HUMAN-INTERACTION-BASED INFORMATION AND MANAGERIAL LEARNING FROM STOCK PRICES: EVIDENCE FROM THE COVID-19 PANDEMIC

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DISSERTATION ABSTRACT

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Despite growing evidence managers learn information from stock prices that guide their investment decisions, the forms of information that underlie this learning mechanism are not well understood.

This paper explores whether information produced by investors' in-person human interactions is a key form of this information. Using foot traffic based on GPS location data from customers' smartphones as a proxy for human-interaction-based information in stock prices, I find that investment-*q* sensitivity increases with foot traffic, consistent with managerial learning from prices increasing with the amount of human-interaction-based information in prices. To mitigate omitted variable bias, I use lockdowns triggered by the COVID-19 pandemic as exogenous shocks to information produced by human interactions. I find a decrease in investment-*q* sensitivity during the pandemic. The decrease is more pronounced when foot traffic decreases in places where human interactions are most likely to produce new information (e.g., cafés and restaurants) and among local firms, for which human-interaction-based information production was more active pre-pandemic. I further find that the decrease is more marked among young and growing firms, which investors have a comparative advantage in evaluating. Lastly, I

show that my findings are not explained by noise trading, financial constraints, managers' direct acquisition of human-interaction-based information, and local economic conditions.

Taken together, I provide novel evidence of human-interaction-based information being a key form of information underlying managerial learning from stock prices.

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1. INTRODUCTION

A nascent literature in financial economics suggests that financial markets affect the real economy through managerial learning channel (see Bond et al. 2012 for a review). In essence, stock prices aggregate information that is dispersed among different traders who have few means of communicating with managers beyond their trading (e.g., Hayek 1945; Grossman and Stiglitz 1980; Glosten and Milgrom 1985; Kyle 1985). As a result, stock prices can reveal traders' private information that is otherwise unavailable to managers and affect managers' real decisions. For example, studies show that managers are likely to cancel mergers and acquisition decisions when they observe negative market feedback on the announcement of proposed deals (Luo 2005). Although managers might have already considered numerous aspects of the acquisition, the value of a deal is contingent on synergies between firms and what a reasonable price might be. In this respect, investors will have additional insights, and the aggregation of their thoughts can affect managers' real decisions. A growing number of studies provide evidence consistent with managers learning from stock prices in this way (e.g., Chen, Goldstein, and Jiang 2007; Zuo 2016; Edmans, Jayaraman, and Schneemeier 2017; Jayaraman and Wu 2019; 2020; Goldstein, Yang, and Zuo 2022; Ye, Zheng, and Zhu 2022; Kim, Park, and Wilson 2022). However, the forms of information that underlie this learning from stock prices are not well understood (Goldstein 2022).

I examine whether human-interaction-based information (i.e., information that is produced via investors' in-person interactions), a type of soft information, helps drive managerial learning from stock prices when managers are making corporate investment decisions. The literature discusses various types of soft information: human-interaction-based information, text-based information, or unquantifiable information (Liberti and Petersen 2019; Bai and Massa 2022). My primary interest is soft information generated locally through investors' in-person interactions and

I denote it as human-interaction-based information.[1] Human-interaction-based information can be produced from investors' informal meetings in local cafés, restaurants, and bars. What distinguishes it from quantifiable information (so-called hard information) or other types of soft information such as text-based information is that the context of its collection and its producers matter more (Liberti and Petersen 2019), and thus, human-interaction-based information is harder to standardize. If it is summarized into standardized reports, some or all of is the critical nuance is inevitably lost (Liberti and Petersen 2019; Bai and Massa 2022).

When making investment decisions, managers are expected to utilize all sources and forms of information available to them (Goldstein 2022), including information produced by in-person interactions among outside investors. However, learning theories indicate that managers can be inefficient in acquiring this kind of information because it is difficult to standardize (Rajan and Zingales 2003; Gao and Liang 2013). As a result, the information is difficult to transmit to managers through the internal accounting system without losing its content. Also, managers cannot acquire all human-interaction-based information directly from investors because doing so is time-consuming, and managers have limited time and resources (Geanakopolos and Milgrom 1991).

Stock prices can better aggregate diverse pieces of human-interaction-based information because investors' profit-seeking motives encourage them to acquire information by interacting with others and trading on it, where it is then impounded into prices. Loss of information content is less likely to occur since the information is impounded by its producers. For these reasons, stock prices are likely to aggregate human-interaction-based information that is otherwise difficult to

[1] I denote human-interaction-based information as the one generated via in-person interactions, not virtual ones. I define information collected virtually as virtual information.

capture. Thus, I expect that managers are likely to glean from stock prices new information, produced via investors' physical interactions, when making investment decisions.[2]

To capture the extent of information from human interactions in stock prices, I use a database provided by SafeGraph that tracks foot traffic. SafeGraph captures in-person interactions by tracking foot traffic patterns to 3.6 million commercial points-of-interest from over 45 million anonymous smartphones in the United States. Since information from human interactions is generated locally, I aggregate foot traffic on headquarters-located core-based statistical areas (CBSAs)-level at which areas that socioeconomically tie adjacent counties.[3] To provide evidence that trading impounds this information into stock prices, I examine whether foot traffic is correlated with private information in stock prices, measured with price nonsynchronicity.[4] I find a positive association between foot traffic and price nonsynchronicity, which suggests that the information generated by physical interactions is impounded into prices.

To examine the effect of human-interaction-based information in prices on managerial learning from stock prices, I employ the investment-*q* sensitivity framework, which has been widely used in the managerial learning literature (e.g., Jayaraman and Wu 2019). I expect investment-*q* sensitivity to increase with foot traffic if managers glean from prices new information that guides their investment decisions. If human-interaction-based information in stock prices is

[2] An example of human-interaction-based information that is aggregated by investors can be information about firm-specific consumer demand after the announcement of inflation rates. Once inflation rate is announced, investors can form their own opinions about the effect of inflation rates on firm-specific consumer demand by interacting with other investors at cafes. Although managers can also form their own opinions by reading reports and directly interacting with investors, a key assumption is that their information set is not complete in part to the characteristics of human-interaction-based information. Thus, they still care to learn investors' human-interaction-based information from stock prices.

[3] CBSAs include both metropolitan and micropolitan statistical areas. Metropolitan statistical areas have at least one urbanized area of 50,000 people plus adjacent territory. Micropolitan statistical areas have at least one urban cluster of at least 10,000 but less than 50,000 population plus adjacent territory (U.S. Census Bureau).

[4] Using price nonsynchronicity as a measure of private information is subject to limitations. While some studies use price nonsynchronicity to measure private information in stock prices (e.g., Chen et al. 2007), other studies use the measure to capture total amount of information in prices (e.g., Edmans et al. 2017). In line with Chen et al. (2007), I use price nonsynchronicity as a measure of private information in stock prices that is unavailable to managers.

more likely to reveal information already known to managers, this will move prices but not affect investment decisions (as it is reflected to past investments), leading to decreases in investment-q sensitivity. Conversely, if prices more likely reveal information previously unknown to managers, this will move prices as well as investments (as managers' investment decisions respond to price signals), leading to increases in investment-q sensitivity. My results show a positive relation between investment-q sensitivity and foot traffic, which is consistent with my expectation that information impounded to prices through investors' in-person interactions reveal new information which is useful for managers' investment decisions.

Although the positive association between foot traffic and investment-q sensitivity indicates a learning channel, market prices can be correlated with firms' investments for various reasons (Goldstein 2022).[5] To mitigate such concerns, I exploit the lockdowns triggered by the COVID-19 pandemic as exogenous shocks to investors' production of human-interaction-based information. The lockdowns exogenously decreased physical interactions, a key channel through which human-based-information is produced. Put differently, investors were less likely to interact in person and trade based on what they learned from those interactions during the lockdowns. An empirical challenge in the learning literature is that prices and investment decisions are often affected by the same factors (Goldstein 2022). Thus, shocks to the amount of information in prices allow me to examine whether prices influence managerial investment decisions.

To determine whether a specific CBSA is subject to lockdown, I rely on decreases in foot traffic during the pandemic, compared to the pre-pandemic level, instead of using official enforcement dates. Although enforcements were mandatory, they were not necessarily strictly enforced on real business activities across different states (Bai and Massa 2022). As a result,

[5] Prices and investments can be correlated mostly because both are positively affected by firms' fundamentals.

enforcement dates may not accurately capture actual human interactions. Defining lockdowns with foot traffic, however, enables me to capture decreases and rebounds in actual human interactions across CBSAs. Accordingly, I classify as treatment (control) firms those that are located in CBSAs that experienced (did not experience) a sizable decrease (e.g., 60% or above) in foot traffic, compared to the pre-pandemic period level. A generalized difference-in-differences analysis shows that investment-*q* sensitivity significantly decreases during the lockdowns. This result is robust to various combinations of fixed effects at industry, firm, year-quarter, CBSA, and industry-times-year-quarter levels. This further supports my hypothesis that managers are less likely to learn new information from prices when prices contain less human-interaction-based information.

Although the decrease in investment-*q* sensitivity during lockdowns is consistent with my hypothesis, the decrease could be due to time-varying omitted variables. To reinforce price-based learning as the mechanism, I conduct a set of cross-sectional analyses. First, I examine whether the decrease in investment-*q* sensitivity is concentrated when decreases in foot traffic affect places where human-interaction-based information is most likely to be generated. Bai and Massa (2022) show that in-person interactions that produce information are most likely in places like cafés, restaurants, bars, and fitness centers and least likely in places like childcare services, personal care services, and amusement parks. Thus, if the decrease in investment-*q* sensitivity during lockdowns was driven by decline in human-interaction-based information in prices, I would expect the decrease to be stronger when lockdowns are defined based on foot traffic from the former group of places but weaker when lockdowns are defined based on foot traffic from the latter group. The results are precisely consistent with these predictions, supporting my inference that the drop in human-interaction-based information in prices is attributable to the decrease in investment-*q* sensitivity through the managerial learning channel.[6]

Second, I examine whether the decrease in investment-*q* sensitivity associated with lockdowns is more pronounced for local firms, where human-interaction-based information mattered more before the pandemic. Studies suggest that local investors have an information advantage about local firms because they are more likely to produce soft information through in-person interactions (e.g., Baik, Kang, and Kim 2010) and soft information is likely to cluster near corporate headquarters (i.e., local) (e.g., Coval and Moskowitz 1999; 2001; Bai and Massa 2022). Thus, managers at local firms were likely to be more active in gleaning new information produced via human interactions, which they used when making investment decisions pre-pandemic. When investors' in-person interactions declined during lockdowns, these managers were also likely to have suffered a greater decrease in their learning from prices. Using two proxies (local institutional ownership and geographic concentration of firms' operations) for firms' localness, I find the decrease in investment-*q* sensitivity is more pronounced among local firms.

