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Essays on Managerial Learning from Market Prices

A dissertation submitted in partial satisfaction of the

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in Management

by

Ho Joon Kim

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ABSTRACT OF THE DISSERTATION

Essays on Managerial Learning from Market Prices

by

Ho Joon Kim

Doctor of Philosophy in Management

University of California, Los Angeles, 2023

Professor Judson Caskey, Chair

The first essay investigates whether managers learn about their own default risk through feedback from credit default swap (CDS) spreads and, if so, whether this learning influences their risk management. I find that managers who learn more from CDS market feedback lower the leverage ratio and are more likely to record contingent liabilities in the following year than those who do not. Also, I find that overconfident managers, who are likely to rely less on outsiders' judgment about their own firms, are less likely to record impairments or writedowns, compared to those who learn from CDS spreads. Finally, I find that the CDS learning channel is more effective with higher analyst following and disagreement. Overall, the feedback from CDS spreads appears to be more relevant when learning about downside risk, compared to the feedback from stock prices that resolve upside uncertainties such as potential investment opportunities.

The second essay is on investor disagreement and learning from stock prices. The divergence of opinions among investors brings two conflicting effects on the managers' ability to glean information from stock prices. On the one hand, investors' divergent opinions could supply more information and signals to the price, improving the chance of learning new information from stock prices. On the other hand, they could inhibit managers' ability to learn from stock prices since signals with different directions can confuse managers. Generally, my findings align more with the latter: higher investor disagreement appears to inhibit managerial learning from stock prices, leading to reduced investment-q sensitivity. However, these results become more nuanced when price movements are likely influenced by informed traders.

The dissertation of Ho Joon Kim is approved.

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Daniel Saavedra Lux

Jessica Kim

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2023

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VITA

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CHAPTER 1

Feedback Effects of CDS Spreads on Corporate Risk Management

1. Introduction

One of the central foci in the accounting and capital markets literature is identifying relationships between accounting measures and market prices, such as the relationship between earnings and stock prices (Ball and Brown 1968). However, the inquiries have predominantly focused on one aspect, i.e., how managers can influence market prices, rather than the reciprocal effect of market prices on managers. The feedback effect literature argues that managers are uniquely positioned to both influence and learn from secondary market prices (Bond, Edmans & Goldstein 2012). A central conjecture in the literature is that market prices may contain information that is not readily available to managers, and these managers could potentially learn from it. The literature documented many ways that managers learn from stock prices.[1] If managers indeed learn from stock market feedback, can they also learn from other market prices?

One such channel I explore in this article is the feedback effect via credit default swap (CDS) spreads. The main finding of the paper is that the managers who learn from CDS spreads take more conservative actions in managing corporate risks, such as lowering leverage or increasing contingent liabilities. Learning from CDS spreads can potentially provide unique information to managers in several aspects. First, managers can learn different content via CDS

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[1] Managers who learn from stock market feedback revise their investment and M&A decisions (Chen, Goldstein & Jiang 2007, Kau, Linck & Rubin 2008, Foucault and Fresard 2013, Luo 2005), improve their forecasts (Zuo 2016), and change product portfolios (Markovitch, Steckel, & Yeung 2005).

spreads compared to stock prices. The difference in information content stems from the different payoff structures of stock prices and CDS spreads. Stock prices have a call-option-like structure because the equity holders do not get paid when the firm defaults. In contrast, CDS spreads have a put-option-like structure in the sense that the CDS buyers get paid when the firm faces a credit event, such as failure to pay.[2]

Second, CDS participants are primarily institutional investors, while individual investors play a more significant role in the equity market. Thus, the private information contained in CDS spreads represents the sum of more sophisticated investors, and it can potentially be more helpful for managers, especially with respect to the downside risks.

Third, since a CDS contract does not require either party to have a position or relationship with the underlying bond, "naked" CDS trading is possible, unlike the stock market where naked short-selling is banned. Thus, while most participants in the CDS market use the product for credit protection, it can also be used as a tool for speculation. Due to this regulatory difference, we can expect that speculators' information about adverse outcomes will be more freely reflected in CDS trading and spreads.

Given these expectations about the managerial learning opportunities in the CDS market, I empirically investigate whether managers learn about their own default risk through the feedback from the CDS market and, if so, whether the learning affects their risk management. Since information flows between CDS and equity markets, I focus on learning from CDS after controlling for the information transferred from the equity market.

A key challenge when we study the feedback effect in any market is measuring private information in the market. In most feedback studies in the stock market, researchers typically

[2] Credit event details are described in Appendix B.

use the stock price nonsynchronicity, i.e., how a firm's stock price moves differently from other stocks in the industry and the overall market, and the PIN (probability of informed trading) measures. However, working with CDS brings unique challenges. First, CDS spreads (or prices) are quoted in basis-point spreads, while stock prices are quoted in dollars per share. Thus, a researcher must decide how to define a concept of return with respect to CDS when employing nonsynchronicity. Second, typical CDS datasets available to researchers, such as Markit and CMA data, do not have volume information, making it difficult to use the PIN-type measures.

I employed the following two measures of private information in the CDS market: CDS nonsynchronicity and bid-ask spreads. CDS nonsynchronicity measures how differently CDS returns react compared to other firms' CDS returns in the same industry and the market. While there can be many ways to define CDS returns, I adopt the daily percentage change of 5-year CDS mid prices, following Hilscher, Pollet, & Wilson (2015). Since different industry classifications can lead to different nonsynchronicity measures, I adopted both Fama-French 12 and 48 industry classifications. For the bid-ask spread, I chose the normalized bid-ask spread, i.e., the bid-ask spread divided by the mid-price. While the bid-ask spread measure captures both liquidity and private information in general, CDS bid-ask spreads are less likely to be driven by liquidity factors than the CDS alternatives, such as corporate bonds, where liquidity plays a significantly more important role.

With two measures of private information in CDS spreads, I first test whether learning from CDS spreads influences managers' risk management decisions. If managers do not learn from CDS spreads, then we would only find the relationship between CDS spreads and risk management measures regardless of the amount of private information. However, if managers do learn from CDS spreads, then the CDS-risk management relationship can be strengthened or weakended by the learning. Specifically, I use the leverage ratio and contingent liabilities as measures of risk management and conservative actions by managers. I interpret lower leverage as managers taking more conservative actions. Also, I expect that managers who become more conservative will be more likely to record contingent liabilities. I find that the managers who can learn more about their default risks from the CDS market feedback reduce their leverage and are more likely to record contingent liabilities in the following year than those who do not.

Second, I test whether managers who learn more from the CDS market are more likely to record impairments and writedowns. Similar to contingent liabilities, if managers do learn from CDS spreads when spreads widen, indicating a higher default probabilty, we should expect them to take more conservative actions. However, one challenge with impairments is that they are relatively rare, and even if they find something troubling, firms typically record them much later. Hayn and Hughes (2006) documented that the time lag between deterioration in the performance of an acquired business and the timing of a writedown of goodwill is typically three to four years. For this reason, I test whether the managerial learning from CDS spreads is associated with more writedowns and impairments in the next three years. For this test, I find no evidence that managers recognize impairments more often with learning from CDS spreads.

I test a related hypothesis: whether a subset of managers who are more likely to ignore other learning sources — namely, overconfident managers — will be less likely to record writedowns and impairments. Following Core and Guay (2002), I use a method approximating Malmendier and Tate's (2005) measure of overconfidence to estimate this trait. I expect overconfident managers to be less likely to learn from market prices, focusing more on their own agenda than other types of managers do. I find that overconfident managers are less likely to record impairments or writedowns than those who learn from CDS spreads.

Finally, I test how the information environment with respect to sample firms affects learning from CDS spreads. Specifically, I test whether the number of analysts following the firms and forecast dispersion among analysts affect the relationship between managerial learning from CDS spreads and leverage. If having a high number of analysts following the firm improves the information environment significantly, managers can have fewer incentives to learn more from the market due to reduced incremental information they can get from market prices. On the other hand, if more analysts represent a higher attention among the institutional investors and CDS market participants, it could make learning from CDS more valuable, thanks to more potential private information contained in CDS spreads. While the results are not robust with all measures, I find evidence consistent with the view that more analysts can improve the CDS learning channel. Next, I test whether the disagreements among analysts impact the CDS learning channel. If more analysts disagree with one another, then the private information from CDS spreads can become more valuable, and we should expect this information to help the managers more. I find that CDS learning is more effective when security analysts' dispersion is relatively high.

Overall, the learning channel from CDS spreads seems to offer a different set of information compared to the learning from the stock price (Figure 1 and 2). Unlike the case with the learning from the stock price where the stock price-investment sensitivity plays a key role, I find no evidence of CDS-investment sensitivity. Given these differences and the relevance of CDS learning to risk management, the feedback from the CDS spreads appears to be more relevant when learning about downsides, compared to the feedback from stock prices where managers can learn more about upsides, like potential investment opportunities.

The paper's contribution is threefold; first, it contributes to the literature on the feedback effect. I show how managers can learn different content from the CDS market than they do from the equity market. This is especially timely given that a recent review article on the feedback effect called for future research on learning from "other financial securities and derivatives (Goldstein 2022)." Second, the paper contributes to the ongoing discussion on the role of and information in CDS spreads, especially when the information flows between the stock and CDS markets. I show that, while the two markets are related, there is a unique area where CDS markets can deliver incremental information. Finally, it contributes to the literature on accounting with managerial discretion, i.e., contingent liabilities and impairments. The paper shows that the managers' tendency to record these can vary depending on their learning from the markets.

2. Background

In this section, I review relevant literature, from the feedback effect to CDS-related works in accounting, with special attention to those closely related to this article. Then, I review studies on whether CDS can serve as a better learning channel than some alternatives, such as corporate bonds, and whether CDS can provide unique information compared to equities. Finally, I develop hypotheses given the expected properties of CDS and managers' learning.

2.1 A review of the feedback effect and CDS literature

While the idea of market prices as an important source of information goes back to Hayek (1945), more recent works on market feedback began with studies in finance related to public equity offerings, such as Jegadeesh, Weinstein & Welch (1993). Jegadeesh, et al. (1993) argued that the market could be better informed than the manager given a high return on the IPO date, and managers can use this information and raise additional capital via seasoned offerings.

More studies focusing exclusively on the feedback effect started in the 2000s. Many of them look into the relationship between learning from stock prices and investments. Luo (2005) observes that managers learn from the market reaction when the firm announces M&A plans. He focuses on cases where learning is most likely, i.e., when the deal is reversible and when the market most plausibly has information that the manager does not, and shows that the probability of a project cancellation is higher after a low announcement return.

Similar to Luo (2005), Chen, Goldstein & Jiang (2007) focus on investment and stock price feedback. However, while Luo (2005) focuses on M&A, Chen et al. (2007) focus on more general relationships between investment and price informativeness using PIN and price nonsynchronicity measures. Also, Foucault and Fresard (2013) show that managers not only learn from their own stock prices but also from their peers.

Finally, instead of examining the overall effect, Markovitch, Steckel & Yeung (2005) focus on the pharmaceutical industry to test the feedback effect. They find that firms whose stocks are performing well in the market do not change their behavior, while the laggards tend to acquire or implement more changes to their product portfolio to signal to the market.

Besides the related feedback studies in finance, there have been a number of significant feedback studies in accounting. For example, Zuo (2016) shows that managers' forecast revisions and forecast accuracy can be improved with private information from the stock market. Also, Kim, Wiedman & Zhu (2018) show that the initiation (availability) of CDS trading can improve stock price informativeness to managers. This article closely relates to that paper in the sense that both consider managerial learning from market prices as well as CDS trading. However, a crucial difference is that they look at indirect effect of CDS spreads via stock prices but not learning directly from CDS spreads. In this article, I measure the private information within CDS spreads and test whether managers use this information to inform their risk management.

Apart from Kim, Wiedman & Zhu (2018), there have been a number of studies in accounting that look into the availability of CDS trading and accounting variables. Many studies that use the initiation of CDS trading build upon the empty creditor problem suggested by Bolton and Oehmke (2011). Bolton and Oehmke (2011) argue that the empty creditor problem could arise in the presence of credit default swaps because the creditors can hold both debt and CDS at the same time. If creditors own both, they can remove a significant portion of the risk in lending and potentially have incentives to prefer bankruptcy over renegotiation.

Related to this idea, some researchers hypothesize that CDS availability would lead to less monitoring from creditors, and thus, shareholders will demand more monitoring from managers (Kim, Shroff, Vyas, & Wittenberg-Moerman 2018). The learning in this paper has some similarities with the monitoring mechanism from Kim et al. (2018) because both concern increased managerial action. However, the critical difference is that their mechanism is about being traded in the CDS market vs. not traded, while this paper's focus is the learning from the CDS spreads for those already being traded.

