Expert Network Calls

Sean S. Cao, T. Clifton Green, Lijun Lei, Shaojun Zhang*

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Abstract

Expert networks provide investors with in-depth discussions with subject matter experts. Expert call demand is higher for younger, technology-oriented firms and those with greater intangible assets, consistent with demand for information regarding hard-to-value firms. We find that expert call volume is associated with hedge fund sales, greater short interest, more efficient price response to negative news, and poor firm performance. The evidence is stronger for calls that are negative in tone, and expert sentiment plays a more prominent role than client sentiment. The findings are consistent with expert networks helping investors discern complicated bad news.

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* Cao is from Smith School of Business at the University of Maryland, College Park (scao824@umd.edu), Green is from Goizueta Business School, Emory University (clifton.green@emory.edu), Lei is from Bryan School of Business and Economics at the University of North Carolina, Greensboro (l_lei2@uncg.edu), and Zhang is from Fisher College of Business, The Ohio State University, Columbus (zhang.7805@osu.edu). We are grateful for helpful comments from Simona Abis (discussant), Brian Bushee, Ville Rantala (discussant), Susan Shu (discussant), and seminar participants at the SFS Cavalcade, The EFA (European) conference, the CAPANA Annual Conference, University of Kentucky, and Huazhong University of Science and Technology.

1. Introduction

Active fund managers increasingly rely on nontraditional information sources to shape their investment decisions. New unstructured quantitative data such as satellite imagery, social-media trends, and consumer shopping behavior has received considerable attention from academics.[1] However, investment managers have also sought out alternative sources of qualitative information. Over the last two decades, a $1.9 Billion industry has sprung up to connect investors seeking deep-dive research with subject matter experts, and hedge funds rank expert networks among their top alternative data sets.[2] In this article, we study a sample of 15,000 expert calls to shed light on the financial market implications of the expert network industry. Our analysis studies the relation between expert calls and measures of informed trading, firm performance, and price efficiency.

Although company management is well motivated to help investors process information that casts the firm in a positive light, their incentives to disclose negative information are less strong (e.g., Kothari, Shu, and Wysocki, 2009; Bushee, Taylor, Zhu, 2022). Another traditional source for qualitative firm information, brokerage analysts, also faces conflicts of interest that can lead to censoring of negative views (e.g., Chan et al., 2018). As a result, we hypothesize that expert networks may be particularly useful for helping investors uncover unfavorable value-relevant firm information.

We begin by examining the factors that drive expert call demand. Farboodi et al. (2021) argue that alternative data is more valuable for high-growth firms, and we conjecture that investors

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[1] For example, Zhu (2019), Gerken and Painter (2022), and Katona et al. (2022) study satellite imagery of retail parking lots, Chen et al. (2014), and Green et al. (2019) study social media posts, and Froot et al. (2017), Huang (2018), and Zhu (2019) study consumer behavior.
[2] https://www.integrity-research.com/expert-network-industry-nears-2-billion/; https://www.aima.org/educate/aima-research/casting-the-net.html

will seek out experts especially when researching firms with fundamentals that are hard to value. Consistent with this view, we find that expert calls are more likely to focus on younger, growing firms with high intangible assets, those with increases in the number of business segments, and firms more exposed to disruptive technologies. We next employ textual analysis to compare the content of expert calls with an important source of firm-disclosed qualitative information: earnings conference calls. We find that expert calls emphasize topics related to technology, strategy, and operational topics, whereas they are considerably less likely to discuss financial topics relative to earnings conference calls.

An important feature of the expert network that we analyze is that call transcripts become available after a delay to all network subscribers, which greatly expands the reach and potential impact of each call.[3] If expert networks shape investment decisions, we expect increased call volume to be followed by institutional trading. Analyzing quarterly portfolio holdings, we find that an increase in expert calls in a calendar quarter is associated with significant changes in institutional portfolio holdings in the next quarter, and no evidence of elevated trading in the previous quarter, consistent with investors reacting to information revealed by expert calls. Moreover, the evidence of position changes is significantly stronger for the subset of hedge funds, which are common participants in expert network calls.

We hypothesize that expert networks may be uniquely effective at helping investors uncover negative information, and we therefore anticipate that call volume will be specifically associated with future fund sales. Supporting this view, we find significant evidence of position reductions among hedge funds in the quarter after increased call volume. Hedge funds often have mandates that allow shorting stocks, which provides additional opportunities to trade based on

[3] The expert network that provided our sample indicated that their service is used by roughly 1000 institutions.

negative views. We find that increased call volume in one month is associated with greater short interest in the following month, offering additional evidence consistent with calls generating negative investment signals on average. We also consider the informed trading intensity (ITI) measure of Bogousslavsky, Fos, and Muravyev (2023), and we find evidence consistent with elevated informed trading in the month after increases in expert call volume.

If expert network calls provide investors with an opportunity to discern negative value-relevant information, then call volume may be associated with lower firm performance. We examine return on assets and earnings per share, and we calculate changes relative to four quarters ago. For both performance measures, we observe evidence of a negative relation between call volume and future performance. In addition, if market participants do not fully anticipate the negative firm performance, call volume may help predict stock returns. We find supporting evidence, with expert call volume in one month being associated with negative abnormal stock returns in the following month. The finding that call volume is associated with future stock returns helps mitigate concerns that calls indirectly proxy for public information, which should generally be quickly incorporated into stock prices.

Expert networks may also have implications for capital markets. Hedge funds have been shown to improve pricing efficiency (Cao et al., 2018), and we conjecture that expert calls are one channel by which hedge funds facilitate the incorporation of information into prices. Our first proxy for price efficiency is a measure of price delay that captures the speed of adjustment to market-wide information (Hou and Moskowitz, 2005; Boehmer and Wu, 2013; Busch and Obernberger, 2017). We also consider the intraperiod timeliness (IPT) measure, which captures the speed with which information is incorporated into prices over the span of quarterly earnings cycles (Butler, Kraft, and Weiss, 2007; Bushman, Smith, and Wittenberg-Moerman, 2010; Blankespoor, deHaan, and Zhu, 2018).

We find evidence of reduced price delay in the month after increased expert call volume, consistent with stock prices incorporating market news more quickly when market participants have a better understanding of the firm's fundamentals. Moreover, the evidence of improved price efficiency is concentrated on days with negative market returns, supporting the view that expert networks help investors better understand the implications of unfavorable news. We also find evidence that expert calls are associated with improved intraperiod timeliness, consistent with more timely price discovery of earnings information. Analogous to the price delay evidence, we find that the relation between expert calls and intraperiod timeliness in the next quarter is more robust for negative earnings announcements.

We acknowledge that our setting hinders attempts to make strong causal statements. In particular, we do not observe the identity of the investor client on the call, and we are not able to track institutional trading at a high frequency around calls. Our lower frequency approach is motivated by two considerations. First, call transcripts become available to all network subscribers after a delay, which significantly broadens their reach but may lead to a more gradual impact. And second, we argue that expert call's in-depth nature helps provide investors with a lens for interpreting future information rather than producing short-term trading signals. We interpret the correlations between expert network call activity and institutional selling, lackluster firm performance, and improved price efficiency as supporting the idea that expert networks aid investors in discovering unfavorable firm information.

Another potential explanation for the findings is that unobserved firm information causes call volume and the ensuing capital market outcomes, with expert calls merely indirectly proxying for the news. Alternatively, it is also possible that sophisticated investors specifically seek out expert information on stocks that they view as overvalued, with firm selection explaining the results rather than expert calls containing information. Analyzing call sentiment provides a way to help distinguish between a call informativeness interpretation versus explanations related to firm selection or unobserved news. If the outcomes we observe are unrelated to the expert call tone, it would support the view that calls are merely proxying for other news. Alternatively, if the strength of the evidence varies with the tone of the client who arranged the call, and it is generally unrelated to the tone of the expert on the call, it would corroborate the client firm selection interpretation. On the other hand, if the negative outcomes we observe are strongest when the expert on the call is also negative in tone, it would support the view that expert networks serve an informational role.

Our approach relies on the FinBERT large language model of Huang, Wang, and Yang (2022) to classify individual call sentence tone,[4] and we categorize calls as favorable or unfavorable in sentiment based on the fraction of negative and positive sentences in the client or expert segments of the call. We then repeat the analysis while including separate negative and positive call volume measures. We observe that for both clients and experts, hedge fund selling, short interest, informed trading, price efficiency, and firm performance are all significantly related to negative call volume and insignificantly related to positive call volume. Notably, the relation is consistently stronger for expert tone than for client tone, which supports the information channel and suggests that the evidence is not likely to be fully explained by unobserved news or firm selection.

Taken together, the findings suggest that expert networks influence sophisticated investor stock positions and enhance price efficiency. Moreover, the evidence that calls are specifically

[4] We note that expert network calls are considerably less positive in tone than conference calls. For example, 9.4% of sentences are classified as positive on average for expert calls, compared with 26.7% for conference calls.

associated with short interest, and that price efficiency improves particularly in response to negative information and following negative tone calls, supports the view that expert networks are uniquely effective at helping investors understand weaknesses in firm fundamentals.

Our analysis adds to several areas of research. A well-established literature studies the capital market implications of earnings conference calls (Brown, Hillegeist, and Lo, 2004; Kimbrough, 2005; Cohen, Lou, and Malloy, 2020), investor conferences (Green et al., 2014; Kirk and Markov, 2016; Bushee, Taylor, and Zhu, 2022), and private meetings with management (Soltes, 2014; Bushee, Gerakos, and Lee, 2018; Bradley, Jame, and Williams, 2021). However, firm management has been shown to be prone to selective disclosure by withholding bad news (Kothari, Shu, and Wysocki, 2009; Bushee, Taylor, Zhu, 2022; Blankespoor et al., 2022), which aligns with our evidence that expert calls appear particularly effective for helping investors discern fundamental weaknesses that may be downplayed by firm management.

Our work also extends research that examines institutional investor demand for information. Past work has studied Bloomberg terminal searches (Ben-Rephael, Da, and Israelsen, 2017; Liu, Peng, and Tang, 2019; and Ben-Rephael et al., 2021), SEC EDGAR web traffic (Chen et al., 2020; Cao et al., 2021; and Crane, Crotty, and Umar, 2022), and news media consumption (Kwan, Liu, and Matthies, 2022). We study an important alternative source of qualitative information for institutional investors. Expert network calls represent costly, investor-initiated discussions with subject matter experts that signal institutional demand for information.

Our findings that expert network calls are associated with reduced price delay and greater intraperiod timeliness adds to studies of price efficiency. Boehmer and Kelly (2009), Kacperczyk, Sundaresan, and Wang (2021), and Cao et al. (2018) provide evidence that institutional investors enhance price efficiency, and Saffi and Sigurdsson (2011) and Boehmer and Wu (2013) show that short sellers contribute to price discovery. In particular, Engelberg, Reed, and Ringgenberg (2012) show that short sellers' trading advantage arises in large part due to their ability to process public information. Our analysis highlights the role of expert networks in helping sophisticated investors understand firm fundamentals that can facilitate their interpretation of public information signals.

In addition, our research connects with the literature that explores new alternative data. Existing studies emphasize unstructured quantitative data. For example, Zhu (2019), Gerken and Painter (2023), and Katona et al. (2022) study satellite imagery of retail parking lots, Chen et al. (2014), and Green et al. (2019) study social media posts, and Froot et al. (2017), Huang (2018), and Zhu (2019) study consumer behavior. Our work highlights that alternative qualitative information, in particular hour-long conversations with subject matter experts, helps shape sophisticated investor decisions and contributes to price efficiency.

2. The Expert Network Sample

In this section, we describe the expert network industry and provide descriptive statistics for our sample of call transcripts.