Lastly, I examine whether young and growing firms exhibit a more marked decrease in investment-*q* sensitivity. Learning models assume that investors' information lies in assessing growth options, whereas managers are adept at analyzing assets-in-place (Gao and Liang 2013). Empirical research provides evidence consistent with this idea (Goldstein et al. 2022). Further, young and growing firms are more likely to suffer from lack of hard historical data (e.g., accounting numbers), making managers more likely to rely on the market's soft information. In line with this prediction, I find that the decrease in investment-*q* sensitivity is stronger for young and growing firms. Taken together, the results of the cross-sectional analyses firmly support my

[6] Further, this result suggests that information produced in the virtual world based on Zoom/Skype and remote networks likely will not sufficiently replace human-interaction-based information.

inference that the decrease in investment-*q* sensitivity during lockdowns is driven by managers' inability to glean new information, especially that produced via human interaction, from prices when making investment decisions.

Finally, I explore several alternative explanations for the decrease in investment-*q* sensitivity during lockdowns. First, I mitigate the possibility that noise trading and the market panic associated with the pandemic are driving my results. Second, I show that the results are not driven by worsened financial constraints during the pandemic. Third, I find that my results are not ascribable to a decrease in managers' ability to learn by directly interacting with investors. Fourth, I control for time-varying CBSA-level factors such as local GDP growth that can affect investment-*q* sensitivity. Lastly, I find that the decrease in investment-*q* sensitivity is not due to a general decrease in investment opportunities during the pandemic.

A central contribution of my paper is to demonstrate that information generated from human interaction is a key form of information that managers learn from stock prices when making investment decisions. Studies have provided evidence consistent with managerial learning (Chen et al. 2007; Jayaraman and Wu 2019; 2020; Fox, Kim, and Schonberger 2021; Kim et al. 2022; Goldstein et al. 2022; Ye et al. 2022). Yet the form of information underlying that learning is not well understood. My study contributes to this nascent literature by providing a new framework for classifying information underlying the learning. Prior studies have categorized information based on its *contents*. In particular, they have distinguished between firm-specific and macroeconomic/industry-wide information and have commonly assumed that the market is better at analyzing the latter than the former. My new framework categorizes information based on its *form* and assumes that the market as a whole is better at aggregating human-interaction-based information than non-human-interaction-based information. The distinction between human-interaction-based information and non-human-based information is more about how information is collected and delivered, while the distinction among firm, industry, and macroeconomic information primarily concerns contents. My findings suggest that managers are likely to glean from stock prices information that originates in investors' in-person interactions. This indicates that managers care about learning information that is difficult to standardize since this kind of information is not easily transmitted through an internal accounting system.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Managerial learning from stock prices

Different from the conventional notion that information flows between firms and capital markets as one way—from firms to capital markets—the managerial learning (i.e., market feedback) channel implies that information can also flow in the opposite direction. (See Bond et al. 2012 for a review) In essence, stock prices aggregate information that is dispersed among traders, and managers can look to prices to glean this information to guide their actions. While a manager has a great deal of information about his or her firm, the manager's decisions also benefit from obtaining information about competitors, industry factors, and macroeconomic conditions. Learning theories commonly assume that investors' information advantage lies in analyzing these factors (Gao and Liang 2013; Goldstein and Yang 2019; Goldstein 2022).

One setting in which market feedback is easier to detect is an acquisition decision. A firm makes an announcement, to which the market reacts, and then the firm changes its plan based on that reaction. A classic example of the effect of market feedback on a firm's acquisition decision was Coca-Cola's attempted acquisition of Quaker Oats. On November 20, 2000, *The Wall Street Journal* reported that Coca-Cola was attempting to acquire Quaker Oats. Shortly afterward, Coca-Cola confirmed the report. Traders in the market, who believed that the acquisition would destroy value, reacted negatively, causing Coca-Cola's shares to drop 8 percent that day. On November 21, the board of Coca-Cola rejected the attempted acquisition, and, the following day, the shares rebounded 8 percent. This example shows how market feedback can change firms' real decisions. Although managers might have already considered various aspects of the acquisition, such a deal is eventually about synergies and what a reasonable price might be. In this regard, investors will have insights, and the aggregation of their thoughts can affect managers' real decisions. Luo (2005) provides evidence broadly consistent with this example.

Beyond acquisitions, studies examine the informational feedback from stock prices in other corporate decisions, such as firm investments. Chen et al. (2007) were the first researchers to empirically examine the managerial learning hypothesis using the sensitivity of investment to stock prices. They found that the sensitivity of investment to prices increases with the amount of private information in prices, measured with price nonsynchronicity and the probability of informed trading (PIN). The idea is that, if investments are more sensitive to prices when prices reveal more private information, then the information in prices is used for investment decisions. Edmans et al. (2017) employ insider trading enforcement as a shock to the amount of private information in prices. They show that, when laws force managers to less trade on insider information, that reduces competition between insiders and outside investors and encourages outsiders to trade more on their private information, which leads to an increase in the sensitivity of investments to prices. More recently, Ye et al. (2022) use the randomized controlled tick-size experiment by the SEC and find that a larger tick size increases a firm's investment sensitivity to the stock price, supporting the idea that managers glean more new information from stock prices in guiding their investment decisions as the widened tick size discourages algorithmic trading and increases informed trading.

Gao and Liang (2013) theoretically study a role of mandatory disclosures in impeding the information feedback effect of prices. The idea is that, to the extent that firm disclosures are positively correlated with the private information of informed traders, an increase in disclosures can discourage informed traders' private information acquisition, leading to a decrease in market feedback. Jayaraman and Wu (2019) empirically test this model using the mandatory change in segment disclosures (SFAS 131) as their setting. They find that an increase in firm disclosures decreases informed traders' private information acquisition, leading to a decrease in investment-*q* sensitivity to stock prices. Similarly, Goldstein et al. (2022) employ the implementation of the EDGAR system and show that broader information dissemination crowds out investors' private information acquisition and reduces managerial learning from stock prices. Kim et al. (2022) examine the credibility of disclosures by credit rating agencies. They show that, when credit ratings become a more precise estimate of firms' creditworthiness, informed traders spend less time collecting information about firm-specific uncertainties (known to managers) and more producing information about industry- or market-wide uncertainties (new to managers). As a result, they find an increase in managerial learning from stock prices when disclosures by credit rating agencies become more credible.

So far, studies have provided evidence consistent with the idea that managers learn private information from stock prices to guide their investment decisions and that disclosures can facilitate or hinder such a feedback mechanism. Studies further suggest that the particular information managers glean from stock prices concerns macroeconomic conditions and industry-wide factors (e.g., consumer demand). However, the *forms* of information that underlies managerial learning from stock prices are not well understood. I extend the learning literature by examining whether human-interaction-based information is likely to be a form of information that facilitates managerial learning.

2.2 Human-interaction-based information and hypothesis development

My primary focus is human-interaction-based information which is a subset of soft information. Soft information has been extensively discussed in the accounting and finance literatures along with hard information (e.g., Stein 2002; Petersen 2004; Liberti and Petersen

2019). Hard information comes from quantifiable sources, such as analyst reports and firms' financial statements. It is easily transmitted across parties without losing its content (Liberti and Petersen 2019). As a result, corporate managers can obtain hard information mostly through the internal accounting system (e.g., standardized reports). On the other hand, soft information is difficult to quantify or standardize thus harder to transfer via the internal accounting system. Existing literature discusses various types of soft information – human-interaction-based information, text-based information, or unquantifiable information (Bai and Massa 2022; Liberti and Petersen 2019). Although they share a common feature of "difficult to quantify," human-interaction-based information is especially hard to standardize since it is collected through in-person interactions, and the context under which it is collected, and the producer of information are important parts of the process (Giroud 2013; Liberti and Petersen 2019; Bai and Massa 2022). For example, such information may come from investors' informal chats at cafés and bars.

Human-based information and non-human-based information (i.e., any information not produced through in-person interactions) are not mutually exclusive from firm, industry, and macroeconomic information because the former is defined based on their form (Liberti and Petersen 2019), while the latter is defined based on their contents (Edmans et al. 2017; Goldstein and Yang 2019). Thus, the term "human-interaction-based information" speaks more to how information is collected and delivered, while distinctions among firm, industry, and macroeconomic information primarily concern the nature of the information. Thus human-based information can convey any type of information content.

I hypothesize that managers rely on stock prices to glean human-interaction-based information in making investment decisions. First, managers utilize all types of information available, including information collected via investors' in-person interactions in making investment decisions (Chen et al. 2007; Goldstein 2022). However, it is difficult for managers to obtain all human-based information by directly interacting with outside investors because it would be too costly to meet all relevant people. They can learn to some degree, but learning all relevant information from direct interaction is likely infeasible. Second, while investors' human-interaction-based information can be delivered to managers through the internal accounting system, part of its information content will be inevitably lost. Learning theories also indicate that managers can be inefficient in acquiring information that is difficult to standardize and hard to interpret, while the stock market has a competitive advantage at aggregating such information (Gao and Liang 2013). Thus human-based information that is produced via investors' physical interactions is likely to be information that managers want to learn from stock prices. And stock prices, for their part, can serve to aggregate, via the trading process, informed traders' information produced through their physical interactions. By considering stock prices, managers can glean that information and use it for their investment decisions. As a result, I present my main hypothesis in the alternative form.

Hypothesis: Managerial learning from stock prices increases with the amount of human-interaction-based information in prices.

3. DATA AND RESEARCH DESIGN

3.1. Data and sample

Data for this paper come from six primary sources. I obtain quarterly firm financial statement information data from the quarterly Compustat file, stock price and return data from Center for Research in Security Prices (CRSP), analyst following data from Institutional Brokers Estimate System (IBES) summary statistics, institutional ownership data from Thomson Reuters 13F, and insider trading data from Thomson Reuters Insiders Data. Finally, I obtain foot traffic data from SafeGraph, specifically, the SafeGraph Places Patterns dataset, which measures foot traffic patterns to 3.6 million commercial points-of-interest from over 45 million smartphones in the United States.

SafeGraph aggregates anonymized data from numerous smartphone applications that rely on location services. SafeGraph conducts a set of tests to mitigate concerns of sampling bias. The Pearson correlation between the number of smartphone devices and the census population across 3,281 counties in the United States is as high as 97 percent.[7] The raw data includes a panel of GPS pins, obtained from anonymous smartphones, and includes roughly 10 percent of the U.S. population. The data illustrates the number of visits people make to a certain place during a given time interval. At granular level, SafeGraph provides the number of visits to a certain place in a given day, and each observation provides zip code information of a place that people visit to (e.g., 153 people visited Starbucks located in 98101 on July 7, 2022).[8]

To capture foot traffic around firm locations, using zip code variables in foot traffic data, I merge each observation with core-based statistical area (CBSA) information obtained from the

[7] For more details, find the link: https://colab.research.google.com/drive/1u15afRytJMsizySFqA2EPlXSh3KTmNTQ##offline=true&sandboxMode=true.

[8] Examples of places in the data include cafés, bars, restaurants, fitness centers, etc.

