Institutional Investors and Echo Chambers: Evidence from Social Media Connections and Political Ideologies

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Abstract
This study examines the role of exposure to confirmatory information in the decision making of institutional investors. We exploit geographic variation in social media connections and political ideologies to identify plausible variation in the extent to which institutional investors interact with people of differing political persuasions. We find that firms whose institutional investors are more likely to be connected with more likeminded individuals are subject to greater earnings responses and significant return reversals following their earnings announcements, indicative of investor overreactions. We also provide evidence that such firms are the subject of more extreme tweets around their earnings announcements, while firms with richer information environments are less affected. Finally, firms whose investors have more likeminded networks exhibit substantially lower future returns. Overall, our results suggest that connections to people with diverse beliefs and information sets can improve the financial decision making of more sophisticated investors, leading to more efficient markets.

Keywords: social media; political ideology; sophisticated investors; echo chambers
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"I tend to think things like social media make the market less, not more, efficient... People don't hear counter-opinions, they hear their own, and in politics that can lead to some dangerous craziness and in markets that can lead to some really weird price action."

– Cliff Asness in *The Economist*

1. Introduction

Exposure to differing beliefs and information is expected to inform an investor about not only how other market participants may behave, but also about the wisdom of their own investment opinions (Mill 1859). For example, interactions with people who have different information or weight signals differently may augment an investor's information set, reducing the likelihood of making naive, biased, or extreme decisions (Veldkamp 2006a, 2006b; Gentzkow and Shapiro 2008; Blankespoor et al. 2020). However, evidence on how exposure to differing beliefs ultimately impacts investors' decisions is limited.[1] In addition, while much of the prior research on poor financial decisions has focused on retail investors' lack of sophistication (Stambaugh 2014), institutional investors also have cognitive limitations that can lead to biased decisions (Coval and Shumway 2005; Frazzini 2006).

Given that institutions own and trade most corporate equity (French 2008), any biased investment decisions they make as a result of limited information sets likely have substantial implications for the firms in their portfolios. In this study, we develop a novel measure of the extent to which an institutional investor is likely to interact with more likeminded individuals, and we examine the pricing efficiency implications of a lack of exposure to diverse perspectives.

We identify institutional investors' lack of exposure to differing views and investment opinions by combining county-level data on social media connections and political ideology.

[1] This is largely because the beliefs of others are rarely directly observable (by either investors or researchers). For this reason, inferences are often based on noisy aggregations of beliefs and behavior such as stock prices (Grossman and Stiglitz 1980; Diamond and Verrecchia 1981; Brunnermeier 2005).

Social media connections often reflect the information shared through investors' professional and personal interactions (Bailey et al. 2018a; Hirshleifer et al. 2023), which have also been shown to influence their portfolio decisions (Hong et al. 2005; Hvide and Ostberg 2015).[2] For better or worse, such interactions often revolve around politics explicitly, or at least are implicitly shaped by the participants' political ideologies (Bakshy et al. 2015; Gentzkow 2016; Chen et al. 2023). Moreover, a growing literature suggests that market participants' political beliefs and behavior influences almost all aspects of daily life, including financial decision making (e.g., Hong and Kostovetsky 2012; Cookson et al. 2020; Rees and Twedt 2022; Chen et al. 2023). For example, recent surveys indicate that companies' political or social stances are a major reason that many consumers have boycotted brands (Asay 2023; NBC News 2023).

Both social media and politics have been shown to polarize and alienate people, leading to isolation and reduced exposure to differing beliefs (Pew Research Center 2014; Boxell 2020). Thus, while there are a variety of types of interpersonal interactions that can elicit variation in beliefs, social media connections and political ideology are particularly suitable for addressing our research question. Namely, we expect that the intensity of an institutional investor's likely social media interactions with politically diverse vs. homogeneous peers will influence their financial decisions and, as a result, the pricing efficiency of the firms in their portfolios.

To create our measure, we first identify all Facebook connections between individuals in a given institutional investor's county and individuals in all other U.S. counties (Bailey et al. 2018b) during our sample period of 2008 to 2017. We then incorporate each county's position on the left-right political spectrum (i.e., Gallup's liberal vs. conservative scale) in order to identify how

[2] Investors' interactions do not have to exclusively take place via social media for our purposes; indeed, many people also connect with their social media contacts via phone calls, emails, in-person visits, etc. Prior studies examine offline interactions between Facebook connections (e.g., Gilbert and Karahalios 2009; Hampton et al. 2012).

similar the connected counties are politically. Our measure (*LikeMind*) is the product of the intensity of social connections and similarity of political ideology across counties, which gives us an estimate of the extent to which an investor is located in a county where, for example, liberals interact primarily with liberals vs. also interacting with conservatives. In other words, this variable captures whether an investor is in a part of the country that more closely resembles an echo chamber, which has been defined as a closed system in which existing beliefs are reinforced and/or amplified by repeated communication (Levy and Razin 2019).

We begin our analyses by presenting a descriptive portrait of the characteristics of our likemindedness measure and conducting tests to validate its connection to investment behavior. For example, we observe significant geographic variation in likemindedness. Among locations with substantial concentrations of investors, Hamilton County OH (which includes Cincinnati), Dallas TX and San Diego CA score high on likemindedness, whereas New York NY, Denver CO, and San Francisco CA score low on likemindedness. This suggests likemindedness is not limited to the largest cities or to regions dominated by a particular ideology.

In support of the validity of our measure, we provide evidence that institutional investors in higher likemindedness areas tend to concentrate their holdings in firms that are headquartered in counties with a similar political ideology to their own county. Importantly, this finding is robust to excluding firms in the same state as the investor, suggesting the result is not driven by local bias. This finding reflects investors' propensity to invest in ideologically similar firms, indicating that the political ideology of their surroundings and their investment opportunities play a role in their capital allocation decisions. This evidence also suggests the possibility that investments in likeminded firms may reinforce the walls of an investor's echo chamber, or in other words, that they may get ideologically consistent and confirmatory information from the people who live and work around them *as well as* from the firms in their portfolio.

For our main analyses, we aggregate our likemindedness measure to the firm-level. We do this by taking the average *LikeMind* of all institutional investors holding a given firm's stock at a point in time, weighted by their proportional ownership in the firm. We note that this firm-level weighted average measure is based on the extent to which a firm's institutional investors individually reside in counties that could be described as echo chambers, not whether the firm's investor base as a whole is itself an echo chamber (i.e., a concentration of liberal or conservative investors).[3] Thus, this measure (*LikeMind Firm*) captures information that investors get from their entire networks, and identifies the on-average exposure of the firm's investor base to people with similar political ideologies.

Our primary results are that firms held by a greater proportion of institutional investors who are more likely to be connected with politically likeminded individuals exhibit stronger earnings announcement (EA) return reactions, followed by significant post-EA return reversals. This combination of results suggests that firms whose investor bases are subject to greater echo chamber effects are more likely to experience overreactions during their earnings announcements. This evidence is consistent with the notion that exposure to confirmatory information leads to investors' overconfidence in the precision of their private information (Daniel et al. 1998). This is also consistent with theoretical research on information (and/or noise) cascading and compounding through feedback loops due to investors reacting to and imitating others in their networks (Banerjee 1992; Bikhchandani et al. 1992, 1998; Welch 1992; Hirshleifer 2020).

[3] However, as discussed in more detail later, we do find that our results are concentrated among firms that have both investors that reside in echo chambers *and* investor bases that more closely resemble echo chambers.

We next explore one type of signal that could plausibly contribute to the above findings – the amount and type of social media discussion about the firm around its earnings announcement. For this analysis, we rely on data from Twitter, which prior research has established as a significant channel through which echo chamber effects can operate, as political and financial opinions are confirmed and become more extreme (Cota et al. 2019; Cinelli et al. 2021; Di Tella et al. 2021; Campbell et al. 2022). Consistent with these arguments, we find that firms with investors whose connections are more likeminded tend to be the subject of more tweets in general, as well as more tweets expressing extreme sentiment, around their earnings announcements. This evidence is suggestive of one mechanism through which investors' exposure to likeminded networks may translate into an overreaction at the earnings announcement.

We next examine whether a richer firm information environment can help ameliorate the overreaction effects of likeminded investor networks. For example, an investor who otherwise lacks exposure to diverse points of view would likely benefit from information provided by the firm, analysts, and the media that challenges their investment thesis. Consistent with this idea, we find that our results are concentrated among firms with more opaque information environments. This evidence suggests that the effects of investors' lack of exposure to differing private beliefs and opinions can be at least partially offset by plentiful and precise public information. Relatedly, we find that our results are strongest for firms with less political ideological variation among their investor bases, suggesting that the firm's investor base as a whole being an echo chamber can exacerbate the effects of its investors residing within echo chambers.

In our final analysis, we consider the implications of our results for the cross-section of stock returns. Our likemindedness measure is based on identifiable institutional investors with long positions. Intuitively, a lack of exposure to differing perspectives could make them unduly optimistic about their long position. Said differently, given that their long position implies a positive investment thesis about the firm, exposure to those who disagree with them could make them more likely to sell a portion of their holdings, contributing to a reduction in the current stock price and an increase in expected returns. Consistent with this reasoning, we find that the future returns of firms whose investors have more likeminded networks are substantially *lower* than firms whose investors have more diverse networks.