Similar to Kim et al. (2018), Shan, Tang, & Winton (2019) study whether banks' monitoring behaviors are affected by the initiation of CDS trading. They find that the introduction of CDS trading makes debt contracting more effective because firms enjoy lower collateral and financial covenants with CDS' monitoring function. Similarly, Kang, Williams, and Wittenberg-Moerman (2020) find that adverse selection for new lending relationship is also lessened with the introduction of CDS trading.

While the studies above focus more on the effect of CDS trading on lending relationships, a few studies also look into supply chains. For example, Li and Tang (2016) show that when customer firms are referenced in the CDS market, a supplier firm's leverage is lower, reflecting the information spillover in the supply chain via CDS trading. Instead of leverage, Cedergren, Luo, Wu & Zhang (2020) focus on management forecasts of supplier firms and find that firms with a high portion of CDS-referenced customers lower their frequency of forecast issuance.

Finally, Cheng and Lim (2020) study the relationship between abnormal earnings accruals and CDS initiation. They argue that CDS initiation creates new information that contributes to a reduction in information asymmetry.

A common challenge faced by the availability of CDS literature is potential selection bias; the firms that become available in the CDS markets may be quite different from those that do not. For this reason, I focus only on the firms that are already covered by CDS and their managerial learning from CDS spreads.

Overall, while there has not been a direct study on the feedback effect of CDS spreads, it seems reasonable to expect the potential role of CDS as a source of private information as well as a venue for the feedback effect, given the prior literature's findings on feedback in the stock market as well as CDS' role in monitoring risks.

2.2 CDS vs. corporate bonds and credit ratings

If managers can learn from private information available in secondary market prices, then corporate bond yields will serve a similar role to CDS, given that they contain default risk information as well. To study managers' learning from these market "prices," CDS has several advantages over corporate bonds.

First, CDS spreads contain more direct information about default risks compared to corporate bonds. While the most significant portion of the corporate bond yields is due to default risk (Longstaff, Mithal & Neis 2005), there are still other factors mixed with them, such as liquidity, the market's expectation of buy-backs, and bond covenants (Berman 2005). In this sense, CDS spreads provide a more direct default risk measure than corporate bond yields.

Second, CDS price adjustment is faster than that of corporate bonds. For example, Zhu (2006) shows that bonds and CDS spreads move together in the long run, but they can differ significantly in the short run. Also, Zhu (2006) finds that CDS spreads move ahead of bond prices.

Third, thanks to better liquidity, it is easier for speculators to access the CDS market. Oehmke & Zawadowski (2017) argue that while bond and CDS markets provide a venue for the same motive (hedging motives), speculative trading volume is primarily concentrated in the CDS market, which can attract the participation of privately informed traders. Also, they demonstrate that the liquidity for CDS trading exceeds that of the bond market.

Finally, many studies have provide evidence that CDS is faster and more efficient than credit ratings. For example, Norden and Weber (2004) focus on the response of the CDS and the stock markets to credit rating announcements and found evidence that the CDS market reacted faster regarding downgrades.

2.3 CDS: unique information source or a sideshow

Before considering the feedback effect of CDS spreads, another aspect that requires attention is the information equivalence hypothesis between the stock market and CDS (Figure 3 and 4). To date, it has been a subject of great controversy whether CDS provides new information and can lead price discovery compared to the equity market, or if it is just a sideshow. For example, Hilscher, Pollet, & Wilson (2015) argue that CDS are a sideshow, and the information mostly flows from the equity market to the CDS market.

However, there are many studies with counter-evidence to this claim. For example, Acharya and Johnson (2007) find significant incremental information revelation in the credit default swap market relative to the equity market. Also, Fung et al. (2008) investigate the relationship between the CDS market and the equity market using CDX indices. Their results indicate that, for investment-grade firms, the equity market leads the CDS market in terms of price discovery. However, they also find that CDS play a more significant role in volatility spillover than the stock market. Thus, they argue that investors need to pay attention to both markets.

One of the most recent studies on this topic is Lee, Naranjo & Velioglu (2018). They find that CDS spreads contain unique firm credit risk information not captured by other markets, such as stock and bond markets, and play an essential role in price discovery. Also, they find that credit information uni-directionally flows from CDS to bonds, and CDS returns can predict stock returns as well.

Also, it's important to note that due to their information structure, CDS and stock prices have different sensitivities to various types of events. Like put options, CDS spreads are sensitive to low-state events and relatively insensitive to high state events. Like call options, stock prices are sensitive to high-state events and relatively insensitive to low state events (Figure 3).

Overall, it seems that there is some truth on both sides; that is, while information flows between the equity and CDS markets with some overlap, there are unique areas where CDS seem to lead price discovery.

2.4 Hypothesis development

The main tasks of the article are to test (1) whether the private information from CDS spreads influences managers' risk management decisions and (2) whether this relationship is influenced by different types of managers or information environment characteristics.

For the first goal, I begin with the the relationship between the private information in CDS spreads (or the amount of potential learning opportunities in CDS spreads) and the sensitivity of leverage to CDS spreads. The sensitivity of leverage to CDS spreads is important because we are not interested in the direct relationship between CDS spreads and leverage but how the private information from CDS spreads can affect the relationship between the two. If managers learn more from the CDS spreads about their potential credit risks, I expect they will react by adopting conservative measures, such as lowering the leverage ratio. This leads us to the first hypothesis:

(H1) When there is more private information in CDS spreads, an increase in CDS spreads is associated with larger decreases (smaller increases) in leverage

In other words, if managers find a high level of private information in CDS spreads, then I expect managers to have relatively lower leverage ratios than those who do not find a high level of private information in CDS spreads in the following period.

Other than the leverage ratio, we can also expect that managers will act to take other conservative and risk-managing actions. Especially, we should expect to find those conservative actions where managerial discretion matters more. One such example is contingent liabilities. Managers only record contingent liabilities when it is likely that they will incur the liabilities and when they can be reasonably estimated. I expect that managers who learn more from the CDS spreads will be more proactive about risk-managing actions, increasing the size of contingent liabilities they recognize. This leads us to the second hypothesis:

> *(H2) When there is more private information in CDS spreads, an increase in CDS spreads is associated with smaller decreases (larger increases) in contingent liabilities*

In addition, I conduct a similar test with impairments and writedowns. If managers learn more about their corporate risk from CDS spreads, I expect managers to record impairments and writedowns faster. However, prior literature documents that impairments are relatively rare, and firms typically record them with a time lag of three to four years after learning about deterioration of assets (Hayn and Hughes 2006). Therefore, I test for impairments and writedowns in the next three years. This leads us to the third hypothesis:

> *(H3) When there is more private information in CDS spreads, an increase in CDS spreads is associated with smaller decreases (larger increases) in impairments and writedowns*

Next, I examine whether different types of CEOs differ in their learning from CDS. I focus on overconfident managers. Since overconfident managers forgo current cashing-out opportunities from option holdings, I expect they are less likely to listen to the market than other CEOs. If they learn less from the market, I expect them to recognize less on impairments and writedowns. Thus, the fourth hypothesis is the following:

> *(H4) For overconfident CEOs, when there is more private information in CDS spreads, a higher level of CDS spreads is associated with larger decreases (smaller increases) in impairments and writedowns compared to non-overconfident CEOs*

Lastly, I study how the information environment of the firm can affect the relationships I described earlier. I focus on the information provided by analysts. First, having more analyst coverage can have two competing forces regarding the effectiveness of learning from CDS. If having more analysts improves the information environment, then I should expect fewer needs for the managers to learn from CDS spreads, holding all else equal. However, if the high number of analysts represents greater attention and interest from market participants, then the total information contained in CDS spreads can be even more valuable for managers, making the learning channel more effective. Second, if analysts disagree with one another, I expect there will be a higher need for the managers to learn from the private information available in CDS spreads. If they learn more from CDS spreads, I expect them to take conservative actions, such as lowering the leverage ratios. Thus, this leads us to the last hypothesis:

(H5a) As the number of analysts increases, the amount of private information in CDS spreads can be positively or negatively associated with the sensitivity of leverage to CDS spreads depending on the size of two competing forces

(H5b) As the disagreement among analysts increases, the amount of private information in CDS spreads is more negatively associated with the sensitivity of leverage to CDS spreads

3. Research Design and Data

3.1 Measures of private information in CDS spreads

For the measure of the private information in CDS ($INFO_{i,t-1}$), I use the following three measures: CDS nonsynchronicty with Fama-French 12 industries, CDS nonsynchronicty with Fama-French 48 industries, and normalized CDS bid-ask spreads.

The price nonsynchronicity measure is one of the most commonly used measures in capturing private information in the stock market (Chen, Goldstein & Jiang 2007). The basic idea is that it measures how a certain firm's stock return moves differently from other firms in the same industry and the overall market. However, I cannot directly apply this concept to CDS because CDS spreads are not in dollar prices but basis-point spreads. Thus, I first need to define CDS returns and then apply the concept of nonsynchronicity to CDS spreads.

For the CDS return, I follow Hilscher, Pollet, & Wilson (2015), where they approximated the CDS return as the percentage change in CDS spreads adjusted by the ratio of two annuity factors. However, since the annuity ratios are always close to 1, I assume they are one and define the CDS return as the percentage change in credit spreads as in Hilscher, Pollet, & Wilson (2015).

Given this definition of CDS return, I estimate the $1-R^2$(nonsynchronicity) and R^2(synchronicity) from the following regression:

$$r_{i,j,t} = \beta_{i,0} + \beta_{i.m} r_{m,t} + \beta_{i,j} r_{j,t} + \epsilon_{i,t} \tag{1}$$

where $r_{i,j,t}$ represents the CDS return for firm i in industry j at time t, $r_{m,t}$ is the market return, and $r_{j,t}$ is the industry return. Using the daily CDS return data, I estimate $1-R^2$ (nonsynchronicity) with a 90-day rolling window. Since the CDS nonsynchronicity can be affected by different industry classifications, I use both Fama-French 12 and 48 classifications.

Finally, I use the normalized CDS bid-ask spread, which I define as the 5-year bid-ask spread divided by the 5-year mid CDS spread, as another measure of private information in CDS spreads. In other studies on the feedback effect with stock prices, PIN (probability of informed trading) is often used as another measure. However, the CMA CDS data I use in this article does not have volume data needed to calculate PIN type measures. Thus, I use the bid-ask spread as an alternative.

3.2 Research design

Hypothesis 1

For (H1), I use the following linear regression model modified from Chen, Goldstein & Jiang (2007)'s model for the stock price learning to examine the relationship between the amount of private information in CDS spreads and the sensitivity of leverage to CDS spreads:

$$Leverage_{i,t} = \alpha_t + \eta_j + \beta_1 Leverage_{i,t-1} + \beta_2 CDS_{i,t-1} + \beta_3 INFO_{i,t-1}$$

$$+\beta_4 CDS_{i,t-1} * INFO_{i,t-1} + \beta_5 CONTROLS_{i,t} + \epsilon_{i,t} \quad (2)$$

The main coefficient of interest is β_4 which represents the effect of private information in CDS spreads on the sensitivity of leverage to CDS spreads. $Leverage_{i,t}$ and $Leverage_{i,t-1}$ represent the leverage ratios in the current and previous periods, $CDS_{i,t-1}$ is the logarithm of CDS spreads following Griffin (2014), and $\alpha_t + \eta_j$ represent year and industry-fixed effects. $INFO_{i,t-1}$ represents three measures of private information in CDS spreads I define in the previous section. *CONTROLS* include $Q_{i,t-1}$, $Q_{i,t-1} * INFO_{i,t-1}$, $cumul.return_{i,t+3}$, $1/AT_{i,t-1}$, $CF_{i,t}$, $ROA_{i,t}$, and $tangibility_{i,t}$. Q_{t-1} represents Tobin's Q, and I use it as a proxy for the stock price, similar to Chen, Goldstein & Jiang (2007). $Q_{i,t-1} * INFO_{i,t-1}$ is also included to control for the learning in the stock market. $cumul.return_{i,t+3}$ represents future stock returns for the next three years, and this is included to control for managers' market timing (e.g. a manager can invest more when their stocks are overvalued). $1/AT_{i,t-1}$ is included to control for spurious correlations due to the common variable ($AT_{i,t-1}$), and $CF_{i,t}$ is included because cash flows and liquidity are closely related to CDS trading. Subrahmanyam, Tang, & Wang (2017) show that CDS-referenced firms hold more cash because they want to avoid renegotiations with more exacting creditors who can potentially have CDS. $ROA_{i,t}$ is included to control for management efficiency, and $tangibility_{i,t}$ is included to control for the size of PP&E holdings, which can be related to the debt level and leverage.

