible to draw causal conclusions from Figure 2. Counties differ along many observable and unobservable dimensions, and it is likely that some of the factors that cause people to adopt social media also make them more likely to own stocks. An obvious example could be differences in wealth. If Twitter is more popular with people living in wealthier areas, and wealthier individuals are more likely to invest in the stock market, social media may have no causal effect. In the next section, we present the results based on our IV strategy which allows us to overcome this identification challenge.

4.2 IV estimation

Table 2 presents the IV estimates from jointly estimating equations 2 and 3. The dependent variable is the change in log dividends per capita between 2005 and 2015. The reduced-form and IV coefficients are statistically significant at the 1%-level. The IV coefficient of 0.177

in the most saturated model in column (5) implies that a 10% increase in Twitter usage is associated with a 1.8% higher growth in dividends per capita. This magnitude is somewhat smaller than the estimated effect of broadband internet on stock market participation studied by Hvide et al. (2022).

The F -statistics for the first-stage relation between SXSW attendance and Twitter usage range between 30 and 80. Bias as a result of a weak instrument is thus an unlikely concern for our results.

Table 3 shows that the results are similar when using alternative measures of stock market participation. In columns (1) and (2), we find that social media adoption also matters for changes in dividends per tax filing and the share of dividends in total income. Columns (3)-(5) look at rates of participation as of 2015. These estimates imply that a 10% higher Twitter adoption increases the level of dividends per capita or per tax filing by around 2.5%, and the share of income coming from dividends by around 2.2%.

An important question is whether social media only increases ownership of stocks or also the quality of financial decision-making. Hvide et al. (2022), for example, show that the rollout of broadband internet in Norway is associated with improved portfolio performance of retail investors. Columns (6) and (7) provide some suggestive evidence that social media adoption is associated with higher wealth gains, not just higher participation rates. In column (6), we look at the change in total stock market wealth per capita between 2005 and 2015, taken from Chodorow-Reich, Nenov, and Simsek (2021). The point estimate of 0.072 is statistically significant at the 1% level and suggests a 0.8% increase in stock market wealth for every 10% increase in Twitter adoption. Column (7) proxies for the return equity investors achieve by looking at the ratio of capital gains (a measure of changes in wealth) relative to the previous year's level of stock market wealth.¹² The coefficient of 0.005 suggests that 10% higher exogenous Twitter adoption is associated with a 1.7% ($0.005 * 10\%$) increase relative to the mean of capital gain, 0.03) increase in returns on initial wealth. While this set of tests can only be interpreted as suggestive, they provide some indication that social media may improve the quality of financial decision-making, in addition to its effect on stock ownership rates. We will investigate this possibility further in Section 5.

¹²The IRS data on capital gains has several limitations as a measure of returns. First, it includes gains from selling any asset, not just stocks. Second, these data only become available in 2010, so we cannot look at their change relative to the pre-period. Third, we lack administrative data on stock market wealth we could use in the denominator, so we rely on the capitalized dividend method from Chodorow-Reich, Nenov, and Simsek (2021).

4.3 Dynamic estimates

Next, we investigate the timing of the link between social media adoption and stock ownership. Figure 3 plots the results from estimating variants of Equation (3) where we vary the horizon of the dependent variable. For each year since the start of the IRS data, we calculate the change in stock market participation relative to 2005, akin to an event study specification. For example, 2015 marks the specification reported in column (6) of Table 2.

We find that counties with many SXSW 2007 attendees followed similar trends in stock market participation to other counties between 1990 and 2010. These results support the parallel trends assumption, suggesting that our instrument is not picking up unobserved factors correlated with SXSW attendance. If selection into attending SXSW in 2007 was driving our results, these counties should also show differences in stock market participation *before* the 2007 event. We find no evidence that this is the case, even for the period of the internet bubble and ensuing bust. As such, our instrument does not seem to be picking up interest in new technologies more generally, but instead the specific exposure to social media adoption.

After 2010, we observe a rapid increase in stock market participation in counties with many SXSW attendees. This timing aligns closely with the spike in Twitter accounts in 2009-10 and the effect of SXSW on Twitter adoption we documented in Figure 1. We interpret these patterns as evidence that Twitter adoption spurred by SXSW 2007 caused an increase in stock market participation in the United States.

4.4 Intensive vs Extensive Margin

We next investigate if Twitter increases investments by people who already own stocks (intensive margin) or convinces more people to purchase stocks in the first place (extensive margin). To see how our measure of stock ownership can be decomposed into the extensive and intensive margins, consider the following identity:

$$\frac{\text{Dividends paid}}{\# \text{ of tax returns}} = \underbrace{\frac{\# \text{ of returns with dividends}}{\# \text{ of tax returns}}}_{\text{extensive margin}} \times \underbrace{\frac{\text{Dividends paid}}{\# \text{ returns with dividends}}}_{\text{intensive margin}}$$

Table 4 reports the results from three regressions. Column 1 uses dividends per tax return as the dependent variable, which combines the extensive and intensive margin of stock market

participation. Columns 2 and 3 report the results on the extensive and intensive margin, respectively.¹³

We find that social media increases stock market participation at both the extensive and intensive margin, but the magnitudes differ substantially. The coefficient of 0.09 in column 2 suggests that a 10% higher Twitter usage increases the number of tax filers reporting dividend income by around 0.9%. Column 3 shows a larger effect on the intensive margin of 1.5% for the same increase in Twitter usage. Put differently, we estimate that two thirds of the effect of social media on stock market participation in column 1 is driven by people who already own stocks, and only one third by people buying stocks that did not before.

4.5 Robustness and alternative explanations

In this section, we conduct a series of robustness tests and address potential alternative explanations.

As a first robustness check, we consider alternative specifications in Table A.3. In column (1), we find similar magnitudes to our baseline estimates when we do not weigh by population. In column (2), we restrict the sample to counties where we have either SXSW attendees in March 2007 or SXSW followers before 2007. Column (3) addresses concerns about outliers in our data by winsorizing the dividends per capita measure. In column (4), we apply the inverse hyperbolic sine instead of the logarithmic transformation to all dependent and independent variables.¹⁴ None of these changes make a material difference to our estimates.

A potential confounding factor for our results is the housing boom of the 2000s and the 2007-08 financial crisis. The concern is that areas with more SXSW attendees may differ in their exposure to the housing boom and bust.

Two sets of results make it unlikely that our findings are driven by this alternative explanation. First, the event study patterns in Figure 3 are entirely inconsistent with the idea that we are picking up county differences in business cycle exposure. SXSW-induced differences in Twitter adoption across counties were uncorrelated with trends in stock market participation before around 2010, going back all the way to 1990. This time period spans the 1990-91 recession, the dot-com bubble of the 1990s and 2001 recession, the 2000s housing boom, and the 2007-08 financial crisis. Put differently, the major macroeconomic

¹³Note that the variable on the number of reports containing dividends is only available since 2010. As such, we restrict our analysis to the “level” of stock market participation in 2015 rather than the change relative to 2005.

¹⁴In contrast to the log transformation, the inverse hyperbolic sine is defined for zero values.

events during the 20-year period before Twitter reached mass adoption were not associated with differences in stock market adoption in counties with higher SXSW attendance.

Second, controlling for exposure to the housing boom and bust has no effect on our estimates. Table 5 shows that our coefficient of interest remains virtually unchanged when we control for proxies of a county's exposure to the housing boom and subsequent recession. In particular, we control for the following variables: (1) the change in house prices index during the boom, 2002-2006 (2) the change in house prices index during the bust, 2006-2009 (3) the expansion in mortgage credit, (4) the household debt-to-income ratio as of 2006, and (5) the change in household debt-to-income ratios during the boom 2002-2006. We first add these metrics to our baseline specification one by one, and then control for them jointly. These variables have limited predictive ability for changes in stock market participation between 2005 and 2015.

4.6 Heterogeneous effects

The results in the previous sections suggest that social media can affect stock market participation. In this section, we explore heterogeneous effects within and across counties. This exercise provides evidence on which groups are more likely to react in their investment behavior to a shock to social media adoption, which matters from a policy perspective.

As a starting point, we investigate heterogeneity by income, a key predictor of stock ownership. We present the results of estimating the effect of social media on changes in dividends per capita across the six income buckets that are available in the IRS data. Table 6 shows that the effect of social media adoption is concentrated among people with incomes of \$100,000 and above, who are already disproportionately more likely to hold stocks. The coefficient 0.134 in column (6) implies that a 10% increase in social media usage is associated with an 1.3% higher stock market participation among high-income earners. These results are consistent with the finding in section 4.4 that the majority of the social media effect is driven by the intensive margin of existing investors investing more, rather than new investors entering the market.

Next, we investigate heterogeneity across counties. We implement these tests by interacting the instrument, SXSW attendees, with county-level variables in a reduced form specification. Table 7 plots the estimates. Column (1) shows that the effect of social media usage on stock market participation is larger in areas with higher inequality. Consistent with our results in Table 6, this suggests that social media interacts with pre-existing differences in income inequality when affecting stock ownership. Similarly, column (2) shows an interaction

with a higher initial poverty rate. Column (3) shows a positive interaction with city size, as measured by population, and column (4) shows a negative interaction with the share of the population identifying as white. This could indicate that Twitter might matter more for groups who are traditionally underrepresented when it comes to stock market investments.