Our paper makes several contributions to the literature. First, we provide novel evidence on how exposure to differing beliefs influences the investment decisions of institutional investors. In doing so, our results add to the growing literature on the far-reaching effects of echo chambers. This literature emphasizes the increasing role of social media in creating echo chambers and has mostly focused on non-financial contexts (e.g., Quattrociocchi et al. 2016; Allcott et al. 2020). Within a financial context, Cookson et al. (2020) finds that StockTwit users in a political echo chamber put less weight on macro events when evaluating micro investments, while Cookson et al. (2023) finds that they are much more likely to follow users whose views coincide with their own. These studies focus on less sophisticated retail investors who presumably do not have large ownership stakes in public firms. Our results extend this literature by providing evidence that a lack of exposure to diverse views has substantial implications for sophisticated institutional investors and, crucially, the price discovery of the firms in their portfolios.

Second, related contemporaneous research by Hirshleifer et al. (2023) and Dyer et al. (2023) uses the same social connectedness data as us to show that social centrality and proximity, respectively, influence information gathering, disagreement, and price discovery. However, these studies do not speak to the potential role of ideological similarities vs. differences (e.g., political preferences) among social connections. By incorporating this likemindedness dimension, our findings complement those of these studies because being in an echo chamber limits the extent of belief revision that occurs when acquaintances converse, which is a central component of these papers' hypotheses (e.g., "social churning" as discussed in Hirshleifer et al. 2023).

Third, we highlight a new and distinct aspect of investor sophistication. In particular, we move beyond traditional splits such as institutional vs. retail, passive vs. active, and transient vs. quasi-indexer vs. dedicated (Bushee 1998), or characteristics that are often used as proxies for investor sophistication, such as their assets under management, the number of stocks in their portfolio, or how they search for information (Drake et al. 2012, 2015; Ben-Rephael et al. 2017). Instead, we measure the likelihood that investors interact with people who have similar beliefs, approaches, and information, and we provide evidence that this appears to influence their ability to make sophisticated investment decisions. Our measure is admittedly indirect, as it relies on and emphasizes the role of an investor's community and surroundings broadly speaking. Nonetheless, our results suggest this new dimension of investor sophistication has important implications for markets that future research should consider.

Finally, we build on the heterogeneous information literature, which is often theoretical and debates whether information diversity leads to more efficient price discovery (e.g., Harris and Raviv 1993; Kim and Verrecchia 1994) or inefficiencies such as price drifts (e.g., Allen et al. 2006). However, empirical evidence on how differing beliefs, as well as *exposure* to differing beliefs, ultimately influences investors' decisions is limited, in large part because the beliefs of others are typically unobservable. Thus, inference is often based on noisy aggregations of beliefs and behavior such as stock prices (Grossman and Stiglitz 1980; Diamond and Verrecchia 1981; Brunnermeier 2005). In a recent exception, Chen (2022) finds that firms whose SEC filings are requested by a more geographically diverse subset of investors have greater earnings announcement trading volume and faster price discovery. Our study complements the findings of Chen (2022) by creating a measure of a lack of exposure to ideological diversity. Our results suggest that social connections to people with diverse beliefs and information sets can improve the decision making of sophisticated investors and lead to more efficient pricing at the firm level.

2. Research Design

2.1. Measuring Likemindedness

We proxy for the extent to which institutional investors are primarily exposed to more likeminded information using the intensity of social media connections between residents of their county and residents of other ideologically similar counties across the U.S. We measure connectedness using Facebook friendships and ideology using Gallup's liberal vs. conservative political scale.

A large literature relies on Facebook data to measure social connections. Within a few years of Facebook's founding, Nadkarni and Hofmann (2012) identified and reviewed dozens of studies on the factors contributing to Facebook use, concluding that the needs for psychological belonging and self-presentation are key motivators. Other studies suggest a role for additional motivators, or at the very least by-products, of social media activity, such as financial gain. For example, Ammann et al. (2022) find that mutual fund managers who are Facebook friends with a firm's executives earn substantial alpha trading the firm's stock, especially when the connection is not included in their public profile(s).

We incorporate ideology because we are interested in the content, not merely the existence, of professional and personal connections. In particular, an individual's behavior, and therefore the content of their interactions with others, has been shown to be heavily influenced by their political beliefs and preferences (Bakshy et al. 2015; Gentzkow 2016; Chen et al. 2023). In addition, political ideology has been found to be correlated with other characteristics that influence behavior and interactions, such as age, socio-economic status, religiosity, and education. Thus, variation across the political spectrum likely captures a broad swath of the factors that influence interaction and diversity in investors' social networks.

Our measure is based on the product of social connectedness and political differences across U.S. counties. Specifically, we compute *LikeMind* for each institutional investor *j* as follows:

$$LikeMind\ Investor_{j,t} = -\frac{1}{N}\sum_{m}^{N} SCI_{j,m} \times |PoliticalIdeo_{j,t} - PoliticalIdeo_{m,t}|. \qquad (1)$$

$SCI_{j,m}$ is a social connectedness index between investor *j*'s location (i.e., county *j*) and another U.S. county *m*, based on Facebook connections as of August 2020.[4] A higher value of *SCI* represents a higher probability that individuals in the county pair are connected, and is formally defined as follows:

$$SCI_{j,m} = \frac{FB\ Connections_{j,m}}{FB\ Users_j \times FB\ Users_m}, \qquad (2)$$

where $FB\ Connections_{j,m}$ is the number of friendship links between residents of counties *j* and *m*, and $FB\ Users_j$ is the number of residents of county *j* with a Facebook account. $PoliticalIdeo_j$ is the political ideology of county *j* using the one to five scale (with one being very conservative and five being very liberal) from the Gallup daily poll.[5] The ideological distance between counties *j*

[4] These data are introduced by Bailey et al. (2018a and 2018b). They find, among other things, that people's Facebook friends influence their financial decisions, such as the decision to transition from renting to owning their housing, even when those friends are geographically distant.
[5] The Gallup Daily U.S. Poll was administered to gauge Americans' opinions and perceptions of political and economic issues. Gallup surveyed between 500 and 1,500 adults per day between 2008 and 2017. The survey data is weighted to account for unequal selection probabilities and to ensure that analysis performed using the responses is representative of the U.S. population. We aggregate individual responses to the county-quarter level to match with the frequency of institutional investor location data.

and m is computed using the absolute difference, with a maximum value of four when one county is very liberal and the other is very conservative.

By incorporating the average political difference between county j and all 3,220 other counties m in the U.S., weighted by the intensity of social interaction between county j and each county m, the measure captures the extent to which the average individual in county j interacts with people of different political persuasions. Finally, we multiply the weighted average by negative one so that higher values reflect greater interaction with people of a similar political persuasion (i.e., greater likemindedness). The maintained assumption of this approach is that the ideologies of institutional investors will be, on average, positively correlated with the overall ideologies of the communities in which they are headquartered.[6] Moreover, even investors with politics that do not line up with the overall ideology of their county will be exposed to and influenced by the opinions expressed by the dominant ideology of that community.

We obtain data on the holdings of institutional investors from quarterly reports of common stock holdings of 13(f) institutions from Thomson Reuters. We obtain the headquarter locations of institutional investors from Nelson's Directory of Investment Managers and by scraping SEC filings. Requiring non-missing data to calculate *LikeMind* and investors' holdings results in a final sample of 82,329 investor-quarter observations during the years 2008 through 2017.

For our primary analyses, we aggregate our investor-level likemindedness measure to the firm-level. We do this by aggregating the degree of exposure to likeminded ideologies across the firm's institutional investor base. This aggregation is weighted by each investor's proportion of holdings each firm-quarter. Specifically, the firm-level likemindedness measure is defined as follows:

[6] Consistent with this assumption, the political science literature has established the importance of local networks on the political behavior of individuals (Weatherford 1982; Zuckerman 2005).

$$LikeMind\ Firm_{i,t} = \sum_{j=1}^{N} (w_{i,j,t} \times LikeMind\ Investor_{j,t}), \qquad (3)$$

where $w_{i,j,t}$ is the proportion of firm i's total institutional holdings held by investor j in quarter t. *LikeMind Investor*$_{j,t}$ is the likemindedness exposure of investor j, as defined above.

2.2. Sample and Variable Definitions

Our sample consists of all U.S. based common stocks listed on the NYSE, NYSE American (formerly AMEX), and NASDAQ exchanges between January 1, 2008 and December 31, 2017. The sample ends in 2017 due to the availability of the Gallup survey data needed to calculate the social connectedness index. Following prior research, we eliminate stocks with prices below $5 to ensure that results are not driven by illiquidity issues, and we require the reporting dates of the earnings announcement in I/B/E/S and COMPUSTAT to be within five calendar days (DellaVigna and Pollet 2009).