Hypothesis 2 and 3

For (H2) and (H3), I use a regression similar to (2) except that the dependent variables are contingent liabilities and impairments/writedowns respectively. Also, I do not control for prior leverage but instead control for current leverage.

$$contin.\,liab._{i,t} = \alpha_t + \eta_j + \beta_1 CDS_{i,t-1} + \beta_2 INFO_{i,t-1} + \beta_3 CDS_{i,t-1} * INFO_{i,t-1} + \beta_4 CONTROLS_{i,t} + \epsilon_{i,t} \qquad (3)$$

$$\sum_t^{t+2} impair + writedown_i = \alpha_t + \eta_j + \beta_1 CDS_{i,t-1} + \beta_2 INFO_{i,t-1} + \beta_3 CDS_{i,t-1} * INFO_{i,t-1} + \beta_4 CONTROLS_{i,t} + \epsilon_{i,t} \qquad (4)$$

where *CONTROLS* are the same as in (1), i.e., $Q_{i,t-1}$, $Q_{i,t-1} * INFO_{i,t-1}$, $cumul.return_{i,t+3}$, $1/AT_{i,t-1}$, $CF_{i,t}$, $Leverage_{i,t}$, $ROA_{i,t}$, and $tangibility_{i,t}$. The leverage and tangibility controls are now added since contingent liabilities, impairments, and writedowns are likely to be related to non-current assets and since CDS is closely associated with leverage.

Hypothesis 4

I test Hypothesis 4 using a similar regression to (4) but with overconfident manager as an interaction term. For the overconfidence measure, I adopt a method that approximates Malmendier and Tate’s (2005) overconfident CEO measure, which is defined as CEOs who hold stock options that are more than 67% in the money. The approximation method was adopted from Core and Guay (2002), and the steps for the calculation are specified in the appendix. I classify a CEO as overconfident if the CEO holds stock options that are more than

67% in the money for more than two years.

For the test, I use a similar linear regression as before but with added interaction terms:

$$\sum_t^{t+2} impair + writedown_i = \alpha_t + \eta_j + \beta_1 CDS_{i,t-1} + \beta_2 INFO_{i,t-1} + \beta_3 Overconfident\ CEO_{i,t-1} + \beta_4 CDS_{i,t-1} * OverCEO_{i,t-1} + \beta_5 CDS_{i,t-1} * INFO_{i,t-1} + \beta_6 OverCEO_{i,t-1} * INFO_{i,t-1} + \beta_7 OverCEO_{i,t-1} * CDS_{i,t-1} * INFO_{i,t-1} + \beta_8 CONTROLS_{i,t} + \epsilon_{i,t} \quad (5)$$

where *CONTROLS* include $Q_{i,t-1}$, $Q_{i,t-1} * INFO_{i,t-1}$, $cumul.return_{i,t+3}$, $1/AT_{i,t-1}$, $CF_{i,t}$, $Leverage_{i,t}$, $ROA_{i,t}$, and $tangibility_{i,t}$.

The main coefficient of concern is the triple interaction term (β_7), which captures the incremental sensitivity of leverage to CDS spreads for the overconfident CEOs.

Hypothesis 5a and 5b

(H5a) and (H5b) are similar to (H4), but now the interaction is with analysts variables instead of overconfidence variables. Thus, the regression specifications are:

$$leverage_{i,t} = \alpha_t + \eta_j + \beta_1 CDS_{i,t-1} + \beta_2 INFO_{i,t-1} + \beta_3 analysts_{i,t-1} + \beta_4 CDS_{i,t-1} * analysts_{i,t-1} + \beta_5 CDS_{i,t-1} * INFO_{i,t-1} + \beta_6 analysts_{i,t-1} * INFO_{i,t-1} + \beta_7 analysts_{i,t-1} * CDS_{i,t-1} * INFO_{i,t-1} + \beta_8 CONTROLS_{i,t-1} + \epsilon_{i,t} \quad (6)$$

where *CONTROLS* include $DISP_{i,t-1}$ (for number of analysts only), $NUMEST_{i,t-1}$ (for dispersion only), $DISP\ LT_{i,t-1}$, $Q_{i,t-1}$, $Q_{i,t-1} * INFO_{i,t-1}$, $cumul.return_{i,t+3}$, $1/AT_{i,t-1}$, $CF_{i,t}$, $ROA_{i,t}$, $tangibility_{i,t}$, For the analysts variables, I use (1) the number of analysts (H5a) and (2) EPS forecast dispersion among analysts (H5b).

Similar to (H4), the main coefficient of concern is the triple interaction term (β_7).

3.3 Data

I use CMA CDS data accessed from S&P Capital IQ as the primary source of CDS spreads. The CMA data offers several advantages over other CDS data sources. Most importantly, its quality surpasses that of other datasets. For example, Mayordomo et al. (2014) identified both CMA and Markit CDS data as leaders in price discovery. Additionally, CMA CDS data includes all three types of spreads (bid, ask, and mid), while Markit CDS only provides mid spreads.

I retrieve data related to company fundamentals from Compustat and data pertinent to stock returns from CRSP. For overconfidence data, I extract CEO options information from Execucomp. I retrieve analysts' data from IBES.

3.4 Sample construction

I begin my sample construction with CMA CDS data, ranging from October 2004 to December 2020. Since building the measures of CDS private information takes a year's daily CDS returns, the earliest possible date in the sample is November 2005. I choose 5-year CDS spreads only since this is the most commonly used tenor in industry and prior literature (Griffin 2014). Also, the currency restriction is USD only, and all are contracts with senior unsecured debt. From the CMA CDS data, I construct three measures of private information in CDS.

Then I merge the CDS data with yearly observations from Compustat and CRSP. Finally, if available, CEOs' option-holding information and overconfidence variables (calculation specified in the appendix) are retrieved from Execucomp and added to the main dataset. Finally, IBES analysts data are added to the main dataset. Compared to other parts of the analysis, the tests with IBES data have a relatively lower number of observations due to the difference in sample firms between CMA CDS data and IBES firms.

3.5 Summary statistics

I report descriptive statistics for the sample for the test of (H1) in Table 1. The average five-year CDS spreads for firms in the sample was 155.53 (in basis points), meaning that a protection buyer pays the seller 1.5553% of the nominal amount each year as a premium for credit protection. The average level of leverage was 33.4%, tangibility was 29.2%, and the average number of analysts following was 15. Also, it seems that impairments and writedowns are extremely skewed, supporting our assumption that they are rare and concentrated in a few firms.

Table 2 provides correlations. As we can expect, the correlation between the two INFO variables with industry differences is very high (0.968). These two INFO variables are also closely related to INFO_bid-ask which is based on the bid-ask spread (0.450), but the correlation is not as strong as between the industry INFO variables.

4. Empirical Analysis

4.1 Hypothesis 1

Table 3 reports the regression results for (H1). The dependent variable is leverage for year t, and the main independent variable is *CDS x INFO* for year t-1. Column 1 shows the baseline linear regression results with CDS private information (*INFO*) based on Fama-French

48 industries, without controlling for learning from the stock market. Column 2 adds the controls for learning from the stock market. Columns 3 and 4 show the same test results but with *INFO* based on 12 industries, and Columns 5 and 6 use *INFO* based on CDS bid-ask spreads.

Overall, regardless of different measures of private information in CDS and control variables, I find that CDS is positively associated with leverage in the following year, while *CDS x INFO* is negatively associated with leverage in the following year. Since the test is controlling for the leverage in the previous year, the positive coefficient for *CDS* reflect anticipation of increased leverage in the following year. However, if the manager learns more from private information in the CDS spreads (high *INFO*), they tend to have a lower leverage in the following year than those who do not learn much from CDS spreads. Thus, this result is consistent with (H1).

4.2 Hypotheses 2 and 3

Table 4 reports the regression results for (H2). The dependent variable is contingent liabilities for year t, and the main independent variable is *CDS x INFO* for year t-1. Column 1 shows the linear regression results with CDS private information (*INFO*) based on Fama-French 48 industries. Column 2 shows the same test results but with the *INFO* variable based on different industry classifications (12 industries). Columns 3 uses the *INFO* variable based on CDS bid-ask spreads. I find that, while *CDS* is negatively associated with contingent liabilities in the following year, *CDS x INFO* is positively associated with contingent liabilities in the following year. This result implies that the managers who learn more from CDS spreads take more conservative actions in the following year than those who do not learn from CDS spreads. Thus, this result is consistent with (H2).

For (H3), I test a similar specification with a different dependent variable—impairments and writedowns (the table not included in the current draft). However, I do not find any significant results and fail to reject the null hypothesis that there is no relationship (or, learning from CDS does not help managers reduce impairments and writedowns in the next three years). This result can be potentially due to the weak (or no) relationship between impairments/writedowns and CDS learning for the entire sample, or it could be due to the large time gap between the year (*t-1*) change in CDS and the next three years' accounting changes.

4.3 Hypothesis 4

For (H4), I focus on a subset of the sample from (H3). In particular, I focus on overconfident managers to see whether they are more likely to ignore learning from CDS spreads. Table 5 reports the regression results for (H4). The dependent variable is the logarithm of impairments and writedowns for the years from t to t+2, and the main independent variable is the triple interaction term *OverCEO x CDS x INFO* for year *t-1*. Column 1, 2, and 3 show the regression results with CDS private information variable (*INFO*) based on Fama-French 48 industries, Fame-French 12 industries, and bid-ask spreads, respectively.

While the results with nonsynchronicity *INFO* measures fail to reject the null hypothesis, the result with bid-ask *INFO* measure supports the hypothesis, i.e., for overconfident managers, the amount of private information in CDS spreads is negatively associated with the sensitivity of impairments and writedowns to CDS spreads. In other words, overconfident managers, even with those with private information available in CDS, are less likely to record impairments or writedowns in the next three years compared to other CEOs.

4.4 Hypotheses 5a and 5b

(H5) predicts whether the information environment influences managerial learning from the CDS spreads. I expect that the number of analysts could have a result in either direction; if a higher number of analysts represent more attention and interest from market participants, it can be beneficial for managers because there can be more private information in CDS spreads. On the other hand, more information from more analysts can lower their incentives to learn from other information sources, including the feedback from the market. In Table 6, I do not find any significant results with nonsynchronicty measures. However, with the bid-ask measure, I find that a higher number of analysts makes the learning channel more effective and lowers the leverage ratio in the following year (H5a).

(H5b) also predicts that the triple interaction term *CDS x INFO x DISP* would be negative given that more disagreement among analysts will increase the needs for other information sources, such as the feedback from CDS spreads. The results from Table 7 seem to be in favor of the hypothesis. While I do not find significant results with the nonsynchronicty measures, I find significant results with the bid-ask spread measure.

5. Summary and Conclusions

The article investigates whether managers learn about their own default risk through feedback from CDS spreads and whether the learning influences their risk management. I find that the managers who learn more from CDS spreads lower the leverage ratio and are more likely to record contingent liabilities in the following year. I find that overconfident managers are less likely to impair or writedown, compared to those who are more likely to learn from CDS spreads; however, I do not find a significant relation between CDS spreads and writedowns for the overall sample. Finally, I find that CDS learning is more effective when there are more analysts following the firm and when analysts disagree with each other.

Controlling for the potential feedback through the stock market channel, the results suggest that there is information content unique to CDS spreads, and those managers who learn from CDS feedback perform better on risk management.

With the results from this article, there are additional questions that require further inquiries. For example, do other tenors of CDS (such as 1-year or 3-year) deliver similar learning effects, or do managers ignore this information since it matters less than 5-year CDS? How does the CDS feedback interact with other potential feedback channels such as options? More inquiries like the above will improve our understanding of the role that CDS spreads plays in managerial learning from secondary market prices.