5 Mechanisms

The existing literature is divided on whether social media makes market participants more or less informed. On one hand, there is evidence that social media can provide useful information about, among others, firm earnings (Bartov, Faurel, & Mohanram, 2018) and the likelihood of merger withdrawals (Cookson, Niessner, & Schiller, 2022), and institutional investors routinely use social media information when making investment decisions (Coalition Greenwich, 2019). On the other hand, social media has been tied to behavioral biases (Heimer, 2016), information silos (Cookson, Engelberg, & Mullins, 2022), and trading frenzies (Pedersen, 2022; Tengulov et al., 2021). In this section, we study both of these mechanisms in the context of the rollout of Twitter across U.S. counties, which allows us to speak to the real effects on investor portfolios.

5.1 Information provision, financial advice, and investor beliefs

A first potential channel through which social media could affect stock market investments is by providing information. The idea is that, by providing curated and targeted content for free, social media platforms could considerably reduce the fixed costs of getting access to financial advice.

As an initial set of tests, we run reduced-form regressions similar to those in Table 7 where we interact our instrument with several proxies for the availability of information about stock markets before Twitter’s launch. If Twitter provides useful information to investors, we would expect that it has a larger effect in counties where such information was previously harder to come by. To aid interpretability, we standardize the instrument and all proxies for access to information to have a mean of zero and standard deviation of one.

Table 8 plots the results. Column (1) shows that the interaction of SXSW attendance with the number of financial advisors per capita of -0.036 is negative and statistically significant at the 5% level. The estimates imply that the effect of social media on stock ownership is 45% larger in a county with a one standard deviation lower number of financial advisors before. This finding is consistent with Twitter as a partial substitute for offline information via financial advisors.

Columns (2)-(4) use alternative proxies for the pre-existing information environment. Column (2) shows a negative interaction with the number of bank branches per capita. Because banks also serve as a common source of information about stock market investments, this corroborates our finding on financial advisors. Column (3) uses survey data from the National Financial Capability Study on the share of individuals who believe they have considerable knowledge about financial markets as a proxy. Column (4) uses the share of people with a bachelor's degree or higher. Both proxies also point in the direction of social media as providing information to previously underserved population.

To more directly test the idea that social media could partially substitute for other sources of information about the stock market, we look at the effect of Twitter adoption on financial advisors. In particular, we use data from Charoenwong, Kwan, and Umar (2019) and rerun our baseline regression model in Equation (3), where the dependent variable is now the log-difference in financial advisors in a county. Figure 4 shows event study estimates where the excluded period is 2007. Twitter adoption was not associated with differences in the number of financial advisors before the pivotal SXSU event. From 2010 onwards, however, we find an increasing and statistically significant negative effect, consistent with Twitter adoption causing a displacement of offline financial advice. Table A.4 plot regression estimates, suggesting a decline of around 1% in the number of financial advisors for every 10% increase in Twitter usage. These findings suggest that social media can provide access to information, which leads to a decrease in the demand for offline financial advice or the profitability for firms to provide it.

Do higher rates of social media adoption indeed make potential investors better informed? To shed light on this question, we turn to individual-level survey data from Gallup. These data contain two key questions that are relevant for our analysis: (i) a question on whether an individual owns stocks directly or through a fund or retirement plan, and (ii) a question on which types of assets individuals think are the “best long-term investment.”

Equipped with these data, we estimate modified versions of equations 2-3, which replace the dependent variable with dummy variables for whether an individual owns stock or whether they believe an asset is the best investment choice. We estimate these models using a linear probability model. In addition to our county-level control variables, we also control for individual-level demographic information such as age, gender, income group, education, race, and marital status. Table 9 presents the resulting estimates.

Column (1) shows the results for stock ownership. The coefficient for Twitter adoption is 0.042 and significant at the 5% level. A 10% increase in Twitter usage is associated with a 0.5% increase in the probability of an individual owning a stock. This finding aligns closely

with our main results based on the county-level measure of stock market participation. In columns (2)-(6), we investigate people's evaluation of different asset classes. Exposure to social media increases the share of people who regard stocks as the best long-term investment. The coefficient in column (2) suggests that a 10% increase in social media usage is associated with a 0.5% increase in the share of people who regard stocks as the best investment. For gold, real estate, and other investments, we find negative coefficients, which are statistically significant for gold and real estate.

To put these results in perspective, it is important to note that stocks are trusted considerably less than would be warranted by their expected risk-adjusted returns vis-à-vis other asset classes. Although stocks have considerably higher expected returns and Sharpe ratios than gold, they do not enjoy a much better reputation: around 24% of people believe stocks are the best investment, while 18% believe gold is. As such, our interpretation of the evidence in Table 9 is that social media can potentially facilitate information acquisition about the return profile of different asset classes.

5.2 Echo chambers and trading frenzies

Social media differs from the traditional news media with respect to the production and dissemination of information. While traditional media rely on strongly moderated editorial oversight, social media facilitate the peer-to-peer transmission of information with limited fact-checking or responsibility for the correctness of the information (Chawla et al., 2021; Jiao, Veiga, & Walther, 2020). Taking Twitter as an example, users acquire information from “tweets” posted by accounts they follow, and can subsequently propagate this information via retweeting it. Such information diffusion patterns could create “echo chambers”, where investors self-select into information that resonates with their own view and interpret the repetitive information as genuinely new information. This dynamic could boost the confidence of behavioral traders and give rise to persistent disagreement (Cookson, Engelberg, & Mullins, 2022; DeMarzo, Vayanos, & Zwiebel, 2003). Consequently, investors may overreact to information found on social media, leading to elevated trading volumes and increased return volatility (Jiao, Veiga, & Walther, 2020). This phenomenon could be particularly pronounced among retail investors, who tend to be relatively inexperienced and more subject to behavioral biases (e.g., Barber & Odean, 2000, 2001; Coval & Shumway, 2005; Odean, 1998).

We test the hypothesis that an exogenous adoption of social media usage is associated with higher investment in volatile, lottery-type assets by focusing on “meme stocks.” These stocks are arguably an example of investments where trading volume and price movements are

often driven by sentiment and heated discussions on social media rather than by fundamental information. Meme stocks such as GameStop and AMC gained popularity in early 2021 because of an investment craze initially started by trading communities on social media platforms like Reddit, Twitter, and Facebook. At the time, these stocks were traded mostly based on their popularity among retail traders rather than their underlying fundamentals, which may exacerbate deviations from the stocks' true value and bring about periods of high volatility (Tengulov et al., 2021). In January 2021, a short squeeze of GameStop investors targeting the short selling of certain hedge funds was triggered by users posting on the subreddit r/WallStreetBets, causing the price of GameStop to spike within a short time period (The Guardian, 2021). Another widely-discussed topic popular among these communities is cryptocurrencies, with considerable investor attention fueled by discussion and interaction on social media (Li, Shin, & Wang, 2021).

Figure 5 plots event study estimates where we relate SXSW-induced Twitter adoption to Google searches for "GME" and "AMC," the tickers of the two most prominent meme stocks around the onset of the short squeeze episode in early 2021. These figures show a significant increase in search interest in counties with higher Twitter usage starting from January 2021 onward, when the GME short squeeze gained widespread attention on social media and the news media. Before this shock to the salience of meme stocks, we find no statistically significant difference depending on a county's Twitter adoption. Table 10 shows the results for regressions of the type in Equations 2-3 on the DMA-level, where the dependent variable is the 2021 average re-normalized search volume index (*SVI*) for a list of meme stocks, including GME and AMC, as well as the term "crypto." The IV estimate of 0.335 in column (1) suggests that a 10% increase in Twitter usage is associated with a 3.3% higher interest in meme stocks.

To shed more light on the idea that higher exposure to social media may be associated with higher retail ownership and increased market volatility through an "echo chamber" effect, we analyze the characteristics of stocks that are especially frequently discussed on Twitter. In particular, we collect data on how often stocks are mentioned on Twitter relative to financial news papers. The difference in the mentions of stocks on Twitter relative to financial newspapers gives us an idea of how "overrepresented" stocks are on social media, and we relate this simple measure of excess mentions to stock characteristics.

Figure 6 plots a stock's average return volatility and retail ownership share against excess Twitter mentions relative to newspapers. Stocks that are more likely to be mentioned on social media are considerably more volatile and have a higher share of retail investors. Together with our findings above, this suggests that social media may particularly attract retail

investors who lack experience and tend to be more subject to behavioral biases.

6 Conclusion

Social media has become an increasingly common source of information for retail and institutional investors. However, our understanding of whether and how it affects households' personal finance decisions, including portfolio choice, is limited. This paper uses exogenous variation in Twitter adoption across counties in the United States to show that social media increases stock market participation, particularly for people with higher incomes who are likely to own stocks in the first place.

We document that Twitter-fuelled stock market investments are a double-edged sword. On one hand, it increases stock ownership in areas that traditionally had less access to financial information. It may also shift people's beliefs about the stock market in a way that is more aligned with financial theory: after a shock to social media adoption, retail investors evaluate stocks more positively relative to gold or real estate. On the other hand, we also find that social media increases the appetite to invest in risky, volatile assets such as meme stocks. While we find suggestive evidence of an increase in returns on initial wealth, social media may fuel investments in particularly volatile asset classes, which could also have implications for financial markets as a whole.