Besides likemindedness, the main variables of interest in our models (discussed below) include the earnings surprise and stock returns around the earnings announcement period. *Surprise* is defined as the difference between earnings per share and the most recent consensus analyst forecast, scaled by price ten days before the announcement. *CAR[0,1]* is the difference between the cumulative buy-and-hold return of the announcing firm and that of a size and book-to-market matched portfolio over the two-day period starting on the day of the earnings announcement, while *CAR[2,60]* is the analogous return over the sixty day period starting two days after the announcement.

Further, our interest lies in the effects of likemindedness among investors' networks, as opposed to the effects of a firm's investors' political preferences. Accordingly, we control for the average political ideology of the firm's institutional investor base. We do this through the inclusion of two indicator variables, one for firms with a conservative (*Cons. Investor Base*) and one for firms with a liberal (*Lib. Investor Base*) investor base. Firms are classified as having a conservative (liberal) base if more than 65% of their total institutional ownership is held by investors in right-(left-)leaning counties.[7] Firms with a moderate investor base constitute the omitted category.

We also include several control variables that prior research has found to be related to firms' stock prices and earnings. *Firm Size* is the log of market capitalization. *Book-to-Market* is the log of one plus the book-to-market ratio. *Illiquidity* is the average during the quarter before the earnings announcement of the daily Amihud (2002) measure, calculated as absolute returns divided by dollar trading volume. *Idiosyncratic Volatility* is the standard deviation of daily market-adjusted returns during the quarter before the earnings announcement. *Past Year Return* is the cumulative buy-and-hold market-adjusted return during the prior year. *Analyst Coverage* is the number of analysts forecasting earnings in the prior 30 days. *Analyst Forecast Dispersion* is the standard deviation of analyst forecasts divided by the absolute value of the median forecast. Requiring non-missing data to calculate the variables used in our analyses results in a final sample of 34,617 firm-quarter observations during the years 2008 through 2017.

2.3. Descriptives

We provide a graphical illustration of the geographical variation in likemindedness in Figure 1 at the end of our sample period. We use darker (e.g., red) hues to denote counties with greater values of likemindedness, and lighter (e.g., yellow) hues to denotes counties with lower values of likemindedness. A few patterns emerge from the figure, including that there is substantial variation both across and within regions, and that likemindedness is higher in the eastern U.S. than in the western U.S., on average.

[7] An investor is classified as conservative or liberal if the political ideology of the fund's county is below or above 3 respectively on the Gallup scale with 1 being very conservative and 5 being very liberal.

In Table 1, we list several key data points for the counties with the highest concentration of institutional investors at the end of our sample period. Specifically, we present their likemindedness score, level of social connectedness (SCI), Gallup political ideology, number of investors, total net assets, and population. This table reinforces and adds to the observations arising from Figure 1.[8] For example, San Diego and San Francisco, two large counties within the same state, exhibit quite different social connectedness and political ideology values, which results in San Diego having one of the highest values of likemindedness and San Francisco having one of the lowest.

We present summary statistics for likemindedness and other variables of interest in Table 2. Panel A presents the distribution of the likemindedness measures. The mean of *LikeMind Investor* (*LikeMind Firm*) is about -0.43 (-0.48), which translates to a firm's investors living in a county that is connected with other counties that are almost half a point away from them on the five-point political ideology scale. Panel B shows that investors in counties with lower likemindedness (i.e., low *LikeMind Investor*) tend to hold more stocks and manage more net assets. Panel C shows that there are several significant differences between the highest and lowest *LikeMind Firm* terciles. For example, firms with more ownership by investors in higher *LikeMind* areas have significantly higher earnings surprise and returns, book-to-market ratio, illiquidity, volatility, and past year returns. These differences suggest that *LikeMind* captures a key aspect of investors' portfolio allocation decisions. We are also careful to control for these firm-level economic characteristics throughout our analyses, in addition to firm fixed effects.

[8] In untabulated analyses, our results hold after excluding top-performing funds based on value-weighted quarterly fund returns over the past year, which helps ensure that our results are not driven by skilled funds.

3. Portfolio Concentration

Next, in order to validate that our likeminded measure is connected with institutional investors' decisions, we examine its association with the extent to which they concentrate their portfolios in ideologically similar firms. Intuitively, if an institutional investor is in an echo chamber dominated by a particular political ideology, then we expect them to be more aware of, favorably disposed towards, and likely to invest in, firms that share that same ideology.

We identify firm ideology following the same approach we used for investors; namely, $PoliticalIdeo_{i,t}$ is the political ideology of the county of the headquarters of firm i in quarter t. Similar to our investor-level measure, our maintained assumption is that the ideology of the firm will be correlated with the overall ideology of the community in which the firm is headquartered. We calculate the extent of each investor's portfolio concentration (PC) in firms with similar political ideologies as follows:

$$LikeMind\ PC_j = -\sum_{n}^{N} w_{i,j,t} \times \left|PoliticalIdeo_{j,t} - PoliticalIdeo_{i,t}\right|, \qquad (4)$$

where $w_{i,j,t}$ is the fraction of investor j's total portfolio held in firm i in quarter t, $PoliticalIdeo_{j,t}$ is the political ideology of investor j in quarter t, and $PoliticalIdeo_{i,t}$ is the political ideology of firm i in quarter t.

In Table 3 we present the results of regressing investors' portfolio concentration in ideologically similar firms (*LikeMind PC*) on likemindedness of the location where the investor is headquartered (*LikeMind Investor*). The first four columns present results for the full sample of firms across various fixed effects specifications, all of which include as controls the average number of stocks and total net assets in the investor's portfolio. As shown, we find a positive and statistically significant association between *LikeMind PC* and *LikeMind Investor* in all four regressions, suggesting that investors in locations with high likemindedness are more likely to invest in stocks located in communities with similar political ideologies. An alternative explanation for this result is the possibility that the well-documented local bias in investment is stronger for investors in high likemindedness locations. Thus, in the last four columns of Table 3, we exclude firms headquartered in the same state as the investor and recalculate *LikeMind PC*. As shown, we again observe the same result. Thus, investors in an ideological echo chamber appear to concentrate their portfolios in stocks within the same echo chamber, even when those stocks are geographically distant.

This novel finding provides evidence that the political ideology of sophisticated investors' surroundings and investment options plays a role in their capital allocation decisions. Furthermore, investments in likeminded stocks likely reinforce the walls of an investor's existing echo chamber, or in other words, they receive ideologically consistent and confirmatory information from the people who live and work around them *as well as* from the firms in their portfolio.

4. Primary Analyses – Earnings Response

4.1. Earnings Announcement Window Returns

For our primary tests, we first examine whether likemindedness among a firm's investor base is associated with the immediate return response to earnings surprises. The more a firm's investor base is exposed to likeminded information, the more similar we expect the firm's investors to interpret the earnings news, make conclusions, and trade. Moreover, we expect for likeminded investors to have a more limited awareness of other investors' private information, leading them to put greater weight on the public signal (as well as their own priors). As a result of more investors trading in the same direction and trading on the public signal when likemindedness is high, we predict a larger price reaction in response to the earnings surprise.

Panel A of Figure 2 illustrates the difference in immediate return responses for likeminded and different-minded firms. To measure the difference in return response for likeminded versus different-minded firms, we sort earnings announcements into deciles ordered by earnings surprise, with the sorting done separately by industry-year. Within each decile, we separate the announcements by the likemindedness of the firm; that is, the likeminded (different-minded) firms are those that fall above (below) the median of *LikeMind Firm*. The figure shows that, relative to the immediate return response for different-minded firms, likeminded firms experience a more pronounced reaction to earnings, especially for positive earnings.

To more formally examine this relation, we estimate the following regression:

$$\begin{aligned} CAR_{i,t}^{[0,1]} = {} & Surprise_{i,t} + Surprise_{i,t} \times LikeMind\ Firm_{i,t} \\ & + LikeMind\ Firm_{i,t} + Surprise_{i,t} \times Controls_{i,t} + Controls_{i,t} + FirmFE_i \\ & + YearQuarterFE_t + \varepsilon_{i,t}. \qquad (5) \end{aligned}$$

The coefficient of interest is the interaction between *Surprise* and *LikeMind Firm*. If, as predicted, likeminded firms experience larger return responses after earnings surprises, on average, the coefficient of this interaction should be positive and significant.

We control for the variables discussed in Section 2.2 as well as the interaction between each control and earnings surprise. All independent variables are standardized so that the coefficient units are basis points per standard-deviation increase in the independent variables. Importantly, we include firm fixed effects to control for any time-invariant firm characteristics that may correlate with both investors' exposure to likeminded information as well as the stock price's responsiveness to earnings news. We also include year-quarter fixed effects to control for the differences in return sensitivity across years and quarters. Standard errors are clustered at the firm level.

Table 4 presents the results. In the first column we do not include any fixed effects, while in the second column we add year-quarter fixed effects, and in the third column we additionally add firm fixed effects. As predicted, in all three columns the interaction between *Surprise* and *LikeMind Firm* is positive and significant, indicating that firms whose institutional investors have ideologically homogeneous surroundings experience a larger immediate return response following an earnings surprise. In addition, the economic significance is substantial in that a one standard deviation increase in likemindedness is associated with about a 10% increase in earnings response (based on the baseline coefficients on *Surprise* and *Surprise x LikeMind Firm* in the third column, i.e., 0.232/2.237 = 0.104). Overall, these results support our prediction that firms whose institutional investors tend to reside in echo chambers are subject to stronger earnings responses.