2.1 The Expert Network Industry

Several Wall Street developments combined in recent decades to help to fuel the Expert Networks industry (Groysberg, Healy, and Abbott, 2012). Regulation Fair Disclosure in 2000 prohibited public companies from selectively disclosing material information, which helped to level the playing field but also encouraged investors to seek out unique information sources to gain an investing edge. In addition, regulatory concerns about conflicts of interest at sell-side research departments lead to the Global Analyst Research Settlement in 2003, which resulted in reduced analyst coverage and led investors to look elsewhere for investment expertise.[5] This period also coincided with the considerable growth in hedge funds, whose considerable financial resources and high portfolio turnover made them prime customers for expert network firms.

These economic forces have led to rapid growth in the expert network industry, which is currently comprised of over 100 firms with estimated industry revenues of $1.9 Billion in 2021.[6] Expert network firms work to recruit and connect subject matter experts with clients seeking to do deep dive research on a company or market segment.

Expert calls are primarily client driven, with a client contacting an expert network firm to obtain information regarding a firm and topic and providing screening questions. The expert firm then typically reaches out to a handful of potential experts requesting a brief discussion of their suitability (and hourly rate). This information is shared with the client and a call moves forward if there is a successful match.[7] Expert network firms often rely on LinkedIn to identify candidates, and they source experts across industries and regions as well as at varying levels of experience. Experts are typically competitors, customers, suppliers, industry experts, or former employees of the business that the client would like to research. The standard engagement is a 45-60 minute question and answer discussion between the expert and the client. Consulting rates are generally $100-$250 for people earlier in their careers and $300-$500 for mid-career professionals, with rates of over $1,000 an hour for high-level executives or specialists.[8]

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[5] Kadan et al. (2008), Mola, Rau, and Khorana (2013), and Corwin, Larocque, and Stegemoller (2017) study the effects of Reg FD and the Global Settlement on brokerage research, and Lang, Pinto, and Sul (2021) examine European Mifid II rule changes in 2018 that unbundled broker research from execution services and find evidence of reduced analyst coverage.
[6] https://www.integrity-research.com/expert-network-industry-nears-2-billion/
[7] An alternative expert network business model involves hosting conferences and generating research materials akin to sell-side research firms. Our call sample is obtained from a client-driven expert network firm.
[8] https://expertopportunities.com/what-is-an-expert-network/

A number of high-profile insider trading cases exposed the potential for experts to be corrupted by traders in search of illegal insider information (e.g. Keefe, 2014). In response, expert network firms have put in place rigorous compliance procedures to protect clients and the firm. For example, experts are prohibited from engaging in projects about their own company or participating in projects where conflicts of interest might be present.[9] A key tool for compliance is the creation of call recordings and transcriptions.

The availability of call transcripts has led expert network firms to create content libraries that can be sold to multiple clients. Clients pay $10-25k per user to gain access to all transcripts in the library, typically after a delay.[10] Transcripts from other client calls can help reduce the need for one-on-one meetings and may be particularly valuable for public market investors that track many stocks. The sample for our study is based on the content library for one expert network.

2.2 Expert Network Data

We obtain call data from an expert network for the period January 2017 to January 2022. The dataset includes information on the date of the call, the name of the focal company, and the call transcript for 19,285 calls covering 2,551 companies. We match the focal companies by the point-in-time ticker with common stocks in the CRSP and COMPUSTAT databases. Expert calls where the focal company is not in COMPUSTAT-CRSP are dropped from the sample. The resulting dataset is comprised of stock-month and stock-quarter observations from January 2017 to January 2022.

An initial screening of transcripts reveals that calls are occasionally only tangentially related to the stated focal firm (for example not mentioning the firm name during the call). To help

[9] https://glginsights.com/compliance/
[10] https://inex.one/blog/expert-networks-2022

eliminate potential focal firm classification errors and focus on calls that are likely to be value-relevant, we calculate the cosine similarity between the expert call transcript and Item 1 of the listed focal company's 10-K. A cosine similarity of one (zero) indicates the two texts are highly similar (orthogonal). In our sample, the mean cosine similarity between expert calls and focal firm 10-Ks is 0.34. In our analysis, we exclude calls with cosine similarity below 0.111, which corresponds to bottom decile of similarity. The final sample consists of 15,353 expert calls covering 1,789 focal companies.

We gather other data from standard databases. Quarterly 13F institutional holdings data is obtained from Reuters, and we identify hedge funds using the approach in Agarwal, Jiang, Tang, and Yang (2013). Monthly short interest data is from the Compustat short interest database. Stock market data are from CRSP. Information on firm 8Ks is gathered from EDGAR, and news article coverage is obtained from the Dow Jones version of Ravenpack.

2.3 Sample Statistics

Table 1 presents summary statistics for the sample. We observe that the average call is comprised of roughly 7,600 words, indicating calls of lengths of between 50 and 63 minutes based on average speaking rates of 120 to 150 words per minute.[11] Firms with calls in the sample are the focus of 8 calls on average during the sample period, with a standard deviation of 15.7, suggesting a long right tail for the call distribution. To facilitate the analysis, we also count the number of calls for each firm quarter. Panel B of Table 1 shows an average of 0.54 calls per firm each quarter, with a standard deviation of 2.96.

Larger firms will naturally attract more investors and be the subject of more calls. To control for the role of size, for our primary measure we construct a measure of abnormal expert

[11] https://virtualspeech.com/blog/average-speaking-rate-words-per-minute

calls that scales the number of calls in a calendar quarter by the market capitalization of the firm. Table IA1 in the Internet Appendix lists the ten firms with the highest abnormal call volume by year. While there are a few familiar names (Amazon, Alphabet, etc.), the majority of names are less well known (e.g., Attunity, Livongo Health, TrueCar, and Arc Group Worldwide). We also observe that expert calls cover a variety of industries. Table IA2 in the Internet Appendix lists the distribution of firms by industry. The software and services industry represents the largest fraction of the call sample (17.6%), followed by health care equipment & services (9.7%), and pharmaceuticals, biotechnology and life science (7.2%). Utilities and Media companies comprise the smallest fraction (0.7% and 0.1%).

2.4 Topic Distribution

We begin by comparing the content of expert network calls to another common source of qualitative firm information: earnings conference calls. Specifically, we use natural language processing techniques to determine whether the distribution of covered topics significantly differs across call type. Our topic categorization approach relies on the widely used Latent Dirichlet Allocation (LDA) model (Blei, Ng, and Jordan, 2003). Early LDA models identify topics based solely on word co-occurrences, yet unsupervised approaches often generate topics that are difficult to interpret. We therefore follow recent literature that emphasizes seeded LDA (Watanabe and Zhou, 2022), where both knowledge-based and frequency-based seed words are used to determine pre-defined topics and a seed word dictionary. In particular, knowledge-based seed words are selected based on researchers' knowledge in the field, and frequency-based key words are chosen from the most frequent words in the documents.

We begin by carefully reading the transcripts of 200 expert calls. We identify seven common topics that emerge from the calls: *Competition*, *Consumer*, *Financial*, *Product*, *Operation*, *Strategy*, and *Technology*. We then obtain a list of the most frequent non-stop words in the call transcripts. From this list, we retain 50 knowledge-based root words that we use to construct the final seed word dictionary, and we manually classify the words into relevant topics, if applicable. This ensures the selected seed words offer operational definitions of the topics and high coverage across expert call transcripts, which improves training outcomes. Table IA.3 in the Internet Appendix lists the topic categories and root words.

To compare expert calls with earnings calls, we randomly select an observation-matched sample of 15,353 earnings calls from the 2017 to 2022 sample period, and we classify earnings calls using the same topics and seed word dictionary. Table 2 reports the fraction of expert calls and earnings conference calls that discuss each of the topics, where calls are assigned the topic that accounts for the largest weight in the call. We see that *Financial* discussions comprise the most common topic for earnings conference calls, present in 36.4% of calls, whereas this topic is considerably less prevalent in expert network calls (9.4%). Instead, expert calls are more likely to emphasize *Technology* (21.0% of expert calls vs 7.6% for earnings calls), and *Operations* (16.5% vs 7.1%). The different topic emphasis is consistent with expert calls being less oriented towards financial statement information and more geared to understanding industry segments and trends.

2.5 Determinants of Expert Network Calls

In this section, we examine the factors that influence expert call demand. We consider a variety of firm characteristics. Farboodi et al. (2021) argue that alternative information is more valuable for large, high-growth firms, and we include market capitalization and asset growth as well as age and recent stock returns. We conjecture that investors will seek out experts particularly when researching firms with fundamentals that are hard to value. We consider measures of intangible assets (Ewens, Peters, and Wang, 2020) and a measure of disruptive technology (Bloom et al, 2021). We also include several variables that capture aspects of the information environmental of the firm: analyst coverage, the number of news articles, and the number of firm 8-Ks over the previous quarter. Finally, to gauge firm complexity we include a conglomerate indicator for multi-segment firms and changes in segments to capture mergers or divestitures.

Our primary expert call volume measure is the abnormal call percentile rank in the month or quarter.[12] We count the number of calls during the period using the transcript posted date, and we scale by lagged market capitalization. We then rank the observations and divide by the total number of firms in the period. The resulting expert call volume measure is between the range of zero and one with a larger value indicating more expert calls.

To investigate the determinants of expert calls, we estimate the following model:

$$\textit{Expert Calls}_{i,t} = \alpha_{i,t} + \boldsymbol{\beta X}_{i,t} + \varepsilon_{i,t}, \qquad (1)$$

where *Expert Calls* is the abnormal call percentile rank measure, and ***X*** is a vector of determinants. The regression includes year-quarter fixed effects and standard errors are clustered by firm. The results are reported in Table 3. We observe that call volume is higher for larger, growing firms, younger firms, and those operating in disruptive industries.

Call volume is also higher for firms with higher levels of intangible assets, consistent with these assets being harder to value. Companies with higher analyst coverage and more news articles are more likely to be the subject of expert calls, consistent with broader demand for information on these companies. Finally, we observe that firms with changes in business segments have increased call volume, consistent with investors seeking a better understanding of how mergers or divestitures impact the firm.

[12] We measure call volume monthly when analyzing the monthly dependent variables (short interest, informed trading intensity, stock returns, and price delay), and quarterly for the quarterly dependent variables (institutional holdings, ROA and EPS, and intraperiod timeliness). We also consider several alternative call measures in Table 9.

3. Expert Network Calls and Institutional Trading

Although a single client participates in the call, transcripts are available to network subscribers after a two-week delay. The expert network that provided our call sample indicated that their service is used by over 1000 institutions, including more than 100 accounts with assets under management of over $20B. If access to expert networks influence investor decision making, we would expect to observe a relation between call volume and future position changes. In this section, we consider quarterly measures of institutional holdings to capture position changes, and we focus on hedge funds, which are frequent participants in expert network calls. Conventional sources of qualitative information such as firm management and brokerage analysts often face conflicts of interest that may serve to censor negative information. We conjecture that expert networks may be uniquely effective at helping investors uncover negative information, and we hypothesize that expert calls may be associated with fund sales. In addition to absolute position changes, we also analyze signed position changes to explore whether call volume is associated with future fund sales.

3.1 Institutional Trading

Institutional stock positions and expert call volume are likely to be persistent across quarters. We therefore analyze the effects of changes in call volume on position changes. Specifically, we examine the impact of expert calls on institutional holding changes by estimating the following model:

$$\Delta PortWt_{i,t+1} = \alpha_{i,t} + \beta_1 \Delta ExpertCalls_{i,t} + \boldsymbol{\beta_2 X}_{i,t} + \varepsilon_{i,t,}. \tag{2}$$

where $\Delta PortWt$ is either the absolute or signed change in fund portfolio weight in firm i from quarter t to quarter t+1. The portfolio weight of a stock for a fund is computed as the value of the stock divided by the total value of the stocks held by the fund. The fund value is the total value of stock held by the hedge fund.