It is important to highlight that the welfare implications of our results on social media are not clear-cut. The literature on prize-linked savings accounts, for example, finds that gambling incentives can be a powerful instrument to get people to save more (see e.g. Cole, Iverson, & Tufano, 2022; Cookson, 2018). Even if they lose some money initially because of inexperienced trading in volatile stocks, social media could induce people that otherwise would not have had sufficient information to earn the equity premium, which may outweigh any potential "gambling losses" in the long-run.

Another important question is how our results should be interpreted given that, over the time period we study, stock market participation in the United States was flat or even slightly decreased.¹⁵ One possible interpretation is that stock ownership would have decreased even more in the absence of social media.

Social media is likely here to stay. As such, a better understanding of the channels through which it can affect financial decision-making is important. While our paper makes

¹⁵We would like to thank Andreas Fuster for raising this point.

a first step in this direction by providing evidence of its effect on participation in the stock market, we hope that future work will provide additional insights from other settings.

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Table 1: Descriptive Statistics

	Mean	Std.	Min.	25%	50%	75%	Max.	N
Dividend, Income and Twitter variables								
Δ Log(Dividend)	0.34	0.38	-2.15	0.16	0.35	0.54	3.85	3104
Δ Log (Dividend(%))	-0.02	0.33	-2.17	-0.14	0.02	0.16	2.89	3104
Δ Log (Dividend p.c.)	0.30	0.35	-2.06	0.15	0.32	0.48	3.58	3104
Δ Log (Dividend per tax filers)	0.16	0.33	-2.26	0.03	0.18	0.33	3.42	3104
Δ Log (Stock wealth p.c.)	0.26	0.30	-3.06	0.17	0.26	0.36	10.55	3083
Capital wealth	0.03	0.03	0.00	0.02	0.02	0.03	1.35	3106
Log(Twitter users)	5.29	1.76	0.00	4.06	5.13	6.33	12.35	3108
Log(SXSW followers, pre)	0.02	0.18	0.00	0.00	0.00	0.00	3.61	3108
Log(SXSW 2007 attendees)	0.06	0.32	0.00	0.00	0.00	0.00	4.98	3108
Log(Google search for SXSW, pre)	0.93	0.88	0.00	0.00	1.10	1.39	4.62	3108
Demographic controls								
% aged 20-24	0.06	0.02	0.01	0.05	0.06	0.07	0.27	3108
% aged 25-29	0.06	0.01	0.03	0.05	0.06	0.07	0.15	3108
% aged 30-34	0.06	0.01	0.03	0.05	0.06	0.06	0.12	3108
% aged 35-39	0.06	0.01	0.03	0.05	0.06	0.06	0.11	3108
% aged 40-44	0.06	0.01	0.02	0.05	0.06	0.06	0.10	3108
% aged 45-49	0.06	0.01	0.02	0.06	0.06	0.07	0.09	3108
% aged 50+	0.39	0.07	0.11	0.35	0.39	0.43	0.75	3108
Geographical controls								
Population density	261.27	1733.47	0.10	17.60	45.60	114.85	69468.40	3108
Distance from Austin, TX (in miles)	1450.64	612.61	5.04	1055.25	1464.66	1863.85	3098.88	3108
Race and religion controls								
% white	0.77	0.20	0.03	0.65	0.84	0.93	0.98	3108
% black	0.09	0.14	0.00	0.01	0.02	0.10	0.85	3108
% native American	0.02	0.06	0.00	0.00	0.00	0.01	0.90	3108
% Asian	0.01	0.02	0.00	0.00	0.01	0.01	0.37	3108
% Hispanic	0.09	0.14	0.01	0.02	0.04	0.09	0.96	3108
Socioeconomic controls								
Gini index	0.44	0.03	0.33	0.42	0.44	0.46	0.65	3108
Log(Median household income)	10.72	0.24	9.87	10.56	10.71	10.86	11.72	3107
% below poverty level	16.74	6.58	1.40	12.10	16.00	20.30	53.30	3108
% adults with high school degree	34.77	7.07	7.50	30.30	35.20	39.60	54.80	3108
% adults with graduate degree	7.05	4.12	0.00	4.40	5.80	8.30	44.40	3108
Media Controls								
% watching prime time TV	0.43	0.01	0.40	0.43	0.43	0.44	0.47	3107
Log(Facebook SCI)	9.81	1.01	6.95	9.16	9.82	10.49	13.24	3107
Recession Controls								
HPI Change 2002-2006	29.57	22.10	-8.23	16.17	22.09	34.02	134.94	3108
HPI Change 2006-2009	-1.22	18.54	-154.83	-3.17	2.94	7.77	50.73	3108
Mortgage Amount Change 2002-2006	0.73	0.77	-0.33	0.21	0.56	1.03	4.17	3098
Number of Mortgage Change 2002-2006	0.42	0.50	-0.36	0.08	0.33	0.65	2.46	3098
Debt to income from NY Fed 2006	1.57	0.58	0.58	1.16	1.44	1.84	4.93	2209
Debt to income Change 2002-2006	0.30	0.19	-0.36	0.18	0.28	0.40	1.61	2209
Pre-event information environment								
Financial advisors p.c.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1946
Bank branches p.c.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3088
High financial knowledge	0.10	0.02	0.06	0.08	0.10	0.11	0.15	2919

Table 2: Social Media and Changes in Stock Market Participation

<i>Dependent variable:</i>	$\Delta_{'05 \rightarrow '15} \text{Log}(\text{Dividends p.c.})$				
	(1)	(2)	(3)	(4)	(5)
Log(Twitter users)	0.201*** (0.046)	0.208*** (0.047)	0.198*** (0.045)	0.160*** (0.042)	0.177*** (0.051)
Log(SXSW followers, pre)	-0.027 (0.044)	-0.027 (0.044)	-0.033 (0.042)	-0.028 (0.039)	-0.036 (0.044)
Population deciles	Yes	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes	Yes
Selection controls		Yes	Yes	Yes	Yes
Geographical controls			Yes	Yes	Yes
Socioeconomic controls				Yes	Yes
Media Controls					Yes
Observations	3,104	3,104	3,104	3,104	3,104
Mean of DV	0.548	0.548	0.548	0.548	0.548
Robust F-stat	50.28	47.05	42.48	91.66	52.13

Notes: This table presents first difference regressions as in equation 3, where the dependent variable is the difference in $\text{Log}(\text{Dividends per capita})$ between 2005 and 2015. $\text{Log}(\text{Twitter usage})$ is the number of unique Twitter users in a county in natural logarithm, instrumented with $\text{Log}(\text{SXSW 2007 attendees})$ (the number of SXSW attendees in 2007 in natural logarithm with one added inside). $\text{SXSW followers, Pre}$ is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles and Census division fixed effects. Selection controls include the linear distance from the SXSW festival location (Austin, Texas) and Google search intensity for the SXSW festival before 2007. Geographical controls is population density. Socioeconomic controls include age buckets (the share of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and those over 50) and ethnic composition (the share of people identifying as white, African American, Native American or Pacific Islander, Asian or Hispanic), the Gini coefficient, log median household income, the share of high school graduates, and the share of people with a graduate degree. Media controls include the prime time TV viewership to population ratio and the Facebook Social Connectedness Index (SCI). Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3: Alternative Measures of Stock Market Participation and Returns on Wealth

<i>Dependent variable:</i>	$\Delta_{'05 \rightarrow '15} \text{Log}(\text{Participation})$		Log(Participation in 2015)		Returns on wealth		
	$\frac{\text{Dividends}}{\text{Tax filers}}$ (1)	$\frac{\text{Dividends}}{\text{Income}}$ (2)	$\frac{\text{Dividends}}{\text{Population}}$ (3)	$\frac{\text{Dividends}}{\text{Tax filers}}$ (4)	$\frac{\text{Dividends}}{\text{Income}}$ (5)	$\Delta \text{Log}(\frac{\text{St. wealth}}{\text{Pop.}})$ (6)	$\frac{\text{Capital gains}}{\text{Stock wealth}}$ (7)
Log(Twitter users)	0.169*** (0.050)	0.136*** (0.044)	0.251** (0.097)	0.241** (0.092)	0.216*** (0.079)	0.072** (0.027)	0.005*** (0.001)
Log(SXSW followers, pre)	-0.030 (0.043)	-0.029 (0.035)	-0.037 (0.070)	-0.043 (0.068)	-0.043 (0.053)	-0.024 (0.024)	-0.000 (0.001)
Population deciles	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Media Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,104	3,104	3,104	3,104	3,104	3,083	3,105
Mean of DV	0.377	0.192	-0.593	0.178	-3.971	0.274	0.030
Robust F-stat	52.13	52.13	52.13	52.13	52.13	52.41	52.37

Notes: This table presents regressions as in equation 3. The dependent variables are different measures of either changes in stock market participation between 2005 and 2015 in columns 1-2 or the level of stock market participation as of 2015 in columns 3-5. In column 6, we examine changes in stock market wealth per capita between 2005 and 2015 using data from Chodorow-Reich, Nenov, and Simsek (2021). In column 7, the dependent variable is the ratio of capital gains in 2015 relative to stock market wealth in 2014, a proxy for portfolio returns. *Log(Twitter usage)* is the number of unique Twitter users in a county in natural logarithm, instrumented with *Log(SXSW 2007 attendees)* (the number of SXSW attendees in 2007 in natural logarithm with one added inside). *SXSW followers*, *Pre* is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the full set of county-level controls in Table 2. Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Intensive vs. Extensive Margin of Stock Market Participation