4.2. Post Earnings Announcement Window Returns

A stronger earnings response could indicate multiple scenarios, including a more efficient earnings response in which the price more quickly impounds the news, or a less efficient earnings response in which investors have overreacted to the announcement. Thus, we next investigate how the initial return response to likeminded firms' earnings announcements is associated with subsequent returns. A post-earnings announcement return reversal would suggest a correction and be consistent with an initial overreaction.

To examine this possibility, we estimate the following regression:

$$\begin{aligned} CAR_{i,t}^{[\tau,T]} = {} & CAR_{i,t}^{[0,1]} + CAR_{i,t}^{[0,1]} \times LikeMind\ Firm_{i,t} \\ & + LikeMind\ Firm_{i,t} + CAR_{i,t}^{[0,1]} \times Controls_{i,t} + Controls_{i,t} + FirmFE_i \\ & + YearQuarterFE_t + \varepsilon_{i,t} \qquad (6) \end{aligned}$$

where $CAR_{i,t}^{[\tau,T]}$ is the difference between the cumulative buy-and-hold return of the announcing firm and that of a size and book-to-market matched portfolio over the period from day τ (the second day following the earnings announcement) to day T in the future.

Table 5 presents the results. The estimates in column (1) indicate that a one standard deviation increase in CAR[0,1] is associated with an approximately 42 basis points lower return over the next 60 days. This finding is consistent with the intuition that more information has been incorporated into prices for firms with larger immediate reactions to earnings news, which should, therefore, experience less drift or even a reversal. More importantly, the coefficient on *CAR[0,1] x LikeMind Firm* indicates that the reversal increases by about 30 basis points, or 70%, for each standard deviation increase in *LikeMind Firm*.

In columns (2) through (4), we examine this phenomenon at longer horizons to better understand the nature of the pricing effects of likemindedness on earnings news. We find that most of the reversal occurs during the 60 days immediately following the earnings announcement. In particular, the result becomes less pronounced as we progressively expand the return measurement window from 60 to 120 days. Together, the results in Tables 4 and 5 are consistent with likemindedness exacerbating overreactions to earnings announcement news.

5. Additional Analyses

5.1. Mechanism Test – Twitter

In this section we provide evidence on one potential mechanism through which institutional investors' exposure to likeminded networks may translate into the overreactions to earnings announcement news documented in the prior section – namely, social media discussion about the firm around its earnings announcement. To do this, we analyze the amount and information content of tweets issued on the day the firm announces earnings, as Twitter is a key channel through which homogenous beliefs have been shown to be reinforced and propagated (Cota et al. 2019; Cinelli et al. 2021; Di Tella et al. 2021; Campbell et al. 2022). Such reinforcement of preexisting attitudes can lead individuals to hold more extreme beliefs (Sunstein 2002) and, among other things, overreact to earnings news. Accordingly, we predict that the amount and extreme emotion of earnings announcement Twitter activity related to firms with more likeminded investor bases will increase due to echo chamber effects.

We use the Twitter Academic Research API to collect information on all tweets containing each firm's cash tag on the date of their earnings announcement. In addition, we identify those tweets that fall in the top 10% of extreme sentiment, which we measure based on the percentage of words related to anger, fear, happiness, sadness, or surprise, using the word lists developed by Ekman (1992). Our expectation is that higher levels of likemindedness are associated with more total tweets overall, as well as more tweets that contain extreme emotional language.

Table 6 presents the results of our Twitter analysis. In column (1), we find that there are significantly more tweets on earnings announcement days for firms with investors that have higher likemindedness. In column (2), we see that the use of emotional language in announcement-day tweets about these firms is significantly higher compared to other firms. These findings support the conjecture that likemindedness leads to more extreme beliefs and overreaction to news. Overall, the Twitter landscape reflects both higher activity and more extreme sentiment following the earnings announcements of firms with more likeminded investor bases. This evidence is consistent with our prior findings that the announcements of firms held by more likeminded investors incite more extreme reactions to earnings news due to the echo chambers created among more ideologically homogeneous actors.

5.2 Likemindedness in the Cross-Section: Information Environment

Next, we investigate the impact of a firm's information environment on the effects of likemindedness on price reactions to earnings news. Our basic conjecture is that a rich information environment can help offset the harmful effects of investor likemindedness. Intuitively, if less information is made publicly available by the firm and information intermediaries, investors are more likely to put weight on ideologically driven and sentiment-based information from their social networks, leading them to overreact to earnings news.

We identify five characteristics as proxies for various aspects of the firm's information environment: firm size, analyst coverage, analyst forecast dispersion, idiosyncratic volatility, and illiquidity. *Firm Size* is measured as the market capitalization one day prior to the earnings announcement. Small firms are less diversified and have less information available for the market than large firms. Small firms also likely have fewer customers, suppliers, and shareholders, and are covered less by intermediaries such as analysts and the media.

Analyst Coverage is measured as the number of analysts that make an earnings forecast for the current quarter. Analysts collect, digest, and distribute information about a firm's performance. There is evidence that larger analyst coverage corresponds to more information available about the firm, which implies less uncertainty. Lang and Lundholm (1996) find that analyst coverage is positively associated with disclosure scores. Hong et al. (2000) use larger analyst coverage as an indicator for less information asymmetry. *Analyst Forecast Dispersion* is measured as the standard deviation of analyst forecasts for the current earnings quarter scaled by the stock price ten trading days prior to the earnings announcement. In prior literature, forecast dispersion is widely used to proxy for the uncertainty about future earnings or the degree of consensus among analysts or market participants (e.g., Barron et al. 1998).

Idiosyncratic Volatility is measured as the average market-adjusted stock volatility in the trading week prior to the earnings announcement. Idiosyncratic volatility has been shown to be associated with higher levels of private information and less informed trading (Ferreira and Laux 2007). *Illiquidity* is the average during the quarter before the earnings announcement of the daily Amihud (2002) measure, calculated as absolute returns divided by dollar trading volume. Illiquidity is increasing in the asymmetry of information between traders (Glosten and Milgrom 1985; Kyle 1985; Easley et al. 2002).

To test how these five dimensions of information quality and uncertainty moderate the association between likemindedness and stock price responses to earnings announcements, we repeat our main tests on subsamples that include the highest and lowest terciles of these measures. Panel A of Table 7 presents the results for the immediate return response to earnings news. We find that our main results are concentrated among firms with poorer information environments. Specifically, the likemindedness of a firm's investor base is associated with larger earnings responses for small firms, firms with low analyst coverage and high analyst dispersion, and firms with high idiosyncratic volatility and high illiquidity. In contrast, we do not observe a significant association between likemindedness and the earnings response in any of the subsamples of firms with richer information environments. In addition, the differences in coefficients are significant in the analyst following and forecast dispersion regressions.

Panel B of Table 7 presents analogous results for our return reversal tests. The results are largely consistent with Panel A in that they demonstrate that likemindedness leads to stronger reversals for informationally opaque firms. Specifically, the association between long-term return reversals and likemindedness is greater for small firms, firms with low analyst coverage, firms with high idiosyncratic volatility, and firms with high liquidity. For analyst forecast dispersion, the coefficient on *CAR[0,1] x LikeMind Firm* is significantly more negative for the high tercile than the low tercile, although neither coefficient is statistically significant by itself. Overall, the evidence in this section suggests that echo chamber effects among institutional investors are more likely to occur when there is a poorer information environment that leads to investment uncertainty. Similarly, the lack of a significant association between likemindedness and earnings responses or reversals in the subsamples of firms with richer information environments suggests that a healthy amount of public information can reduce the negative effects of likeminded investor networks.

5.3 Likemindedness in the Cross-Section: Within Investor Base Variation in Political Ideology

Our primary tests emphasize the role of an investor's local community and are therefore based on the extent to which a firm's institutional investors individually reside in counties that could be described as echo chambers. However, investors often interact with others holding the same investments, such as at investor conferences. Thus, in this section we also consider whether the firm's investor base as a whole is itself an echo chamber. We do so by measuring variation in the political ideologies of a given firm's institutional investors.

To do this, we measure the standard deviation (SD) of the political ideologies of the counties of all of the firm's institutional investors, weighted by the fraction of total institutional ownership held by each investor. We then create a binary indicator, *Low PolIdeo SD,* which takes the value of 1 if the standard deviation of the weighted political ideology of a firm's investor base is below the sample median, and 0 otherwise. We then augment our main regressions (see equations 5 and 6) with a triple interaction between *Low PolIdeo SD*, *LikeMind Firm,* and either *Surprise* or *CAR[0,1]*.