U.S. Census Bureau data. CBSA is a U.S. geographic area defined by the Office of Management and Budget (OMB) and consists of one or more counties anchored by an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center by commuting (U.S. Census Bureau). I aggregate foot traffic patterns at the CBSA-quarter level and then merge them with my main dataset. Thus, this allows me to capture people's physical interactions in socioeconomically tied areas near a firm's headquarter in a given quarter.

To construct my sample, I begin with Compustat quarterly data during the period from the first quarter of 2018 to the third quarter of 2021. To obtain information about a firm-located zip code, I use historical header information.[9] Using zip code information in each observation, I merge with the Census data to obtain CBSA information of each firm. Then I merge with SafeGraph's foot traffic, CRSP, IBES, and Thomson Reuters data. I exclude financial and utility firms (standard industrial classification codes 6000–6999 and 4900–4999). After requiring the availability of variables needed in my baseline regression, I have a baseline sample with 27,937 firm-quarter observations.

3.2. Baseline regression model

I follow prior studies (e.g., Chen et al. 2007; Bai, Philippon, and Savov 2016; Edmans et al. 2017; Jayaraman and Wu 2019) and use the investment-q sensitivity framework (where future investment is regressed on current Tobin's q) to proxy for managerial learning from prices. The learning hypothesis predicts a positive association of the sensitivity of investment to q for the following reasoning. If stock prices are more likely to divulge human-interaction-based soft information that is already known to managers, this will change prices but not affect investment

[9] Unlike header information in Compustat, which only provides most up-to-date header information, the CRSP/Compustat merged database provides historical header information. It provides the date and the new headquarter state when a firm changes its headquarter. I further cross-checked with the header information obtained from EDGAR.

decisions (as it is reflected to past investments), leading to decreases in investment-q sensitivity. In contrast, if prices are more likely to reveal human-interaction-based information that is new to managers, this will move prices and investments (as managers are more likely to respond to price signals), leading to increases in investment-q sensitivity (Chen et al. 2007).

To test my hypothesis on whether human-interaction-based information in prices is likely to reveal new information for managers' investment decisions, I augment the classical investment-q sensitivity regression by interacting q with foot traffic. Specifically, I estimate the following ordinary least squares (OLS) regression model with firm subscripts omitted.

$$INV_{t+1} = \alpha + \gamma + \delta + \beta_1 q_t + \beta_2 CFO_t + \beta_3 FOOT\_TRAFFIC_t + \boldsymbol{\beta_4} q * FOOT\_TRAFFIC_t + \beta_5 CFO * FOOT\_TRAFFIC_t + \beta_6 SIZE_t + \varepsilon_t, \quad (1)$$

where INV_{t+1} represents future investment of firm i as of quarter t+1, defined as capital expenditures deflated with fixed assets plus R&D expense scaled by the total assets. *FOOT_TRAFFIC* captures the amount of foot traffic in a CBSA in a given quarter, scaled by the population of the CBSA. I use q to represent Tobin's q, defined as the ratio of market value of assets (market value of equity plus book value of debt) divided by book value of assets. q is a price-based measure of a firm's investment opportunity set, and I also include *CFO* (cash flows from operations scaled by total assets) as a nonprice measure to control a general trend in investment opportunities. I follow Jayaraman and Wu (2019) and Foucault and Frésard (2012) and include firm size (*SIZE*) as a control, which is defined as the natural log of market value of equity. Finally, I include firm (α), industry-time (γ), and CBSA (δ) fixed effects. Standard errors are clustered at the CBSA level. If investors' physically produced information impounded in prices reveals new information to managers and managers rely on it in making investment decisions, the coefficient on β_4 will be positive.

3.3. Quasi-natural experimental design: lockdowns during the COVID-19 pandemic

The OLS estimates in equation (1) can be biased due to correlated omitted variables. For example, firm investments and prices are frequently impacted by the same fundamentals, such as investment opportunities, which drive the sensitivity of investments to prices (Goldstein 2022). Also, investment-*q* sensitivity may drive foot traffic (a reverse causality bias). To mitigate these concerns, I employ the lockdowns triggered by the COVID-19 pandemic as exogenous shocks to human-interaction-based information production.

The lockdown exogenously reduces physical interactions, a key channel through which human-interaction-based information is generated. Thus, investors are less likely to interact in-person, produce new information, and trade based on it. Moreover, the lockdowns help overcome empirical challenge in the learning literature. The challenge is that prices and investment decisions are often affected by the same fundamentals (Edmans et al. 2017; Goldstein 2022). Another challenge is to find empirical measures that capture information in prices (Goldstein 2022). This information is unobservable to researchers, and measures face limitations in capturing its impact on prices. Accordingly, instead of measuring information in prices directly, many papers in the learning literature rely on firm characteristics to identify a set of firms for which managerial learning from stock prices is expected to be more or less pronounced. For example, the literature generally assumes that investors' information advantage lies in analyzing growth options, whereas managers are better at analyzing assets-in-place (Gao and Liang 2013; Goldstein et al. 2022). In this paper, I utilize the lockdowns during the pandemic as a shock to the amount of human-interaction-based information in prices.[10]

[10] In Section 5, I conduct a set of cross-sectional analyses to examine whether the learning effect is more pronounced for firms with greater incentives to learn investors' human-interaction-based information from the market.

To define lockdowns, I use decreases in foot traffic in CBSAs around the onset of the pandemic, instead of using state-level enforcement dates. Although the enforcements were mandatory, they were not necessarily strictly enforced on real business activities (Bai and Massa 2022). Due to these compliance issues, enforcement dates may not accurately capture effects on actual human interactions (Bai and Massa 2022). For example, people in Democrat-dominated states, like California, tended to abide by lockdown enforcements, whereas those in Republican-dominated states, like Florida or Texas, were less likely to. In contrast, defining lockdowns with foot traffic captures decreases and rebounds in actual human interactions in different CBSAs. Furthermore, even within same states, different areas have different lockdown policies.[11]

Figure 1, Panel A, illustrates foot traffic by county before the COVID-19 outbreak (the second quarter of 2019). In Figure 1, Panel B, I show the same information during the onset of the COVID-19 pandemic (the second quarter of 2020). As we can see foot traffic sharply declined after the outbreak. In Figure 2, I find a precipitous decline in foot traffic by CBSA starting the second quarter of 2020 and it continues to rebound and drop during the pandemic. This tendency is consistent with the onset of COVID-19 and its effect of lockdowns on business activity in the United States.

To test whether managerial learning from stock prices decreases when information in prices produced by human interactions exogenously declines, I estimate the following generalized difference-in-differences model.

$$INV_{t+1} = \alpha + \gamma + \delta + \beta_1 q_t + \beta_2 CFO_t + \beta_3 LOCKDOWN_t + \boldsymbol{\beta_4} q*LOCKDOWN_t + \beta_5 CFO*LOCKDOWN_t + \beta_6 SIZE_t + \varepsilon_t, \quad (2)$$

[11] For example, adjacently located in Florida, Duval county closed its beaches in March 2020 while St. John's county did not.

where *LOCKDOWN* is coded as 1 if foot traffic in a firm-located CBSA contracted below 60%, relative to that of the same quarter in the pre-pandemic period (e.g., if foot traffic in the second quarter of 2020 is below 60%, relative to that of the second quarter of 2019, it is coded as 1). The threshold of 60% is close to the mean (median) pandemic drop of foot traffic, which is 63% (60%), relative to the pre-pandemic.[12] All other variables are defined as in equation (1). To control for the heterogenous, time-varying impact of the pandemic across industries, I use two-way industry-time fixed effects. The pandemic severely hit some industries, such as airlines, but benefitted others, such as e-commerce. The industry-time fixed effect controls for time-varying industry changes. Thus β_4 captures differential changes in investment-*q* sensitivity across firms located in different CBSAs within the industry-quarter cohort. I also include firm fixed effects to control for firm-specific factors that potentially affect investment-*q* sensitivity and include CBSA fixed effects to control for time variation in investment-*q* sensitivity across CBSA. Standard errors are clustered at the CBSA level. I also include different sets of fixed effects to examine the robustness of my findings.

[12] My inferences remain unchanged when 50% or 70% is used as the threshold.

4. RESULTS

4.1. Summary statistics

Table 1 presents the summary statistics. In Panel A, I provide descriptive statistics of the variables used in the baseline sample. The mean (median) investment rate is 7.5% (4.8%). The mean (median) q is 2.546 (1.759). Panel B presents descriptive statistics of foot traffic before and after the onset of the COVID-19 pandemic. Average (median) foot traffic activity in 2019, the year before the Covid-19 outbreak, is roughly 58 (55) million. As expected, foot traffic plummets during the pandemic. Average foot traffic in the first year of the COVID-19 outbreak (the second quarter of 2020 – the first quarter 2021) is roughly 35 (22) million, representing about a 61% (57%) decrease, relative to same quarters pre-Covid.

4.2. Validation of foot traffic as a proxy of human-interaction-based information in prices

Before discussing the empirical results, I validate foot traffic as a proxy for human-interaction-based information in stock prices in two ways. First, studies document that foot traffic captures the human-interaction-based information produced by market participants. For example, defining lockdowns with foot traffic, Bai and Massa (2022) find that fund managers reduce proximate stocks, for which human-interaction-based information plays an important role in trading, in their portfolios during lockdowns. This result is consistent with the idea that foot traffic captures market participants' production of human-interaction-based information. If investors have profit-driven motives, the information produced via their in-person interactions should be impounded in prices through their trading. Thus, I examine an association between foot traffic and informed trading, measured with price nonsynchronicity (Chen et al. 2007). If investors trade on information generated through their in-person interactions, I expect a positive association between foot traffic and price nonsynchronicity. I present the results in Table 2. I include a set of control variables that studies have shown are associated with price nonsynchronicity (e.g., Piotroski and Roulstone 2004; Kim, Su, Wang, and Wu 2021). I standardize *FOOT_TRAFFIC* (by deducting its respective sample means and scaling by its respective sample standard deviation) so that the coefficient can be interpreted as the marginal impact of a one standard deviation change. The coefficient of 0.108 on *FOOT_TRAFFIC* indicates a 10.8% increase in price nonsynchronicity in response to a one standard deviation increase in *FOOT_TRAFFIC.* This result supports my inference that investors' trade on information they produce through in-person interactions, and that this information is more likely to be private information.