<i>Dependent variable:</i>	Log(Participation in 2015)		
	$\frac{Dividend}{Tax\ filer}$ (1)	$\frac{No. Divd}{Tax\ filer}$ (2)	$\frac{Dividend}{No. Divd}$ (3)
Log(Twitter users)	0.241** (0.092)	0.090*** (0.025)	0.151** (0.074)
Log(SXSW followers, pre)	-0.043 (0.068)	-0.034* (0.018)	-0.009 (0.059)
Population deciles	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes
Selection controls	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes
Media Controls	Yes	Yes	Yes
Observations	3,104	3,104	3,104
Mean of DV	0.178	-1.781	1.959
Robust F-stat	52.13	52.13	52.13

Notes: This table presents county-level regressions as in equation 3, where we differentiate between the effect of social media on the extensive and intensive margin of stock market participation. The dependent variable is a measure of stock market participation as of 2015. Column (1) shows estimates where the dependent variable is dividends per tax filer (in logarithm), which combines the extensive and intensive margins of stock ownership. Column (2) plots estimates for the extensive margin, the number of tax filings with reporting any dividend income relative to all tax filings. Column (3) focuses on the intensive margin, total dividend income per tax filing declaring any dividend income. $Log(Twitter\ usage)$ is the number of unique Twitter users in a county in natural logarithm, instrumented with $Log(SXSW\ 2007\ attendees)$ (the number of SXSW attendees in 2007 in natural logarithm with one added inside). $SXSW\ followers, Pre$ is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the full set of county-level controls in Table 2. Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Robustness Tests – 2000s Housing Boom and Bust

<i>Dependent variable:</i>	$\Delta_{'05 \rightarrow '15} \text{Log}(\text{Dividends p.c.})$				
	(1)	(2)	(3)	(4)	(5)
Log(Twitter users)	0.177*** (0.051)	0.177*** (0.049)	0.181*** (0.052)	0.174*** (0.052)	0.193*** (0.057)
HPI Change 2006-2009		0.000 (0.001)			0.000 (0.001)
HPI Change 2002-2006		-0.000 (0.001)			-0.001 (0.001)
Mortgage Amount Change 2002-2006			-0.014 (0.046)		0.083 (0.071)
Number of Mortgage Change 2002-2006			0.057 (0.086)		-0.055 (0.106)
Debt to income from NY Fed 2006				-0.054 (0.039)	-0.051 (0.052)
Debt to income Change 2002-2006				0.017 (0.073)	0.036 (0.084)
Population deciles	Yes	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes	Yes
Selection controls	Yes	Yes	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes
Observations	3,104	3,104	3,097	2,209	2,208
Mean of DV	0.548	0.548	0.548	0.554	0.554
Robust F-stat	52.13	69.43	52.36	53.82	63.41

Notes: This table presents first difference regressions as in equation 3 with additional control variables for the 2000s housing boom and bust, including the change in a county's house price index, growth in mortgage debt, and changes in household debt-to-income ratios. *Log(Twitter usage)* is the number of unique Twitter users in a county in natural logarithm, instrumented with *Log(SXSW 2007 attendees)* (the number of SXSW attendees in 2007 in natural logarithm with one added inside). *SXSW followers, Pre* is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the full set of county-level controls in Table 2. Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Social Media and Stock Market Participation Across Income Groups

<i>Dependent variable:</i>	$\Delta_{'05 \rightarrow '15} \text{Log}(\text{Dividends p.c.})$				
	<\$25k (1)	\$25-50k (2)	\$50-75k (3)	\$75-100k (4)	>\$100k (5)
Log(Twitter users)	0.002 (0.008)	0.001 (0.006)	-0.004 (0.011)	0.010 (0.016)	0.134** (0.057)
Log(SXSW followers, pre)	0.012** (0.005)	0.009** (0.004)	0.011 (0.008)	-0.004 (0.010)	-0.063* (0.036)
Population deciles	Yes	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes	Yes
Selection controls	Yes	Yes	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes
Media Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,106	3,106	3,106	3,106	3,105
Mean of DV	-0.164	-0.037	-0.019	0.007	0.030
Robust F-stat	52.13	52.13	52.13	52.13	52.13

Notes: This table presents first difference regressions as in equation 3, where the dependent variable is the difference in $\text{Log}(\text{Dividends per capita})$ between 2005 and 2015. We estimate separate regressions for five income groups. $\text{Log}(\text{Twitter usage})$ is the number of unique Twitter users in a county in natural logarithm, instrumented with $\text{Log}(\text{SXSW 2007 attendees})$ (the number of SXSW attendees in 2007 in natural logarithm with one added inside). $\text{SXSW followers, Pre}$ is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the full set of county-level controls in Table 2. Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Heterogeneity Tests

<i>Dependent variable:</i>	$\Delta_{'05 \rightarrow '15} \text{Log}(\text{Dividends p.c.})$			
	(1)	(2)	(3)	(4)
Log(SXSW 2007 attendees)	-0.675 (0.458)	-0.035 (0.086)	-0.025 (0.040)	-0.083 (0.108)
Log(SXSW 2007 attendees) \times Gini coefficient	1.739* (1.024)			
Log(SXSW 2007 attendees) \times Poverty rate		0.012* (0.006)		
Log(SXSW 2007 attendees) \times White Population (%)			-0.119*** (0.034)	
Log(SXSW 2007 attendees) \times Log(Population)				0.082* (0.046)
Population deciles	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes
Selection controls	Yes	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes	Yes
Observations	3,104	3,104	3,104	3,104
Mean of DV	0.548	0.548	0.548	0.548

Notes: This table presents reduced-form heterogeneity tests where we regress the difference in *Log(Dividends per capita)* between 2005 and 2015 directly on our instrument and interactions with county characteristics. *Log(SXSW 2007 attendees)* is the number of SXSW attendees in 2007 in natural logarithm (with one added inside). *Log(SXSW followers, Pre)* is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the county-level controls in column 3 of Table 2 interacted with the interaction variable of interest. Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8: Social Media and Information Provision

<i>Dependent variable:</i>	$\Delta_{05 \rightarrow 15} \text{Log}(\text{Dividends p.c.})$			
	(1)	(2)	(3)	(4)
Log(SXSW 2007 attendees)	0.090*** (0.019)	-0.025 (0.054)	0.081*** (0.018)	0.144*** (0.037)
Log(SXSW 2007 attendees) \times Financial advisors p.c.	-0.036* (0.018)			
Log(SXSW 2007 attendees) \times Bank branches p.c.		-0.139* (0.070)		
Log(SXSW 2007 attendees) \times High financial knowledge			-0.038** (0.016)	
Log(SXSW 2007 attendees) \times Share bachelor's degree				-0.041* (0.022)
Population deciles	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes
Selection controls	Yes	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes
Media Controls	Yes	Yes	Yes	Yes
Observations	1,946	3,088	2,915	3,104
Mean of DV	0.565	0.548	0.550	0.548

Notes: This table presents reduced-form heterogeneity tests where we regress the difference in *Log(Dividends per capita)* between 2005 and 2015 directly on our instrument and interactions with variables proxy for the availability of information about stock markets before Twitter's launch. *Log(SXSW 2007 attendees)* is the number of SXSW attendees in 2007 in natural logarithm (with one added inside). *SXSW followers, Pre* is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the county-level controls in column 5 of Table 2 interacted with the interaction variable of interest. Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9: Survey Evidence – Stock Ownership and Investment Preferences

	What is the best long-term investment?					
	Stock ownership (1)	Stock (2)	Real Estate (3)	Fixed Income (4)	Gold (5)	Others (6)
Log(Twitter users)	0.042** (0.020)	0.053* (0.030)	-0.049* (0.027)	0.028 (0.023)	-0.042* (0.025)	-0.005 (0.006)
Population deciles × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census division × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Selection controls	Yes	Yes	Yes	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Media Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,535	12,421	12,421	12,421	7,958	12,421
Mean of DV	0.563	0.246	0.330	0.293	0.184	0.013
Robust F-stat	40.358	38.418	38.418	38.418	38.980	38.418

Note: This table presents individual-level linear probability estimates from regressing dummy variables measuring stock ownership or investment preferences on Twitter usage (instrumented with SXSW attendees). The sample period is 2007 to 2020. The dependent variable in column (1) is a dummy variable that equals to 1 if the respondent of the Gallup survey answers *Yes* to the question *Do you personally or jointly with a spouse, have any money invested in the stock market right now – either in an individual stock, a stock mutual fund, or in a self-directed 401-K or IRA?*, and 0 otherwise. The dependent variables from column (2) to column (6) are dummy variables that capture individuals’ preferences for investing in different asset classes. The dependent variable *Stock* in column (2) equals to 1 if the respondent believes stock market or mutual funds are the best long-term investment compared to other asset classes when answering the question *Which of the following do you think is the best long-term investment – [bonds, real estate, savings accounts or CDs, (or) stocks or mutual funds]? Or gold?*. The dependent variables in columns (3) to (6) are defined similarly. All regressions control for population decile × year fixed effects, Census division × year fixed effects, and the full set of county-level controls in Table 2. We also include individual control variables for age groups, race, gender, income groups, education, and employment status. Standard errors in parentheses are clustered by state and we apply survey weights. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