We report the results in Table 8. Panel A shows that the greater response to earnings news among firms with higher likemindedness is strongest for those firms with concentrated investor base political ideologies (*Low PolIdeo SD* = 1). Similarly, Panel B shows that the greater post-earnings-announcement reversal among firms with higher likemindedness is concentrated among firms with *Low PolIdeo SD* = 1; although this latter result only becomes statistically significant with the inclusion of time and firm fixed effects. These results provide evidence that the firm's investor base being an echo chamber can exacerbate issues arising from its institutional investors residing in echo chambers. This result is intuitive, as it seems plausible that an investor who gets confirmatory information from others in their community would be more likely to make investment mistakes if they get further confirmatory information from other investors of the same firm.

5.4 Portfolio Sorts

Our results to this point are consistent with the notion that greater likemindedness among a firm's investor base is associated with overreactions to earnings announcement news. Likemindedness may similarly lead investors to overreact more broadly to any other information in their possession, up to and including their overall investment thesis about the firm. If so, then likemindedness could influence the overall price level beyond price discovery around earnings announcements. For example, a lack of exposure to differing perspectives could result in a firm's current investors being unduly optimistic about their long positions. Said differently, given that their long positions imply a positive investment thesis about the firm, exposure to those who disagree with them could make them more likely to sell a portion of their holdings, contributing to a reduction in the current stock price and an increase in expected returns. To provide evidence on whether likemindedness has this type of broad impact on asset prices, in our final analysis we examine the performance of a portfolio that is long firms with high likemindedness and short firms with low likemindedness.

Specifically, each month we form a zero-cost portfolio that is long (short) stocks in the top tercile (bottom) of *LikeMind Firm*, where *LikeMind Firm* is calculated at the start of the month. Panel A of Table 9 shows the raw average monthly returns of both equal- and value-weighted portfolios sorted by terciles of *LikeMind Firm*. We see that the returns of a portfolio containing the highest tercile of likeminded firms performs significantly worse than the portfolio containing the lowest tercile. On an annual basis, the raw underperformance of likeminded firms amounts to 4.78% (4.36%) for the equal (value)-weighted portfolio.

In Panel B of Table 9, we control for risk by regressing the returns of the long-short likemindedness portfolio on the returns to major risk factors, including the market return, size, book-to-market, momentum, profitability, and investment. Standard errors are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with four lags. The likemindedness portfolio consistently yields significant negative alphas. Moreover, the economic significance of the alphas is nearly as large as the raw returns. That is, based on the Fama-French Five Factor plus Momentum model in the final column, the alpha amounts to 4.26% for the equal-weighted portfolio and 3.89% for the value-weighted portfolio. While these results help rule out our results being driven by differential risk across stocks, they do not necessarily suggest that likemindedness is a risk or mispricing factor. For example, likemindedness at the firm level could be correlated with other factors not included in the models, such as the many anomalies identified in prior research that seem to be related to overreaction and other biases.

These results are consistent with the notion that firms with more likeminded investor bases can be overpriced relative to other firms. It is unclear why arbitrageurs do not step in to correct the mispricing. One possibility is that it is riskier to do so when more of a firm's significant investors are biased (i.e., insulated from differing perspectives) and could further exacerbate mispricing at any time, which would at least temporarily move the price against the arbitrageur's position. Relatedly, this finding dovetails with our previous evidence that the effect of likemindedness on prices is more pronounced for informationally opaque firms, which are notoriously more difficult to arbitrage.

6. Conclusion

There is a vast quantity of information that is relevant to investors' portfolio decisions. Because each investor can only be exposed to a subset of the total available information, diversity within that subset may help them obtain a more representative, complete picture that leads to better investment decisions. In this study, we measure the ideological diversity of institutional investors' surroundings using the social media connections and political beliefs of the communities where they reside. Our results suggest that likemindedness in institutional investors' surroundings influences which stocks they hold, how they react to earnings news, and the resulting price discovery and price levels of public stocks.

Specifically, we find that institutional investors in U.S. counties with greater likemindedness are more likely to hold stocks of firms that are headquartered in counties with a similar political ideology. Most importantly, we find that the stock prices of firms held by a greater proportion of investors from high likemindedness areas react more strongly to earnings surprises, and that these firms experience stronger subsequent return reversals. We provide evidence that extreme Twitter activity may be one channel through which these overreactions to earnings effects occur. These results are concentrated among firms with poorer information environments, and firms with more likeminded investor bases appear to be more likely to experience overpricing more generally, suggesting that likemindedness leads investors to be overly optimistic about their investment theses. Overall, our findings contribute to the literature by providing evidence that even relatively sophisticated investors may be subject to echo chamber effects, by highlighting a novel aspect of investor sophistication, and by demonstrating how exposure to heterogeneous beliefs can influence investors' portfolio allocation decisions and, ultimately, market efficiency.

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Figure 1: Geographic Dispersion in Likemindedness

This figure illustrates county-level likemindedness in 2017. Darker red hues denote counties with higher values of *LikeMind*.

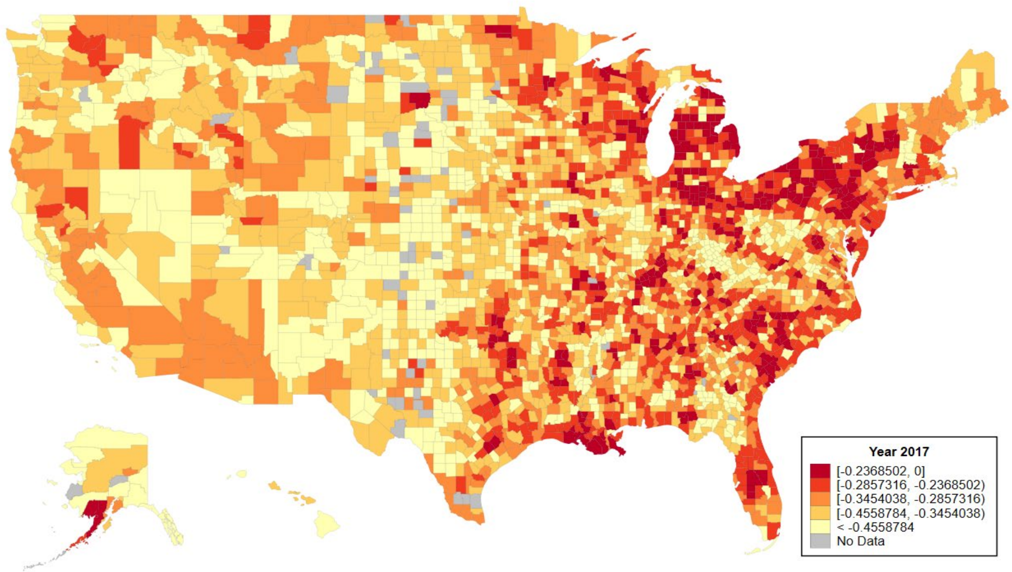
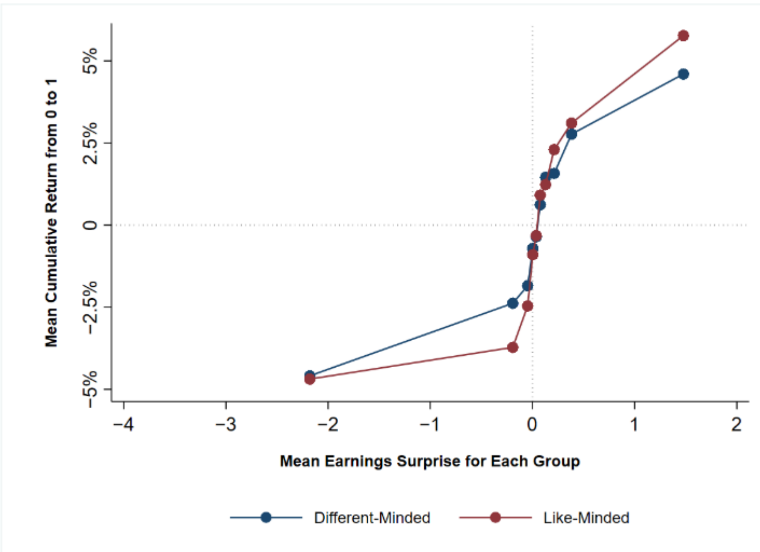


Figure 2: Likemindedness and Returns Following Earnings News

This figure illustrates our main results on the return response to earnings news. Panel A shows earnings announcement returns (i.e., during the trading day of and the trading day following the earnings announcement) across earnings surprise deciles. Panel B shows returns during the quarter following the earnings announcement (i.e., from 2 to 60 trading days following the earnings announcement) across deciles of earnings announcement returns. Before calculating mean returns, we split the sample based on *LikeMind Firm*. The like-minded (different-minded) firms are those that fall above (below) the median of *LikeMind Firm*.