4.3. Results of baseline regressions

I present the baseline OLS regression results of estimating equation (1) in Table 3.[13] Model 1 presents the baseline estimation without treatment effects, where future investment is regressed on current *q*. Following the learning literature, I also include cash flow from operations (*CFO*) as a nonprice-based measure of investment opportunities (Edmans et al. 2017). I also include firm size (*SIZE*) to control for the fact that heterogeneity in firm size affects investment-*q* sensitivity. The association between investment and *q* is positive and is consistent with prior studies (e.g., Jayaraman and Wu 2019). In Model 2, I interact *q* with *FOOT_TRAFFIC*. The positive and significant coefficient of 0.089 on *q*FOOT_TRAFFIC* indicates that investment-*q* sensitivity increases 8.9% in response to a one standard deviation increase in the amount of human-interaction-based information, suggesting that information produced by in-person interactions is likely new and guides managers' investment decisions. In Model 3, I include *CFO* and its interaction with *FOOT_TRAFFIC*, and the coefficient on *q*FOOT_TRAFFIC* remains positive and significant. However, the coefficient on *CFO*FOOT_TRAFFIC* is insignificant, suggesting

[13] In all regression models, *q* and *CFO* have been standardized to have a mean of 0 and a standard deviation of 1 so that the coefficients can be interpreted as the marginal impact of one standard deviation (Jayaraman and Wu 2019).

that the sensitivity of investment to cash flow, a nonprice measure of investment opportunities, is effectively near zero and insignificant. This suggests that the increase in investment-*q* sensitivity associated with foot traffic is not part of a general trend in which investment becomes more responsive to investment opportunities (Edmans et al. 2017; Jayaraman and Wu 2019).

All my tests use industry×time (year-quarter) fixed effects, so my findings cannot be explained by any factor that does not change across firms within a given industry and time, such as industry-wide investment opportunities or the position of the business cycle. In other words, I compare firms within the same industry-quarter cohort but located in different CBSAs. My results are also robust to including firm fixed effects, so any firm-level time-invariant unobservable variable that may affect foot traffic and investment-*q* sensitivity cannot influence my findings. Collectively, the results in Table 3 suggest that human-interaction-based information in prices delivers new information to managers and managers use that information to guide their investment decisions.

4.4. Results of difference-in-differences estimation using a quasi-natural experiment

Although the finding that investment-*q* sensitivity increases with the amount of investors' human-interaction-based information is suggestive of the learning channel, investment-*q* sensitivity can be affected by other variables (Goldstein 2022). To mitigate this concern, I employ the pandemic-triggered lockdowns as exogenous shocks to production of information through human interactions. If this kind of information is driving managerial learning from stock prices, I expect the sensitivity of investments to prices likely decreases with an exogenous reduction in human-interaction-based information available.

In Table 4, I present results of estimating equation (2). Model 1 presents the baseline results without including treatment effects. The association between investment and *q* is positive and is consistent with prior studies (Jayaraman and Wu 2019). In Model 2, I provide results of the effect of lockdowns on investment-*q* sensitivity. The coefficient on *q*LOCKDOWN* is -0.087 and significant, indicating that the sensitivity reduced 8.7% during lockdowns. Since lockdowns are exogenous shocks to the production of human-interaction-based information, the result mitigates the concern that investment-*q* sensitivity is driven by other omitted factors.

In Model 3, I additionally include *CFO*-interacted variables and find that the coefficient on *q*LOCKDOWN* remains negative and significant. In Models 4 and 5, to examine robustness of my findings, I include different sets of fixed effects and find that my inferences remain unaffected.

Taken together, the results of Table 4 show that investments are less responsive to stock prices when prices contain less human-interaction-based information, supporting my inference that human-interaction-based information helps drive managerial learning from stock prices.

4.5. Cross-sectional results

A concern remains that the sensitivity of investments to prices is impacted through other pandemic-associated channels (other than the learning channel). For example, not only does human-interaction-based information in prices decrease during the pandemic, but prices themselves become less informative signals. In this case, outsiders suffer greater information asymmetry, causing them to be less willing to provide capital in response to price signals (Edmans et al. 2017). As a result, investment-*q* sensitivity decreases through the capital raising channel (not the learning channel). This concern is not necessarily mitigated, even when lockdowns are used as exogenous shocks, since prices themselves can also become less informative signals during the pandemic.

To further support my inference that the decrease in investment-*q* sensitivity is driven by the managerial learning from human-interaction-based information in prices, I conduct a set of cross-sectional analyses. First, I examine whether the decrease in investment-*q* sensitivity is more pronounced when decreases in foot traffic are concentrated among places where human-interaction-based information is most likely to be generated. Bai and Massa (2022) show that human-interaction-based information is more likely to be produced in places like cafés, restaurants, bars, and fitness centers, and less likely to be produced in places like childcare services, personal care services, and amusement parks. Thus, if the decline in human-interaction-based information in prices is driving the decrease in investment-*q* sensitivity during lockdowns, I expect the decrease to be stronger when lockdowns are defined based on foot traffic from the former group of places but weaker when defined based on foot traffic from the latter group. I define *LOCKDOWN_INFO_PLACES* as an indicator variable that equals one if foot traffic to the former group of places contracted below 60%, relative to that of the same quarter pre-pandemic. I define *LOCKDOWN_NONINFO_PLACES* as an indicator variable that equals one if foot traffic to the latter group of places contracted below 60%, relative to the same quarter pre-pandemic.

I present results in Table 5. The coefficient on *q*LOCKDOWN_INFO_PLACES* is -0.097 and significant at the 5% level, whereas the coefficient on *q*LOCKDOWN_NONINFO_PLACES* is insignificant. The results support my inference that the drop in human-interaction-based information in prices is a key driver of the decrease in investment-*q* sensitivity through the learning channel.

Second, I examine whether the decrease in investment-*q* sensitivity associated with lockdowns is more pronounced for local firms, where human-interaction-based information production was more active in pre-pandemic. Studies suggest that local investors have an information advantage in producing and acquiring soft information about local firms (Baik et al. 2010) and human-based information production is likely to cluster near corporate headquarters

(Bai and Massa 2022). Thus, investors' production of information through physical interactions is more abundant in the prices of local firms, and managers of these firms are expected to be more active in gleaning new information from prices when making investment decisions pre-pandemic. When human-interaction-based information production declines during lockdowns, these managers are also likely to suffer a decrease in managerial learning from prices to a greater extent, compared to managers at nonlocal firms.

I use two proxies—local institutional ownership and the geographic concentration of firms' operations—to capture firm localness. Similar to Baik et al.'s (2010) definition of local institutional ownership, I define *HIGH_LOCAL_INST* as an indicator variable that equals one if a treatment firm's local institutional ownership (the extent of shares held by institutional investors who are located in the same state as the firm's headquarters) is above-median value pre-pandemic. I define *GEO_CONCEN* as an indicator variable that equals one if a treatment firm has an above-median value of the geographic concentration measure. Studies document that investors view U.S. states that are frequently mentioned in a firm's 10-K as economically meaningful locations for a firm's operations (e.g., Garcia and Norli 2012; Bernile, Kumar, Sulaeman and 2015). Thus, to capture a firm's geographic concentration, I conduct a textual analysis and count the number of mentions of a firm's headquarters state in its 10-K. I also count the number of mentions of all U.S. states in the same 10-K. The measure is the number of mentions of the firm's headquarters state divided by the number of mentions of all U.S. states.

I present results in Table 6. In Panel A of Table 6, the coefficient on *q*HIGH_LOCAL_INST*LOCKDOWN* is -0.094 and statistically significant at the 5% level, while the coefficient on *q*LOCKDOWN* is insignificant. This suggests that relative to firms with low local institutional ownership, firms with high local institutional ownership experience an incrementally greater decrease in investment-*q* sensitivity, supporting that local firms that learned new information more actively in the pre-pandemic experience a larger decrease in investment-*q* sensitivity during lockdowns. In Panel B of Table 6, the coefficient on *q*GEO_CONCEN*LOCKDOWN* is -0.122 and statistically significant at the 1% level, while the coefficient on *q*LOCKDOWN* is insignificant and near zero. This result also supports the idea that geographically concentrated firms whose managers are expected to have gleaned new information from prices more actively in the pre-period, exhibit a more pronounced decrease in investment-*q* sensitivity, relative to geographically dispersed firms. Thus, the results substantiate my inference that the decrease in investment-*q* sensitivity associated with the pandemic is due to managers' being less able to learn from prices new information aggregated through human interactions.

Lastly, I present results for whether young and growing firms whose managers are more likely to learn new information from prices in the pre-pandemic experience a more marked decrease in investment-*q* sensitivity during lockdowns. Studies on managerial learning establish that firms with growth opportunities are keen to learn information from the market (Gao and Liang 2013; Goldstein et al. 2022). Young and growing firms are also more likely to suffer from lack of historical hard data (e.g., accounting numbers), making managers more likely to rely on soft information produced via investors' local physical interactions. To capture firms' growth opportunities, I use market-to-book ratio pre-pandemic. I sort firms' market-to-book ratio into deciles and denote *GROWTH* as an indicator variable that equals one if a firm has a value in the top three deciles of the measure and zero if a firm has a value in the bottom three deciles. To define young firms, I sort firms' ages into deciles and denote *YOUNG* as an indicator variable that equals one if a firm has a value in the bottom three deciles of the measure and zero if a firm has a value in the top three deciles of the measure.

I present results in Table 7. In Panel A, the coefficient on *q*GROWTH*LOCKDOWN* is -0.092 and statistically significant at the 5% level, which supports the idea that growing firms that are more likely to learn from soft information in prices in the pre-period exhibit a more marked decrease in investment-*q* sensitivity. In Panel B, the coefficient on *q*YOUNG*LOCKDOWN* is -0.127 and significant at the 1% level, consistent with young firms experiencing a more pronounced decrease. These results suggest that growth firms and young firms suffer a greater decrease in their managers' ability to glean new human-interaction-based information from prices to guide their investment decisions during the pandemic.

Collectively, the results of cross-sectional analyses firmly support my hypothesis that the decrease in investment-*q* sensitivity during the pandemic is due to a decrease in managers' ability to learn new information in prices when making investment decisions. At the same time, these results help mitigate the concern that other channels, such as capital raising, are driving the results. For example, alternative explanations for my findings would need to explain why the decrease in investment-*q* sensitivity is only pronounced when exogenous decreases in physical interactions are concentrated among places such as cafés, restaurants, and bars where interactions produce the most information, as well as why the decrease is more pronounced for local firms where investors' production of human-based-information matters more.

5. ALTERNATIVE EXPLANATIONS AND ROBUSTNESS TESTS

A challenge that the literature on managerial learning from stock prices faces is the absence of a direct proxy for managerial learning (Edmans et al. 2017). Although the learning channel contributes to the sensitivity of investments to prices, this sensitivity is also affected by alternative economic forces, such as noise in stock prices and financial constraints. If these forces also vary with the onset of the pandemic, the identification of the effect of human-interaction-based information on managerial learning from stock prices using the investment-q sensitivity framework is threatened. Even though cross-sectional results strongly support that my result is driven by the learning channel, to further strengthen my argument, I explore the plausibility of each alternative explanation.

5.1. An increase in noise trading and the market panic

First, I mitigate a concern that the decrease in investment-q sensitivity might be explained by an increase in noise trading or by the market's overreaction during the pandemic. Increased noise trading moves prices but does not affect managers' investment decisions because rational managers do not alter their investment plans. As a result, I would observe a decrease in investment-q sensitivity during lockdowns in the absence of a decrease in human-interaction-based information in prices. In addition, when investors observe a stark decrease in local foot traffic, they may panic and sell stocks. To the extent that the resulting decline in stock prices is not justified by declines in firms' growth opportunities, managers will not adjust their investment plans, resulting in a decrease in investment-q sensitivity. In sum, under both explanations, stock prices will move due to nonfundamental reasons, but rational managers will not respond by changing investment plans.