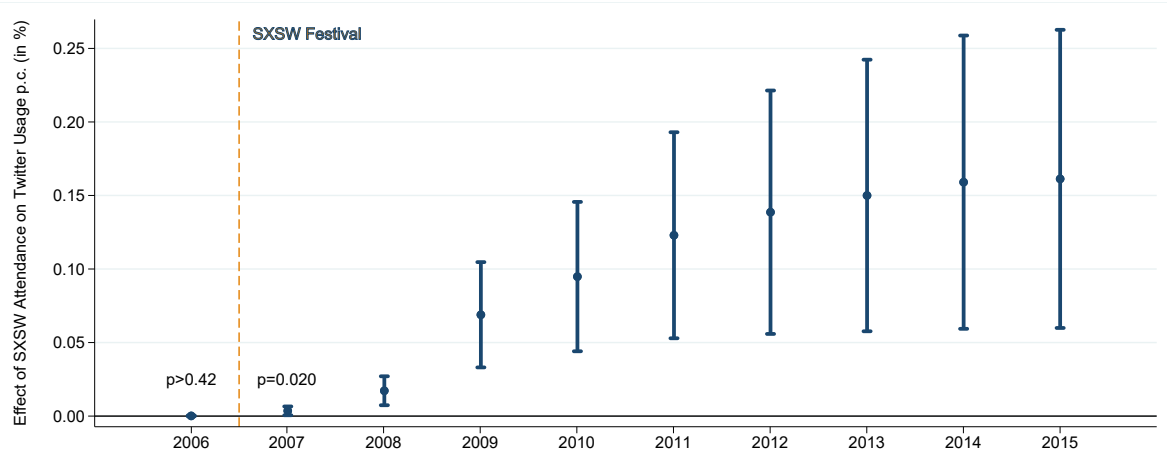
Table 10: Social Media and Search Interest in Meme Stocks

<i>Dependent variable:</i>	Log(Google searches for meme stocks)				
	(1)	(2)	(3)	(4)	(5)
Log(Twitter users)	0.335** (0.132)	0.344** (0.135)	0.366** (0.174)	0.232** (0.113)	0.225** (0.106)
Log(SXSW followers, pre)	0.038 (0.056)	0.026 (0.057)	0.032 (0.051)	-0.026 (0.041)	-0.012 (0.041)
Population deciles	Yes	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes	Yes
Selection controls		Yes	Yes	Yes	Yes
Geographical controls			Yes	Yes	Yes
Socioeconomic controls				Yes	Yes
Media Controls					Yes
Observations	205	205	205	205	205
Mean of DV	2.500	2.500	2.500	2.500	2.500
Robust F-stat	18.66	19.70	16.79	15.53	14.13

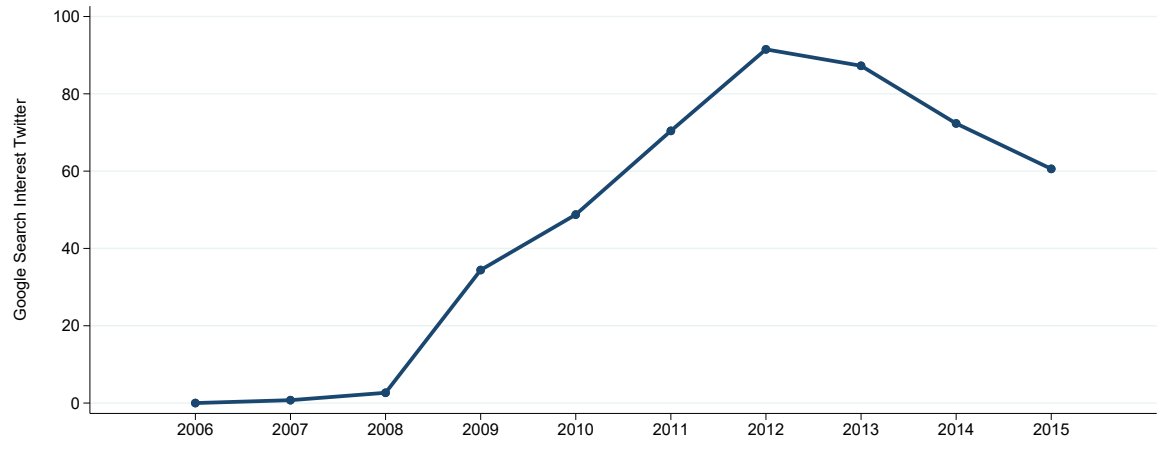
Notes: This table presents DMA-level regressions where the dependent variable is the average Google Trends SVI for a list of meme stocks in 2021, including “GME” (“GameStop Corp.”), “AMC” (“AMC Entertainment Holdings Inc”), “UPST” (“Upstart Holdings Inc”), “BBBY” (“Bed Bath & Beyond Inc.”), “BBIG” (“Vincovest Ventures Inc”), “BB” (“BlackBerry Ltd.”), “NOK” (“Nokia Corp.”), “SAVA” (“Cassava Sciences, Inc”), “CLOV” (“Clover Health Investments Corp”), “PLTR” (“Palantir Technologies.”), “SPCE” (“Virgin Galactic Holdings”), “LCID” (“Lucid Group, Inc.”), and “Crypto.” $\text{Log}(\text{Twitter usage})$ is the number of unique Twitter users in a county in natural logarithm, instrumented with $\text{Log}(\text{SXSW 2007 attendees})$ (the number of SXSW attendees in 2007 in natural logarithm with one added inside). $\text{SXSW followers, Pre}$ is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the full set of county-level controls in Table 2. Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 1: South by Southwest 2007 and Twitter Adoption

(a) Effect of SXSW on Twitter Adoption

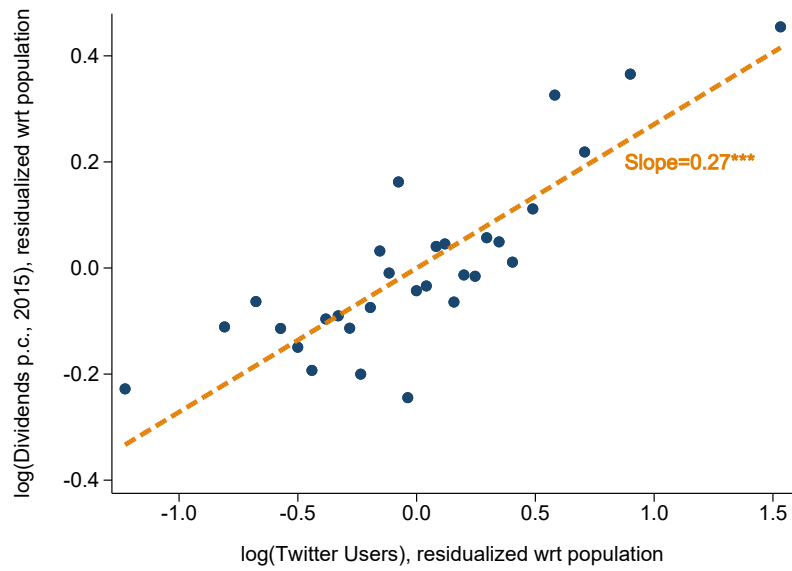


(b) Search Interest for Twitter



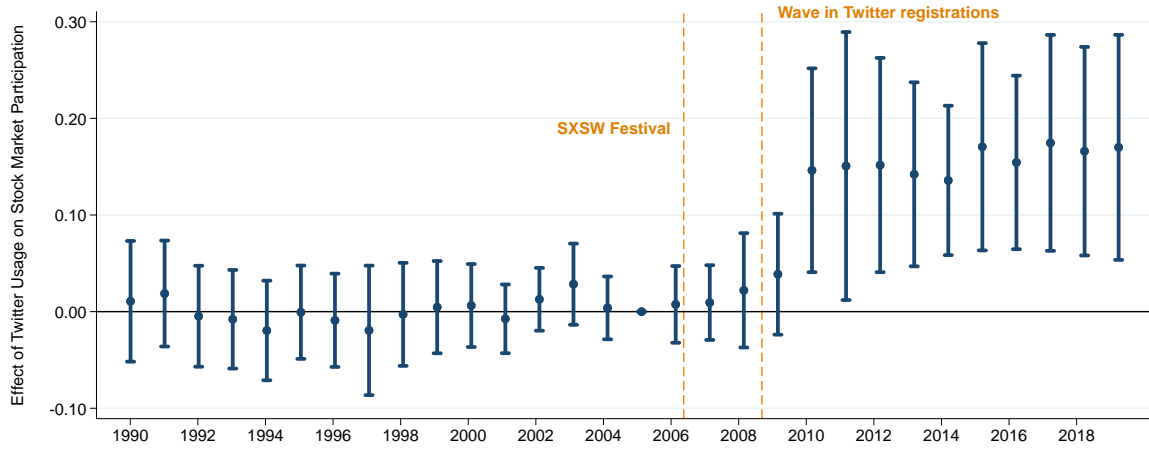
Notes: This figure provides evidence on the link between SXSW attendance in 2007 and the geography of Twitter adoption. Panel (a) shows the estimates of θ from repeated cross-sectional regressions $x_i = \theta z_i + \mathbf{X}'\beta + \epsilon_i$, where x_i is Twitter users per capita in county i for the year indicated on the x-axis, z_i is the natural logarithm of SXSW 2007 attendees (with one added inside), \mathbf{X}'_i a control vector including among other population deciles and census division fixed effects. We plot 95% confidence intervals based on standard errors are clustered by state. Panel (b) plots the search interest for Twitter on Google between 2006 and 2015.