When calculating changes in portfolio weights, we fix the price to be measured at the beginning of the quarter to focus on active changes in holdings. Specifically, quarterly changes in portfolio weights for each stock are measured as $\frac{\#share_t \times price_{t-1}}{\sum \#share_t \times price_{t-1}} - \frac{\#share_{t-1} \times price_{t-1}}{\sum \#share_{t-1} \times price_{t-1}}$.[13] *ΔExpert Calls* is our primary independent variable which is measured as the change from quarter *t*-1 to *t* in the abnormal call percentile rank measure. $\boldsymbol{X_{i,t}}$ is a vector of control variables for fund holdings based on prior literature (e.g. O'Brien and Bhushan, 1990), including market capitalization (*Market Capitalization*), the number of analysts following (*Analyst Coverage*), past quarterly stock return (*Stock Return*), mean daily trading volume (*Volume*). We also include as controls the full set of explanatory variables from Table 3, including the intangibles measures, media coverage and the number of 8-K filings, and the firm complexity measures.

Since our dependent variable is the change in portfolio weights, we include changes for the independent variables (except for market capitalization and stock returns). We also include the lagged dependent variable. Year-quarter and firm fixed effects are included, and we cluster standard errors by firm and year-quarter. We estimate Equation (2) using a dynamic GMM panel approach (e.g., Arellano and Bond, 1991; Arellano and Bover, 1995) using Stata xtabond2 (Roodman, 2009). The System GMM estimator allows us to obtain efficient estimates while controlling for firm-fixed effects and dynamic relation between current and past values (Wintoki, Linck, and Netter, 2012).[14]

[13] In Table IA4 in the Internet Appendix, we find similar evidence when we consider both active (share change) and passive (price change) variation in portfolio weights by including the effect of price changes on portfolio weights.
[14] In robustness Table 9, we repeat the analysis using OLS without firm fixed effects.

Hedge funds are the archetypal participants in expert call networks, and we anticipate that the holdings of hedge funds will be more responsive to expert call volume. We therefore consider hedge funds and other institutional investors separately. We first analyze absolute changes in portfolio weights in order to explore whether expert call volume is associated with sophisticated investor trading in general.

The results are reported in Table 4. Specifications (1) and (3) indicate that sophisticated investors exhibit elevated position changes in stocks in the quarter after increased expert call volume. As predicted, we find evidence that the effect of network calls on hedge fund positions is stronger than for other institutional investors. To get a sense of the economic magnitude, the absolute portfolio weight change evidence in Specification (1) suggests that a change from zero to one expert call is associated with 0.402 basis point change in hedge fund portfolio weight, compared to the mean change of 3.1 basis points. Using a stacked regression approach, we find that coefficient for hedge funds is significantly larger than for other institutional investors (F-statistic=3.60, p-value=0.058). Specification (2) shows that expert calls in quarter t are associated specifically with decreases in hedge fund holdings in the subsequent quarter.[15]

One concern in this setting is that institutional trading activity is persistent, and fund position changes may begin before expert network calls take place (that is, unrelated to the call). We check for this possibility by repeating the analysis after replacing $\Delta ExpertCalls_{i,t}$ in Equation (2) with $\Delta ExpertCalls_{i,t+2}$, i.e. with position changes measured in the quarter prior to call volume. The findings are tabulated in Table IA5 in the Internet Appendix. We observe no evidence of heightened institutional investor or hedge fund trading activity in general or selling in particular in the quarter before an increase in expert calls. Together, the evidence is consistent with a relation

[15] We analyze whether institutional trading reacts before the call by replacing $\Delta ExpertCalls_{i,t}$ in Equation (2) with $\Delta ExpertCalls_{i,t+2}$.

between expert call demand and subsequent position changes by sophisticated investors, and it specifically supports the idea that expert calls are useful at uncovering firm's fundamental weaknesses.

3.2 Short Interest

Hedge funds often have mandates that permit selling stocks short, and firm-level short interest has been shown to be associated with future firm performance (e.g., Senchack and Starks, 1993; Diether, Lee, and Werner, 2009). We argue that expert networks offer one channel by which sophisticated investors can learn about weaknesses in firm fundamentals. To examine the impact of expert calls on short interest, we estimate the following regression:

$$\Delta ShortInterest_{i,t+1} = \alpha_{i,t} + \beta_1 \Delta ExpertCalls_{i,t} + \boldsymbol{\beta_2 X_{i,t}} + \varepsilon_{i,t}, \quad (3)$$

where $\Delta ShortInterest$ is the change of short interest in firm i from month t to month t+1. We measure short interest using Compustat data, which provides information on the ratio of the number of shares sold short to the number of shares outstanding each month. $\Delta Expert\ Calls$ is the change from month t-1 to t in the abnormal call percentile rank, and $\boldsymbol{X_{i,t}}$ is the same set of explanatory variables in Table 3. Since our dependent variable is the change in short interest, we include changes for the independent variables, and we also include the lagged dependent variable. Year-month and firm fixed effects are included, and we cluster standard errors by firm and year-month.

The results are reported in Specifications (1) of Table 5. The coefficients indicate that an increase in the abnormal volume of calls in one month is associated with a significant increase in short interest in the following month.[16] The coefficient estimate indicates that the short interest

[16] We find no evidence of elevated short interest in the month prior to abnormal call volume. In particular, we adapt Equation (3) to examine the relation between short interest in month t+1 with abnormal call volume in month t+2

increase associated with a change from zero to one expert call is 13 percent of the standard deviation of monthly changes in short interest. As for the controls, we observe that higher trading volume is associated with lower short interest, and there is also some weak evidence that the changes in the number of 8-K filings and news articles correlate positively with short interest.

3.3 Informed Trading Intensity

Bogousslavsky, Fos, and Muravyev (2023) (BFM) employ a novel machine learning approach to construct measures of informed trading by evaluating market conditions during periods of trading by Schedule 13D filers, opportunistic insiders, and short sellers. We focus on the informed trading intensity measure constructed based on Schedule 13D filers, as activist investors trade much larger quantities than insiders and short sellers and thus provide a higher "signal-to-noise ratio" (Bogousslavsky et al., 2022).[17] In addition to the overall ITI measure, we also examine the BFM's measure of patient and impatient informed trading, based on whether the activist trades took place during the first 40 days of the 13D filing window (*ITI_patient*) or the last 20 days of the filing window (*ITI_impatient*). *ITI_patient* captures less aggressive informed trading that tends to decrease volatility, whereas *ITI_impatient* captures more aggressive informed trading that is associated with increased volatility (Bogousslavsky et al., 2022). We construct the daily average of the three *ITI* measures each month.

In order to examine the impact of expert calls on informed trading intensity, we estimate the following regression:

$$\Delta ITI_{i,t+1} = \alpha_{i,t} + \beta_1 \Delta ExpertCalls_{i,t} + \boldsymbol{\beta_2 X}_{i,t} + \varepsilon_{i,t,}, \quad (4)$$

(similar to the approach in Table IA5). In untabulated analysis, the resulting coefficient on $\Delta ExpertCalls_{i,t+2}$ is 0.152 with a *t*-stat of 1.094.

[17] We thank Dmitriy Muravyev for sharing the data.

where ΔITI is the change in one of the informed trading intensity measures for firm i from month t to month t+1. We consider overall trading intensity as well as patient and impatient trading. *ΔExpert Calls* is the change from month t-1 to t in the abnormal call percentile rank. $\boldsymbol{X_{i,t}}$ is the same vector of control variables as above, and we continue to include the lagged dependent variable as a control. The sample size for this analysis is smaller due to limited availability of the informed trading intensity measures.

The results are reported in Specifications (2) and (4) of Table 5. The coefficients point towards significantly elevated informed trading in the month after elevated increases in expert call volume. For example, a change from zero to one expert call is associated with an increase in informed trading intensity equal to 40 percent of the standard deviation of monthly changes in informed trading. The evidence indicates that expert call volume is associated with both patient and impatient informed trading measures, suggesting that calls are associated with both aggressive as well as less aggressive informed trading.

4. Expert Network Calls and Future Firm Performance

The evidence in Section 3 indicates that expert call volume is associated with reductions in hedge fund holdings and increases in short interest. If expert networks help investors become better informed by helping them to process unfavorable firm news, then call volume may also predict lower firm performance. In this section, we examine the relation between expert network call volume and future operating and return performance.

4.1 Operating Performance

We consider two measures of operating performance, quarterly return on assets (ROA) and earnings per share (EPS). Changes in performance are calculated relative to the same calendar quarter in the previous year. We analyze the relation between expert network calls and future operating performance using the following model:

$$\Delta Perf_{i,t+1} = \alpha_{i,t} + \beta_1 \Delta ExpertCalls_{i,t} + \boldsymbol{\beta_2 X}_{i,t} + \varepsilon_{i,t}, \quad (5)$$

where *Perf* is either ROE or EPS for firm *i* in quarter *t*. $\Delta ExpertCalls_{i,t}$ is the change in the abnormal call percentile rank for *i* from quarter *t*-1 to quarter *t*. $\boldsymbol{X_{i,t}}$ is a vector of control variables as above. We include year-quarter and firm fixed effects, and standard errors are clustered by firm and year-quarter. The regression results are presented in Specifications (1) and (2) of Table 6. The coefficient estimates are consistent with expert call volume being associated with lower growth in ROA and EPS, although the significance level is only 10% for the ROA regression.

4.2 Stock Returns

The reduced firm growth following expert calls may be fully anticipated by market participants. On the other hand, it is possible that expert networks provide investors with information that helps them anticipate future stock performance. We measure return performance at the monthly frequency, consistent with the analysis of short interest and informed trading. In particular, we measure cumulative abnormal returns, $CAR_{i,t+1}$, from the first to the 21st trading days of each month.

We analyze the relation between expert network calls and future return performance using the following regression:

$$CAR_{i,t+1} = \alpha_{i,t} + \beta_1 \Delta ExpertCalls_{i,t} + \boldsymbol{\beta_2 X}_{i,t} + \varepsilon_{i,t}, \quad (6)$$

where $\Delta ExpertCalls_{i,t}$ is the change in the abnormal call percentile rank for firm *i* from month *t*-1 to month *t*. $\boldsymbol{X_{i,t}}$ is the vector of control variables. Year-month fixed effects are included, and standard errors are clustered by year-month. The results are reported in Specifications (3) and (4) of Table 6. The estimates suggest that abnormal stock returns are significantly lower in the month after increased expert call volume, and the results hold in the first week of the month. In particular, the coefficients suggest that going from zero to one call in month t is associated with returns in the next month that are 0.345% lower in month t+1.

5. Expert Network Calls and Price Efficiency

The evidence in the preceding sections is consistent with expert networks helping investors discern valuable information about firm fundamentals. In this way, expert networks may also have broader implications for capital markets. Specifically, we hypothesize that expert call volume will be associated with improved price efficiency. We consider a price efficiency measure that captures how prices react to market-wide information, and we also examine a measure that focuses on firm-specific information.

5.1 Price Delay

The price delay measure reflects how quickly market-wide information is incorporated into stock prices by examining the sensitivity of a firm's returns to contemporaneous and lagged market returns (Hou and Moskowitz 2005). We follow Boehmer and Wu (2013) and compute price delays using daily observations and five days of lagged market returns. We first estimate the following regression for each quarter:

$$r_{i,t} = \alpha_i + \beta_j R_{m,t} + \sum_{n=1}^{4} \delta_{jn} R_{m,t,n} + \varepsilon_{j,t}, \qquad (7)$$

where $r_{i,t}$ is the return on stock i on day t and $R_{m,t}$ is the value-weighted market return on day t. We then estimate a second specification in which the coefficients on lagged market returns are constrained to be zero. The price delay measure is calculated by comparing the two R-squares. In particular, price delay is defined as $1-[R^2(\textit{restricted model}) / R^2(\textit{unrestricted model})]$.