To mitigate these concerns, I drop the second and the third quarters of 2020 because the market panic and noise trading were most substantial at the beginning of the pandemic (Aggarwal, Nawn, and Dugar 2021). I present the result in Panel A of Table 8. The coefficient on *q*LOCKDOWN* remains negative and significant after dropping those firm-quarter observations. Further, the result still holds when I additionally drop the first quarter of 2020 (untabulated). This suggests that the decrease in investment-*q* sensitivity is unlikely due to increased noise trading or investors' overreaction during the pandemic.

5.2. Financial constraints

Second, I mitigate a concern that the difficulty of obtaining external financing during the pandemic is driving a decrease in investment-*q* sensitivity. As described earlier, investment-*q* sensitivity can also be affected through the capital raising channel, which makes firms alter investments less readily in response to investment opportunities (Edmans et al. 2017). Under this channel, financially constrained firms in the pre-period will be less responsive to investment signals (such as *q*) to the greater extent than unconstrained firms, leading to a more marked decrease in investment-*q* sensitivity for constrained firms.

In this section, I evaluate the plausibility of this alternative channel. If the financing channel is only relevant for the decrease in investment-*q* sensitivity, the result should be stronger among firms that were financially more constrained. Given the difficulty of measuring financial constraints, I follow Li (2011) and construct a proxy based on average ranks of three commonly used measures: the WW index of Whited and Wu (2006), the HP index of Hadlock and Pierce (2010), and the inverse of market capitalization. I rank treatment firms into quartiles based on each measure and take the average of ranks and define *CONSTRAINT* as a variable that equals one for firms with top tercile measures of constraints. I present the results in Panel B of Table 8. The coefficient on *q*CONSTRAINT*LOCKDOWN* is insignificant, suggesting that financially constrained firms are not experiencing a more marked decrease in investment-*q* sensitivity, relative to unconstrained firms. This mitigates a concern that the financing channel solely explains the decrease in investment-*q* sensitivity during the pandemic.

5.3. Managers' ability to learn by directly interacting with investors

Third, I address the concern that managers' direct learning from their interactions with investors is affecting the decrease in investment-*q* sensitivity. In the pre-pandemic period, if managers learn soft information by interacting with people directly, they should have better information sets. Richer information sets likely make managers better able interpret information in prices, thus improving investment-*q* sensitivity. During the pandemic, these firms are likely to experience a greater decrease in investment-*q* sensitivity since their managers' ability to interact and learn is deterred, making them less able to interpret information in prices. If this explanation is relevant, I expect the decrease in investment-*q* sensitivity to be more pronounced among firms at which managers were more informed pre-pandemic.

Although directly measuring the managers' information sets is challenging, I build on prior studies (e.g., Chen et al. 2007; Jayaraman and Wu 2020) and use two proxies to capture managers' information sets: insider trading activities and insider trading profits. I measure insider trading activities as the sum of the total sales and buys of management, deflated by the beginning-of-the-quarter market capitalization. I measure insider trading profits following Jagolinzer, Larcker, and Taylor (2011), calculating the intercept from the four-factor Fama and French (1993) and Carhart (1997) model estimated over the 180 days following each insider transaction. The results are reported in Panel C of Table 8. I present the result using insider trading activities as a proxy in Model (1) and present the result using insider trading profits as a proxy in Model (2). In both models, the coefficients on *q*LOCKDOWN* interacted with proxies of managerial information sets are insignificant, mitigating the concern that managers' ability to learn from directly interacting with people is solely driving the decrease in investment-*q* sensitivity.

5.4. Control for CBSA-level factors

Next, I address an alternative explanation that CBSA-level factors are attributable to the decrease in investment-*q* sensitivity. Since I include industry*time fixed effects in all my regressions, the identification of the treatment effect of lockdowns arises from variation across firms that operate in the same industry at the same time but are located in different CBSAs. I also include CBSA fixed effects, ruling out the confounding effect of time-invariant CBSA effects. However, it remains possible that the decrease in investment-*q* sensitivity across CBSAs around the onset of the pandemic is due to time-varying local economic conditions, rather than a decrease in human-interaction-based information. Thus, I include CBSA-level GDP growth, population, employment, and wage as time-varying control variables. The result in Panel D of Table 8 shows that my inference remains unaffected. However, note that, if managers respond to a decline in local investment opportunities by reducing investments during the pandemic, one would observe an increase in investment-*q* sensitivity. I will explore this issue in the following section.

5.5. A general trend in investment opportunities

Lastly, I address a concern that a general trend in investment opportunities is driving investment-*q* sensitivity. One potential concern is that investment-*q* sensitivity is affected during the pandemic by a decrease in investment opportunities. However, this possibility is likely remote. First, if the general decrease in investment opportunities during the pandemic is a confounding variable, I should observe *positive* association of investment-*q* sensitivity interacted with *LOCKDOWN*, since managers will decrease investments in response to the drop in price signals about investment opportunities. However, I find the opposite. Second, controlling for cash flows from operations (*CFO*) mitigates this concern as cash flows represent a nonprice measure of investment opportunities and learning from prices only occurs through prices but not through cash flows (Edmans et al. 2017; Jayaraman and Wu 2019; Goldstein et al. 2022). As I described previously, I include *CFO* in investment-*q* sensitivity analyses and find coefficients on *CFO*LOCKDOWN* are insignificant. This suggests that the change in investment-*q* sensitivity is impacted by price-based learning, not by changes in investment opportunities.

5.6. Sensitivity analysis

In Table 9, I present results of sensitivity analysis using different benchmarks for defining lockdowns using the foot traffic measure. In my difference-in-differences analyses, I define lockdowns when foot traffic in a CBSA contracted below 60%, relative to the benchmark quarter (the same quarter in the pre-pandemic period). I use 50% and 70% as alternative thresholds and present my results in Table 9 (50% threshold in Model (1) and 70% threshold in Model (2)). In both models, the coefficients on *q*LOCKDOWN* remain negative and significant.

6. CONCLUSION

This study contributes to the managerial learning from stock prices literature by documenting that human-interaction-based information is a key form of information that managers glean from prices to guide their investment decisions. Studies have established that managers glean private information from prices and use it for investment decisions (e.g., Chen et al. 2007; Edmans et al. 2017; Jayaraman and Wu 2019; Goldstein et al. 2022; Kim et al. 2022; Ye et al. 2022) and that industry-wide and macroeconomic information is likely to be what managers glean from stock prices. However, *the forms* of information underlying managerial learning are not well understood. I extend the literature by documenting that human-interaction-based information is likely to be a key form of information that stock prices reveal for managerial decision-making.

My study also contributes to the literature that highlights the effect of local information advantage on managers' real decisions. Giroud (2010) shows that soft information that corporate managers directly gather improves their investment decisions. My findings extend the work of Giroud (2010) by documenting that, when making investment decisions, managers glean soft information from prices, which is collected through investors' physical interactions and is incorporated into prices through trading.

APPENDIX A: VARIABLE DEFINITIONS

Outcome Variables	
NONSYNC	Measure of stock price nonsynchronicity, calculated as 1-R^2, where R^2 is obtained from regressing firm weekly returns on the market and industry current and lagged weekly returns over the year. Source: CRSP
INV_{t+1}	Future investment measured as capital expenditures for firm *i* in a quarter *t+1* scaled by the beginning net property, plant, and equipment plus R&D expenses scaled by the beginning total assets. Source: Compustat
Explanatory and partitioning Variables	
FOOT_TRAFFIC	The number of foot traffic in a CBSA, scaled by the population of the CBSA. Source: SafeGraph
LOCKDOWN	An indicator variable that equals one if foot traffic (total number of visits) in a CBSA of a given quarter contracted below 60% relative to that of the benchmark quarter (same quarter in the pre-pandemic period, which is 2019). Source: SafeGraph
q	The market value of equity plus total assets minus common equity, scaled by total assets. Source: Compustat
LOCKDOWN_INFO_PLACES	I follow Bai and Massa (2022)'s criteria and denote the variable as an indicator variable equals one if foot traffic to the places where human-interaction-based information is most likely to be produced (e.g., cafes, restaurants, drinking places, bookstores) in a CBSA of a given quarter contracted below 60% relative to that of the benchmark quarter (same quarter pre-pandemic period). Source: SafeGraph
LOCKDOWN_NONINFO_PLACES	I follow Bai and Massa (2022)'s criteria and denote the variable as an indicator variable equals one if foot traffic to the places where human-interaction-based information is less likely to be produced (e.g., amusement parks, childcare services, personal care services, bowling centers, and golf courses) in a CBSA of a given quarter contracted below 60% relative to that of the benchmark quarter (same quarter pre-pandemic period). Source: SafeGraph
HIGH_LOCAL_INST	Similar to Baik et al (2010), I define the variable as an indicator variable that equals one if a treatment firm has above-median value of local institutional ownership in the pre-period. Local institutional ownership is calculated as the number of shares of a firm held by local institutional investors (institutional investors who are located in the firm's headquarter state) scaled by the beginning-of-quarter total assets.
GEO_CONCEN	An indicator variable that equals one for treatment firms with above-median value of the geographic concentration measure in the pre-period. The measure is calculated as the number of mentions of the headquarter state in a firm's 10-K, scaled by the number of mentions of all U.S. states in the same report. Source: EDGAR
GROWTH	An indicator variable that equals one if a treatment firm's pre-period market-to-book ratio belongs to the top 3 deciles, and to zero if a firm's pre-period market-to-book ratio belongs to the bottom 3 deciles. Source: Compustat
YOUNG	An indicator variable that equals one if a treatment firm's age belongs to the bottom 3 deciles in the pre-period, and to zero if a firm's age belongs to the bottom 3 deciles in the pre-period. Source: CRSP
CONSTRAINT	An indicator variable that equals one for a treatment firm with top tercile value of the financial constraints measure in the pre-period, which is based on average ranks of three measures of financial constraints (Whited and Wu (2006) index, Hadlock and Pierce (2010) index, and the inverse of market capitalization), and to zero otherwise. Source: Compustat