Figure 2: Correlation between Twitter Usage and Stock Market Participation



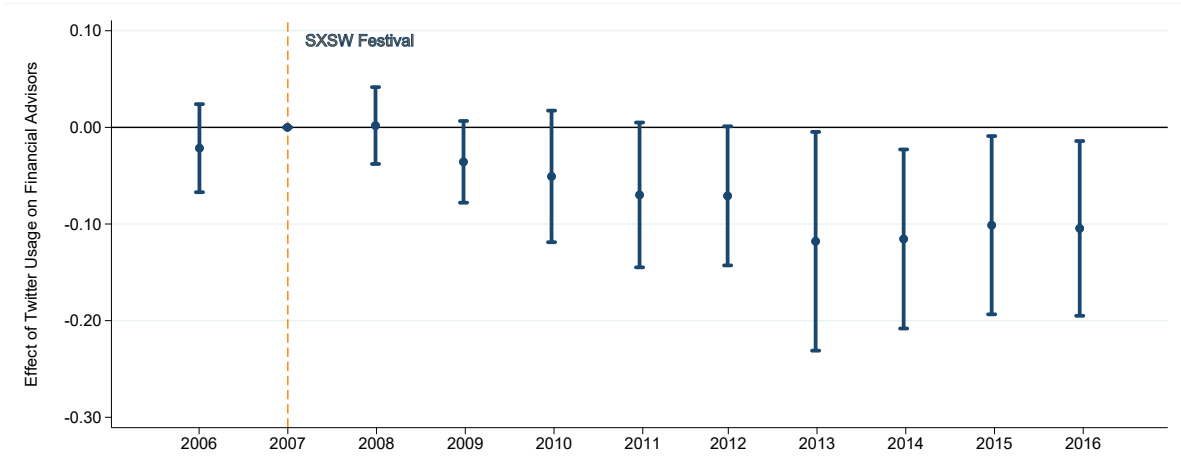
Notes: This figure shows a binned scatter plot where dividends per capita (in logs, as of 2015) are binned into 30 buckets of log(Twitter usage). Both variables are residualized with respect to population deciles.

Figure 3: Dynamic IV Estimates



Notes: This figure plots the estimates β from cross-sectional IV regressions as in Equation (3), where the dependent variable is the change in dividends per capita relative to 2005 (the year before Twitter's launch). We include the full set of controls as in column 5 of Table 2. Standard errors are clustered by state, and we plot 95% confidence intervals.

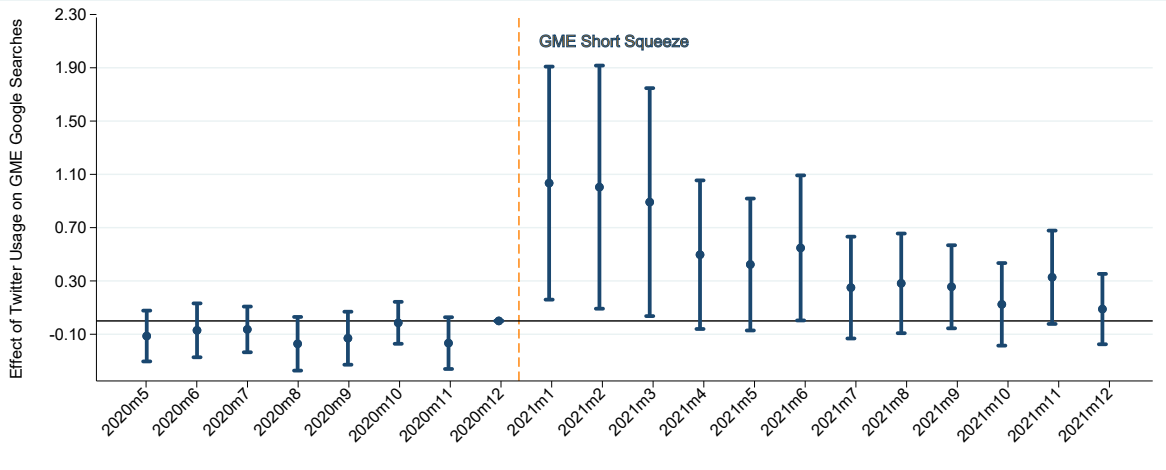
Figure 4: Social Media Adoption and Financial Advisor Displacement



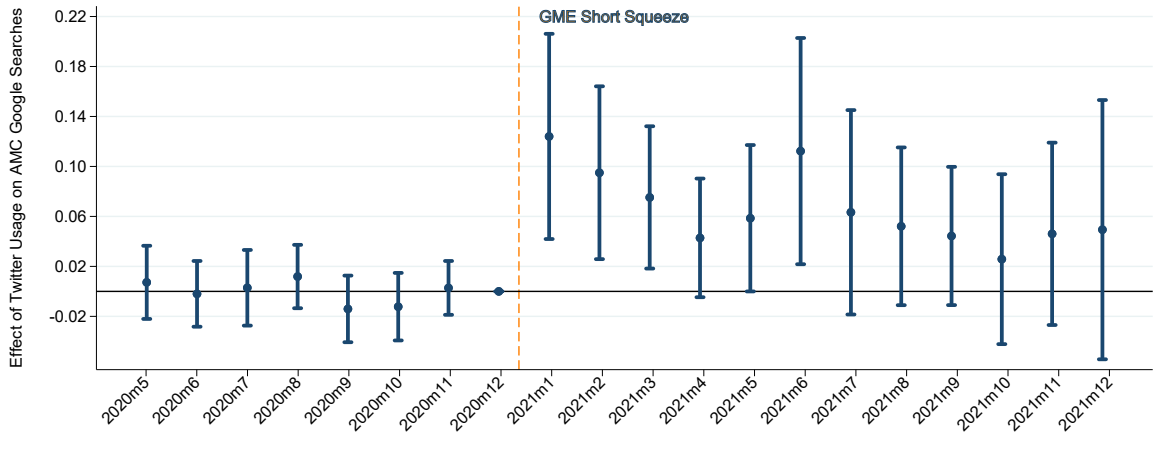
Notes: This figure plots the estimates β from cross-sectional IV regressions as in Equation (3), where the dependent variable is the change in the number of financial advisors (in logs with 1 added inside) relative to 2006 (the first year for which we have data). The data on financial advisors is taken from Charoenwong, Kwan, and Umar (2019). We include the same controls as in column 4 of Table 2. Standard errors are clustered by state, and we plot 95% confidence intervals.

Figure 5: Social Media and the GameStop Short Squeeze Episode

(a) Google Searches for GME



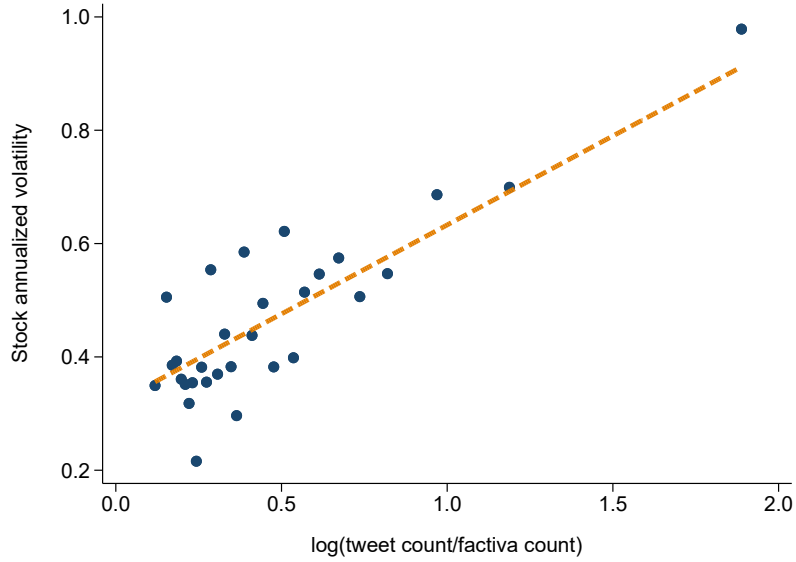
(b) Google Searches for AMC



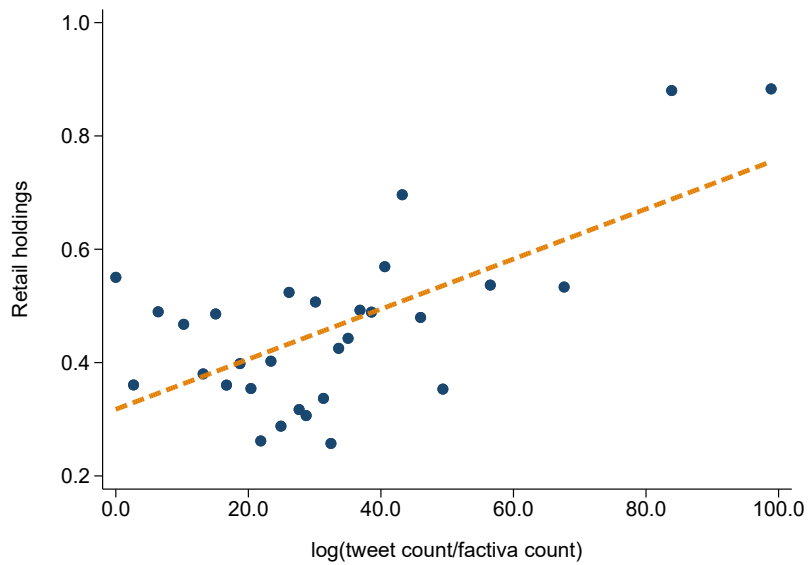
Notes: This figure plots the estimates β from cross-sectional IV regressions as in Equation (3), where the dependent variable is the change in Google search index for “GME” and “AMC” relative to 2005 in panel (a) and (b), respectively. We include the full set of controls as in column 5 of Table 2. Standard errors are clustered by state, and we plot 95% confidence intervals.