We then examine the relation between expert network calls and price delay using the following model:

$$\Delta Price\ Delay_{i,t+1} = \alpha_{i,t} + \beta_1 \Delta ExpertCalls_{i,t} + \boldsymbol{\beta_2 X}_{i,t} + \varepsilon_{i,t}, \quad (8)$$

where *ΔPrice Delay* is the change in price delay in firm *i*'s stock price from month *t* to month *t*+1, and $\Delta ExpertCalls_{i,t}$ is the change of expert calls about firm *i* from month *t*-1 to month *t*. $\boldsymbol{X_{i,t}}$ is a vector of control variables that are potentially associated with price delays as documented in prior studies (e.g. Boehmer and Kelley, 2009; Boehmer and Wu, 2013). We include market capitalization (*Market capitalization*), mean trading volume (*Volume*), the number of analysts following (*Analyst following*), and institutional ownership (*Institutional holding*). We also include the other explanatory variables from Table 3. Equation (8) also includes firm and year-month fixed effects, and the standard errors are clustered by firm and year-month.

Specification (1) of Table 7 reports the results. Overall, higher expert call volume is associated with reduced price delay, consistent with information contained in the expert network calls improving the price efficiency of covered stocks. The coefficient estimate suggests that a change from zero to one expert call reduces price delay by 0.040, which is 11 percent of the standard deviation of changes in price delay.

Our evidence that expert network call volume is associated with institutional sales and greater short interest suggests that expert networks may be particularly effective at helping prices incorporate negative information. We evaluate this hypothesis by constructing separate measures of price delay for positive and negative market news. In particular, we construct the price delay to the negative and positive information as follows:

$$r_{i,t} = \alpha_i + \beta_j R^{-}_{m,t} + \sum_{n=1}^{4} \delta^{-}_{jn} R^{-}_{m,t-n} + \varepsilon_{j,t}, \quad (9a)$$

$$r_{i,t} = \alpha_i + \beta_j R^{+}_{m,t} + \sum_{n=1}^{4} \delta^{+}_{jn} R^{+}_{m,t-n} + \varepsilon_{j,t}, \quad (9b)$$

In the equation, $R^{-}_{m,t}$ is the daily market return when it is negative and $R^{+}_{m,t}$ is the daily market return when it is positive. Analogous to the overall price delay measure, the price delay to negative and positive information is calculated as one minus the ratio of the restricted R-squared to the unrestricted R-squared of models 9a and 9b, respectively.

Specifications (2) and (3) of Table 7 present the results of estimating Equation (8) with the separate price delay measures. We observe that increases in expert call volume are associated with large and statistically significant decreases in the price delay with respect to the negative market information, but less so with for the price delay with respect to the positive market information. Using a stacked regression approach, we find that coefficient for the price delay with respect to the negative market information is significantly larger than for the price delay with respect to the positive market information (Chi^2-statistic=7.61, p-value=0.006). Taken together, the evidence is consistent with expert networks providing a lens for helping investors more quickly interpret market news.

5.2 Intraperiod Timeliness

The price delay measure captures how well prices incorporate market information. In this section, we consider a measure of price efficiency that gauges how well prices reflect firm specific information. In particular, the intraperiod timeliness (*IPT*) measure captures the speed of price discovery around earnings announcement dates using an area-under-the-curve approach (Butler, Kraft, and Weiss 2007; Bushman, Smith, and Moerman 2010). Following Blankespoor, deHaan, and Zhu (2018), for each day zero to five relative to the earnings announcement date, we calculate the cumulative abnormal return from day zero through day *t* as the firm's raw return minus equal-weighted market return. We then plot these daily cumulative returns scaled by the final cumulative return. *IPT* is the area under the curve minus two times any "overreaction area," or reaction greater (less) than the final positive (negative) cumulative return. Specifically, *IPT* is computed as:

$$IPT_{i,t} = \sum_{t=0}^{5} 1 - \frac{|CAR_5 - CAR_t|}{|CAR_5|}.$$

We examine the relation between expert call volume and future intraperiod timeliness using the following model:

$$\Delta IPT_{i,t+1} = \alpha_{i,t} + \beta_1 \Delta ExpertCalls_{i,t} + \boldsymbol{\beta_2 X}_{i,t} + \varepsilon_{i,t}. \quad (10)$$

ΔIPT is the change in intraperiod timeliness of firm i's stock price from quarter t to quarter t+1, $\Delta ExpertCalls_{i,t}$ is the change of the abnormal call percentile rank from quarter t-1 to quarter t, and $\boldsymbol{X_{i,t}}$ is the vector of control variables. As with the other specifications, we include firm and year-quarter fixed effects and lagged dependent variables, and standard errors are clustered by firm and year-quarter. The results are presented in Table 8. Specification (1) shows that, for an average focal firm, increases in expert calls in one quarter are associated with improved intraperiod timeliness in the next quarter.

In order to explore whether the effect of expert networks varies for positive and negative news, we adapt Equation (10) to separate quarters into positive earnings and negative earnings announcements. In particular, an earnings announcement is considered as positive (negative) if the cumulative abnormal return from day zero through day ten relative to the earnings announcement date is positive (negative). The intraperiod timeliness for the negative and positive earnings announcement days are constructed accordingly.

Specifications (2) and (3) of Table 8 report the results. We observe that increases in call volume are associated with increases in the future intraperiod timeliness for both the negative and positive news, but the evidence is more robust economically and significantly for negative earnings announcements. In sum, the analysis above is consistent with expert network calls improving the price efficiency of focal firms in response to market and firm-specific information, and specifically with regards to negative information.

5.3 Robustness Analysis

Our primary expert call measure scales the number of calls by market capitalization and calculates the percentile rank that ranges from 0 to 1. In Table 9, we repeat the analyses in Tables 4-8 using several of alternative call measures. Panel A repeats the baseline analysis for reference. Panel B considers a quartile indicator (instead of percentile rank) for the number of abnormal calls during the quarter. Panel C analyzes the call percentile rank not scaled by size. Panel D scales the number of calls by the number of news articles about the firm in the quarter, and then creates the percentile rank. For each panel, we replicate the earlier analysis using the alternative call measures. Consistent with the baseline results, the increase in expert calls is associated with increased hedge fund selling, short interest, and informed trading, improved price efficiency, and lower operating and return performance.

Our main analysis includes firm fixed effects throughout, which emphasizes variation in calls over time for a given firm. In Panel D, we drop firm fixed effects and estimate the regressions using OLS, and we also report the resulting R-squares. We again find that the increase in expert calls is associated with increased hedge fund selling, short interest, and informed trading, improved price efficiency, and lower operating and return performance.

In Table IA6 in the Internet Appendix, we repeat the analysis after dropping calls for the different expert types. In particular, Panel A reports the results after dropping calls in which the expert is a former *Executive* of the focal firm (41.5% of calls), Panel B drops *Customer* calls (23.2%), Panel C drops *Competitor* calls (10.0%), and Panel D drops *Industry Consultants* and *Partners* (25.3%).[18] The findings are generally robust in each panel, which suggests the results are not driven by a certain type of expert. Table IA7 in the Internet Appendix again repeats the

[18] We group together *Industry Consultants* and *Partners* due to the small number of partner experts in the sample.

analysis, but this time dropping calls that emphasize different textual topics as described in Table 2 (*Competition*, *Consumers*, *Financials*, *Operations*, *Products*, *Strategy*, or *Technology*). We find that the evidence does not appear to be driven by any one specific expert call topic.

6. Firm Selection vs Call Informativeness: The Role of Call Sentiment

Sections 3-5 document relations between expert network call volume and institutional investor selling, short sales, and poor firm performance, as well as improved price efficiency in response to negative news. The evidence is consistent with expert networks helping sophisticated investors discern unfavorable value-relevant information. On the other hand, the set of findings is also consistent with two important alternative interpretations. First, it is possible that unobserved firm events separately cause expert call volume and the ensuing capital market outcomes, with calls merely indirectly proxying for firm information. And second, it is possible that sophisticated investors specifically seek out expert information on stocks that are overvalued, perhaps to confirm a hunch the stock is overvalued. In this case, the results are explained by firm selection rather than expert calls being informative.

One approach for distinguishing between firm selection and information channels is to condition on the tone of the call. If expert networks are informative, we would expect greater fund selling and worse firm performance to follow calls that are more negative in tone. If the outcomes we observe are unrelated to the expert call tone, however, it would support the view that calls are merely proxying for other news. Differentiating between the sentiment of the client and the expert can offer additional insights. If the findings are sensitive to the tone of the client who arranged the call and generally unrelated to the sentiment of the expert, it would support the view that client firm selection drives the results. In contrast, if the results are more closely related to the tone of the expert on the call, it is consistent with expert networks serving an informational role.

6.1 Measuring Call Tone

Our approach relies on Huang, Wang, and Yang (2022)'s FinBERT, a deep learning large language model based on the Google BERT algorithm that incorporates finance domain knowledge. Huang, Wang, and Yang (2002) provide evidence that FinBERT excels at sentiment classification relative to previous methods because it uses contextual information in financial text. We use FinBERT to categorize each sentence as negative, neutral, or positive. To focus on firm sentiment, we drop the last five sentences of each call, as the conversation wraps up and turns to expressions of appreciation that are markedly more positive in tone than the rest of the discussion.

Panel A of Table 10 presents call tone descriptive statistics. We observe that expert calls are comprised of 428 sentences on average, with a standard deviation of 153 sentences. On average, 9.8% of expert call sentences are classified as negative, with 9.4% being positive and the remaining sentences classified as neutral. The average difference in the fraction of negative and positive sentences within a call is 0.46%, suggesting a generally neutral tone.

As a benchmark, we compare expert call tone to similar measures constructed from firm conference calls using the sample described in Table 2. Consistent with the notion that firm management have strong incentives to emphasize good news, we observe that conference calls contain significantly more positive sentences than expert calls (26.7% vs 9.4%). Conference calls are also comprised of fewer sentences that are classified at negative (6.6% vs 9.8%) although the difference is not statistically significant. The average difference in the fraction negative and positive sentences within a conference call is -20.1%, compared vs 0.46% for expert calls, consistent with conference calls being considerably more positive than expert calls.

In Panel B, we separate expert calls into the questions posed by the client and the responses by the expert on the call. We see that experts account for roughly 70% of the discussion, with a mean of 302 sentences compared to 127 sentences for the client. Experts tend to be neutral on average, with 10.0% of their sentences being classified as negative and 10.5% as positive. Clients' average sentiment is slightly more negative, with 10.6% of their sentences being classified as negative and 6.4% positive.

6.2 Expert Call Tone and Capital Market Outcomes

Our information hypothesis holds that the relation between expert call volume and negative market outcomes should be stronger for the subset of negative sentiment calls. We explore this hypothesis by constructing call volume measures separately for negative and positive calls. In particular, we separate calls into negative and positive groups based on the median of the difference between the fraction of negative and positive sentences. We then compute the abnormal call volume percentile rank measures separately for negative and positive calls. The correlation between the resulting two call volume measures is relatively modest, with negative and positive call volume exhibiting a monthly correlation of 0.47.

Using the separate negative and positive expert call volume measures, we repeat the analysis in Tables 4-8. The findings are tabulated in Panel A of Table 11. The evidence supports the view that expert calls contain useful information. In particular, we find that hedge fund selling, short interest, informed trading, price efficiency, and firm performance are all significantly related to negative call volume and insignificantly related to positive call volume. The call tone evidence is not supportive of the interpretation that unobserved firm events drive the results.

As highlighted above, if expert calls are informative then we would expect the tone evidence to be more robust for expert sentiment than for client sentiment. We explore this hypothesis by differentiating between the client and expert portions of the call. Specifically, we categorize calls as negative or positive in client sentiment using the median of the difference between the fraction of negative and positive sentences in the client portion of the call, and we similarly classify calls as negative or positive in expert sentiment using the expert portions of the call. For reference, the monthly correlation between negative client call volume and negative expert call volume is 0.38, whereas the correlation between positive client call volume and positive expert call volume is 0.75.