6. Appendix A. Variable definitions

Variable Name	Definitions (all variables winsorized at 1% and 99% level unless noted otherwise; Data Source in parenthesis)
CDS $_{t, bid}$	5-year CDS bid Spread (CMA, accessed from S&P Capital IQ)
CDS $_{t, ask}$	5-year CDS ask Spread (CMA, accessed from S&P Capital IQ)
CDS $_{t, mid}$	5-year CDS mid Spread (CMA, accessed from S&P Capital IQ)
log(CDS $_{t, mid}$)	Logarithm of 5-year CDS mid Spread (CMA, accessed from S&P Capital IQ)
INFO_12	The yearly average of $1 - R^2$(nonsynchronicity) from the regression $r_{i,j,t} = \beta_{i,0} + \beta_{i.m}r_{m,t} + \beta_{i,j}r_{j,t} + \epsilon_{i,t}$ with a 90-day window using Fama-French 12 industries. The daily CDS return $r_{i,j,t}$, market return $r_{m,t}$, and industry return $r_{j,t}$ are from 5-year CDS mid spread (CMA, accessed from S&P Capital IQ)
INFO_48	The yearly average of $1 - R^2$(nonsynchronicity) from the regression $r_{i,j,t} = \beta_{i,0} + \beta_{i.m}r_{m,t} + \beta_{i,j}r_{j,t} + \epsilon_{i,t}$ with a 90-day window using Fama-French 48 industries. The daily CDS return $r_{i,j,t}$, market return $r_{m,t}$, and industry return $r_{j,t}$ are from 5-year CDS mid spread (CMA, accessed from S&P Capital IQ)
INFO_bid-ask	The yearly average of (CDS $_{t, ask}$ – CDS $_{t, bid}$) / CDS $_{t, mid}$ (CMA, accessed from S&P Capital IQ)
Q $_t$	Market capitalization + book value of assets - book value of equity, scaled by book value of assets (Compustat and CRSP)
Leverage $_t$	Total debt (current and long-term) divided by lagged assets (Compustat)
Tangibility $_t$	PP&E divided by total assets (Compustat)
Cumul. Returns $_{t+3}$	Value-weighted market return adjusted firm return (cumulative abnormal return) for next three years (CRSP)
Total Assets	Total assets (Compustat)
CF	Net income before extraordinary item + depreciation and amortization expenses +R&D expenses, scaled by lagged assets (Compustat)

ROA	Return on Assets; net income divided lagged assets (Compustat)
Contingent liab.	The sum of all contingent liability items (Compustat)
Impairment Prob.	A dummy variable equalts to 1 if Impair. & Write-down > 0 (Compustat)
Impair. & Write-down	Impairments of goodwill (pre-tax) + writedowns (pretax) (Compustat)
Overconfident CEO	A dummy variable equals to 1 if the number of years with the overconfidence indicator exceeds 2. The number of overconfidence indicator is calculated as the following: first, the realizable value per option is calculated as OPT_UNEX_EXER_EST_VAL / OPT_UNEX_EXER_NUM from Execucomp. Second, the average exercise price is generated as the of the fiscal year stock price - the realizable value per option. Finally, the percentage of the option's moneyness is calculated as the realizable value per option divided by the average exercise price. If this ratio is higher than 0.67, then I classify it as an overconfidence year (Execucomp)
Num. of Analyst (NUMEST)	The number of analysts following (IBES)
Analyst Dispersion (DISP)	Standard deviation of EPS forecasts divided by the mean EPS forecast
Analyst LT Dispersion (DISP LT)	Standard deviation of logn-term EPS forecasts divided by the mean long-term EPS forecasts

6. Appendix B. Credit event definitions[‡]

Credit Event is the event-triggering settlement under the CDS contract. The Determinations Committees (DCs) determine whether a credit event has occurred, and whether an auction should take place to settle trades. Since the original ISDA Agreement in 1999, six categories of Credit Events have been defined:

Bankruptcy – although the ISDA 2003 Definitions refer to different ways a bankruptcy can occur, the experience has been that the reference entity has filed for relief under bankruptcy law (or equivalent law).

Failure to pay – The reference entity fails to make interest or principal payments when due, after the grace period expires (if grace period is applicable in the trading documentation).

Debt restructuring – The configuration of debt obligations is changed in such a way that the credit holder is unfavorably affected (maturity extended and/or coupon reduced). For more details, see the definition for Restructuring Credit Event further below.

Obligation default, obligation acceleration, and repudiation/moratorium – The 2003 ISDA definitions define these three credit events, but they are very rare.

[‡] The following definitions are from Markit Credit Indices: A Primer (2012)

Figure 1. British Petroleum (BP)'s 5-year CDS vs. stock price from February 2007 to September 2015

In 2010, BP experienced an oil-spillover disaster in the Gulf of Mexico (Deepwater Horizon oil spill)

Source: Bloomberg Finance L.P.

Source: Yahoo Finance

Figure 2. Campbell Soup's 5-year CDS vs. stock price from February 2007 to September 2015

Source: Bloomberg Finance L.P.

Figure 3. Information in CDS vs. stock price

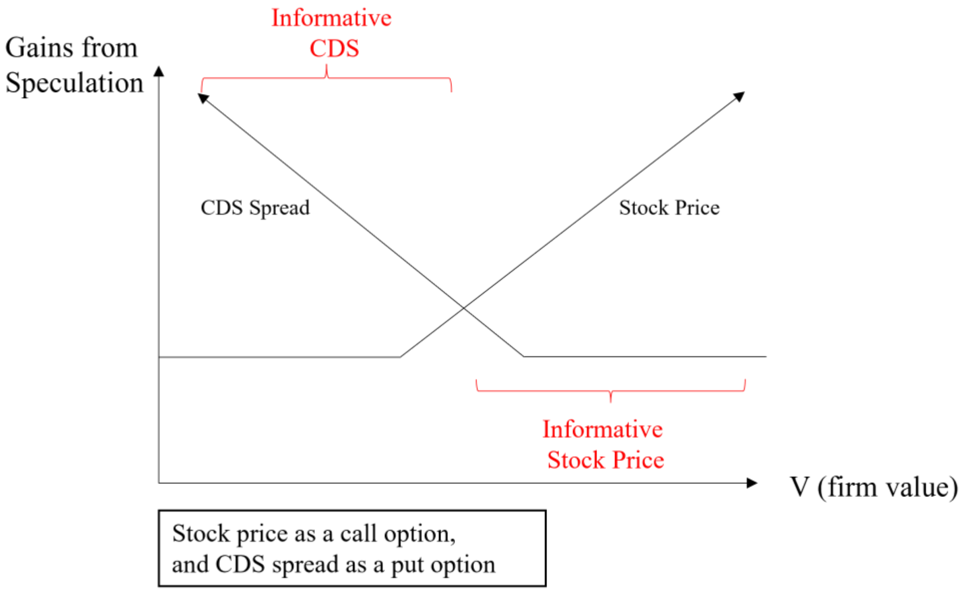

Figure 4. Information equivalence hypothesis between CDS and stock price

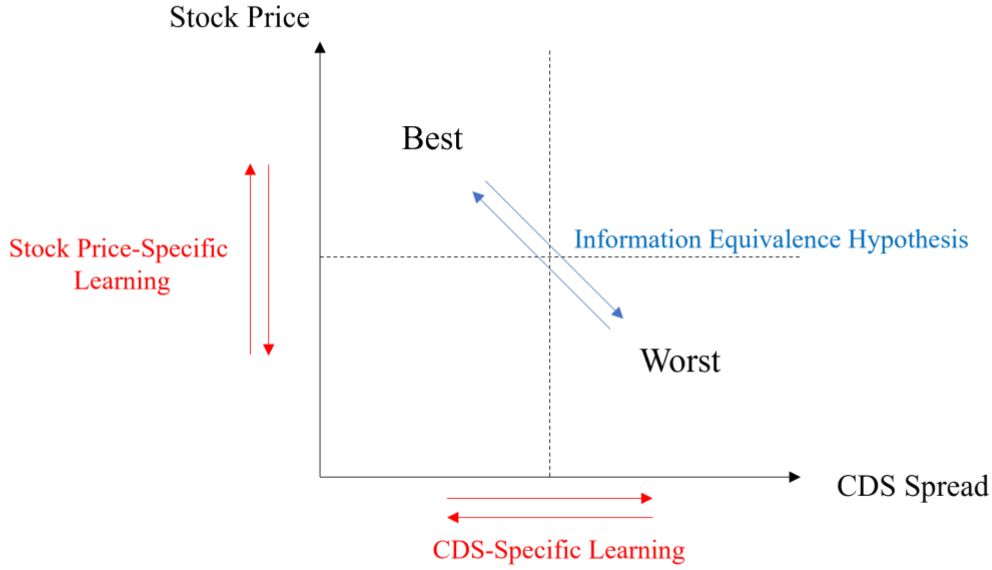

Table 1: Descriptive Statistics

	Obs	Mean	SD	Min	P25	Median	P75	Max	Skew.	Kurt.
CDS $_{t, bid}$	5642	141.267	197.765	9.9	40.857	74.752	155.163	1603.9	3.818	21.503
CDS $_{t, ask}$	5642	155.532	210.401	13.65	48.381	85.986	170.197	1727.98	3.848	21.916
CDS $_{t, mid}$	5642	148.41	204.06	11.921	44.69	80.727	161.821	1665.62	3.834	21.715
log(CDS $_{t, mid}$)	5642	4.486	.954	2.478	3.8	4.391	5.086	7.418	.472	2.991
INFO_12	5625	.652	.199	.004	.505	.671	.82	.987	-.431	2.447
INFO_48	5539	.638	.206	0	.483	.661	.812	.987	-.42	2.376
INFO_bid-ask	5642	.139	.094	.001	.075	.111	.177	1.151	2.102	11.229
Q $_{t}$	5413	1.564	.815	.448	1.045	1.297	1.792	11.881	3.215	22.049
Leverage $_{t}$	5398	.335	.215	0	.185	.307	.454	2.729	1.687	11.253
Tangibility $_{t}$	4898	.292	.283	0	.051	.196	.491	4.771	1.608	15.561
Cumul. Returns $_{t+3}$	5519	.018	.458	-.952	-.24	-.034	.204	5.914	3.097	29.032
Total Assets	5837	115133.4	320774.2	786.348	8323	21859	61902	3386071	5.176	33.298
CF	5418	.085	.085	-.458	.026	.073	.128	.778	.829	7.81
ROA	5418	.045	.064	-.514	.012	.037	.074	.546	-.124	10.657
Contingent liab.	5837	962.302	7123.271	0	0	0	0	101899	10.482	124.299
Impairment Prob.	5837	.246	.431	0	0	0	0	1	1.178	2.389
Impair. & Writedown	5837	-135.051	995.304	-32853	0	0	0	942	-17.838	423.482
Overconfident CEO	5837	.262	.44	0	0	0	1	1	1.085	2.177
Num. of Analyst	5412	15.413	8.131	1	9	16	21	53	.258	2.933
Analyst Dispersion	5262	.172	.473	0	.025	.05	.122	4.25	6.379	48.967
Analyst LT Dispersion	3814	.424	.521	0	.148	.266	.471	2.661	2.967	12.234

Table 2: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
log(CDS $_{t, mid}$)	1.000																	
INFO_12	-0.298	1.000																
INFO_48	-0.305	0.968	1.000															
INFO_bid-ask	-0.525	0.450	0.452	1.000														
Q $_t$	-0.317	0.221	0.221	0.316	1.000													
Leverage $_t$	0.188	-0.005	0.007	-0.090	0.157	1.000												
Tangibility $_t$	-0.025	0.041	0.076	0.015	-0.023	0.269	1.000											
Cumul. Returns $_{t+3}$	0.066	-0.048	-0.047	-0.032	0.027	-0.060	0.001	1.000										
Total Assets	-0.019	-0.187	-0.206	-0.081	-0.172	-0.053	-0.199	-0.093	1.000									
CF	-0.352	0.191	0.214	0.252	0.645	0.063	0.178	0.014	-0.214	1.000								
ROA	-0.384	0.160	0.173	0.247	0.595	0.025	0.078	-0.007	-0.158	0.860	1.000							
Contingent. Liab.	0.014	-0.090	-0.132	-0.062	-0.079	0.022	-0.105	-0.043	0.760	-0.116	-0.081	1.000						
Impairment Prob.	0.071	-0.023	-0.019	-0.079	-0.018	0.082	0.006	0.019	-0.071	-0.072	-0.145	-0.037	1.000					
Impair. & Write-down	-0.046	0.029	0.026	0.041	0.056	0.012	0.015	-0.015	-0.068	0.144	0.202	-0.050	-0.220	1.000				
Overconfident CEO	0.022	-0.046	-0.060	-0.026	0.101	-0.016	-0.026	0.172	-0.117	0.029	0.077	-0.064	-0.042	0.016	1.000			
Num. of Analyst	-0.226	-0.103	-0.099	0.122	0.231	-0.093	0.041	-0.024	0.188	0.216	0.172	0.085	-0.042	-0.036	0.094	1.000		
Analyst Dispersion	0.308	-0.030	-0.060	-0.151	-0.132	0.026	0.024	0.060	-0.011	-0.259	-0.348	0.011	0.095	-0.074	0.009	-0.063	1.000	
Analyst LT Dispersion	0.169	-0.062	-0.052	-0.094	-0.145	-0.043	0.077	-0.032	-0.002	-0.036	-0.103	0.003	0.028	-0.089	-0.078	0.039	0.117	1.000

Table 3: Private information in CDS and the sensitivity of leverage to CDS spreads

Table 3 reports the linear regression results for (H1). The dependent variable is leverage for year t, and the main independent variable is *CDS x INFO* for year *t-1*. Column 1 shows the linear regression results with no controls for the learning channel in the stock market with CDS private information variable (*INFO*) based on Fama-French 48 industries. Column 2 adds the controls for learning in the stock market. Columns 3 and 4 show the same test results but with a *INFO* variable with different industry classifications (12 industries), and Columns 5 and 6 use *INFO* variable based on CDS bid-ask spreads.