Figure 6: Which Stocks Are Overrepresented On Social Media?

(a) Stock volatility



(b) Retail Ownership



Notes: These figures plots stock volatility and retail ownership against the difference between the share of a stock's mentions on Twitter and traditional media sources (the Wall Street Journal or Dow Jones Institutional News).

A Online Appendix

Table A.1: Descriptive Statistics – Gallup Data Variables

	Mean	Std.	Min.	25%	50%	75%	Max.	N
Stock ownership								
Yes	0.57	0.64	0.00	0.00	0.50	0.84	4.12	22341
No	0.42	0.74	0.00	0.00	0.00	0.63	4.12	22341
Best Long-term Investment								
Stocks or mutual funds	0.16	0.45	0.00	0.00	0.00	0.00	4.12	22341
Fixed income	0.19	0.53	0.00	0.00	0.00	0.00	4.12	22341
Gold	0.08	0.34	0.00	0.00	0.00	0.00	4.12	22341
Real Estate	0.22	0.52	0.00	0.00	0.00	0.00	4.12	22341
Others/DK	0.03	0.20	0.00	0.00	0.00	0.00	3.79	22341
Gender								
Male	0.49	0.66	0.00	0.00	0.28	0.75	4.12	22341
Female	0.51	0.73	0.00	0.00	0.00	0.79	4.12	22341
Age								
< 20	0.05	0.33	0.00	0.00	0.00	0.00	4.12	22341
20-24	0.08	0.39	0.00	0.00	0.00	0.00	4.12	22341
25-34	0.16	0.51	0.00	0.00	0.00	0.00	4.12	22341
35-44	0.17	0.51	0.00	0.00	0.00	0.00	4.12	22341
45-54	0.18	0.47	0.00	0.00	0.00	0.00	4.12	22341
55-64	0.16	0.39	0.00	0.00	0.00	0.00	4.05	22341
65+	0.19	0.40	0.00	0.00	0.00	0.30	4.05	22341
Education								
High School or Less	0.39	0.75	0.00	0.00	0.00	0.59	4.12	22341
Some college	0.30	0.59	0.00	0.00	0.00	0.44	4.12	22341
College Grad only	0.16	0.37	0.00	0.00	0.00	0.00	4.12	22341
Post-grad	0.15	0.35	0.00	0.00	0.00	0.00	4.12	22341
Marital Status								
Currently Married	0.50	0.65	0.00	0.00	0.34	0.79	4.12	22341
Divorced	0.10	0.35	0.00	0.00	0.00	0.00	4.05	22341
Living together with Partner	0.08	0.36	0.00	0.00	0.00	0.00	4.12	22341
Never Married	0.20	0.57	0.00	0.00	0.00	0.00	4.12	22341
Separated	0.03	0.22	0.00	0.00	0.00	0.00	4.05	22341
Widowed	0.07	0.28	0.00	0.00	0.00	0.00	4.12	22341

Table A.1: Summary Statistics – Gallup Data Variables (Continued)

	Mean	Std.	Min.	25%	50%	75%	Max.	N
Employment								
Employed	0.57	0.73	0.00	0.00	0.40	0.90	4.12	22341
Unemployed	0.07	0.34	0.00	0.00	0.00	0.00	4.12	22341
Homemaker	0.06	0.31	0.00	0.00	0.00	0.00	4.12	22341
Retired	0.22	0.42	0.00	0.00	0.00	0.36	4.05	22341
Student	0.06	0.35	0.00	0.00	0.00	0.00	4.12	22341
Disabled	0.03	0.21	0.00	0.00	0.00	0.00	4.05	22341
Race								
Asian	0.02	0.17	0.00	0.00	0.00	0.00	4.12	22341
Hispanic	0.11	0.46	0.00	0.00	0.00	0.00	4.12	22341
Non-Hispanic White	0.73	0.66	0.00	0.30	0.59	0.98	4.12	22341
Non-Hispanic Black	0.11	0.44	0.00	0.00	0.00	0.00	4.12	22341
Other	0.03	0.19	0.00	0.00	0.00	0.00	3.59	22341
Income								
< 10K	0.04	0.26	0.00	0.00	0.00	0.00	4.12	22341
10-20K	0.07	0.34	0.00	0.00	0.00	0.00	4.12	22341
20-30K	0.09	0.39	0.00	0.00	0.00	0.00	4.12	22341
30-40K	0.10	0.38	0.00	0.00	0.00	0.00	4.12	22341
40-50K	0.09	0.35	0.00	0.00	0.00	0.00	4.12	22341
50-75K	0.13	0.42	0.00	0.00	0.00	0.00	4.12	22341
75-99K	0.09	0.34	0.00	0.00	0.00	0.00	4.12	22341
100-149K	0.08	0.32	0.00	0.00	0.00	0.00	4.12	22341
150-249K	0.05	0.23	0.00	0.00	0.00	0.00	3.69	22341
250-500K	0.02	0.14	0.00	0.00	0.00	0.00	3.04	22341
500K+	0.00	0.08	0.00	0.00	0.00	0.00	4.05	22341

Notes: This table presents summary statistics of individual-level survey data from Gallup. We apply survey weights.

Table A.2: First Stage – South by Southwest 2007 and Twitter Diffusion

<i>Dependent variable:</i>	Log(Twitter usage)				
	(1)	(2)	(3)	(4)	(5)
Log(SXSW 2007 attendees)	0.733*** (0.103)	0.721*** (0.105)	0.710*** (0.109)	0.615*** (0.064)	0.491*** (0.068)
Log(SXSW followers, pre)	0.096 (0.122)	0.089 (0.123)	0.079 (0.121)	0.041 (0.102)	0.133 (0.102)
Population deciles	Yes	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes	Yes
Selection controls		Yes	Yes	Yes	Yes
Geographical controls			Yes	Yes	Yes
Socioeconomic controls				Yes	Yes
Media Controls					Yes
Observations	3,108	3,108	3,108	3,107	3,106
Mean of DV	8.368	8.368	8.368	8.368	8.369
R^2	0.911	0.912	0.913	0.936	0.948

Notes: This table presents county-level first stage regressions as in Equation (2) where the dependent variable is the number of Twitter users as of 2015 (in natural logarithm). *Log(SXSW 2007 attendees)* is the number of SXSW attendees in 2007 in natural logarithm (with one added inside), our instrument. *SXSW followers, Pre* is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles and Census division fixed effects. Selection controls include the linear distance from the SXSW festival location (Austin, Texas) and Google search intensity for the SXSW festival before 2007. Geographical controls is population density. Socioeconomic controls include age buckets (the share of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and those over 50) and ethnic composition (the share of people identifying as white, African American, Native American or Pacific Islander, Asian or Hispanic), the Gini coefficient, log median household income, the share of high school graduates, and the share of people with a graduate degree. Media controls include the prime time TV viewership to population ratio and the Facebook Social Connectedness Index (SCI). Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3: IV Estimation – Robustness Tests

<i>Dependent variable:</i>	$\Delta\text{Log}(\text{Dividends p.c.})$			
	No weights (1)	SXSW counties only (2)	Winsorize outcome (3)	Inverse hyperbolic sine (4)
Log(Twitter users)	0.136*** (0.037)	0.223*** (0.075)	0.172*** (0.046)	0.070** (0.034)
Population deciles	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes
Selection controls	Yes	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes	Yes
Observations	3,104	172	3,104	3,106
Mean of DV	0.305	0.736	0.539	0.255
Robust F-stat	89.68	14.26	33.01	78.44

Notes: This table presents regressions as in equation 3, where the dependent variable is the change in Log(Dividends per capita) between 2005 and 2015 unless otherwise specified. Column (1) reruns our baseline estimates without weighting by population. Column (2) restricts the sample to counties where we have either SXSW attendees or other SXSW followers before 2007. Column (3) winsorizes the dependent variable at the 1st and 99th percentile. In Column (4), we use the inverse hyperbolic sine instead of the logarithmic transformation of dividends per capita, Twitter users, and SXSW attendees. $\text{Log}(\text{Twitter usage})$ is the number of unique Twitter users in a county in natural logarithm, instrumented with $\text{Log}(\text{SXSW 2007 attendees})$ (the number of SXSW attendees in 2007 in natural logarithm with one added inside). $\text{SXSW followers, Pre}$ is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the full set of county-level controls in Table 2. Standard errors in parentheses are clustered by state, and observations are weighted by county population except in column 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