Panels B and C of Table 11 report the results using separate client and expert sentiment call volume measures. The evidence generally confirms the findings in Panel A, with the results being stronger for negative sentiment call volume. More importantly, the results are notably stronger for expert tone than for client tone. For each of the seven dependent variables that we consider, the coefficient on negative expert call volume is economically larger than the coefficient on negative client call volume, and the statistical significance is stronger for six of the seven variables. We also find modest evidence of positive stock return performance after positive expert sentiment calls, which provides additional evidence for the information channel.

The evidence that market outcomes are related to client call sentiment suggests that we are not able to rule out that the findings are due in part to firm selection, i.e. that clients request expert calls for firms considered to be overvalued. However, the fact that the results are strongest for the subset of expert calls with negative sentiment by the expert supports the view that expert calls are useful at uncovering firm's fundamental weaknesses.

7. Conclusion

Expert networks provide investors with in-depth discussions with subject matter experts and have become a popular source of alternative qualitative information for active fund managers. However, this emerging industry is opaque and not well-understood. Employing proprietary call transcripts from an expert network company, we study the determinants of expert calls, describe their content, characterize their impact on investors, and study their effects on capital markets.

We find that the expert call demand is higher for younger, technology-oriented firms and those with greater intangible assets, consistent with demand for information on hard-to-value firms. Moreover, expert calls are more (less) likely to emphasize technology and operational (financial) topics relative to earnings calls. As such, they supplement traditional sources of information.

We find evidence suggesting that expert calls have capital market implications, with call volume being associated with hedge fund position changes and greater price efficiency. The relation is asymmetric, with call volume preceding hedge fund sales, greater short interest, and negative firm performance. In additional tests, we uncover that the evidence is stronger for the subset of calls with more negative tone, and that expert sentiment is more relevant than client sentiment. Taken together, the findings are consistent with the view that expert networks help investors discern negative firm information.

Appendix A: Variable Definitions

A.1 Key Explanatory Variables

- *Expert Calls* – The abnormal call percentile rank, defined as the percentile rank of the number of expert network calls a firm in quarter *t* scaled by the log of market capitalization at the end of quarter *t-1*. Source: Expert Network Data and CRSP.
- Alternative Call Measures
  - $Expert\ Calls_{Quartile}$ – The quartile rank of the number of calls about a firm in quarter *t* scaled by market capitalization at the end of quarter *t*. Source: Expert Network Data and CRSP.
  - $Expert\ Calls_{Unscaled}$ – The percentile rank of the number of calls about a firm in quarter *t*. Source: Expert Network Data.
  - $Expert\ Calls_{News}$ – The percentile rank of the number of calls about a firm in quarter *t* scaled by the number of news articles about the firm in quarter *t*. Source: Expert Network Data and Ravenpack.

A.2 Call Determinants

- *Market capitalization* – The natural logarithm of market capitalization computed as share price times total shares outstanding at the end of the quarter *t*. Source: COMPUSTAT
- *Leverage* – The leverage ratio computed as the sum of long-term and short-term debt divided by total assets Source: COMPUSTAT
- *Asset Growth* – Quarter-on-quarter asset growth computed as the change in total assets from quarter *t*-1 to quarter *t* divided by total assets at the end of quarter *t*-1 Source: COMPUSTAT
- *Sales Growth* – Quarter-on-quarter sales growth computed as the change in sales revenue from quarter *t*-1 to quarter t divided by sales revenue in quarter *t*-1 Source: COMPUSTAT
- *Stock Return* – The cumulative abnormal returns (raw return minus CRSP equal weighted index return) in the past quarter. Source: CRSP
- *Firm Age* – The number of years since initial public offering. Source: COMPUSTAT
- *Disruptive Technology* – The normalized share of job posting in cloud computing, social networking, and smart devices for an industry in year *t*; industries are defined at the four-digit NAICS code level. Source: Bloom et al. (2021)
- *Expensed Intangible* – The average of the organizational capital scaled by total assets and the knowledge capital scaled by total assets at the end of quarter *t*-1. The organizational capital is the capitalization of a portion of selling, general, and administrative expenditures. It captures the knowledge used to combine human skills and tangible capital into systems for producing and delivering want-satisfying products. The knowledge capital is the capitalization of research development expenditures. It captures information learned about processes, plans, or designs that can lead to economic benefits in future periods. Source: Ewens, Peters, and Wang (2020).
- *Capitalized Intangible* – Intangible assets scaled by total assets at the end of quarter *t*-1. Source: COMPUSTAT
- *PPE Intensity* – One minus property, plant, and equipment scaled by total assets at the end of quarter *t*-1. Source: COMPUSTAT

- *Analyst Coverage* – The natural logarithm of the number of analysts issuing earnings forecasts during the quarter plus one. Source: IBES
- *Institutional Ownership* – The percentage of shares held by institutional investors at the end of the quarter. Source: Thomson Reuters
- *Number of 8-K Filings* – The natural logarithm of the number of 8-K filings during the quarter. Source: SEC EDGAR
- *Change in Business Segments* – The change in business segments from year t-1 to year t. Source: COMPUSTAT
- *Conglomerate firm* – An indicator variable that equals one if a firm has more than one segment at the end of quarter t-1, and zero otherwise.

A.3 Measures of Institutional Trading

- *Short Interest* – The short positions held on the 15th business day of each month scaled by the number of shares outstanding at the end of the prior quarter multiplied by 100. Source: COMPUSTAT.
- *Hedge Fund Portfolio Weight* – Portfolio weights are computed as the value of the stock divided by the total value of all stocks held by the hedge fund. Fund portfolio weights are weighted across funds each quarter using the value of stock holdings of each fund. Portfolio weights are analyzed in basis points. Source: Thomson Reuters.
- *Other Institutional Portfolio Weight* – Portfolio weights are computed as the value of the stock divided by the total value of all stocks held by the (non-hedge fund) institutional investor. Fund portfolio weights are weighted across (non-hedge) funds each quarter using the value of stock holdings of each fund. Portfolio weights are analyzed in basis points. Source: Thomson Reuters.

A.4 Measures of Price Efficiency

- *Price Delay* – Monthly price delay measure computed as 1-R^2(restricted model)/R^2(unrestricted model). R^2(unrestricted model) is the R^2 from estimating $r_{j,t} = \alpha_j+\beta_j R_{m,t}+\Sigma\delta_{jn}R_{m,t,n}+\varepsilon_{j,t}$, where $r_{j,t}$ is the daily return on stock j and $R_{m,t}$ is the value-weighted market return on day t. R^2(restricted model) forces the coefficients on lagged market returns to be zero. Source: CRSP.
  - *Price Delay Negative News* – Monthly price delay measure computed as 1-R^2(restricted model)/R^2(unrestricted model). R^2(unrestricted model) is the R^2 from estimating $r_{j,t} = \alpha_j+\beta_j R_{m,t}+\Sigma\delta_{jn}R_{m,t,n}+\varepsilon_{j,t}$, where $r_{j,t}$ is the daily return on stock j and $R_{m,t}$ is the value-weighted market return on day t when the market return is negative. Source: CRSP.
  - *Price Delay Positive News* – Monthly price delay measure computed as 1-R^2(restricted model)/R^2(unrestricted model). R^2(unrestricted model) is the R^2 from estimating $r_{j,t} = \alpha_j+\beta_j R_{m,t}+\Sigma\delta_{jn}R_{m,t,n}+\varepsilon_{j,t}$, where $r_{j,t}$ is the daily return on stock j and $R_{m,t}$ is the value-weighted market return on day t when the market return is positive. Source: CRSP.
- *IPT* – Intraperiod timeliness measure of the speed with which earnings information is impounded into price, measured over the ten-day earnings announcement window, adjusted

for overreaction and subsequent reversal to final cumulative abnormal return following Blankespoor, deHaan, and Zhu (2018). Specifically, $IPT_{(0,+5)}=\Sigma(|CumAR_5-CumAR_t|)/(|CumAR_5|)$ Source: COMPUSTAT, CRSP.

- *Informed Trading* – The measure of informed trading intensity trained on trades by Schedule 13D filers. Source: Bogousslavsky, Fos, and Muravyev (2023).
    - *Patient Informed Trading* – The measure of informed trading intensity trained on trades during the first 40 days of the 60-day filing window by Schedule 13D filers. Source: Bogousslavsky, Fos, and Muravyev (2023).
    - *Impatient Informed Trading* – The measure of informed trading intensity trained on trades during the last 20 days of the filing window by Schedule 13D filers. Source: Bogousslavsky, Fos, and Muravyev (2023).

A.5 Performance Measures

- *CAR* – The cumulative abnormal returns (raw return minus CRSP equal weighted index return) from the first to the 21st trading days of the month. Source: CRSP.
- *ROA* – Return on assets computed as income before extraordinary items scaled by total assets at the end of the quarter. *ROA* is winsorized at the 5th and 95th percentiles. Source: COMPUSTAT.
- *EPS* – Earnings per share excluding extraordinary items of the quarter. *EPS* is winsorized at the 5th and 95th percentiles. Source: COMPUSTAT.

A.6 Control Variables

- *Volume* – The mean trading volume of a stock in the quarter. Source: CRSP.
- *Market-to-Book* – The market-to-book ratio computed as market capitalization divided by the book value of equity at the end of the quarter. Source: COMPUSTAT.
- *Stock Return* – Stock return over the previous month, quarter, or year. Source: CRSP

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Table 1. Expert Call Sample Summary Statistics.

This table reports summary statistics of the expert call sample. Panel A describes the sample of 15,353 calls for 1,789 different firms during February 2017 through January 2022. Panel B reports quarterly firm-level descriptive statistics for the sample of 26,568 firm quarters. Variables are defined in the appendix.

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Panel A. Call Frequency and Length					
Call Word Length	7,595	2,416	6,050	7,652	9,000
Calls per Firm	8.47	15.69	2.00	4.00	8.00
Panel B: Quarterly Firm-Level Summary Statistics					
Number of Expert calls	0.542	2.961	0.000	0.000	0.000
Expert Calls	0.116	0.316	0.000	0.000	0.000
Market Capitalization	8.064	1.952	6.719	8.076	9.412
Leverage	0.306	0.243	0.099	0.285	0.453
Asset Growth	0.043	0.172	-0.015	0.012	0.049
Stock Return	0.013	0.269	-0.124	0.008	0.137
Firm Age	0.225	0.187	0.080	0.180	0.310
Disruptive Technology	0.055	0.086	0.012	0.026	0.088
Institutional Holdings	0.575	0.371	0.213	0.697	0.891
Capitalized Intangible	0.241	0.338	0.019	0.134	0.318
Expensed Intangible	0.245	0.235	0.027	0.174	0.418
PPE Intensity	0.378	0.413	0.000	0.331	0.796
Change in Business Segments	0.283	0.450	0.000	0.000	1.000
Conglomerate Firm	0.111	0.314	0.000	0.000	0.000
Analyst Coverage	8.044	6.433	3.000	7.000	12.000
Number of 8-K Filings	1.308	0.968	0.000	1.609	2.079
Number of News Articles	3.806	2.149	3.296	4.382	5.130
Hedge Fund Portfolio Weight	43.132	83.744	1.504	11.331	39.572
Other Instit. Portfolio Weight	37.040	72.553	1.132	8.685	32.814
Short Interest	5.002	5.635	1.455	2.969	6.487
Informed Trading Intensity (ITI)	0.298	0.061	0.256	0.293	0.335
Price Delay	0.438	0.305	0.167	0.375	0.694
Intraperiod Timeliness (IPT)	4.417	3.954	2.868	5.672	7.248
CAR	0.002	0.122	-0.063	-0.001	0.060
ROA	-0.001	0.041	-0.006	0.008	0.021
EPS	0.413	0.776	-0.090	0.270	0.870

Table 2. Topic Distribution for Expert Network Calls and Earnings Conference Calls.

The table presents the topic distribution for the sample of 15,353 expert network calls and a same-sized sample of earnings conference calls of the same size between January 2017 and January 2022. *, **, and *** denoted significance at the 10%, 5%, and 1% levels.