Panel A: Immediate Return Response to Earnings News



Panel B: Return Reversals vs. Continuation After Earnings News

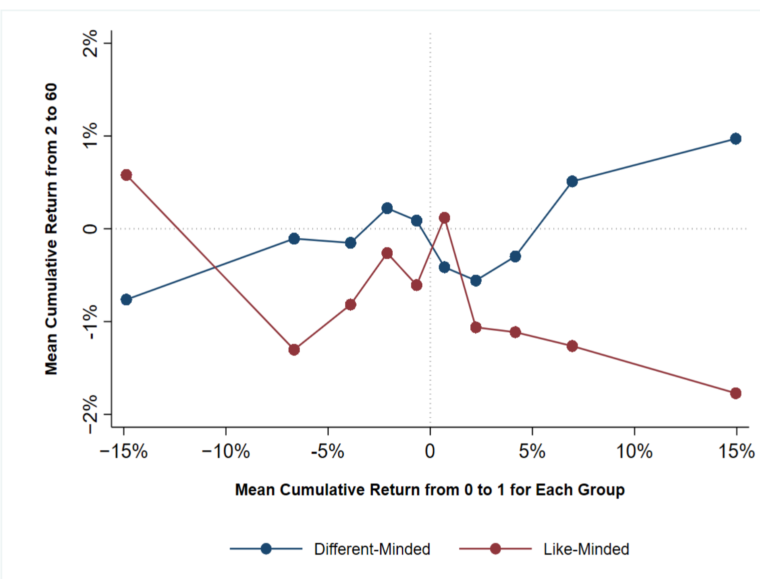


Table 1: U.S. Counties with the Highest Concentrations of Institutional Investors

This table presents descriptive statistics for counties with the highest concentrations of institutional investors as of the 4th quarter of 2017. Counties are ranked by the number of institutional investors located in the county. *LikeMind* is a county-level measure based on the absolute differences in political ideology weighted by the social connectedness between county *j* and all other counties *m-j* in the U.S., as defined in equation (1). *SCI* is the average number of Facebook friendship links between residents of counties *j* and all other counties *m-j* in the US, scaled by the product of the number of Facebook users in counties *j* and all other counties *m-j*. *Political Ideo* is the average political ideology of the county as measured by the Gallup Daily Survey, where 1 is very conservative and 5 is very liberal. #Investors and Total TNA are the sums of the number of 13(f) institutional investors and their total net assets under management, respectively. Population is from the US Census.

County	*LikeMind*	*SCI*	*Political Ideo*	#Investors	Total TNA ($billions)	Population (millions)
New York County, NY	-0.651	1499	3.61	566	2,690	1.600
Suffolk County, MA	-0.536	2050	3.48	143	3,040	1.526
Cook County, IL	-0.489	2091	3.19	107	803	5.200
Los Angeles County, CA	-0.486	1133	3.17	97	954	9.800
Fairfield County, CT	-0.329	1719	3.13	93	197	0.917
San Francisco County, CA	-0.770	1757	3.69	77	405	0.805
Harris County, TX	-0.350	2721	2.80	46	57	4.100
Dallas County, TX	-0.396	3356	2.83	39	103	2.400
Hennepin County, MN	-0.470	4805	3.16	37	121	1.200
King County, WA	-0.669	2188	3.44	36	146	1.900
San Diego County, CA	-0.407	5044	3.07	30	207	3.286
Fulton County, GA	-0.478	1823	3.03	30	35	3.100
St. Louis County, MO	-0.393	4194	2.99	28	29	0.999
San Mateo County, CA	-0.543	1218	3.37	27	185	0.718
Hamilton County, OH	-0.367	3887	2.95	26	159	0.802
Westchester County, NY	-0.410	1535	3.27	26	43	0.949
Allegheny County, PA	-0.407	2881	3.05	25	394	1.200
Montgomery County, PA	-0.335	1961	3.08	25	41	0.861
Marin County, CA	-0.614	2131	3.49	24	31	0.252
Milwaukee County, WI	-0.326	2346	3.02	23	29	0.928
Chester County, PA	-0.311	3379	2.98	23	78	0.948
Denver County, CO	-0.616	2832	3.23	21	551	0.711
Baltimore city, MD	-0.485	1143	2.90	21	55	3.000
Montgomery County, MD	-0.541	4593	3.31	21	36	1.055
Orange County, CA	-0.341	1838	3.34	21	41	0.972
Cuyahoga County, OH	-0.355	2589	3.03	19	59	1.249
Travis County, TX	-0.656	1723	3.40	18	20	1.500
Middlesex County, MA	-0.485	2816	3.03	18	18	0.538
New Castle County, DE	-0.304	3699	3.25	18	229	1.000
Santa Clara County, CA	-0.476	1045	3.24	17	13	1.800

Table 2: Summary Statistics

This table reports the summary statistics for key variables used in the analysis. Panel A presents the statistics for our investor-level and firm-level likemindedness measure. Panel B presents the statistics for investor-level characteristics. Like-minded (different-minded) investors are those that fall above (below) the median of *LikeMind Investor*. Panel C presents the statistics for our main earnings measures as well as several firm-level characteristics. Like-minded (different-minded) firms are those that fall above (below) the median of *LikeMind Firm*.

Panel A: Distribution of Likemindedness Measure

	Mean	Std. Dev.	p25	50th	p75	No. Obs.
LikeMind Investor	−0.437	0.152	-0.567	-0.417	-0.299	82,329
LikeMind Firm	−0.477	0.041	-0.500	−0.473	-0.451	34,617

Panel B: Summary Statistics of Like-Minded and Different-Minded Institutional Investors

	Like-Minded Investors		Different-Minded Investors			
	Mean	Std. Dev.	Mean	Std. Dev.	Difference in Means	t-stat
#Stocks	169.37	(317.65)	178.50	(392.00)	-9.13	-3.878
Total Net Assets (billions)	2.61	(0.296)	5.40	(0.393)	-2.78	-12.146

Panel C: Summary Statistics of Like-Minded Firms and Different-Minded Firms

	Firms with Like-Minded Investors		Firms with Different-Minded Investors			
	Mean	Std. Dev.	Mean	Std. Dev.	Difference in Means	t-stat
Surprise	0.059	(1.431)	−0.017	(1.939)	0.076	3.391
CAR[0,1]	0.318	(7.906)	0.039	(8.610)	0.279	2.564
CAR[2,60]	−0.250	(15.553)	0.131	(17.854)	−0.382	−1.731
Firm Size	7.905	(1.542)	8.007	(1.524)	−0.102	−5.054
Book-to-Market	0.566	(0.441)	0.511	(0.607)	0.055	7.940
Illiquidity	−7.204	(1.901)	−7.400	(1.912)	0.196	7.812
Idiosyncratic Volatility	0.343	(0.188)	0.332	(0.186)	0.011	4.373
Past Year Return	17.071	(66.941)	13.606	(61.087)	3.465	4.108
Analyst Coverage	8.833	(5.754)	8.963	(6.349)	−0.130	−1.626
Analyst Forecast Dispersion	0.196	(0.538)	0.260	(0.971)	−0.064	−6.231

Table 3: Institutional Likemindedness and Portfolio Concentration in Ideologically Similar Firms

This table presents the results from OLS regressions examining the effect of investor-county likemindedness on portfolio concentration in likeminded firms. The regressions are run at the investor-quarter level. Portfolio concentration is the inverse of a holdings weighted average ideological distance between investor *j* and firm *i* in each quarter *t*. Specifically, the Likeminded Portfolio Concentration measure (*LikeMind PC*) is computed as $-\sum w_{ijt}\left|PoliticalIdeo_{j,t} - PoliticalIdeo_{i,t}\right|$, where $w_{i,j,t}$ is the fraction of the investor's total portfolio held in firm *i, PoliticalIdeo*$_{j,t}$ is the political ideology of investor *i* in quarter *t*, and *PoliticalIdeo*$_{i,t}$ is the political ideology of firm *i*. The political ideology is based on the average county-level political ideology from the Gallup Daily Poll. Local firms are considered to be firms headquartered in the same state as the investor. Standard errors are clustered at the investor level. t-statistics are reported in parentheses.

	Portfolio Concentration in Ideologically Similar Firms (Y = *LikeMind PC*)							
	All Firms				**Excluding Local Firms**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LikeMind Investor	**0.417*** **	**0.348*** **	**0.390*** **	**0.312*** **	**0.385*** **	**0.335*** **	**0.374*** **	**0.296*** **
	(32.18)	**(14.68)**	**(14.66)**	**(12.45)**	**(29.79)**	**(14.30)**	**(14.25)**	**(12.08)**
Avg. # of Stocks	0.006***	-0.001	0.001	0.001	0.008***	0.001	0.002	0.002
	(3.88)	(-0.26)	(0.39)	(0.51)	(4.73)	(0.21)	(0.85)	(0.94)
Total Net Assets	0.005***	0.008***	0.001	0.001	0.003***	0.008***	0.001	0.001
	(4.08)	(4.75)	(0.59)	(0.44)	(3.00)	(4.77)	(0.74)	(0.59)
Investor FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year-Quarter FE	No	No	Yes	Yes	No	No	Yes	Yes
County FE	No	No	No	Yes	No	No	No	Yes
N	82,329	82,329	82,329	82,329	82,329	82,329	82,329	82,329
R-squared	0.206	0.773	0.784	0.794	0.179	0.773	0.782	0.793

Table 4: Immediate Return Response to Earnings News

This table reports the results of regressions examining the effect of firm likemindedness on the immediate response to earnings surprises. The dependent variable in all regressions is *CAR[0,1]*, which is the market adjusted return from the close on the trading day prior to the earnings announcement to the close on the trading day after the earnings announcement. *LikeMind Firm* is a firm-level measure. *Surprise* is computed as the difference between the actual reported earnings and the consensus analyst forecast scaled by the price. Controls include the indicators for the political slant of the firm's investor base, log of the average market capitalization, average annual book-to-market ratio, average market-adjusted volatility, past year return, the number of analysts covering the firm in the previous quarter, and the interactions between the controls and earnings surprise. Standard errors are clustered at the firm level. t-statistics are reported in parentheses.