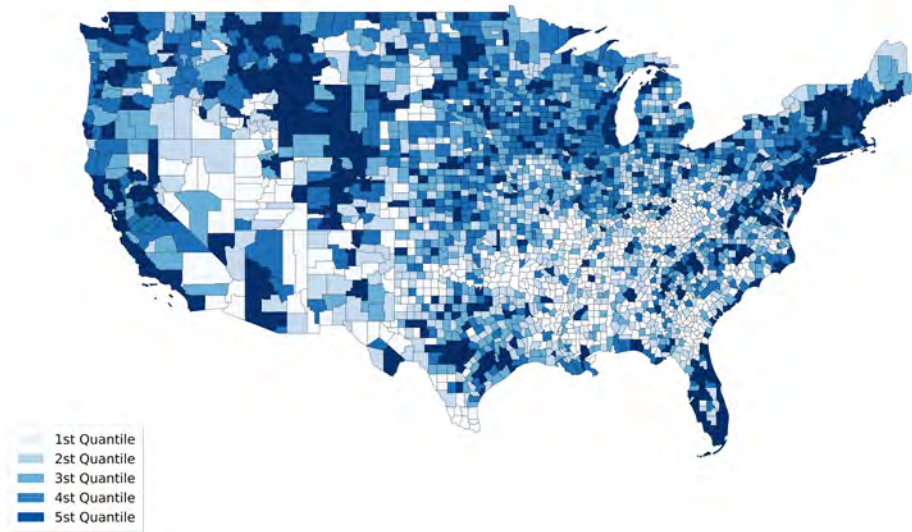
Table A.4: Social Media and Changes in Financial Advisors

<i>Dependent variable:</i>	$\Delta_{'07 \rightarrow '15} \text{Log}(\# \text{ Financial Advisors})$				
	(1)	(2)	(3)	(4)	(5)
Log(Twitter users)	-0.098** (0.047)	-0.096** (0.046)	-0.104** (0.050)	-0.101** (0.046)	-0.179** (0.069)
Log(SXSW followers, pre)	0.112** (0.054)	0.107** (0.050)	0.103* (0.052)	0.079* (0.046)	0.113* (0.057)
Population deciles	Yes	Yes	Yes	Yes	Yes
Census division FE	Yes	Yes	Yes	Yes	Yes
Selection controls		Yes	Yes	Yes	Yes
Geographical controls			Yes	Yes	Yes
Socioeconomic controls				Yes	Yes
Media Controls					Yes
Observations	1,946	1,946	1,946	1,946	1,946
Mean of DV	0.355	0.355	0.355	0.355	0.355
Robust F-stat	50.41	46.70	42.14	84.06	46.98

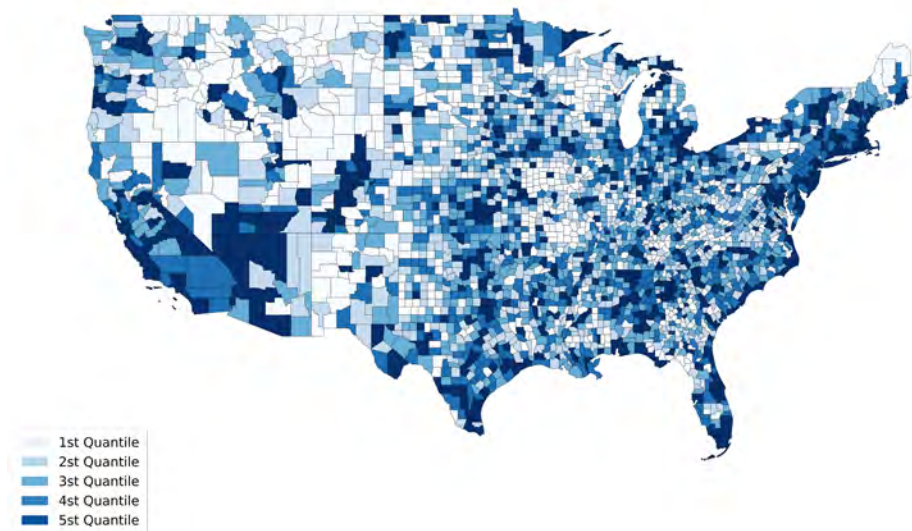
Notes: This table presents first difference regressions as in equation 3, where the dependent variable is the difference in the number of financial advisors (in natural logarithm) between 2007 and 2015. *Log(Twitter usage)* is the number of unique Twitter users in a county in natural logarithm, instrumented with *Log(SXSW 2007 attendees)* (the number of SXSW attendees in 2007 in natural logarithm with one added inside). *SXSW followers, Pre* is the number of SXSW followers who signed up to Twitter before the event in 2007. All regressions control for population deciles, Census division fixed effects, and the full set of county-level controls in Table 2. Standard errors in parentheses are clustered by state, and observations are weighted by county population. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.1: Geographical Variation of Main Variables

(a) Dividends per capita

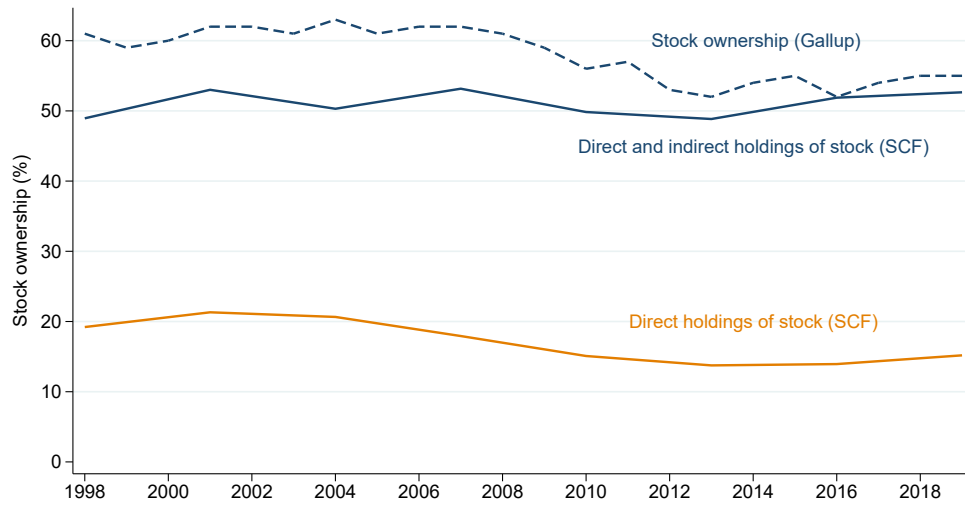


(b) Twitter Usage per capita



Notes: These figures visualize the geographical variation of our main measure of stock market participation (dividends per capita) and Twitter usage across the United States. Panel (a) presents quantiles of dividends per capita measured in 2015. Panel (b) plots the number of Twitter users per capita based on a large dataset of geo-located tweets collected between June and November in 2014 and 2015 by Kinder-Kurlanda et al. (2017).

Figure A.4: Comparing Gallup and SCF Data on Stock Ownership



Notes: This figure compares U.S. stock ownership rates from 1998 to 2019 based on data from the Survey of Consumer Finances (SCF) and Gallup Social Survey.

A.1 Google Search Index Renormalization

We collect data on the frequency of Google searches (Google Search Volume Index, or SVI) using the Google Search API. To construct SVI time series for keywords of interest from 2004 to 2021, we first set the location to be one of the 210 Designated Market Area (DMA) in the United States. The monthly Google SVI is then computed as the normalized query share for the relevant keyword at each DMA location and at a specific point in time. For example, the SVI value for “GME” in Atlanta on 2021-12-01 is the number of queries for “GME” during December, 2021 divided by the highest number of queries for “GME” between 2004 and 2021 in Atlanta. As such, a decrease in the SVI means that a search term is becoming less popular in the specified location over time. We denote the SVI at each time point t and location s for stock i as $SVI_T_{i,t,s}$.

To retrieve regional SVI data, we call the Google Search API in the following way. Given our time period of interest is fixed as 2004 – 2021, the DMA-level SVI values are computed as the number of queries for the relevant stock ticker in each region, e.g., Palm Springs, CA, from 2004 to 2021, normalized by the highest number of queries for that stock ticker across all DMAs. A relatively higher SVI value thus represents higher investor attention in the specific region within a given time period. We denote the SVI for each stock i at location s as $SVI_R_{i,s}$ from 2004 – 2021.

To compare investor attention across DMAs over time, we need to renormalize the $SVI_T_{i,t,s}$ and $SVI_R_{i,s}$ as described above to make it comparable in each region and at each time point of interest. The process works as follows. For each stock ticker, it is trivial to find the location S where $SVI_R_{i,s}$ equals to 100 (the maximum). Let $V_{i,S}$ be the total number of queries for stock ticker i in top state S from 2004 to 2021. Then, the total query volume for each DMA can be expressed as $\frac{SVI_R_{i,s} * V_{i,S}}{100}$. We can also derive the total query volume for each DMA using time series data as $\sum_t \frac{SVI_T_{i,t,s} * W_{i,s}}{100}$, where $W_{i,s}$ is the highest total search volume for stock i in DMA s from 2004 to 2021. Intuitively, $W_{i,s}$ can be rewritten as:

$$W_{i,s} = \frac{SVI_R_{i,s} * V_{i,S}}{\sum_t SVI_T_{i,t,s}} \quad (4)$$

To compute comparable values of the SVI for each region and each point in time, we renormalize it as a percentage form of $W_{i,s}$:

$$SVI\tilde{T}_{i,t,s} = SIV_{Renormalize} = SVI_T_{i,t,s} * \frac{SVI_R_{i,s}}{\sum_t SVI_T_{i,t,s}} \quad (5)$$