	Expert Calls		Conference Calls		
Topic	Calls	%	Calls	%	*z*-statistic
Competition	645	4.2%	633	4.1%	0.343
Consumer	2,046	13.3%	1,867	12.2%	3.063***
Financial	1,444	9.4%	5,590	36.4%	56.273***
Operations	2,527	16.5%	1,094	7.1%	25.356***
Product	2,839	18.5%	2,151	14.0%	10.643***
Strategy	2,626	17.1%	2,850	18.6%	3.339***
Technology	3,226	21.0%	1,168	7.6%	33.530***

Table 3. Determinants of Expert Network Calls

The table presents the results of firm-quarter regressions of expert call volume on lagged firm characteristics. The dependent variable is *Expert Calls*, defined as the percentile rank of the number of expert calls about a firm in quarter *t* scaled by log market capitalization at the end of quarter *t*-1. Firm characteristics are defined in the Appendix. *t*-statistics are reported below each coefficient based on standard errors clustered by firm and year-quarter. *, **, and *** denoted significance at the 10%, 5%, and 1% levels.

Variables		(1)	(2)	(3)	(4)	(5)
Firm Characteristics	*Market Capitalization*	0.010***	0.011***	0.006***	0.011***	0.006***
		(21.392)	(23.966)	(12.224)	(25.100)	(12.293)
	Leverage	0.008***	0.005	0.007**	0.008***	0.004
		(2.596)	(1.548)	(2.203)	(2.717)	(1.288)
	Asset Growth	0.009***	0.009***	0.009***	0.009***	0.009***
		(2.778)	(2.833)	(2.602)	(2.800)	(2.803)
	Stock Return$_{q-1}$	-0.004**	-0.005**	-0.002	-0.004**	-0.003
		(-2.105)	(-2.374)	(-1.179)	(-2.262)	(-1.499)
	Stock Return$_{[q-4,\ q-2]}$	0.008	0.011	0.012	0.008	0.015**
		(1.133)	(1.491)	(1.616)	(1.173)	(2.000)
	Firm Age	-0.040***	-0.045***	-0.040***	-0.042***	-0.045***
		(-7.999)	(-8.878)	(-7.972)	(-8.329)	(-9.029)
	Disruptive Technology	0.186***	0.159***	0.172***	0.186***	0.147***
		(9.471)	(8.153)	(9.210)	(9.423)	(7.897)
	Institutional Holdings	0.005**				-0.003
		(2.092)				(-1.446)
Intangibles	*Expensed Intangible*		0.014***			0.012***
			(11.832)			(10.492)
	Capitalized Intangible		0.042***			0.041***
			(9.291)			(9.277)
	PPE Intensity		0.004**			0.003*
			(2.367)			(1.954)
Information Environment	*Analyst Coverage*			0.003***		0.003***
				(12.607)		(11.312)
	Number of 8-K Filings			0.000		-0.000
				(0.029)		(-0.297)
	Number of News Articles			0.001***		0.002***
				(3.114)		(4.054)
Firm complexity	*Conglomerate Firm*				-0.003	-0.002
					(-1.263)	(-0.828)
	Δ Business Segments				0.016***	0.014***
					(3.970)	(3.546)
	Year-Quarter Fixed Eff	Yes	Yes	Yes	Yes	Yes
	Observations	89,346	89,346	89,346	89,346	89,346
	R-squared	0.041	0.045	0.046	0.041	0.050

Table 4. Expert Network Calls and Institutional Investor Position Changes

The table presents the results of firm-quarter regressions of institutional investor position changes on lagged changes in expert call volume and firm characteristics. Institutional investor position changes are measured by changes in portfolio weight which is computed as the value of the stock divided by the total value of all stocks held by the institutional investor. Fund portfolio weights are weighted across funds each quarter using the value of stock holdings of each fund. Portfolio weights are analyzed in basis points. The control variables are defined in the Appendix. We also include controls related to Intangibles, Information Environment, and Firm Complexity as in Table 3, but the coefficients are suppressed for brevity. Regressions are estimated using System GMM to allow for firm fixed effects and lagged dependent variables. t-statistics are reported below each coefficient based on standard errors clustered by firm and year-quarter. *, **, and *** denoted significance at the 10%, 5%, and 1% levels.

	Hedge Funds		Other Institutional Investors	
	Absolute Δ Portfolio Weight	Δ Portfolio Weight	Absolute Δ Portfolio Weight	Δ Portfolio Weight
	(1)	(2)	(3)	(4)
Δ *Expert Calls*	0.423**	-0.518***	0.282**	-0.270**
	(2.569)	(-2.635)	(2.263)	(-1.961)
Market Capitalization	-0.018	0.073	-0.141***	0.151***
	(-0.376)	(1.244)	(-2.727)	(2.878)
Leverage	-0.158	-0.030	-0.021	0.008
	(-1.085)	(-0.137)	(-0.133)	(0.044)
Asset Growth	-2.220**	3.232***	-0.474	1.246
	(-2.357)	(2.930)	(-0.346)	(0.918)
Stock Return$_{q-1}$	-0.060	0.328	-0.029	0.124
	(-0.133)	(0.505)	(-0.140)	(0.552)
Stock Return$_{[q-4,\, q-2]}$	0.433	-0.836**	-0.075	-0.231
	(1.321)	(-1.984)	(-0.146)	(-0.420)
Δ *Volume*	0.022	0.001	-0.014	0.012
	(0.810)	(0.023)	(-0.459)	(0.343)
| Δ *Hedge Fund Holdings*$_{q-1}$|	-0.042			
	(-1.311)			
Δ *Hedge Fund Holdings*$_{q-1}$		-0.136***		
		(-2.752)		
| Δ *Other Inst. Holdings*$_{q-1}$|			-0.110***	
			(-6.348)	
Δ *Other Inst. Holdings*$_{q-1}$				-0.147***
				(-7.791)
Additional Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes
Observations	85,571	85,571	85,571	85,571

Table 5. Expert Network Calls, Short Interest, and Informed Trading

The table presents the results of firm-month regressions of changes in short interest and informed trading on lagged changes in expert call volume and firm characteristics. Short interest is the short positions held on the 15th business day of each month scaled by the number of shares outstanding at the end of the prior quarter multiplied by 100. Informed trading is a monthly informed trading intensity measure trained on trades by Schedule 13D filers. Patient (Impatient) informed trading is an informed trading intensity measure trained on trades during the first 40 days (last 20 days) of the filing window by Schedule 13D filers. The control variables are defined in the Appendix. We also include controls related to *Intangibles*, *Information Environment*, and *Firm Complexity* as in Table 3, but the coefficients are suppressed for brevity. Regressions are estimated using System GMM to allow for firm fixed effects and lagged dependent variables. *t*-statistics are reported below each coefficient based on standard errors clustered by firm and year-month. *, **, and *** denoted significance at the 10%, 5%, and 1% levels.

	Change in	Change in Informed Trading Intensity		
	Short Interest	All Trading	Patient Trading	Impatient Trading
	(1)	(3)	(4)	(5)
Δ *Expert Calls*	0.334**	0.015***	0.013***	0.020***
	(2.366)	(3.383)	(3.571)	(4.797)
Market Capitalization	0.197**	0.014*	-0.032***	0.004
	(2.284)	(1.780)	(-3.845)	(0.680)
Leverage	0.809**	0.068***	-0.020	0.052***
	(2.493)	(2.964)	(-0.862)	(2.707)
Asset Growth	-0.082	-0.002	0.005	0.001
	(-1.092)	(-0.350)	(1.286)	(0.276)
Stock Return$_{m-1}$	-0.715***	0.017***	0.007	0.013***
	(-6.093)	(3.345)	(1.591)	(2.949)
Stock Return$_{[m-12, m-2]}$	0.733**	-0.002	0.037	-0.007
	(2.263)	(-0.056)	(1.049)	(-0.225)
Δ *Institutional Holding*	-0.424	-1.291***	-0.577*	-0.988***
	(-0.757)	(-3.526)	(-1.825)	(-3.190)
Δ *Volume*	-0.526*	-0.011	-0.017**	-0.017
	(-1.683)	(-0.994)	(-2.003)	(-1.622)
Δ *Short Interest*	-0.729***	0.013		
	(-5.745)	(0.156)		
Δ *ITI*$_{m-1}$			-0.059	
			(-0.546)	
Δ *ITI*$_{m-1,\ Patient}$				0.044
				(0.683)
Δ *ITI*$_{m-1,\ Impatient}$		0.015***	0.013***	0.020***
		(3.383)	(3.571)	(4.797)
Additional Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	270,845	65,154	65,154	65,154

Table 6. Expert Calls and Future Firm Performance.

The table presents the results of firm-quarter operating performance and firm-month stock market performance on lagged changes in expert call volume and firm characteristics. Operating performance is proxied by growth of return on assets (ROA) and earnings per share (EPS) in the current quarter from the same quarter of last year. ROA is computed as income before extraordinary items scaled by total assets at the end of the quarters. EPS is earnings per share excluding extraordinary items. Stock market performance is measured by cumulative daily abnormal returns (raw return minus CRSP equal weighted index return) from the first to the 21st trading day of each month ($CAR_{i,t+1}$). The control variables are defined in the Appendix. We also include controls related to *Intangibles*, *Information Environment*, and *Firm Complexity* as in Table 3, but the coefficients are suppressed for brevity. In Specifications (1)-(2), regressions are estimated using System GMM to allow for firm fixed effects and lagged dependent variables. *t*-statistics are reported below each coefficient based on standard errors clustered by year-quarter in column (1) and (2) and by firm and year-month in column (3). *, **, and *** denoted significance at the 10%, 5%, and 1% levels.

	Firm Fundamentals		Abnormal Stock Returns
	Change in ROA	Change in EPS	CAR
	(1)	(2)	(4)
Δ *Expert Calls*	-0.005*	-0.144***	-0.004**
	(-1.842)	(-2.852)	(-2.181)
Market Capitalization	-0.007*	-0.001	-0.050***
	(-1.794)	(-0.040)	(-29.455)
Leverage	-0.048	-1.502***	-0.022***
	(-0.928)	(-3.061)	(-3.288)
Market-to-Book	-0.000	-0.013	-0.001*
	(-0.222)	(-0.952)	(-1.718)
Asset Growth	0.470***	1.783**	0.019***
	(4.757)	(2.382)	(6.679)
Δ *Institutional Holding*	-0.111*	-0.717	-0.010
	(-1.716)	(-0.615)	(-1.336)
Δ *Volume*	0.003**	0.239***	0.000
	(2.131)	(4.168)	(0.361)
Stock Return$_{t-1}$	0.069***	0.696**	-0.015***
	(3.300)	(2.468)	(-4.231)
Stock Return$_{[t-n,\, t-2]}$	0.200***	0.843	0.061***
	(2.905)	(1.074)	(5.759)
Δ *ROA* $_{q-1}$	-0.621***		
	(-12.750)		
Δ *EPS* $_{q-1}$		-0.694***	
		(-15.164)	
Additional Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter/Month Fixed Eff	Yes	Yes	Yes
Observations	78,774	78,823	266,837

Table 7. Expert Network Calls and Price Delay

The table presents the results of firm-month regressions of changes in price delay on lagged changes in expert call volume and firm characteristics. Monthly price delay is computed as 1-R^2(restricted model)/R^2(unrestricted model); R^2(unrestricted model) is the R^2 from estimating $r_{j,t} = \alpha_j + \beta_j R_{m,t} + \Sigma \delta jn R_{m,t,n} + \varepsilon_{j,t}$ where $r_{j,t}$ is the daily return on stock j and $R_{m,t}$ is the value-weighted market return on day t. R^2(restricted model) forces the coefficients on lagged market returns to be zero. Price delay with respect to negative news is computed using R^2 from estimating a modified unrestricted model $r_{j,t} = \alpha_j + \beta_j R_{m,t} + \Sigma \delta jn R_{m,t,n} + \varepsilon_{j,t}$ where $r_{j,t}$ is the daily return on stock j and $R_{m,t}$ is the value-weighted market return on day t when the market return is negative. Price delay with respect to positive news is computed using R^2 from estimating a modified unrestricted model $r_{j,t} = \alpha_j + \beta_j R_{m,t} + \Sigma \delta jn R_{m,t,n} + \varepsilon_{j,t}$ where $r_{j,t}$ is the daily return on stock j and $R_{m,t}$ is the value-weighted market return on day t when the market return is positive. The control variables are defined in the Appendix. We also include controls related to *Intangibles*, *Information Environment*, and *Firm Complexity* as in Table 3, but the coefficients are suppressed for brevity. Regressions are estimated using System GMM to allow for firm fixed effects and lagged dependent variables. *t*-statistics are reported below each coefficient based on standard errors clustered by firm and year-month. *, **, and *** denoted significance at the 10%, 5%, and 1% levels.