		CAR[0,1]	
	(1)	(2)	(3)
Surprise	2.041***	2.044***	2.237***
	(5.267)	(5.265)	(5.460)
Surprise × LikeMind Firm	**0.248****	**0.251****	**0.232***
	(2.152)	**(2.165)**	**(1.843)**
LikeMind Firm	0.068	0.080	0.213*
	(1.267)	(1.032)	(1.959)
Surprise x Cons. Investor Base	1.590	1.568	0.935
	(1.467)	(1.462)	(0.803)
Cons. Investor Base	0.041	0.036	0.312
	(0.067)	(0.060)	(0.458)
Surprise x Lib. Investor Base	-0.305	-0.303	-0.311
	(-0.751)	(-0.749)	(-0.678)
Lib. Investor Base	0.281**	0.233	0.056
	(2.119)	(1.611)	(0.341)
Surprise × Firm Size	-0.251	-0.232	0.143
	(-0.506)	(-0.467)	(0.275)
Firm Size	0.297**	0.246*	-2.339***
	(2.081)	(1.698)	(-5.665)
Surprise × Book-to-Market	-0.078**	-0.077**	-0.078*
	(-2.273)	(-2.253)	(-1.752)
Book-to-Market	-0.093	-0.087	-0.282**
	(-1.558)	(-1.433)	(-2.116)
Surprise × Illiquidity	-0.095	-0.079	0.161
	(-0.243)	(-0.203)	(0.386)
Illiquidity	0.574***	0.557***	1.147***
	(3.733)	(3.584)	(3.517)
Surprise × Idiosyncratic Volatility	-0.270**	-0.270**	-0.295**
	(-2.356)	(-2.351)	(-2.317)
Idiosyncratic Volatility	-0.083	-0.127*	0.281***
	(-1.233)	(-1.656)	(2.652)

Table 4 – *Continued*

	CAR[0,1]		
	(1)	(2)	(3)
Surprise × Past Year Return	0.356***	0.357***	0.390***
	(3.576)	(3.589)	(3.553)
Past Year Return	-0.090	-0.048	-0.340***
	(-1.498)	(-0.717)	(-4.256)
Surprise × Analyst Coverage	0.448	0.444	0.382
	(1.489)	(1.472)	(1.202)
Analyst Coverage	0.068	0.099*	-0.002
	(1.335)	(1.891)	(-0.030)
Surprise × Analyst Forecast Dispersion	-0.063***	-0.063***	-0.054**
	(-2.818)	(-2.797)	(-2.276)
Analyst Forecast Dispersion	0.207**	0.215**	0.149
	(2.320)	(2.367)	(1.449)
Year-Quarter FE	No	Yes	Yes
Firm FE	No	No	Yes
N	34,617	34,617	34,617
R-squared	0.024	0.026	0.128

Table 5: Likemindedness and Return Reversals After Earnings News

This table reports estimates from regressions examining the effects of firm-level likemindedness on return reversals after earnings surprises. The dependent variable is the cumulative abnormal return beginning two days after the announcement up to 60 days (column 1), 75 days (column 2), 90 days (column 3) and 120 days (column 4) after the announcement. *LikeMind Firm* is a firm-level measure. Controls include indicators for the political slant of the firm's investor base, the log of the average market capitalization, average annual book-to-market ratio, average market-adjusted volatility, past year return, the number of analysts covering the firm in the previous quarter, and the interactions between the controls and *CAR[0,1]*. Standard errors are clustered at the firm level. t-statistics are reported in parentheses.

	CAR[2,60]	**CAR[2,75]**	**CAR[2,90]**	**CAR[2,120]**
	(1)	(2)	(3)	(4)
CAR[0,1]	-0.424***	-0.990***	-0.998***	-1.191***
	(-3.104)	(-6.583)	(-6.260)	(-6.416)
CAR[0,1] × LikeMind Firm	**-0.295****	**-0.287***	-0.257	-0.181
	(-2.032)	**(-1.800)**	(-1.561)	(-0.902)
LikeMind Firm	0.469*	0.558*	0.530	0.753*
	(1.935)	(1.827)	(1.497)	(1.770)
CAR[0,1] x Cons. Investor Base	0.296	0.488	0.446	-0.244
	(0.152)	(0.205)	(0.143)	(-0.085)
Cons. Investor Base	-1.143	-0.305	-0.346	-2.264
	(-0.662)	(-0.148)	(-0.155)	(-0.926)
CAR[0,1] x Lib. Investor Base	0.033	-0.174	-0.018	-0.374
	(0.095)	(-0.454)	(-0.043)	(-0.716)
Lib. Investor Base	-0.099	-0.187	-0.216	-0.254
	(-0.316)	(-0.491)	(-0.491)	(-0.489)
CAR[0,1] × Firm Size	-0.053	0.311	0.277	0.200
	(-0.126)	(0.633)	(0.555)	(0.312)
Firm Size	-8.053***	-11.161***	-12.678***	-15.786***
	(-8.221)	(-8.741)	(-8.497)	(-8.633)
CAR[0,1] × Book-to-Market	-0.043	-0.001	0.020	-0.049
	(-0.331)	(-0.007)	(0.120)	(-0.231)
Book-to-Market	-0.397	-0.725**	-0.649	-1.140**
	(-1.480)	(-1.965)	(-1.513)	(-2.105)
CAR[0,1] × Illiquidity	0.455	0.777	0.552	0.466
	(1.050)	(1.553)	(1.115)	(0.707)
Illiquidity	3.392***	4.936***	5.863***	8.385***
	(4.144)	(4.871)	(4.888)	(5.748)
CAR[0,1] × Idiosyncratic Volatility	-0.397**	-0.430**	-0.358	-0.502*
	(-2.269)	(-2.322)	(-1.632)	(-1.957)
Idiosyncratic Volatility	0.573**	0.635*	0.797**	1.608***
	(2.089)	(1.825)	(2.182)	(3.038)

Table 5 – *Continued*

	CAR[2,60]	CAR[2,75]	CAR[2,90]	CAR[2,120]
	(1)	(2)	(3)	(4)
CAR[0,1] × Past Year Return	0.348***	0.224	0.216	0.396**
	(2.591)	(1.605)	(1.394)	(1.980)
Past Year Return	-1.209***	-1.767***	-2.031***	-2.762***
	(-5.590)	(-5.555)	(-5.104)	(-5.498)
CAR[0,1] × Analyst Coverage	0.468***	0.420**	0.453***	0.529**
	(3.282)	(2.496)	(2.604)	(2.538)
Analyst Coverage	-0.299**	-0.565***	-0.657***	-0.722***
	(-2.164)	(-3.293)	(-3.461)	(-3.299)
CAR[0,1] × Analyst Forecast Dispersion	0.153**	0.024	-0.058	-0.048
	(2.193)	(0.291)	(-0.750)	(-0.519)
Analyst Forecast Dispersion	-0.021	0.137	0.121	0.021
	(-0.126)	(0.648)	(0.655)	(0.097)
Year-Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	34,617	34,543	34,445	34,105
R-squared	0.133	0.150	0.166	0.188

Table 6: Likemindedness and Twitter Activity

This table reports estimates from regressions examining the association between likemindedness and tweets pertaining to the firm at its earnings announcement. The dependent variable in column (1) is the log of the total number of tweets containing a firm's cash tag on the earnings announcement day. The dependent variable in column (2) is a dummy variable that takes a value of 1 if the firm's tweets fall in the top 10% of extreme sentiment, and 0 otherwise. Extreme sentiment is defined by computing the total number of words associated with five extreme emotions (anger, fear, happiness, sadness, and surprise) as a percentage of all words tweeted on earnings announcement dates. Controls include indicators for the political slant of the firm's investor base, the log of the average market capitalization, average annual book-to-market ratio, average market-adjusted volatility, past year return, the number of analysts covering the firm in the previous quarter, and the interactions between the controls and the absolute value of *Surprise*. Standard errors are clustered at the firm level. t-statistics are reported in parentheses.