INFO Measures:	**CDS Nonsynchronicity (Fama-French 48 Industries)**		**CDS Nonsynchronicity (Fama-French 12 Industries)**		**CDS Bid-Ask Spread**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Leverage $_t$	Leverage $_t$	Leverage $_t$	Leverage $_t$	Leverage $_t$	Leverage $_t$
Leverage $_{t-1}$	.691***	.646***	.747***	.699***	.685***	.647***
	(.035)	(.032)	(.031)	(.027)	(.034)	(.032)
CDS $_{t-1}$	.024***	.046***	.03***	.057***	.016***	.026***
	(.009)	(.01)	(.009)	(.01)	(.005)	(.005)
INFO $_{t-1}$ (nonsync + FF48)	.081	.298***				
	(.054)	(.09)				
CDS $_{t-1}$ x INFO $_{t-1\ (FF48)}$	-.021*	-.04***				
	(.012)	(.014)				
INFO $_{t-1}$ (nonsync + FF12)			.137**	.398***		
			(.054)	(.088)		
CDS $_{t-1}$ x INFO $_{t-1\ (FF12)}$			-.034***	-.058***		
			(.012)	(.013)		
INFO $_{t-1(bid\text{-}ask)}$					.295***	.442***
					(.105)	(.163)
CDS $_{t-1}$ x INFO$_{t-1(bid\text{-}ask)}$					-.078***	-.088***
					(.029)	(.033)
Q $_{t-1}$		.122***		.132***		.064***
		(.026)		(.024)		(.014)
Q $_{t-1}$ x INFO $_{t-1}$		-.1***				
		(.029)				
Q $_{t-1}$ x INFO $_{t-1\ (FF12)}$				-.114***		
				(.028)		
Q $_{t-1}$ x INFO $_{t-1\ (bid\text{-}ask)}$						-.084**
						(.041)
Cumul. Return $_{t+3}$	-.007	-.008*	-.005	-.006	-.007	-.008*
	(.005)	(.004)	(.005)	(.005)	(.005)	(.005)
1/AT $_{t-1}$	151.53***	106.346***	147.796***	116.861***	157.88***	116.426***
	(29.881)	(29.001)	(26.301)	(25.652)	(29.088)	(28.5)
CF $_t$	.37***	.063	.292**	.017	.368***	.023
	(.139)	(.148)	(.132)	(.133)	(.14)	(.153)
Tangibility	.158***	.185***	.122***	.142***	.167***	.194***
	(.027)	(.027)	(.019)	(.019)	(.027)	(.027)
ROA	-.306*	-.275	-.192	-.22	-.299*	-.22
	(.163)	(.171)	(.162)	(.16)	(.165)	(.175)
_cons	-.075	-.302***	-.105	-.357***	-.05	-.141**
	(.066)	(.089)	(.068)	(.088)	(.053)	(.06)
Observations	4003	4003	4075	4075	4086	4086
R-squared	.675	.694	.655	.676	.674	.69
Learning from Stock Market	NO	YES	NO	YES	NO	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 4: Private information in CDS and the sensitivity of contingent liabilities to CDS spreads

Table 4 reports the linear regression results for (H2). The dependent variable is contingent liabilities for year t, and the main independent variable is *CDS x INFO* for year *t-1*. Column 1 shows the linear regression results with CDS private information variable (*INFO*) based on Fama-French 48 industries. Column 2 shows the same test results but with a *INFO* variable with different industry classifications (12 industries). Columns 3 uses *INFO* variable based on CDS bid-ask spreads.

	(1) Contin._Liab.	(2) Contin._Liab.	(3) Contin._Liab.
CDS $_{t-1}$	-1901.898***	-2027.065***	-1279.089***
	(494.109)	(503.01)	(220.043)
INFO $_{t-1}$ (nonsync + FF48)	-18695.263***		
	(4457.309)		
CDS $_{t-1}$ x INFO $_{t-1}$ (FF48)	1612.072**		
	(661.899)		
INFO $_{t-1}$ (nonsync + FF12)		-15418.383***	
		(4446.106)	
CDS $_{t-1}$ x INFO $_{t-1}$ (FF12)		1391.044**	
		(661.996)	
INFO $_{t-1}$(bid-ask)			-23050.619***
			(6478.936)
CDS $_{t-1}$ x INFO $_{t-1}$ (bid-ask)			2407.71**
			(1171.786)
Q $_{t-1}$	-3051.07***	-3023.862***	-1107.443***
	(581.513)	(588.629)	(210.003)
Q $_{t-1}$ x INFO $_{t-1}$	4064.792***		
	(797.745)		
Q $_{t-1}$ x INFO $_{t-1}$ (FF12)		3506.717***	
		(772.233)	
Q $_{t-1}$ x INFO $_{t-1}$ (bid-ask)			4908.957***
			(953.959)
Cumul. Return $_{t+3}$	-55.041	-59.032	54.679
	(163.863)	(180.996)	(162.496)
1/AT $_{t-1}$	266126.38	-1846899.1***	-292237.07
	(429763.02)	(403652.76)	(376640.57)
CF $_t$	157.607	302.555	46.343
	(1066.059)	(1136.266)	(1028.319)
Leverage	1213.901**	3311.799***	1210.438**
	(548.905)	(615.278)	(536.914)
Tangibility	-921.156***	-1485.401***	-1089.71***
	(270.805)	(290.456)	(297.443)
ROA	-3133.139**	-3656.943***	-3191.591***
	(1261.658)	(1391.886)	(1226.971)
_cons	17810.866***	15937.058***	7060.328***
	(3463.906)	(3534.81)	(1169.849)
Observations	4357	4435	4449
R-squared	.256	.091	.243
Learning from Stock Market	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1*

Table 5: Overconfident managers, private information in CDS, and the sensitivity of impairments and writedowns to CDS spreads

Table 5 reports the linear regression results for (H4). The dependent variable is the logarithm of impairments and writedowns for the years from *t* to *t+2*, and the main independent variable is the triple interaction term *OverCEO x CDS x INFO* for year t-1. Column 1 shows the linear regression results with CDS private information variable (*INFO*) based on Fama-French 48 industries. Column 2 shows the same test results but with a *INFO* variable with different industry classifications (12 industries). Columns 3 uses *INFO* variable based on CDS bid-ask spreads.

	(1)	(2)	(3)
	log(impair_3y)	log(impair_3y)	log(impair_3y)
CDS $_{t-1}$	.076	.174	-.232**
	(.198)	(.183)	(.099)
INFO $_{t-1}$ (nonsync + FF48)	-.79		
	(1.563)		
Overconfident CEO $_{t-1}$	1.121		
	(1.629)		
CDS $_{t-1}$ x INFO $_{t-1}$ (FF48)	-.221		
	(.276)		
OverCEO x CDS $_{t-1}$	-.366	-.149**	.05
	(.35)	(.073)	(.041)
OverCEO x INFO $_{t-1}$ (FF48)	-.265		
	(2.416)		
OverCEO x CDS x INFO $_{t-1}$ (FF48)	.303		
	(.537)		
INFO $_{t-1}$ (nonsync + FF12)		.245	
		(1.473)	
CDS $_{t-1}$ x INFO $_{t-1}$ (FF12)		-.364	
		(.257)	
OverCEO x INFO $_{t-1}$ (FF12)		1.398**	
		(.709)	
OverCEO x CDS x INFO $_{t-1}$ (FF12)		-.053	
		(.207)	
INFO $_{t-1}$(bid-ask)			-5.595
			(3.469)
CDS $_{t-1}$ x INFO $_{t-1}$ (bid-ask)			.044
			(.718)
OverCEO x INFO $_{t-1}$ (FF12)			8.43*
			(4.338)
OverCEO x CDS x INFO $_{t-1}$ (FF12)			-2.085*
			(1.201)
Q $_{t-1}$	-.074	.227	-.304*
	(.245)	(.236)	(.156)
Q $_{t-1}$ x INFO $_{t-1}$	-.042		
	(.322)		
Q $_{t-1}$ x INFO $_{t-1}$ (FF12)		-.29	
		(.304)	
Q $_{t-1}$ x INFO $_{t-1}$ (bid-ask)			1.251*
			(.681)
Cumul. Return $_{t+3}$	-.364***	-.389***	-.396***
	(.101)	(.097)	(.103)
1/AT $_{t-1}$	-6123.634***	-6231.006***	-5562.928***
	(674.904)	(608.442)	(684.816)
CF $_t$	-.477	.137	-.731
	(1.502)	(1.247)	(1.471)
Leverage	-.034	-.254	.031
	(.3)	(.273)	(.3)
Tangibility	.086	.255	.074
	(.467)	(.368)	(.489)

ROA	-5.726***	-6.751***	-5.659***
	(1.474)	(1.299)	(1.454)
_cons	5.362***	5.158***	6.629***
	(1.06)	(.986)	(.602)
Observations	1941	1987	1993
R-squared	.277	.229	.274
Learning from Stock Market	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 6: Analyst following, private information in CDS, and the sensitivity of leverage to CDS spreads

Table 6 reports the linear regression results for (H5). The dependent variable is the leverage for the year from *t*, and the main independent variable is the triple interaction term *CDS x INFO x NUMEST* for year *t-1* where *NUMEST* represents the number of analysts following. Column 1 shows the linear regression results with CDS private information variable (*INFO*) based on Fama-French 48 industries. Column 2 shows the same test results but with a *INFO* variable with different industry classifications (12 industries). Columns 3 uses *INFO* variable based on CDS bid-ask spreads.

	(1) Leverage $_{t}$	(2) Leverage $_{t}$	(3) Leverage $_{t}$
Leverage $_{t-1}$	.612***	.665***	.61***
	(.04)	(.035)	(.039)
CDS $_{t-1}$	.044	.053*	.015
	(.029)	(.031)	(.012)
INFO $_{t-1}$ (nonsync + FF48)	.254		
	(.186)		
NUMEST $_{t-1}$	-.001	-.002	0
	(.007)	(.007)	(.003)
CDS $_{t-1}$ x INFO $_{t-1}$ (FF48)	-.03		
	(.04)		
CDSxNUMEST $_{t-1}$	.001	.001	0
	(.001)	(.002)	(.001)
INFOxNUMEST $_{t-1}$	.005		
	(.009)		
CDSxINFOxNUMEST $_{t-1}$	-.002		
	(.002)		
INFO $_{t-1}$ (nonsync + FF12)		.385**	
		(.19)	
CDS $_{t-1}$ x INFO $_{t-1}$ (FF12)		-.059	
		(.04)	
INFO $_{t-1}$ (FF12) x NUMEST $_{t-1}$		.003	
		(.01)	
CDSxINFOxNUMEST $_{t-1}$ (FF12)		-.001	
		(.002)	
INFO $_{t-1}$(bid-ask)			-.036
			(.299)
CDS $_{t-1}$ x INFO $_{t-1}$ (bid-ask)			.03
			(.076)
INFO $_{t-1}$ (bid-ask) x NUMEST $_{t-}$			.024
			(.015)
CDSxINFOxNUMEST $_{t-1}$ (bid-ask)			-.008**
			(.004)
Q $_{t-1}$	.101***	.114***	.047***
	(.025)	(.025)	(.014)
Q $_{t-1}$ x INFO $_{t-1}$	-.083***		
	(.028)		
Q $_{t-1}$ x INFO $_{t-1}$ (FF12)		-.094***	
		(.029)	
Q $_{t-1}$ x INFO $_{t-1}$ (bid-ask)			-.034
			(.044)
DISP $_{t-1}$	.001	.006	0
	(.005)	(.005)	(.005)
DISP_LT $_{t-1}$	-.006	-.008*	-.006
	(.004)	(.004)	(.004)
Cumul. Return $_{t+3}$	-.016***	-.011**	-.016***
	(.005)	(.005)	(.006)
1/AT $_{t-1}$	175.187***	188.523***	197.11***
	(42.585)	(37.631)	(43.177)

CF_t	.165	.098	.148
	(.172)	(.152)	(.173)
Tangibility	.237***	.173***	.248***
	(.036)	(.025)	(.036)
ROA	-.426**	-.377**	-.407**
	(.199)	(.186)	(.2)
_cons	-.322**	-.377**	-.131
	(.15)	(.161)	(.084)
Observations	2828	2884	2891
R-squared	.685	.662	.682
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 7: EPS dispersion, private information in CDS, and the sensitivity of leverage to CDS spreads

Table 7 reports the linear regression results for (H5). The dependent variable is the leverage for the year from *t*, and the main independent variable is the triple interaction term *CDS x INFO x DISP* for year t-1 where *DISP* represents the EPS dispersion among the analysts. Column 1 shows the linear regression results with CDS private information variable (*INFO*) based on Fama-French 48 industries. Column 2 shows the same test results but with a *INFO* variable with different industry classifications (12 industries). Columns 3 uses *INFO* variable based on CDS bid-ask spreads.