HIGH_DIRECT_LEARN (when the proxy is insider trading activities)	An indicator variable that equals one for treatment firms with above-median value of insider trading activities as of the pre-period, and to zero otherwise. Insider trading activities are measured as the sum of total sell and buy of management, deflated by the beginning-of-quarter market capitalization. Source: Thomson Reuters Insiders Data
HIGH_DIRECT_LEARN (when the proxy is insider trading profits)	An indicator variable that equals one for treatment firms with above-median value of insider trading profits as of the pre-period, and to zero otherwise. Insider trading profits are measured following Jagolinzer, Larcker, and Taylor (2011). Codes are available at: https://danieltayloranalytics.com/data/ Source: Thomson Reuters Insiders Data
Control variables	
CFO	Cash flows from operations available from the cash flow statement scaled by quarter-end book value of total assets of firm *i* in quarter *t*. Source: Compustat
SIZE	The natural logarithm of firm *i*'s market value of equity as of the end of quarter *t*. Source: Compustat
MTB	Market value of equity divided by book value of equity. Source: Compustat
LEV	Long-term debt plus debt in current liabilities, divided by the market value of assets. Source: Compustat
ACCRUALS	Absolute value of total accruals (income before extraordinary items minus cashflow from operations) divided by total assets. Source: Compustat
SD_ROA	Standard deviation of ROA over the last five quarters, where ROA is income before extraordinary items divided by total assets. Source: Compustat
REVISIONS	Log of the total number of earnings forecasts and revisions made by analysts over the year. Source: IBES
IND_SIZE	Log of the number of firms in each industry. Source: Compustat
CHG_INST	Change in institutional ownership. Source: Thomson Reuters
CBSA_GDP	CBSA-level GDP calculated as county-level GDPs aggregated on CBSA-levels. Source: Bureau of Economic Analysis. Available at: https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1&acrdn=5
CBSA_POPULATION	CBSA-level population calculated as county-level population aggregated on CBSA-levels. Source: Bureau of Economic Analysis. Available at: https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1&acrdn=5
CBSA_EMPLOYMENT	CBSA-level employment calculated as county-level employment aggregated on CBSA-levels. Source: Bureau of Economic Analysis. Available at: https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1&acrdn=5
CBSA_WAGE	CBSA-level wage calculated as county-level wage aggregated on CBSA-levels. Source: Bureau of Economic Analysis. Available at: https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1&acrdn=5

APPENDIX B: SAMPLE SELECTION

	#Firm-quarter observations
CRSP, Compustat, SafeGraph, IBES, Thomson Reuters merged database 1Q 2018 – 3Q 2021	66,298
Observations in which firms are located in Alaska, Hawaii, Puerto Rico, the Virgin Islands, or with missing headquarter information	(2,788)
	63,510
Utility and financial services industries	(21,207)
	42,303
Observations missing necessary CRSP-Compustat variables	(11,963)
	30,340
Observations missing necessary SafeGraph variables	(2,081)
	28,259
Singletons	(322)
	27,937

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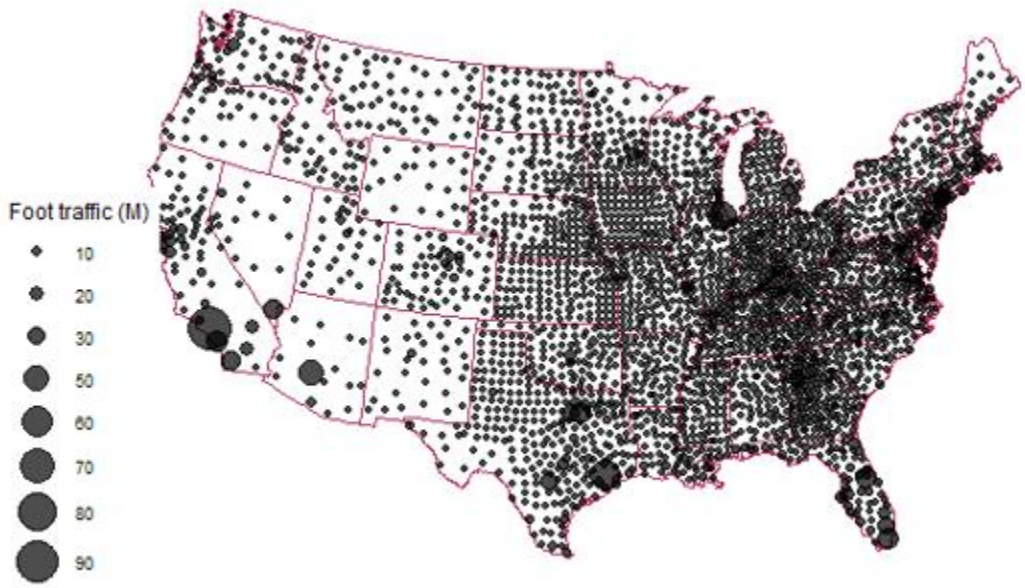
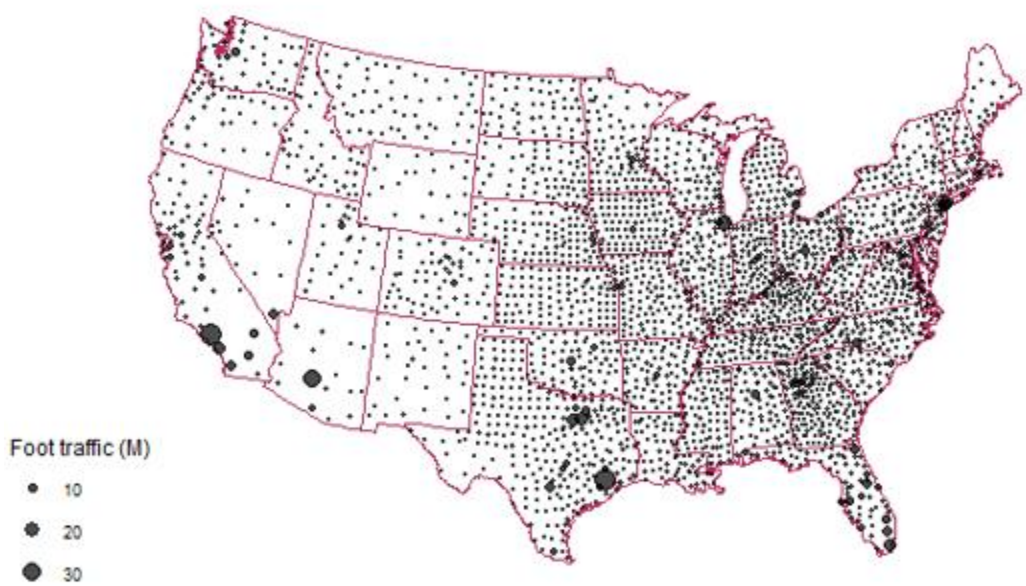
Figure 1. Foot Traffic Before and During COVID-19

Panel A: The second quarter of 2019 (before COVID)

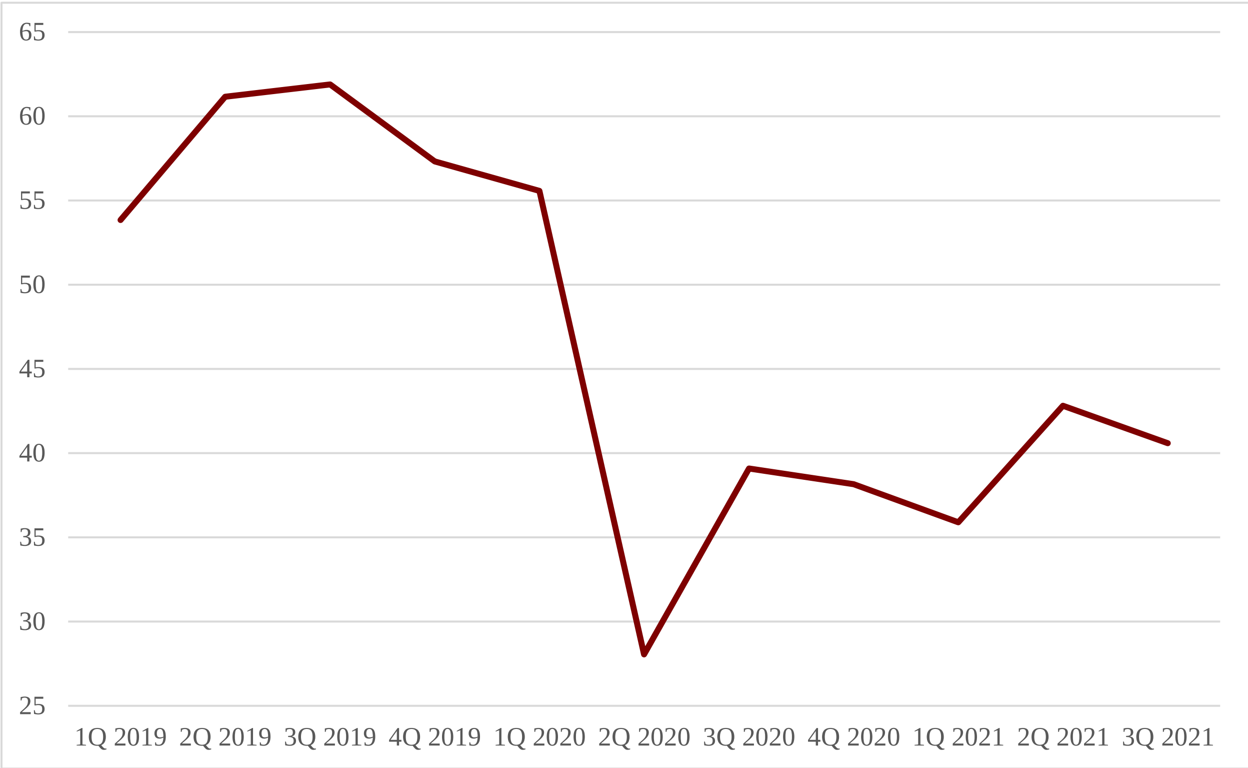


Panel B: The second quarter of 2020 (during COVID)



Panel A and B show foot traffic covered by the Safegraph data by county for the second quarter in 2019 (panel A) and the same quarter in 2020 (panel B).

Figure 2. Changes in Foot Traffic over Time (in Millions)



This figure plots changes in foot traffic (in millions) by CBSA over time from the year before COVID-19 outbreak until the end of my sample period.

Table 1

Summary statistics

Panel A: Descriptive statistics

	Obs.	Mean	SD	P25	P50	P75
NONSYNC	27,937	0.395	0.277	0.149	0.389	0.623
$INV_{(t+1)}$	27,937	0.075	0.091	0.024	0.048	0.091
q	27,937	2.546	2.208	1.211	1.759	2.994
CFO	27,937	-0.017	0.092	-0.023	0.013	0.028
SIZE	27,937	6.851	2.225	5.255	6.909	8.388
MTB	27,937	4.086	9.581	1.235	2.476	5.011
LEV	27,937	0.236	0.235	0.041	0.164	0.361
ACCRUALS	27,937	0.036	0.047	0.010	0.021	0.041
SD_ROA	27,937	0.034	0.057	0.007	0.015	0.034
REVISION	27,937	0.830	1.721	0.000	0.000	0.000
IND_SIZE	27,937	3.343	1.676	2.079	2.944	4.615
CHG_INST	27,937	0.008	0.057	-0.014	0.001	0.021

Panel B: Foot traffic (mil)

	Obs.	Mean	P50
1Q 2018	1,396	35.124	23.639
2Q 2018	1,945	53.659	36.152
3Q 2018	1,938	50.533	32.485
4Q 2018	1,954	56.556	35.614
1Q 2019	1,918	53.851	35.168
2Q 2019	2,057	61.166	41.380
3Q 2019	2,060	61.891	43.587
4Q 2019	2,097	57.320	37.796
1Q 2020	2,006	55.576	37.215
2Q 2020	2,034	28.052	17.186
3Q 2020	2,065	39.088	25.234
4Q 2020	2,117	38.160	24.002
1Q 2021	2,042	35.901	22.271
2Q 2021	2,032	42.823	27.589
3Q 2021	276	40.600	28.520

This table presents summary statistics. Panel A presents descriptive statistics of variables used in my analyses. Panel B reports foot traffic information. Foot traffic is defined as the total number of visits (in millions) in a quarter for CBSAs. The sample is consisted of 27,937 firm-quarter observations over the period 1Q 2018 – 3Q 2021. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. Variable definitions are provided in Appendix A.