Dependent Variables:	***Number of Tweets***	***Extreme Sentiment***
	(1)	(2)
|*Surprise*|	0.089***	-0.009*
	(5.525)	(-1.656)
|*Surprise*| × *LikeMind Firm*	**0.015****	**0.008***
	(2.028)	**(1.960)**
LikeMind Firm	-0.011	0.005
	(-1.029)	(0.894)
Controls and Controls x |*Surprise*|	Yes	Yes
Year-Quarter FE	Yes	Yes
Firm FE	Yes	Yes
N	28,848	28,848
R-squared	0.870	0.366

Table 7: Likemindedness in the Cross-Section

This table presents estimates from subsample regressions. We perform sample splits based on terciles of the following firm characteristics: firm size, analyst coverage, analyst forecast dispersion, idiosyncratic volatility, and illiquidity. A firm is in the *low* (*high*) sample if it falls into the bottom (top) tercile of each of the aforementioned characteristics. The dependent variable in Panel A is the cumulative abnormal return from the close of the day prior to the earnings announcement to the close of the day of the earnings announcement. The dependent variable in Panel B is the cumulative abnormal return from the close of the day after the earnings announcement to the close 60 days after the announcement. Controls include indicators for the political slant of the firm's investor base, the log of the average market capitalization, average annual book-to-market ratio, average market-adjusted volatility, past year return, the number of analysts covering the firm in the previous quarter, and the interactions between the controls and *Surprise* in Panel A and *CAR[0,1]* in Panel B. Standard errors are clustered at the firm level. t-statistics are reported in parentheses for the regression coefficients F-statistics are reported in parentheses for the test of the difference in coefficients.

Panel A: Immediate Return Response to Earnings News

	CAR[0,1]									
	Firm Size		*Analyst Coverage*		*Analyst Forecast Dispersion*		*Idiosyncratic Volatility*		*Illiquidity*	
Subsample	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Surprise	3.067***	5.653***	5.306***	1.540**	25.060	1.855***	17.376***	1.804***	2.220	2.550***
	(3.044)	(3.532)	(3.188)	(2.326)	(1.382)	(5.597)	(7.641)	(4.893)	(1.127)	(3.655)
Surprise × LikeMind Firm	**0.280****	**-0.761**	**0.456*****	**0.189**	**-1.258**	**0.392*****	**-0.192**	**0.379*****	**-0.389**	**0.316*****
	(2.476)	**(-1.595)**	**(3.590)**	**(0.392)**	**(-0.549)**	**(3.017)**	**(-0.313)**	**(2.868)**	**(-0.688)**	**(2.672)**
LikeMind Firm	0.264	-0.120	0.229	0.081	0.171	0.180	0.118	0.604***	-0.429**	0.217
	(1.362)	(-0.704)	(1.322)	(0.422)	(0.811)	(1.011)	(0.781)	(2.887)	(-2.000)	(1.169)
Interaction Coefficient Difference	1.041 (0.28)		0.267** (4.73)		1.650*** (9.75)		-0.571 (-0.14)		-0.705 (-0.09)	
Controls and Controls x *Surprise*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,288	11,611	11,570	11,449	11,183	11,116	11,472	11,238	11,590	11,277
R-squared	0.193	0.112	0.229	0.145	0.237	0.177	0.197	0.182	0.114	0.196

Table 7 – *Continued*

Panel B: Long-Term Return Reversals After Earnings Announcements										
	CAR[2,60]									
	Firm Size		*Analyst Coverage*		*Analyst Forecast Dispersion*		*Idiosyncratic Volatility*		*Illiquidity*	
Subsample	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CAR[0,1]	−0.766	−1.177**	−1.789*	−0.680*	0.920	−0.512	−0.359	−0.629	−1.533***	−1.510***
	(−1.304)	(−2.348)	(−1.718)	(−1.756)	(0.375)	(−1.595)	(−0.441)	(−1.526)	(−2.610)	(−2.677)
CAR[0,1] × LikeMind Firm	**−0.472*** **	**−0.045**	**−0.525** **	**−0.272**	**−0.010**	**−0.313**	**0.407* **	**−0.367* **	**0.068**	**−0.489** **
	(−2.643)	**(−0.226)**	**(−2.541)**	**(−1.205)**	**(−0.046)**	**(−1.530)**	**(1.864)**	**(−1.957)**	**(0.292)**	**(−2.472)**
LikeMind Firm	0.685*	1.033***	0.837**	−0.117	0.815**	0.380	0.241	0.900*	1.032***	0.515
	(1.758)	(2.930)	(2.269)	(−0.260)	(2.172)	(0.808)	(0.864)	(1.835)	(2.709)	(1.274)
Interaction Coefficient Difference	-0.427 (0.00)		-0.253 (2.44)		0.303** (5.90)		0.774* (3.45)		0.557 (0.03)	
Controls and Controls x *CAR[0,1]*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,288	11,611	11,570	11,449	11,183	11,116	11,472	11,238	11,590	11,277
R-squared	0.201	0.106	0.248	0.131	0.198	0.195	0.170	0.192	0.114	0.206

Table 8: Likemindedness and the Standard Deviation of Investor Political Ideology

This table reports estimates from regressions examining variation in the association between *LikeMind Firm* and return reactions across different levels of standard deviation within the political ideologies of a firm's investor base. Panel A examines the immediate response to earnings news and Panel B examines return reversals. *Low PolIdeo SD* is a binary indicator which takes the value of 1 if the standard deviation of the weighted political ideology of a firm's investor base is below the median standard deviation in the sample, and 0 otherwise. Political ideology is the average ideology reported from the Gallup daily poll. The standard deviation of political ideology is weighted by the fraction of total institutional ownership held by each investor. Controls include indicators for the political slant of the firm's investor base, the log of the average market capitalization, average annual book-to-market ratio, average market-adjusted volatility, past year return, the number of analysts covering the firm in the previous quarter, and the interactions between the controls and Surprise (Panel A) or *CAR[0,1] (Panel B).* Standard errors are clustered at the firm level. t-statistics are reported in parentheses.

Panel A: Immediate Return Response to Earnings News

		CAR[0,1]	
	(1)	(2)	(3)
Surprise	2.195***	2.198***	2.373***
	(5.89)	(5.89)	(6.00)
Surprise × LikeMind Firm	**-0.344**	**-0.327**	**-0.324**
	(-1.10)	**(-1.05)**	**(-0.94)**
Surprise × LikeMind Firm x Low PolIdeo SD	**0.365*****	**0.366*****	**0.340*****
	(2.96)	**(2.96)**	**(2.75)**
LikeMind Firm	-0.026	0.010	0.221**
	(-0.56)	(0.14)	(2.13)
Low PolIdeo SD	-0.960***	-0.989***	-2.074***
	(-7.19)	(-7.23)	(-8.96)
Controls and Controls x *Surprise*	Yes	Yes	Yes
Year-Quarter FE	No	Yes	Yes
Firm FE	No	No	Yes
N	34,617	34,617	34,617
R-squared	0.026	0.027	0.131

Panel B: Long-Term Return Reversals After Earnings Announcements

		CAR[2,60]	
	(1)	(2)	(3)
CAR[0,1]	-0.125	-0.133	-0.452***
	(-1.02)	(-1.09)	(-3.68)
CAR[0,1] × LikeMind Firm	**-0.183**	**-0.168**	**-0.147**
	(-0.81)	**(-0.74)**	**(-0.65)**
CAR[0,1] × LikeMind Firm x Low PolIdeo SD	**-0.165**	**-0.173**	**-0.342****
	(-1.10)	**(-1.16)**	**(-2.32)**
LikeMind Firm	-0.136	0.278*	0.473**
	(-1.39)	(1.85)	(2.03)
Low PolIdeo SD	-0.548**	-0.888***	-1.537***
	(-2.12)	(-3.31)	(-3.27)
Controls and Controls x *CAR[0,1]*	Yes	Yes	Yes
Year-Quarter FE	No	Yes	Yes
Firm FE	No	No	Yes
N	34,617	34,617	34,617
R-squared	0.003	0.011	0.133

Table 9: Portfolios Formed on Likemindedness

This table presents the monthly raw returns and alphas of portfolios formed on *LikeMind Firm*. Portfolios are formed each month by buying stocks in the top tercile of *LikeMind Firm* at the start of the month and selling stocks that fall in the bottom tercile of *LikeMind Firm* at the start of the month. Panel A shows the mean raw returns and Panel B shows the mean alphas. In Panel B, factors are added sequentially beginning with the market (column 1), size and book-to-market (column 2), momentum (column 3), and profitability and investment (column 4). Newey and West (1987) standard errors are robust to heteroscedasticity and five months of autocorrelation. t-statistics are shown in parentheses.

Panel A: Raw Returns to *LikeMind Firm* Portfolios

	Equal-Weighted	Value-Weighted
1 (Low)	1.439	1.390
2	1.235	1.186
3 (High)	1.032	1.018
High−Low	−0.407**	−0.371*
t-Statistics	−2.930	−2.692

Panel B: Risk-Adjusted Returns to *LikeMind Firm* Portfolios

	Equal-Weighted			
	CAPM (1)	FF Three-Factor (2)	Carhart Four-Factor (3)	FF Five-Factor + UMD (4)
Alpha	−0.299*	−0.257*	−0.268**	−0.362***
	(−1.948)	(−1.879)	(−2.243)	(−2.958)
N	120	120	120	120
R-squared	0.132	0.296	0.388	0.443
	Value-Weighted			
	CAPM (5)	FF Three-Factor (6)	Carhart Four-Factor (7)	FF Five-Factor + UMD (8)
Alpha	−0.261*	−0.217	−0.228*	−0.330***
	(−1.741)	(−1.629)	(−1.921)	(2.966)
N	120	120	120	120
R-squared	0.138	0.338	0.443	0.507