	(1) Leverage $_{t}$	(2) Leverage $_{t}$	(3) Leverage $_{t}$
Leverage $_{t-1}$	.613***	.666***	.609***
	(.04)	(.035)	(.039)
CDS $_{t-1}$	.047***	.058***	.017**
	(.013)	(.014)	(.007)
INFO $_{t-1}$ (nonsync + FF48)	.313***		
	(.102)		
DISP $_{t-1}$	-.032	.157	-.154***
	(.119)	(.173)	(.057)
CDS $_{t-1}$ x INFO $_{t-1\ (FF48)}$	-.05***		
	(.017)		
CDS $_{t-1}$ x DISP $_{t-1}$	.011	-.015	.03***
	(.022)	(.031)	(.01)
INFO $_{t-1\ (FF48)}$ x DISP $_{t-1}$	-.097		
	(.168)		
CDS x INFO $_{t-1\ (FF48)}$ x DISP $_{t-1}$	.009		
	(.031)		
INFO $_{t-1}$ (nonsync + FF12)		.409***	
		(.105)	
CDS $_{t-1}$ x INFO $_{t-1\ (FF12)}$		-.067***	
		(.018)	
INFO $_{t-1\ (FF12)}$ x DISP $_{t-1}$		-.31	
		(.234)	
CDS x INFO $_{t-1\ (FF12)}$ x DISP $_{t-1}$		.038	
		(.042)	
INFO $_{t-1(bid-ask)}$			.279
			(.185)
CDS $_{t-1}$ x INFO $_{t-1\ (bid-ask)}$			-.084**
			(.037)
INFO $_{t-1\ (bid-ask)}$ x DISP $_{t-1}$			1.398**
			(.679)
CDS x INFO $_{t-1\ (bid-ask)}$ x DISP $_{t-1}$			-.299**
			(.146)
Q $_{t-1}$	.1***	.115***	.047***
	(.024)	(.024)	(.014)
Q $_{t-1}$ x INFO $_{t-1}$	-.082***		
	(.027)		
Q $_{t-1}$ x INFO $_{t-1\ (FF12)}$		-.096***	
		(.028)	
Q $_{t-1}$ x INFO $_{t-1\ (bid-ask)}$			-.038
			(.042)
DISP_LT $_{t-1}$	-.006	-.008**	-.005
	(.004)	(.004)	(.004)
NUMEST $_{t-1}$	0	0	0
	(0)	(0)	(0)
Cumul. Return $_{t+3}$	-.016***	-.011**	-.017***
	(.006)	(.006)	(.006)
1/AT $_{t-1}$	180.944***	185.977***	199.839***
	(42.239)	(37.203)	(43.078)
CF $_{t}$	.158	.101	.121

	(.171)	(.152)	(.173)
Tangibility	.238***	.177***	.245***
	(.036)	(.025)	(.036)
ROA	-.422**	-.378**	-.381*
	(.2)	(.186)	(.202)
_cons	-.32***	-.387***	-.124
	(.103)	(.108)	(.077)
Observations	2828	2884	2891
R-squared	.686	.663	.682
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

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CHAPTER 2

Investor Disagreement and Learning from Stock Prices

1. Introduction

This paper investigates how investor disagreement, or the divergence of opinion among investors, influences managers' ability to learn from stock prices. The feedback effect literature has expanded quickly over the last decade, and many prior studies have shown how managerial learning from market prices could be influenced under various conditions (Luo 2005; Chen, Goldstein & Jiang 2007; Kau, Linck & Rubin 2008; Foucault and Fresard 2014; Zuo 2016; Jayaraman and Wu 2019). While the existing literature studied how the changes in stock prices can influence managers' actions, many overlook the possibility that even the same level of price changes could be interpreted differently by managers depending on how investors reached that price.

I study whether and how investor disagreement influences managerial learning from prices. The key economic tensions that drive the relationship between investor disagreement and learning from stock prices are twofold. First, it could be positive for the learning channel because more signals will be contained in the price. Investor disagreement implies that the price reflects many different opinions, and this can potentially help the manager learn more information from prices. Given that managers can still learn from market prices as long as there is at least *some* information they do not have, this diversity of information contained in the price can be potentially positive for the manager.

On the other hand, a high level of investor disagreement in the stock market could potentially lower managers' ability to learn from stock prices because it can confuse managers with different signals. As we saw from the scenario above, whether managers learn something from stock prices or not heavily depends on how they interpret the signals from prices. Even if there are a lot of signals contained in the price, managers could find it difficult to interpret in a useful form.

Overall, I find results consistent with the latter explanation. Using the average change in daily market-adjusted turnover as a measure of investor disagreement, I find that investment-q sensitivity, a measure of managerial learning from stock prices, deteriorates with a higher level of investor disagreement. This result is robust with a falsification test with a non-price measure of investment opportunities (as in Jayaraman and Wu 2019) and an alternative measure of disagreement (Garfinkel 2009).

In addition, I test cross-sectionally whether the probability of informed trading (PIN), the number of analysts following, and the underlying stock's short interest affect the relationship between investor disagreement and learning from stock prices. I find that managerial learning is enhanced when PIN is higher, more analysts follow the stock, and there is a higher level of short interest.

Finally, I use the Reg SHO pilot program as a natural experiment for a change in the stock market price efficiency.[4] The Reg SHO pilot program, where one-third of the Russell 3000 firms were randomly chosen to be exempt from short-sale price tests from 2005 to 2007, provides an excellent environment for a differences-in-differences (DiD) test. During this period, the selected firms for the pilot program are exposed to an environment where disagreements among investors can be easily converted to shorting. Using this DiD test, I find

[4] This is related to what the feedback literature refers to as forecasting price efficiency (FPE) and revelatory price efficiency (RPE). While FPE will increase in this case, RPE can have effects in either direction (improved or lowered), depending on how two forces (what the manager knows and what the manager wants to learn from the market) interact.

that investment-q sensitivity improves for the treated firms because, given the same level of disagreement, the prices better reflect the downside opinions. In other words, managers can learn easily from stock prices because of improved “downside” messages from prices.

To better illustrate the disagreement dynamics described above, consider a hypothetical CEO learning from stock markets about a new investment project. While the CEO is reasonably confident about the potential benefits of the investment plan, she knows that investors may have contradictory information. In the late afternoon, after trading hours, the company announces the new investment plan with ambitious strategic initiatives, and the stock price fluctuates wildly during after-hours. The fluctuation continues through the following day. At the end of the trading hours, the stock price goes up slightly, but there were many ups and downs and a large trading volume.

What can, if anything, the manager learn from prices? One might say that the manager didn’t learn anything because the closing stock price didn’t move much. Another can say that an increase in the stock price reaffirmed the potential value of the new investment plan. As we can see from this scenario, the manager might or might not learn something from price movements since there were a lot of mixed signals, not just expressed via closing prices but via “movements” in the prices.

Consider an alternative scenario where the market reaction was uniformly positive. After the announcement, the stock price spikes up during after-hours trading. The following morning, the stock price begins with a big jump and closes at a similar price point where it was at the beginning of the day. In this scenario, the manager has received unambiguously positive feedback from the stock markets because the market’s voice was clear and uniform.

As you can see from these imaginary scenarios, what matters in the process of managerial learning from prices is not just the closing price or the price point itself. Another dimension influencing managerial learning is *how* they reached that price. Was it uniformly positive or negative? Were there a lot of ups and downs with massive trading volume? A positive (negative) change in the stock price with wildly different opinions or with a uniformly positive (negative) reaction are two very different things.

This paper contributes to the existing literature in two ways. First, it contributes to the literature on the feedback effect. The feedback effect literature has explored various dimensions of managerial learning from market prices. However, as we saw from the scenario above, it has overlooked how the market reached that price. I showed that when the market seems to be confusing, regardless of whether the price goes up or down, managers may learn less from the market.

Secondly, it contributes to the literature on investor disagreement. Many papers in accounting and finance have studied the origin of investor disagreement and how they impact market efficiency, trades, the cost of capital, etc. This paper specifically looks at how investor disagreement may affect managers' environment for learning from prices. By studying the tradeoffs between more signals vs. clarity of learning content in prices, this paper can contribute to the understanding of the role of investor disagreement in managerial learning.

The rest of the paper is structured as follows. First, the background section covers related existing literature on feedback and disagreement and how they relate to this study. Next, I introduce hypotheses and empirical strategy as well as the description of data and the sample selection process. Finally, I provide interpretations of the test results and conclude the article.

2. Background

In this section, I review relevant literature on the feedback effect, disagreement, and trading volume. Then, I develop hypotheses with two conflicting forces in managerial learning.

2.1 The feedback effect

The notion that market prices contain important information for market participants goes back to Hayek (1945). However, some of the seminal works in the feedback literature came out in the 2000s. The feedback literature argues that the market is not one-directional from managers to investors; rather, it is a two-way process where not only do managers influence market prices but also learn from market prices (Bond, Edmans, and Goldstein 2012; Goldstein 2022). As long as the market has at least *some* information that managers do not have, managers can potentially learn from market prices.

For example, Luo (2005) shows that managers drop or continue their M&A plans depending on the market reaction. Similarly, Chen, Goldstein & Jiang (2007), using the probability of informed trading (PIN) and price nonsynchronicity as private information measures, shows that investment-q sensitivity depends on the level of private information in the market. Also, Foucault and Fresard (2014) shows that managers not only learn from their own stock prices but also from peers' stock prices.

In accounting, there are several studies that look into the role of managers and disclosures in managerial learning from prices. For example, Zuo (2016) studies how private information in the stock market is related to managerial forecast revisions and forecast accuracy. Related to disclosures, Jayaraman and Wu (2019) look at how mandatory disclosure can influence managerial learning from prices. By comparing the costs and benefits of mandatory disclosures, they showed that mandatory disclosures' benefits (improved forecasting price efficiency, or FPE) could be overshadowed by lower revelatory price efficiency (RPE).

2.2 Investor disagreement

One of the key roles of prices is that they aggregate information in the market. If prices summarize market participants' information, can they also perfectly convey this information to the users of prices? This is not entirely true and is an incomplete picture. Price disaggregation can be very different from price aggregation. If market participants want to learn something from the prices, not only do they need to think about the likelihood of the price given the information, but they also need to have priors on information. If priors differ significantly among the market participants, so do what they learn from the prices.

Similarly, we can think about why market participants trade. If I am willing to buy something at $100 and someone else is happy to sell it at $100, is one of us foolish? Should I be concerned that the other person is trying to rip me off? In a seminal paper by Milgrom and Stokey (1982), the "no-trade theorem" states that if risk-averse traders begin at a Pareto-optimal allocation, then the arrival of new private information itself does not generate trades. Thus, if we observe a substantial trading volume after an informational event, then it must be the case that at least one of their assumptions in the model is violated, i.e., either (a) traders did not have concordant beliefs, (b) they did not begin at a Pareto-optimal allocation, or (c) they have a non-speculative motivation to trade. One of the key reasons for the breakdown of the concordant beliefs assumption is that traders have different priors, which lead them to "agree-to-disagree" (Aumann 1976).

Prior studies in accounting and finance have studied how disagreement would influence capital markets. There are generally two directions that researchers have studied related to disagreement: investor-management disagreement and among-investor disagreement. Since this article exclusively focuses on among-investor disagreement, I only review relevant articles in this area.