Table 2

Foot Traffic as a Proxy for Human-Interaction-based Information in Prices

Dependent Variable =	*NONSYNC*
	(1)
FOOT_TRAFFIC	0.011***
	(2.820)
SIZE	-0.012**
	(-2.190)
MTB	-0.000
	(-0.055)
LEV	-0.089***
	(-4.008)
ACCRUALS	0.042
	(1.343)
SD_ROA	0.050
	(1.390)
REVISIONS	-0.003*
	(-1.680)
IND_SIZE	0.0315
	(1.485)
CHG_INST	-0.020
	(-0.645)
Industry×time FE	Yes
Firm FE	Yes
CBSA FE	Yes
Clustering	CBSA
Observations	27,937
Adjusted R^2	0.563

This table presents results of validating foot traffic as a proxy for human-interaction-based information in stock prices. I present the result of an association between price nonsynchronicity and foot traffic. *NONSYNC* is defined as 1-R^2, where R^2 is obtained from regressing a firm's weekly returns on the market and industry current and lagged weekly returns over the year. *FOOT_TRAFFIC* represents the number of foot traffic in a CBSA, scaled by the population of the CBSA.

Table 3
Human-Interaction-based Information in Prices and Investment-*q* Sensitivity

Dependent Variable =	INV_{t+1}		
	(1)	(2)	(3)
q	0.284***	0.318***	0.318***
	(7.034)	(7.405)	(7.416)
CFO	-0.060***	-0.058***	-0.058***
	(-4.260)	(-4.096)	(-4.051)
FOOT_TRAFFIC		0.003***	0.003***
		(2.669)	(2.606)
q*FOOT_TRAFFIC		0.089***	0.090***
		(5.188)	(5.098)
*CFO*FOOT_TRAFFIC*			0.005
			(0.404)
SIZE	0.002	0.002	0.002
	(0.837)	(0.939)	(0.905)
Industry×time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes
Clustering	CBSA	CBSA	CBSA
Observations	27,937	27,937	27,937
Adjusted R^2	0.507	0.508	0.508

This table presents results of the relation between foot traffic and investment-*q* sensitivity. In Model (1), I present the baseline result with variables *q*, *CFO*, and *SIZE* included in the model. In Model (2), I additionally include *FOOT_TRAFFIC* and *q*FOOT_TRAFFIC*. In Model (3), I add *CFO*FOOT_TRAFFIC*. In Model (1), (2), and (3), I include industry-time, firm, and CBSA fixed effects. INV_{t+1} denotes future investment, measured as capital expenditures scaled by the beginning fixed assets plus R&D expense deflated with the beginning total assets for firm *i* in quarter *t+1*. *q* presents Tobin's q, calculated as the market value of equity plus total assets minus common equity, scaled by total assets. *FOOT_TRAFFIC* represents the number of foot traffic in a CBSA, scaled by the population of the CBSA. *CFO* is defined as cash flows from operations available from the cash flow statement scaled by quarter-end book value of total assets of firm *i* in quarter *t*. *SIZE* is calculated as the natural logarithm of firm *i*'s market value of equity as of the end of quarter *t*. Variable definitions are provided in Appendix A. The sample is consisted of 27,937 firm-quarter observations over the period 1Q 2018 – 3Q 2021. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4

The Effect of Lockdowns on Investment-*q* Sensitivity

Dependent Variable =	INV_{t+1}				
	(1)	(2)	(3)	(4)	(5)
q	0.243***	0.270***	0.270***	0.265***	0.322***
	(8.149)	(7.689)	(7.734)	(7.602)	(10.72)
CFO	-0.074***	-0.073***	-0.073***	-0.073***	-0.174***
	(-6.387)	(-6.391)	(-5.695)	(-5.748)	(-9.911)
LOCKDOWN		-0.002	-0.002	-0.003	-0.002
		(-0.749)	(-0.778)	(-1.268)	(-0.873)
q*LOCKDOWN		-0.087**	-0.088**	-0.090***	-0.108***
		(-2.384)	(-2.422)	(-2.601)	(-3.412)
*CFO*LOCKDOWN*			-0.004	-0.002	-0.025
			(-0.237)	(-0.095)	(-1.158)
SIZE	0.005	0.005	0.005	0.006*	-0.001*
	(1.412)	(1.487)	(1.495)	(1.899)	(-1.896)
Industry×time FE	Yes	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes	No
CBSA FE	Yes	Yes	Yes	No	Yes
Industry FE	No	No	No	No	Yes
Time (year×quarter) FE	No	No	No	Yes	Yes
Clustering	CBSA	CBSA	CBSA	CBSA	CBSA
Observations	24,539	24,539	24,539	24,539	24,539
Adjusted R^2	0.536	0.537	0.537	0.542	0.296

This table presents results of the effects of the lockdowns on investment-*q* sensitivity. In Model (1), I present the baseline result with variables *q*, *CFO*, and *SIZE* included in the model. In Model (2), I additionally include *LOCKDOWN* and *LOCKDOWN* interacted with *q*. In Model (3), I add *CFO*LOCKDOWN*. In Model (1), (2), and (3), I include industry-time, firm, and CBSA fixed effects. In Model (4), I include firm and year-quarter fixed effects. In Model (5), I include industry, CBSA, and time (year-quarter) fixed effects. INV_{t+1} denotes future investment, measured as capital expenditures scaled by the beginning fixed assets plus R&D expense deflated with the beginning total assets for firm *i* in quarter *t+1*. *q* presents Tobin's q, which is calculated as the market value of equity plus total assets minus common equity, scaled by total assets. *LOCKDOWN* is an indicator variable equals one if foot traffic (total number of visits) in a CBSA of a given quarter contracted below 60% relative to the benchmark quarter (same quarter pre-pandemic). *CFO* is defined as cash flows from operations available from the cash flow statement scaled by quarter-end book value of total assets of firm *i* in quarter *t*. *SIZE* is calculated as the natural logarithm of firm *i*'s market value of equity as of the end of quarter *t*. Variable definitions are provided in Appendix A. The sample is consisted of 24,539 firm-quarter observations over the period 1Q 2018 – 3Q 2021. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5

Cross-sectional Test: Local Places Where Human-based Information is Most Likely to be Produced

Dependent Variable =	INV_{t+1}
	(1)
q	0.287***
	(8.140)
LOCKDOWN_INFO_PLACES	-0.003
	(-1.119)
LOCKDOWN_NONINFO_PLACES	-0.001
	(-0.401)
q*LOCKDOWN_INFO_PLACES	-0.097**
	(-2.302)
*q*LOCKDOWN_NONINFO_PLACES*	-0.024
	(-0.585)
CFO	-0.074***
	(-5.822)
CFO_LOCKDOWN_INFO_PLACES	0.001
	(0.037)
*CFO*LOCKDOWN_NONINFO_PLACES*	0.006
	(0.247)
SIZE	0.005
	(1.524)
Industry×time FE	Yes
Firm FE	Yes
CBSA FE	Yes
Clustering	CBSA
Observations	24,539
Adjusted R^2	0.538

This table presents the result of cross-sectional analysis where I examine whether the decrease in investment-*q* sensitivity is concentrated when decreases in foot traffic are concentrated among places where human-interaction-based information is most likely to be generated. Following Bai and Massa (2022)'s criteria, *LOCKDOWN_INFO_PLACES* is coded as one if foot traffic to cafes, restaurants, bars, and fitness centers in a CBSA of a given quarter contracted below 60% relative to the benchmark quarter (same quarter in pre-pandemic). *LOCKDOWN_NONINFO_PLACES* is coded as one if foot traffic to childcare services, personal care services, bowling centers, golf courses, and amusement parks and arcades in a CBSA of a given quarter contracted below 60% relative to the benchmark quarter (same quarter pre-pandemic). Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6

Cross-sectional Tests: Local Firms Where Investors' Human-based Information Production was More Active Pre-Pandemic

Panel A: Firms with greater local institutional ownership

Dependent Variable =	INV_{t+1}
	(1)
q	0.321***
	(2.795)
LOCKDOWN	0.004
	(1.360)
HIGH_LOCAL_INST	0.012*
	(1.926)
*q*HIGH_LOCAL_INST*	0.073
	(0.576)
*q*LOCKDOWN*	-0.065
	(-0.821)
q*HIGH_LOCAL_INST*LOCKDOWN	-0.094**
	(-2.170)
CFO	-0.090***
	(-3.471)
*CFO*LOCKDOWN*	0.010
	(0.336)
SIZE	0.001
	(0.274)
Industry×time FE	Yes
Firm FE	Yes
CBSA FE	Yes
State FE	Yes
Clustering	CBSA
Observations	10,553
Adjusted R^2	0.558

This table presents the result of cross-sectional analysis where I examine whether firms with greater local institutional ownership exhibit more marked decrease in investment-*q* sensitivity. I define *HIGH_LOCAL_INST* as an indicator variable that equals one if a firm has above-median value of local institutional ownership, that is the number of shares held by local institutional investors (institutional investors who are located in the firm's headquarter state) scaled by the beginning of quarter total assets, in the pre-pandemic period. I include industry×time fixed effects, firm fixed effects, and CBSA fixed effects. I also include state fixed effects to control for time-invariant state-wide factors that can impact investment-*q* sensitivity and firms' local institutional ownership. Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6, continued

Panel B: Geographically concentrated firms

Dependent Variable =	INV_{t+1}
	(1)
q	0.218***
	(3.946)
LOCKDOWN	-0.003
	(-0.661)
*q*GEO_CONCEN*	0.160*
	(1.736)
*q*LOCKDOWN*	0.000
	(0.005)
q*GEO_CONCEN*LOCKDOWN	-0.122***
	(-3.175)
CFO	-0.079***
	(-4.900)
*CFO*LOCKDOWN*	0.029
	(1.288)
SIZE	0.003
	(0.542)
Industry×time FE	Yes
Firm FE	Yes
CBSA FE	Yes
Clustering	CBSA
Observations	15,988
Adjusted R^2	0.519

This table presents the result of cross-sectional analysis where I examine whether geographically concentrated firms exhibit more marked decrease in investment-*q* sensitivity. I define *GEO_CONCEN* as a variable that equals one if a firm has above-median value of geographic concentration, that is the number of mentions of the headquarter state in a firm's 10-K, scaled by the number of mentions of all U.S. states in the same report. Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Cross-sectional Tests: Growing and Young Firms, Which Investors Have Comparative Advantage at Evaluating