	Change in Price Delay		
	All Days	Negative News Days	Positive News Days
	(1)	(2)	(3)
Δ *Expert Calls*	-0.040***	-0.049***	0.021
	(-3.355)	(-3.796)	(1.317)
Market Capitalization	-0.208***	-0.210***	-0.329***
	(-5.816)	(-3.339)	(-3.883)
Leverage	-0.316	-0.521*	-1.577***
	(-1.317)	(-1.790)	(-2.650)
Asset Growth	-0.588***	-0.641***	-1.497***
	(-5.855)	(-4.153)	(-4.805)
Stock Return$_{m-1}$	-0.680***	-0.889***	-1.624***
	(-6.251)	(-5.029)	(-4.694)
Stock Return$_{[m-12, m-2]}$	-0.798***	-1.001***	-2.219***
	(-3.733)	(-3.048)	(-3.844)
Δ *Institutional Holding*	0.109**	0.083	0.328***
	(2.540)	(1.578)	(2.971)
Δ *Volume*	0.796***	0.898***	2.154***
	(5.691)	(4.062)	(4.680)
Δ *Price Delay*$_{m-1}$	-0.073		
	(-0.640)		
Δ *Price Delay*$_{m-1,Negative}$		-0.128	
		(-0.973)	
Δ *Price Delay*$_{m-1,Positive}$			0.756***
			(4.188)
Additional controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes
Observations	269,094	269,094	269,094

Table 8. Expert Network Calls and Intraperiod Timeliness

The table presents the results of firm-quarter regressions of changes in intraperiod timeliness on lagged changes in expert call volume and firm characteristics. Intraperiod timeliness measures the speed with which earnings information in impounded into price and is measured over the ten-day earnings announcement window, adjusted for overreaction and subsequent reversal to final cumulative abnormal return following Blankespoor, deHaan, and Zhu (2018). Specifically, IPT(0,+5)=Σ(|CumAR5-CumARt|)/(|CumAR5|). The control variables are defined in the Appendix. We also include controls related to *Intangibles*, *Information Environment*, and *Firm Complexity* as in Table 3, but the coefficients are suppressed for brevity. Regressions are estimated using System GMM to allow for firm-fixed effects and lagged dependent variables. *t*-statistics are reported below each coefficient based on standard errors clustered by firm and year-quarter. *, **, and *** denoted significance at the 10%, 5%, and 1% levels.

	Change in Intraperiod Timeliness		
	All Earnings Dates	Negative Earnings Dates	Positive Earnings Dates
	(1)	(2)	(3)
Δ *Expert Calls*$_{t-1}$	0.718**	0.867*	0.241
	(2.186)	(1.923)	(0.499)
Market Capitalization	0.175	-1.083	-1.682
	(0.422)	(-0.984)	(-1.475)
Leverage	-0.542	1.141	-5.205
	(-0.265)	(0.392)	(-1.581)
Asset Growth	0.168	-0.115	1.076
	(0.224)	(-0.131)	(1.030)
Stock Return$_{q-1}$	-0.156	-0.077	-0.294
	(-0.426)	(-0.132)	(-0.433)
Stock Return$_{[q-4,\ q-2]}$	3.520	2.880	2.305
	(1.490)	(0.772)	(0.538)
Δ *Institutional Holding*	0.891	3.735	-0.646
	(0.553)	(1.513)	(-0.310)
Δ *Volume*	0.025	-0.026	0.064*
	(0.885)	(-0.575)	(1.673)
Δ *IPT*$_{q-1}$	-0.574***	-0.533**	-0.772***
	(-2.927)	(-2.321)	(-4.621)
Additional Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes
Observations	84,342	42,495	41,847

Table 9. Expert Network Calls and Informed Trading, Price Efficiency, and Firm Performance: Alternative Call Measures and Empirical Approaches
The table repeats the analysis of Tables 4-8 using alternative expert call measures and model specifications. Panel A represents the baseline analysis using the abnormal call percentile rank. In Panel B, calls are measured using the quartile rank of the number of calls about a firm in quarter *t* scaled by market capitalization at the end of quarter *t*-1. In Panel C, calls are measured using the percentile rank for the number of calls in the quarter (not scaled by size). In Panel D, calls are measured using the percentile rank of the number of calls about a firm in quarter *t* scaled by the number of news articles about the company in quarter *t*. In Panel E, we repeat the base-line approach but remove firm fixed effects to emphasize cross-sectional variation in calls. For brevity, only the coefficients and standard errors for the call measures are reported.

	Δ Hedge Fund Port. Weight	Δ Short Interest	Δ Informed Trading	Δ Price Delay	Δ Intraperiod Timeliness	Δ EPS	CAR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline Results – Abnormal Call Percentile Rank							
Δ *Expert Calls*	-0.648***	0.334**	0.015***	-0.040***	0.718**	-0.144***	-0.004**
	(-3.290)	(2.366)	(3.383)	(-3.355)	(2.186)	(-2.852)	(-2.181)
Panel B: Abnormal Call Quartile Indicator							
Δ *Expert Calls*	-0.052**	0.152***	0.006***	-0.009**	0.196*	-0.059***	-0.002***
	(-2.011)	(2.760)	(3.709)	(-1.985)	(1.655)	(-3.165)	(-3.288)
Panel C: (Unscaled) Call Percentile Rank							
Δ *Expert Calls*	-0.225**	0.338**	0.015***	-0.039***	0.721**	-0.144***	-0.004**
	(-1.970)	(2.433)	(3.367)	(-3.284)	(2.188)	(-2.853)	(-2.181)
Panel D: Calls Scaled by Number of News Articles Percentile Rank							
Δ *Expert Calls*	-0.509**	0.383**	0.030***	-0.093***	1.462**	-0.279***	-0.007**
	(-1.976)	(1.999)	(3.268)	(-4.116)	(2.248)	(-2.788)	(-2.187)
Panel E: OLS Approach without Firm Fixed Effects							
Δ *Expert Calls*	-0.047**	0.047**	0.014***	-0.042**	0.737***	-0.084**	-0.004**
	(-2.361)	(2.066)	(5.045)	(-2.399)	(3.114)	(-2.772)	(-2.511)
R-squared	0.418	0.071	0.036	0.239	0.249	0.643	0.055

Table 10. Expert Network Call Tone

The table presents descriptive statistics for expert network call tone. Each call sentence is classified as negative, neutral, or positive using the FinBERT large language model of Huang, Wang, and Yang (2022). Panel A reports call-level descriptive statistics for the fraction of negative and positive sentences in calls and presents a test for differences in mean between expert network calls and firm conference calls. Panel B reports tone statistics separately for the expert and client portion of the call.

Panel A: Expert Network Calls and Firm Conference Calls

	Expert Calls			Conference Calls	
	Mean	Median	Standard Deviation	Mean	Difference
Negative sentences	9.83%	9.14%	3.74%	6.60%	3.24%
Positive sentences	9.37%	8.97%	3.69%	26.70%	-17.33%***
Difference	0.46%	0.23%	4.63%	-20.11%	-20.57%***
Total sentences	428	423	153	266	

Panel B: Client and Expert Portions of Expert Network Calls

	Client Tone			Expert Tone		
	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
Negative sentences	10.56%	9.29%	6.56%	10.00%	9.19%	5.56%
Positive sentences	6.40%	5.75%	4.02%	10.49%	9.98%	4.39%
Difference	4.17%	3.44%	7.35%	-0.49%	-0.68%	6.60%
Total sentences	127	105	96	302	301	135

Table 11. Expert Network Calls and Informed Trading, Price Efficiency, and Firm Performance: The Roll of Call Tone

The table repeats the analysis in Tables 4-8 using measures of negative and positive expert call volume. Expert calls are categorized into negative and positive groups using the median level of the difference between the percentage of negative and positive sentences, and call volume is calculated separately for negative and positive tone calls. For brevity, only the coefficients and standard errors for the call measures are reported. In Panel A, tone is measured using all sentences in the call. Panel B classifies calls as negative or positive based on the tone of the client portion of the call, and Panel C focuses on the expert portion of the call.

Panel A: Overall Call Tone

	Δ Hedge Fund Port. Weight	Δ Short Interest	Δ Informed Trading	Δ Price Delay	Δ Intraperiod Timeliness	Δ EPS	CAR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ *Negative Calls*	-2.333**	0.457**	0.014*	-0.041***	0.802*	-0.148**	-0.011***
	(-2.454)	(2.570)	(1.892)	(-5.567)	(1.657)	(-2.021)	(-4.363)
Δ *Positive Calls*	1.483	0.070	0.008	0.001	0.049	-0.081	0.004
	(1.537)	(0.425)	(1.278)	(0.061)	(0.086)	(-0.869)	(1.569)

Panel B: Client Tone

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ *Negative Calls*	-0.150	0.281*	0.012	-0.030***	0.794**	-0.131*	-0.006**
	(-0.169)	(1.950)	(1.608)	(-4.154)	(2.128)	(-1.768)	(-2.357)
Δ *Positive Calls*	-0.722	0.230	0.009	-0.028**	-1.666	-0.114	-0.002
	(-0.682)	(1.453)	(1.465)	(-2.253)	(-1.355)	(-1.174)	(-0.663)

Panel C: Expert Tone

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ *Negative Calls*	-3.424**	0.517***	0.014**	-0.038***	0.934*	-0.177**	-0.012***
	(-1.971)	(3.008)	(2.107)	(-5.018)	(1.872)	(-2.349)	(-4.925)
Δ *Positive Calls*	2.733	0.033	0.008	-0.007	-0.156	-0.090	0.004*
	(1.500)	(0.208)	(1.196)	(-0.569)	(-0.270)	(-0.422)	(1.708)

Table IA1. Firms with the Highest Abnormal Expert Call Demand.

The table reports the top ten firms in each year with the highest number of calls scaled by market capitalization.

	2017	2018	2019	2020	2021	2022
1	Tripadvisor Inc	Attunity Ltd	Pivotal Software Inc	Livongo Health Inc	Amazon.com	Regional Health Propert Inc
2	Expedia Group Inc	Amazon.com Inc	Domo Inc	Guidewire Software Inc	Cardlytics Inc	Freshworks Inc
3	Twilio Inc	MongoDB Inc	Cardlytics Inc	Crowdstrike Holdings Inc	Snowflake Inc	Hasbro Inc
4	Booking Holdings Inc	Carvana Co	Smartsheet Inc	Upwork Inc	Alphabet Inc	Innovage Hold Corp
5	AppFolio Inc	TrueCar Inc	Liveramp Holdings Inc	Smartsheet Inc	Microsoft Corp	Backblaze Inc
6	MobileIron Inc	Ellie Mae Inc	Upwork Inc	Cardlytics Inc	Crowdstrike Holdings Inc	Rockwell Automation
7	Ellie Mae Inc	EPAM Systems Inc	MongoDB Inc	Splunk Inc	Olo Inc	Xometry Inc
8	CoreLogic Inc	BlackLine Inc	Eventbrite Inc	LiveRamp Holdings Inc	Splunk Inc	Crowdstrike Holdings Inc
9	Gigamon Inc	ShotSpotter Inc	Echo Global Logistics Inc	Alphabet Inc	JFrog Ltd	Snap Inc
10	Arc Group Worldwide Inc	Asure Software Inc	Elastic Nv	Palo Alto Networks Inc	Salesforce Inc	Henry (Jack) & Associates

Table IA2. Industry Distribution of Expert Network Calls

The table reports industry distribution of expert network calls based on Global Industry Classification (GIC) groups.