Prior studies find that investor disagreement affects firms and financial markets in important ways. For example, Bloomfield and Fischer (2011) argue that the cost of capital depends on how investors perceive other investors interpret information. Also, Mashruwala and Mashruwala (2014) find that investor disagreement and short-selling constraints are related to making stock prices more sensitive to bad earnings news (torpedo effect). Chang, Hsiao, Ljungqvist, and Tseng (2022) use the staggered implementation of EDGAR as a setting and show that it led to lower investor disagreement.

Also, some studies focus on earnings properties and disagreement. Barth, Landsman, Raval, and Wang (2020) study the relationship between asymmetric timeliness of earnings and investor disagreement and showed that a higher level of asymmetric timeliness of earnings is associated with a slower resolution of investor disagreement. Relatedly, Golex and Goyenko (2022) find that higher disagreement is associated with low (high) stock returns after positive (negative) earnings surprises.

Also, there are several studies showing the relationships between disagreement and stock returns. Lu, Wang, and Wang (2014) use the notion that price shocks as a spike in investor disagreement and show that the disagreement and negative abnormal returns take time to resolve. Doukas, Kim, and Pantzalis (2004) show that value stocks are more likely to be subject to greater investor disagreement than growth stocks.

2.3 Investor disagreement and trading volume

Prior studies on investor disagreement also often discuss the relationship between disagreement and trading volume.

On the theoretical side, Banerjee and Kremer (2010) develope a dynamic model that connects investor disagreement and trading volume and show that high disagreement periods are associated with high trading volume. Similarly, Banerjee (2011) also show that investor disagreement is positively related to expected returns, return volatility, and market beta.

On the empirical side, Bamber, Barron, and Stober (1997) find that trading volume around earnings announcements and disagreement (with three different aspects) are positively associated. Similarly, Atmaz and Basak (2018) show that higher disagreement (which they refer to as belief dispersion) leads to higher trading volume and stock volatility. Carlin, Longstaff, and Matoba (2014) use a novel dataset to study this relationship. Using disagreement among mortgage dealers on prepayment speed, they find that higher disagreement is associated with higher expected returns, return volatility, and trading volume. Finally, Booker, Curtis, and Richardson (2022) also find that disagreement and trading volume are positively related using social media-based measures.

Overall, evidence from the vast majority of the prior literature suggests the claim that there is a positive relationship between investor disagreement and trading volume. Thus, in this study, I exclusively focus on trading volume-based measures as the primary measures of investor disagreement.

2.4 Hypothesis development

In the feedback literature, many prior studies use two price efficiency concepts to describe managerial learning from prices: forecasting price efficiency (FPE) and revelatory price efficiency (RPE). FPE refers to the notion of how well market prices reflect future cash flows and capture total information in prices (Jayaraman and Wu 2019). In contrast, RPE is about how well prices reveal new information to the manager. Their tradeoffs and complementarities play a key role in explaining observations in feedback effect studies.

The key question that this article attempts to answer is whether and how investor disagreement affects managerial learning from prices. On the one hand, higher disagreement may enhance managerial learning by providing additional signals contained in the stock price. In the feedback literature jargon, this can be described as a higher FPE.

On the other hand, higher disagreement may lower managers' ability to glean information from stock prices because more signals could confuse managers. In other words, it could lead to a lower RPE by reducing the precision of information that managers could glean from the price. Thus, the main hypothesis of this study is the following:

(Null hypothesis) Higher disagreement is not associated with investment-q sensitivity

(Alternative hypothesis 1) Higher disagreement is associated with higher investment-q sensitivity (enhance managerial learning)

(Alternative hypothesis 2) Higher disagreement is associated with lower investment sensitivity (lower managerial learning)

3. Research Design and Data

3.1 Measures of disagreement

In empirical accounting and finance literature, there have been more than a dozen measures of investor disagreement (Glushkov 2010). For example, analyst forecast dispersion (Abarbanell, Lanen, and Verrecchia 1995), modified analyst-based opinion divergence measures (Moeller, Schlingemann, and Stulz 2007), volume-based measures (Garfinkel and

Sokobin 2006; Garfinkel 2009), bid-ask spread (Handa, Schwartz, and Tiwari 2003), open interest (Bessembinder, Chan, and Seguin 1996), and dispersion of order flow across market makers (Anderson and Dyl 2007) were used to measure investor disagreement.

In this study, I use unexplained volume (change in turnover) as the primary measure of investor disagreement. There are several reasons why I chose unexplained volume (change in turnover) as the primary measure of investor disagreement.

First, almost all prior literature, both theoretical and empirical, points to the relationship between trading volume and disagreement. Second, Garfinkel (2009) directly compares the efficiency of investor disagreement measures and finds that "unexplained volume is the best proxy for opinion divergence." He also finds that between two measures of unexplained volume, change in turnover performs better than standardized unexplained volume. Following this finding, I use change in turnover as the primary measure of disagreement.

In this study, I do not use another commonly used measure of disagreement—analysts' forecast dispersion. The primary reason is that I have a better measure available for this study (volume-based measures). Garfinkel (2009) points out that volume measures almost always perform better than analysts' forecast dispersion. Similarly, Golez and Goyenko (2022) mention that "several papers point out that this measure is a noisy proxy for disagreement, because it is agnostic about whether investors differ in their prior beliefs and how investors process information."

To calculate unexplained volume (change in turnover), I closely follow Garfinkel and Sokobin (2006), Garfinkel (2009), and Glushkov (2010). A firm's daily turnover is calculated as the firm's daily volume divided by shares outstanding. After calculating the same turnover for the market, the difference between the two is daily market-adjusted turnover ($MATO_{i,t}$) for firm i on day t. Since this method can double-count volume for NASDAQ stocks, I follow the rule of thumb suggested by Anderson and Dyl (2005), i.e., scaling down NASDAQ stocks' volume by 38% after 1997 and 50% before 1997. As a result, we can make the volume comparable to that of NYSE stocks. Finally, the market-adjusted turnover is de-trended by 180 trading day median (Glushkov 2010).

3.2 Research design

I use the following linear regression model similar to Foucault and Frésard (2012) and Jayaraman and Wu (2019) to examine the impact of disagreement on managerial learning from prices:

$$Investment_{i,t+1} = \alpha_i + \eta_t + \beta_1 Q_{i,t} + \beta_2 DTO_{i,t} + \beta_3 CF_{i,t}$$

$$+\beta_4 DTO_{i,t} * Q_{i,t} + \beta_5 DTO_{i,t} * CF_{i,t} + \beta_6 CONTROLS_{i,t} + \epsilon_{i,t} \qquad (1)$$

The main coefficient of interest is β_4 which represents the investment-q sensitivity. If managerial learning is positive (negative), I expect the sign to be positive (negative). The measure of investment is the sum of a firm i's CAPEX and R&D. $Q_{i,t}$ represents Tobin's q, which is the market value of assets divided by the book value of assets. As a non-price-based measure of a firm's opportunity set, I included both cash flows $CF_{i,t}$ and $DTO_{i,t} * CF_{i,t}$. Since managerial learning from prices predicts that managers learn from price-based measures, I expect the coefficients of $CF_{i,t}$ and $DTO_{i,t} * CF_{i,t}$ to be both insignificant (i.e., cannot reject the null hypothesis of having no effect).

As control variables, I include the following. First, the inverse of total assets

($INV\_AT_{i,t}$) was included to control for spurious correlation since many variables are divided by total assets. $SIZE_{i,t}$ denotes the control for firm size. Besides these variables, descriptions of all variables are available in Appendix A.

3.3 Data, sample construction, and summary statistics

I use firm fundamentals from Compustat, stock market data from CRSP, Reg SHO pilot data from SEC, [5] and the probability of informed trading (PIN) data from Brown, Hillegeist, and Lo (2004). The main sample includes 12,800 firm-year observations from 1993 to 2010. I exclude financial and utility firms (SIC 4000-4999 and 6000-6999) since they are less generalizable than the rest. All tests include industry- and year-fixed effects. For the industry fixed effects, I use Fama-French 48 industry classification. However, for the last section of the paper on the Reg SHO pilot sample, I use Fama-French 12 industry classification due to the relatively smaller sample size. Also, for all regressions, I cluster at the Fama-French 48 industry level (12 for the Reg SHO pilot sample).

I report descriptive statistics for the main sample in Table 1. The average number of analysts following for the sample firm is about five analysts per firm. The probability of informed trading for the sample is 0.191. The median trading volume in a 252-period rolling window is 140,276.27. The average return on assets (ROA) for the sample firms is 2%.

In Table 2, I report the matrix of correlations for variables in the sample. As we expect, investments in the following year and Tobin's Q seem to have a strong positive relationship. Also, an alternative measure of disagreement, the standardized unexplained volume (SUV),

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[5] Regulation SHO — Pilot Program: https://www.sec.gov/spotlight/shopilot.htm

seems to be positively correlated with the primary measure (DTO).

4. Empirical Analysis

4.1 Main hypothesis

Table 3 reports the linear regression results for the main hypothesis. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is *Q x DTO* for year t where *DTO* is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover) and *Q* is the price-based measure of a firm's investment opportunity set. Column 1 shows the baseline linear regression results without investor disagreement. Column 2 adds investor disagreement. Both specifications include industry- and year-fixed effects.

As we can see from Table 3, the primary relationship between Tobin's Q and investment holds strongly from the positive coefficient on *Q*, as shown in the prior literature (Chen, Goldstein, and Jiang 2007). A negative coefficient on *Q x DTO* implies that investment-q sensitivity drops for firms with high investment disagreement. This result supports the second alternative hypothesis, i.e., higher disagreement is associated with lower investment sensitivity (lower managerial learning).

Finally, the coefficient on CFxDTO is not significant, which implies that the disagreement primarily affects managerial learning from prices, as opposed to the internal learning channel (cash flows).

4.2 Alternative measure – standardized unexplained volume

Table 4 reports the linear regression results with an alternative measure of investor disagreement. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is *QxSUV* for year t, where *SUV* is an alternative measure of investor disagreement (standardized unexplained volume) and *Q* is the price-based measure of a firm's investment opportunity set. Column 1 uses an alternative investor disagreement measure (*SUV*). Column 2 shows the result for the primary measure of disagreement (*DTO*). Both specifications include industry- and year-fixed effects. Both specifications control for the non-price-based measure of a firm's investment opportunity set.

The coefficient on *QxSUV* is also negative and seems to exhibit the same property as the one on *QxDTO*. In both cases, the relationship between Tobin's Q and investments is strong. Also, the coefficients on *CFxSUV* and *CFxDTO* imply that the learning channel is not driven by the effects of cash flows. Overall, the result seems to suggest that both measures seem adequate to gauge the level of investor disagreement in studying managerial learning from stock prices, while the primary measure (*DTO*) was recommended by a prior study as the cleanest measure (Garfinkel 2009).

4.3 Cross-sectional tests

In addition to the main test, I include cross-sectional tests with the probability of informed trading (PIN), the number of analysts following, and the underlying stock's short interest. While the previous tests showed that investor disagreement seems to lower managerial learning from stock prices, these tests add evidence that it is much more nuanced. Specifically, the cross-sectional tests show that the information environment with informed traders can make this lowered managerial learning effect much less apparent.

Table 5 reports the linear regression results with the effects of the probability of informed trading. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is *QxDTO* for year t where *DTO* is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover) and Q is the price-based measure of a firm's investment opportunity set. Controls include *CF, INFO, QxINFO, CFxINFO, INV_AT, SIZE, SUV, CFxSUV, CFxINFOxSUV, DTO, CFxDTO,* and *CFxINFOxDTO*. Column 1 uses an alternative investor disagreement measure (*SUV*). Column 2 shows the result for the primary measure of disagreement (*DTO*). Both specifications include industry- and year-fixed effects. Both specifications control for the non-price-based measure of a firm's investment opportunity set.

As we can see from this example, both specifications show that a higher level of PIN is associated with a higher level of investment-q sensitivity. This finding is consistent with the idea that a higher level of private information contained in price improves managerial learning from stock prices (Chen, Goldstein, and Jiang 2007). Thus, even under a higher level of disagreement, private information contained in price still seems to be positive in improving managerial learning.

Table 6 reports the linear regression results with the effects of the number of analysts following. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is QxDTO for year t where DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover) and Q is the price-based measure of a firm's investment opportunity set. Controls include QxNum.Analyst, CF_t, CFxNum.Analyst, Num.Analyst, INV_AT_t_1, SIZE_t, DTO_t, DTOxNum.Analyst, CFxDTO, CFxDTOxNum.Analyst. The test includes industry- and year-fixed effects as well as a non-price-based measure of a firm's investment opportunity set.