Panel A: Growing firms

Dependent Variable =	INV_{t+1}
	(1)
q	0.406***
	(7.169)
LOCKDOWN	-0.002
	(-0.392)
*GROWTH*LOCKDOWN*	0.003
	(0.614)
*q*GROWTH*	-0.195***
	(-3.188)
*q*LOCKDOWN*	-0.072
	(-0.931)
q*GROWTH*LOCKDOWN	-0.092**
	(-2.199)
CFO	-0.066***
	(-5.006)
*CFO*LOCKDOWN*	0.015
	(0.670)
SIZE	0.005
	(1.465)
Industry×time FE	Yes
Firm FE	Yes
CBSA FE	Yes
Clustering	CBSA
Observations	16,134
Adjusted R^2	0.584

This table presents the result of cross-sectional analysis where I examine whether growth firms experience a greater decrease in investment-*q* sensitivity. I define growth firms using firms' market-to-book ratio. I sort firms' market-to-book ratio into deciles and define *GROWTH* as a variable equals one if a firm has a value in the top three deciles of the market-to-book ratio, and to zero if a firm has a value in the bottom three deciles of the market-to-book ratio. Middle four deciles are dropped. Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7, continued

Panel B: Young firms

Dependent Variable =	INV_{t+1}
	(2)
q	0.263***
	(5.787)
LOCKDOWN	0.002
	(0.626)
*YOUNG*LOCKDOWN*	-0.008
	(-1.281)
*q*YOUNG*	0.042
	(0.485)
*q*LOCKDOWN*	-0.028
	(-0.592)
q*YOUNG*LOCKDOWN	-0.127***
	(-2.707)
CFO	-0.070***
	(-4.960)
*CFO*LOCKDOWN*	0.007
	(0.274)
SIZE	0.006*
	(1.728)
Industry×time FE	Yes
Firm FE	Yes
CBSA FE	Yes
Clustering	CBSA
Observations	15,447
Adjusted R^2	0.574

This table presents the result of cross-sectional analysis where I examine whether young firms experience a greater decrease in investment-*q* sensitivity. I define young firms using firms' ages. I sort firms' ages into deciles and define *YOUNG* as a variable equals one if a firm has a value in bottom three deciles of the measure, and to zero if a firm has a value in top three deciles of the measure. Middle four deciles are dropped. Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Tests of Alternative Explanations

Panel A: An increase in noise trading and the market panic

Dependent Variable =	INV_{t+1}
	(1)
q	0.298***
	(8.785)
LOCKDOWN	-0.002
	(-1.013)
q*LOCKDOWN	-0.091***
	(-2.808)
CFO	-0.074***
	(-5.630)
*CFO*LOCKDOWN*	-0.001
	(-0.065)
SIZE	0.005
	(1.570)
Industry×time FE	Yes
Firm FE	Yes
CBSA FE	Yes
Clustering	CBSA
Observations	22,456
Adjusted R^2	0.513

This table presents the result where I examine an alternative explanation that an increase in noise trading and the market panic is driving the decrease in investment-*q* sensitivity. I drop the second and the third quarter of 2020 for which quarters the market panic and noise trading were most substantial and repeat my analysis. In untabulated analysis, I additionally exclude the first quarter of 2020 and the result holds. Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8, continued

Panel B: Financial constraints

Dependent Variable =	INV_{t+1}
	(1)
q	0.297***
	(7.510)
LOCKDOWN	-0.004**
	(-2.367)
*q*CONSTRAINT*	-0.044
	(-0.458)
*CONSTRAINT*LOCKDOWN*	-0.004
	(-0.651)
*q*LOCKDOWN*	-0.096***
	(-2.900)
q*CONSTRAINT*LOCKDOWN	-0.037
	(-0.549)
CFO	-0.077***
	(-6.011)
*CFO*LOCKDOWN*	0.000
	(-0.004)
SIZE	0.005
	(1.484)
Industry×time FE	Yes
Firm FE	Yes
CBSA FE	Yes
Clustering	CBSA
Observations	23,396
Adjusted R^2	0.517

This table presents the result where I examine an alternative explanation that worsened financial constraints is driving the decrease in investment-*q* sensitivity. To measure financial constraints, I follow Li (2011) and construct a proxy based on average ranks of three commonly used measures: the WW index of Whited and Wu (2006), the HP index of Hadlock and Pierce (2010), and the inverse of market capitalization. I rank treatment firms into quartiles based on each measure, take the average of ranks, and define *CONSTRAINT* as a variable equals one if a firm has a value in top tercile of the measure. Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8, continued

Panel C: Managers' ability to learn by directly interacting with investors

Dependent Variable =	INV_{t+1}	
HIGH_DIRECT_LEARN =	Insider trading activities	Insider trading profits
	(1)	(2)
q	0.322***	0.194***
	(3.363)	(2.664)
LOCKDOWN	-0.001	-0.001
	(-0.287)	(-0.173)
*q*HIGH_DIRECT_LEARN*	0.094	0.257***
	(0.902)	(3.208)
*HIGH_DIRECT_LEARN*LOCKDOWN*	0.002	-0.002
	(0.367)	(-0.707)
*q*LOCKDOWN*	0.006	-0.081*
	(0.140)	(-1.892)
q*HIGH_DIRECT_LEARN*LOCKDOWN	-0.033	-0.041
	(-0.511)	(-0.759)
CFO	-0.095***	-0.059***
	(-3.559)	(-3.558)
*CFO*LOCKDOWN*	0.043	0.025
	(1.471)	(1.307)
SIZE	0.005	0.006
	(0.808)	(1.287)
Industry×time FE	Yes	Yes
Firm FE	Yes	Yes
CBSA FE	Yes	Yes
Clustering	CBSA	CBSA
Observations	5,708	10,753
Adjusted R^2	0.514	0.520

This table presents the result of testing an alternative explanation whether managers' ability to learn by directly interacting with investors is solely driving investment-*q* sensitivity. I capture managerial information set using two proxies: insider trading activities and insider trading profits. Insider trading activities are measured as the sum of total sales and buys of management, deflated by the beginning-of-quarter market capitalization. In Model (1), *HIGH_DIRECT_LEARN* is an indicator variable equals one for lockdown firms with above-median value of insider trading activities as of the last quarter in the pre-period, and to zero otherwise. In Model (2), I use measure of insider trading profits. In Model (2), *HIGH_DIRECT_LEARN* is an indicator variable equals one for lockdown firms with above-median value of insider trading profits as of the last quarter in the pre-period, and to zero otherwise. Insider trading profits are measured following Jagolinzer, Larcker, and Taylor (2011). Codes for calculating insider trading profits are available at Professor Dan Taylor's website: https://danieltayloranalytics.com/data/. Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel D: Controlling for CBSA-level factors

Dependent Variable =			INV_{t+1}		
	(1)	(2)	(3)	(4)	(5)
q	0.270***	0.270***	0.271***	0.270***	0.270***
	(7.736)	(7.718)	(7.666)	(7.699)	(7.721)
LOCKDOWN	-0.001	-0.001	-0.002	-0.002	-0.000
	(-0.424)	(-0.671)	(-0.892)	(-0.727)	(-0.210)
q*LOCKDOWN	-0.086**	-0.090**	-0.091**	-0.090**	-0.083**
	(-2.393)	(-2.491)	(-2.563)	(-2.502)	(-2.287)
CFO	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***
	(-5.737)	(-5.714)	(-5.711)	(-5.713)	(-5.742)
*CFO*LOCKDOWN*	-0.004	-0.005	-0.005	-0.005	-0.003
	(-0.205)	(-0.255)	(-0.268)	(-0.255)	(-0.177)
CBSA_GDP	-0.100***				-0.159***
	(-3.119)				(-3.270)
CBSA_POPULATION		0.108			0.136
		(1.038)			(1.252)
CBSA_EMPLOYMENT			-0.047		0.002
			(-1.125)		(0.028)
CBSA_WAGE				-0.030	0.066*
				(-1.068)	(1.835)
SIZE	-0.100***	0.005	0.005	0.005	0.005
	(-3.119)	(1.509)	(1.447)	(1.492)	(1.480)
Industry×time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes	Yes
Clustering	CBSA	CBSA	CBSA	CBSA	CBSA
Observations	24,491	24,491	24,491	24,491	24,491
Adjusted R^2	0.538	0.537	0.537	0.537	0.538

This table presents the result of testing an alternative explanation where I control for CBSA-level factors. In column (1), I control for *CBSA_GDP*. In column (2), I control for *CBSA_POPULATION*. In column (3), I control for *CBSA_EMPLOYMENT*. In column (4), I control for *CBSA_EMPLOYMENT*. In column (5), I control all CBSA-level factors. *CBSA_GDP* denotes CBSA-level GDP, calculated by county-level GDP aggregated on CBSA-levels. *CBSA_POPULATION* denotes CBSA-level population, calculated by county-level population aggregated on CBSA-levels. *CBSA_EMPLOYMENT* denotes CBSA-level employment, calculated by county-level employment aggregated on CBSA-levels. *CBSA_WAGE* denotes CBSA-level wage, calculated by county-level wage aggregated on CBSA-levels. County-level GDP, population, employment, and wage data can be downloaded from the website of Bureau of Economic Analysis (https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1&acrdn=5). Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Sensitivity Analysis

Dependent Variable =	INV_{t+1}	
	Benchmark=50%	Benchmark=70%
	(1)	(2)
q	0.259***	0.297***
	(8.212)	(8.117)
CFO	-0.073***	-0.069***
	(-5.958)	(-5.426)
LOCKDOWN	-0.003	-0.001
	(-1.480)	(-0.468)
q*LOCKDOWN	-0.090***	-0.107***
	(-4.422)	(-3.708)
*CFO*LOCKDOWN*	-0.007	-0.012
	(-0.334)	(-0.768)
SIZE	0.005	0.005
	(1.466)	(1.523)
Industry×time FE	Yes	Yes
Firm FE	Yes	Yes
CBSA FE	Yes	Yes
Industry FE	No	No
Year×Quarter FE	No	No
Clustering	CBSA	CBSA
Observations	24,539	24,539
Adjusted R^2	0.537	0.537

This table presents the result of sensitivity analysis where I apply different thresholds when defining *LOCKDOWN* variable. In Model (1), 50% is used as the threshold. *LOCKDOWN* is coded as an indicator variable equals one if foot traffic (total number of visits) in a CBSA of a given quarter contracted below 50% relative to the benchmark quarter (same quarter pre-pandemic). In Model (2), 70% is used as the threshold. *LOCKDOWN* is coded as an indicator variable equals one if foot traffic (total number of visits) in a CBSA of a given quarter contracted below 70% relative to the benchmark quarter (same quarter pre-pandemic). Detailed variable definitions are provided in Appendix A. To mitigate the unduly effect of a small number of outlier observations, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the CBSA-level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.