GIC Groups		Number of firms	Percent
1010	Energy	30	1.68%
1510	Materials	57	3.19%
2010	Capital goods	148	8.27%
2020	Commercial & Professional service	69	3.86%
2030	Transportation	35	1.96%
2510	Automobiles & Components	22	1.23%
2520	Consumer Durables & Apparel	67	3.75%
2530	Consumer Services	92	5.14%
2540	Media	1	0.06%
2550	Retailing	118	6.60%
3010	Food & Staples Retailing	16	0.89%
3020	Food, Beverage & Tobacco	47	2.63%
3030	Household & Personal Products	21	1.17%
3510	Health Care Equipment & Services	174	9.73%
3520	Pharmaceuticals, Biotechnology & Life Sciences	129	7.21%
4010	Banks	20	1.12%
4020	Diversified Financials	70	3.91%
4030	Insurance	34	1.90%
4510	Software & Services	315	17.61%
4520	Technology Hardware & Equipment	109	6.09%
4530	Semiconductors & Semiconductor Equipment	52	2.91%
5010	Telecommunication Services	17	0.95%
5020	Media & Entertainment	97	5.42%
5510	Utilities	12	0.67%
6010	Real Estate	37	2.07%
Total		1,789	

Table IA3. Frequency-Based Root Words used to Create Call Topic Seed Words

The table reports the root words used as seeds for the topic modeling. Based on reading 200 calls, we identify seven common topics that emerge from the calls: Competition, Consumer, Financial, Product, Operation, Strategy, and Technology. We then obtain a list of the most frequent non-stop words in the call transcripts. From this list, we retain the 50 most common words that can be categorized into the seven categories. The associated seeds and topics are listed below. For completeness, we also list 7 words that are among the top 50 most frequently used words but were difficult to classify (i.e., the 50 categorized seed words are from the top 57 words by frequency).

Word	Freq	Label	Word	Freq	Label
Compete	67,927	Competition	Product	321,434	Product
Competitor	49,542	Competition	Service	159,218	Product
Player	42,105	Competition	App	10,611	Product
Client	789,613	Consumer	Market	362,810	Strategy
Customer	268,932	Consumer	Price	119,530	Strategy
Consumer	50,928	Consumer	Strategy	101,506	Strategy
User	31,939	Consumer	Brand	95,188	Strategy
Money	91,885	Financial	Partner	86,872	Strategy
Revenue	71,367	Financial	Model	66,895	Strategy
Finance	36,525	Financial	Invest	44,826	Strategy
Costs	30,028	Financial	Acquisition	33,627	Strategy
Spending	20,824	Financial	Demand	26,932	Strategy
Capital	19,022	Financial	Advertise	22,012	Strategy
Budget	16,470	Financial	Technology	156,216	Technology
Tax	12,039	Financial	Solution	109,229	Technology
Profit	10,814	Financial	Cloud	100,602	Technology
Team	128,830	Operation	Software	89,516	Technology
Management	99,743	Operation	Engineering	31,831	Technology
Process	78,175	Operation	Research	23,336	Technology
Operation	51,626	Operation	Innovation	19,543	Technology
Vendor	48,836	Operation			
Supply	31,206	Operation		Unclassified Words	
Inventory	22,291	Operation		Result	
Employee	22,229	Operation		Resource	
Culture	16,464	Operation		Performance	
Capacity	14,943	Operation		Quality	
Staff	13,161	Operation		Platform	
Hire	10,188	Operation		Project	
Board	10,115	Operation		Credit	
Founder	10,035	Operation			

Table IA4. Expert Network Calls and Institutional Investor Position Changes: Including Passive Changes

The table repeats the analysis in Table 4, where the portfolio weight measures capture both active (changes in shares) and passive (changes in stock price) effect on portfolio weights. Specifically, portfolio weight changes are measured as $\frac{\#share_t \times price_t}{\sum \#share_t \times price_1} - \frac{\#share_{t-1} \times price_{t-1}}{\sum \#share_{t-1} \times price_{t-1}}$.

	Hedge Funds		Other Institutional Investors	
	Absolute Δ Portfolio Weight	Δ Portfolio Weight	Absolute Δ Portfolio Weight	Δ Portfolio Weight
	(1)	(2)	(3)	(4)
Δ *Expert Calls*	0.307***	-0.224*	0.128*	-0.152**
	(3.653)	(-1.763)	(1.843)	(-2.027)
Market Capitalization	0.068***	-0.054*	0.026	-0.010
	(2.785)	(-0.193)	(1.239)	(-0.528)
Leverage	-0.036	-0.015	-0.008	0.066
	(-0.574)	(0.218)	(-0.170)	(1.238)
Asset Growth	0.646	1.117*	1.232*	1.230***
	(1.198)	(1.980)	(1.757)	(3.171)
Stock Return$_{q-1}$	0.157	0.101	0.137	-0.046
	(1.102)	(0.478)	(1.563)	(-0.625)
Stock Return$_{[q-4,\ q-2]}$	-0.314*	-0.174	-0.458**	0.281
	(-1.871)	(-0.869)	(-1.967)	(1.296)
Δ *Volume*	-0.016	0.019	-0.011	0.002
	(-0.927)	(0.969)	(-1.002)	(0.238)
| Δ *Hedge Fund Holdings*$_{q-1}$|	-0.312**			
	(-2.258)			
Δ *Hedge Fund Holdings*$_{q-1}$		0.088		
		(0.430)		
| Δ *Other Inst. Holdings*$_{q-1}$|			-0.375**	
			(-2.077)	
Δ *Other Inst. Holdings*$_{q-1}$				-0.299**
				(-2.187)
Additional Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes
Observations	85,571	85,571	85,571	85,571

Table IA5. Future Expert Network Calls and Institutional Investor Position Changes
The table repeats the analysis in Table 4, where the change in expert calls is measured in the quarter after portfolio changes.

	Hedge Funds		Other Institutional Investors	
	Absolute Δ Portfolio Weight	Δ Portfolio Weight	Absolute Δ Portfolio Weight	Δ Portfolio Weight
	(1)	(2)	(3)	(4)
Δ *Expert Calls*	-0.095	0.060	-0.018	-0.002
	(-0.448)	(0.255)	(-0.135)	(-0.011)
Market Capitalization	0.060	-0.033	-0.023	0.019
	(1.038)	(-0.493)	(-0.546)	(0.399)
Leverage	-0.155	0.021	-0.102	0.107
	(-0.960)	(0.097)	(-0.824)	(0.786)
Asset Growth	-2.712**	3.825***	-2.694***	3.621***
	(-2.311)	(3.081)	(-3.118)	(3.866)
Stock Return$_{q-1}$	-0.390	0.712	-0.196	0.294
	(-0.728)	(1.048)	(-1.145)	(1.529)
Stock Return$_{[q-4,\ q-2]}$	0.453	-0.812*	0.539	-0.851*
	(1.202)	(-1.925)	(1.252)	(-1.751)
Δ *Volume*	0.020	-0.013	0.013	-0.019
	(0.700)	(-0.343)	(0.656)	(-0.852)
| Δ *Hedge Fund Holdings*$_{q-1}$|	-0.081**			
	(-2.183)			
Δ *Hedge Fund Holdings*$_{q-1}$		-0.176***		
		(-3.533)		
| Δ *Other Inst. Holdings*$_{q-1}$|			-0.129***	
			(-7.468)	
Δ *Other Inst. Holdings*$_{q-1}$				-0.165***
				(-8.432)
Additional Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes
Observations	85,571	85,571	85,571	85,571

Table IA6. Expert Network Calls and Capital Markets: Expert Type

The table repeats the analysis of Tables 4-8 excluding calls with each type of experts one at a time. For brevity, only the coefficients and standard errors for the call measures are reported.

	Δ Hedge Fund Port. Weight	Δ Short Interest	Δ Informed Trading	Δ Price Delay	Δ Intraperiod Timeliness	Δ EPS	CAR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Excluding Former Executive Calls							
Δ *Expert Calls*	-0.769***	0.306**	0.017***	-0.031**	0.515	-0.165***	-0.005***
	(-3.237)	(3.124)	(3.361)	(-1.995)	(1.220)	(-2.812)	(-2.717)
Panel B: Excluding Customer Calls							
Δ *Expert Calls*	-0.628***	0.348***	0.015***	-0.040***	0.751**	-0.148***	-0.004**
	(-2.794)	(3.124)	(3.193)	(-3.349)	(2.265)	(-2.853)	(-2.139)
Panel C: Excluding Competitor Calls							
Δ *Expert Calls*	-0.591***	0.309**	0.013**	-0.035***	0.767**	-0.153***	-0.004***
	(-2.710)	(2.681)	(2.887)	(-2.774)	(2.272)	(-2.890)	(-2.617)
Panel D: Excluding Industry Partners							
Δ *Expert Calls*	-0.665***	0.272**	0.017***	-0.040***	0.448	-0.171***	-0.003*
	(-2.944)	(2.387)	(3.588)	(-3.170)	(1.723)	(-3.148)	(-1.820)

Table IA7. Expert Network Calls and Capital Markets: Call Topic.

The table repeats the analysis of Tables 4-8 excluding calls one at a time. For brevity, only the coefficients and standard errors for the call measures are reported.

	Δ Hedge Fund Port. Weight	Δ Short Interest	Δ Informed Trading	Δ Price Delay	Δ Intraperiod Timeliness	Δ EPS	CAR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Excluding Calls that Discuss Competition							
Δ *Expert Calls*	-0.576***	0.406***	0.015***	-0.042***	0.692*	-0.134***	-0.004**
	(-2.632)	(3.838)	(3.404)	(-3.771)	(2.072)	(-2.623)	(-2.146)
Panel B: Excluding Calls that Discuss Consumers							
Δ *Expert Calls*	-0.632***	0.412***	0.014***	-0.039***	0.722*	-0.153***	-0.004**
	(-2.773)	(3.765)	(3.052)	(-3.509)	(2.126)	(-3.062)	(-2.179)
Panel C: Excluding Calls that Discuss Financials							
Δ *Expert Calls*	-0.682***	0.420***	0.014***	-0.042***	0.619*	-0.134***	-0.004**
	(-3.056)	(3.866)	(2.996)	(-3.806)	(1.827)	(-2.659)	(-2.202)
Panel D: Excluding Calls that Discuss Operations							
Δ *Expert Calls*	-0.641***	0.413** *	0.014***	-0.039***	0.615*	-0.137***	-0.003**
	(-2.838)	(3.834)	(3.032)	(-3.136)	(1.828)	(-2.666)	(-1.976)
Panel E: Excluding Calls that Discuss Products							
Δ *Expert Calls*	-0.627***	0.392***	0.017***	-0.042***	0.699**	-0.125**	-0.004**
	(-2.855)	(3.536)	(3.122)	(-3.621)	(2.042)	(-2.427)	(-2.193)
Panel F: Excluding Calls that Discuss Strategy							
Δ *Expert Calls*	-0.577***	0.410**	0.014***	-0.042***	0.639*	-0.120**	-0.004**
	(-2.675)	(3.762)	(3.784)	(-3.368)	(1.835)	(-2.367)	(-2.093)
Panel G: Excluding Calls that Discuss Technology							
Δ *Expert Calls*	-0.623***	0.420***	0.014***	-0.041***	0.670**	-0.128**	-0.003**
	(-2.859)	(3.797)	(2.884)	(-3.193)	(2.044)	(-2.460)	(-2.113)