Similar to Table 5, as the number of analysts following increases, the investment-q sensitivity increases. The idea is similar to that of private information; we can interpret that a higher number of analysts following can make the price more informative, which in turn improves the learning channel.

Table 7 reports the linear regression results with the effects of the underlying stock's short interest. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is QxDTO for year t where DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover) and Q is the price-based measure of a firm's investment opportunity set. Controls include CF_t, CFxlog_short, log_short, INV_AT_t_1, SIZE_t, DTO_t, and DTOxlog_short. The test includes industry- and year-fixed effects as well as a non-price-based measure of a firm's investment opportunity set.

As a measure of short interest, I use log(short interest) to account for a relatively large size. A positive triple interaction term suggests a positive relationship between the level of short interest and investment-q sensitivity. The level of short interest seems to be related to the idea of private information as well; if someone observes an unusually high level of short interest, one can potentially imagine that there is someone or a group of investors with private information trading this stock. When we think about the relationship between forecasting price efficiency (FPE) and revelatory price efficiency (RPE), a higher level of short interest seems to improve FPE, and this improved FPE seems to have a positive relationship with RPE.

Overall, all three cross-sectional tests seem to suggest that factors related to private information would improve the learning channel despite a higher level of investor disagreement would lower learning efficiency.

4.4 Reg SHO Pilot program

On June 23, 2004, the SEC adopted Regulation SHO (hereafter Reg SHO) governing rules regarding short sales in the stock market. Rule 202T of Reg SHO enabled them to create a pilot program to evaluate "the overall effectiveness of price test restrictions on short sales." For the pilot program, one-third of the Russell 3000 firms were randomly chosen and were exempt from short-sale price tests from 2005 to 2007.

Due to the setting that the firms were randomly selected and that they were in an artificially different environment in the easiness of short sales, it provides an ideal environment for a differences-in-differences (DiD) test. Specifically, this environment provides a setting where disagreements among investors can be easily converted to shorting.

I follow the DiD setting with Reg SHO pilot program similar to Diether, Lee, and Werner (2009) and Fang, Huang, and Karpoff (2016). First, I match the main data with the Reg SHO pilot program firms. Unlike a typical DiD setting, the Reg SHO pilot setting has three time segments—pre, during, and post—because the short sale restriction came back after the pilot program period. In this study, I used fiscal years falling between 2001 and 2003 as the pre-period, 2005 and 2007 as the during-period, and 2008-2009 as the post-period. Following prior literature, 2004 was not included since it was not clear whether it fell within the pilot program period or not.

I expect that the treated firms will have a higher FPE because the easier shorting environment could lower information asymmetry (Fang, Huang, and Karpoff 2016). However, RPE can be either higher or lower depending on how "what the manager knows" and "what the manager wants to learn" interact. As discussed by Gao and Liang (2013) and Goldstein and Yang (2017), the relationship between these two can be complementary or substitutes. Thus, whether the pilot program improves the learning channel or not with higher disagreement also depends on how these two forces interact.

Table 8 reports regressions results with a differences-in-differences setting using Reg SHO pilot program. For Panel A, the dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is duringxQxDTO for year t where during equals one during the pilot period, DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover), and Q is the price-based measure of a firm's investment opportunity set. Controls for Panel A include CF, INV_AT, SIZE, shortint, during, duringxQ, duringxCF, duringxINV_AT, duringxSIZE, duringxshortint, DTO, and duringxDTO. The test includes industry- and year-fixed effects as well as a non-price-based measure of a firm's investment opportunity set. For Panel B, the dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is regshoxduringxQxDTO for year t where regsho and during are dummy variables, DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover), and Q is the price-based measure of a firm's investment opportunity set.

Panel A tests whether the pilot program brings any changes in the managerial learning channel efficiency. The positive coefficient of *duringxQxDTO* implies that the learning channel was improved for the manager despite an easy-to-disagree environment. Thus, we can interpret the result as a complementary relationship between FPE and RPE.

Based on the results in Panel A, Panel B tests whether the improved efficiency comes from the treated firms (pilot firms) or non-pilot firms. From the positive coefficient on *regshoxduringxQxDTO*, we can find evidence supporting the idea that the treated firms that were exposed to fewer restrictions on short sales have experienced improved learning channel. Thus, despite the negative connotations that come with short selling, it seems to bring positive effects on the efficiency of learning from market prices.

5. Summary and Conclusions

The paper explores whether and how the divergence of opinions among investors affects managerial learning from prices. There are two economic forces that can affect this learning channel. On the one hand, higher disagreement can bring a positive effect on the learning channel by providing more diverse signals to the price. On the other hand, it can inhibit the learning channel by confusing managers with different signals. This paper finds evidence that the latter force is more dominant than the former. This result is robust whether we use a different measure or consider a non-price-based investment opportunity set.

While higher disagreement in general lowers the learning efficiency, more private information in the stock price, more analysts following, and higher short interest seems to mitigate this effect. Finally, evidence from Reg SHO pilot program also suggests that a lower learning efficiency caused by higher disagreement can be mitigated by a higher FPE environment.

Overall, considering the main result as well as results from cross-sectional tests and the natural experiment, FPE and RPE seem to be in a complementary relationship when investor disagreement and managerial learning from prices comingle. In other words, an improvement in FPE seems to be positive in improving RPE with respect to investor disagreement and managerial learning.

6. Appendix A. Variable definitions

Variable Name	Definitions (shortened expressions denote variable names from Compustat and CRSP)
$INV_{i,\,t+1}$	CAPEX + R&D $_{i,\,t+1}$ / total assets
$Q_{i,\,t}$	(Market value of equity + book value of debt) / book value of assets = [(CSHO * PRCC_F) + (AT – CEQ)] / AT
$CF_{i,\,t}$	(IB + DP) / AT
$SIZE_{i,\,t}$	Log (market value of equity) = log (CSHO * PRCC_F)
$ILLIQ_{i,\,t}$	Amihud (2002) illiquidity measure. Log (stock illiquidity) = log (average of daily unsigned return/dollar trading volume * 10^6)
$INFO_{i,\,t}$	Probability of informed trading from Brown et al. (2004)
$DTO_{i,\,t}$	Following Garfinkel and Sokobin (2006), Garfinkel (2009), and Glushkov (2010), a firm's daily turnover is calculated as the firm's daily volume divided by shares outstanding. After calculating the same turnover for the market, the difference between the two is daily market-adjusted turnover MATO for firm i on day t. Since this method can double-count volume for NASDAQ stocks, I follow the rule of thumb suggested by Anderson and Dyl (2005), i.e., scaling down NASDAQ stocks' volume by 38% after 1997 and 50% before 1997. As a result, we can make the volume comparable to that of NYSE stocks. Finally, the market-adjusted turnover is de-trended by 180 trading day median. The measure is summarized with a 252-day rolling window.
$SUV_{i,\,t}$	Following Garfinkel and Sokobin (2006), Garfinkel (2009), and Glushkov (2010), SUV is calculated as a standardized prediction error from a regression of trading volume on absolute-value return. $E[volume] = \alpha + \beta * \lvert R\rvert^{+} + \gamma * \lvert R\rvert^{-}$ $UV = volume - E[volume]$ $SUV = UV/S$ The measure is summarized with a 252-day rolling window.
$RET_{i,\,t}$	Following Glushkov (2010), I use the same estimation period as the unexplained volume. The stock return is calculated with a 252-day rolling window.
$Volatility_{i,\,t}$	Following Glushkov (2010), I use the same estimation period as the unexplained volume. The stock return volatility is calculated with a 252-day rolling window.
$Bid\text{-}Ask_{i,\,t}$	I used the bid-ask spread available in CRSP data also with a 252-day rolling window.
$ROA_{i,\,t}$	IB / [(PRCC_F * CSHO) + (AT - CEQ))
$VOL_{i,\,t}$	Trading volume obtained from CRSP
Num. of Analysts $_{i,\,t}$	Retrieved from IBES
$INV\_AT_{i,\,t}$	The inverse of total assets
$log\_short_{i,\,t}$	The log of short interest obtained from Compustat

during $_{i,t}$	Equals to one during 2005-2007
post $_{i,t}$	Equals to one during 2008-2009 (no further years due to the sample period limitation)
regsho $_{i,t}$	Equals to one if a firm is selected as a pilot firm

Table 1: Descriptive Statistics

	N	Mean	Std. Dev.	min	p25	Median	p75	max	skewness	kurtosis
INV t+1	12800	.118	.297	-.124	.045	.076	.127	22.91	43.884	2974.629
Q t	12795	2.144	2.587	.224	1.184	1.546	2.228	86.256	12.425	266.937
CF t	11235	.043	.602	-37.346	.046	.094	.141	2.85	-36.959	1892.62
DTO t	12800	0	.005	-.016	-.002	-.001	.001	.071	2.855	25.875
SUV t	12800	.148	.961	-1.09	.036	.11	.198	91.615	79.069	7014.668
Volatility t	12800	.03	.018	.004	.018	.025	.036	.471	3.551	43.028
Bid Ask t	12800	.022	.026	0	.005	.015	.029	.253	2.397	10.377
INFO t	12800	.191	.102	0	.116	.169	.246	.97	1.151	4.848
ROA t	12785	.002	.111	-3.363	.003	.029	.042	.745	-9.056	168.701
VOL t	12800	770112.21	2760120.4	89.03	27853.359	140276.27	549019.03	1.279e+08	16.356	496.687
RET t	12800	.001	.004	-.024	0	.001	.001	.413	63.008	5771.785
Num. of Analysts t	10963	5.066	4.904	0	1.243	3.596	7.274	34.522	1.38	4.816
ILLIQ t	12800	-1.446	2.545	-8.48	-3.38	-1.72	.447	5.32	.2	2.307
SIZE t	12795	6.371	2.244	-.276	4.703	6.538	7.908	13.139	-.025	2.602

Table 2: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) INV $_{t+1}$	1.000													
(2) Q $_t$	0.546	1.000												
(3) CF $_t$	-0.325	-0.223	1.000											
(4) DTO $_t$	0.036	0.033	0.049	1.000										
(5) SUV $_t$	0.033	0.031	-0.094	0.079	1.000									
(6) Volatility $_t$	0.150	0.116	-0.282	0.112	0.121	1.000								
(7) Bid_Ask $_t$	0.118	0.032	-0.177	-0.118	0.046	0.517	1.000							
(8) INFO $_t$	0.082	-0.054	-0.145	-0.301	0.071	0.197	0.522	1.000						
(9) ROA $_t$	-0.176	-0.050	0.499	0.006	-0.057	-0.431	-0.274	-0.187	1.000					
(10) VOL $_t$	-0.009	0.010	0.025	0.140	-0.011	0.004	-0.170	-0.286	0.006	1.000				
(11) RET $_t$	0.099	0.215	-0.024	0.053	0.201	0.256	0.056	0.006	0.102	-0.049	1.000			
(12) Num. of Analysts $_t$	-0.016	0.042	0.136	0.324	-0.119	-0.168	-0.381	-0.573	0.117	0.412	-0.064	1.000		
(13) ILLIQ $_t$	0.056	-0.065	-0.130	-0.361	0.058	0.242	0.587	0.805	-0.146	-0.446	0.020	-0.735	1.000	
(14) SIZE $_t$	-0.090	0.086	0.218	0.167	-0.097	-0.431	-0.586	-0.735	0.298	0.396	0.039	0.709	-0.872	1.000

Table 3: Investor disagreement and learning from stock prices

Table 3 reports the linear regression results for the main hypothesis. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is QxDTO for year *t* where DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover) and Q is the price-based measure of a firm's investment opportunity set. Column 1 shows the baseline linear regression results without investor disagreement. Column 2 adds investor disagreement. Both specifications include industry- and year-fixed effects. Both specifications control for the non-price-based measure of a firm's investment opportunity set.

	(1) Investment	(2) Investment
Q_t	.043***	.045***
	(.011)	(.011)
CF_t	-.05	-.051
	(.049)	(.048)
INV_AT_t	.559**	.497**
	(.224)	(.19)
$SIZE_t$	-.004	-.005
	(.004)	(.004)
DTO_t		5.643***
		(1.767)
$QxDTO_t$		-1.991**
		(.82)
$CFxDTO_t$		-2.546
		(4.06)
_cons	-.005	.007
	(.02)	(.019)
Observations	11203	11203
R-squared	.255	.261
Industry FE	YES	YES
Year FE	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 4: An alternative measure of disagreement and learning from stock prices

Table 4 reports the linear regression results with an alternative measure of investor disagreement. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is QxSUV for year *t* where SUV is an alternative measure of investor disagreement (standardized unexplained volume), and Q is the price-based measure of a firm's investment opportunity set. Column 1 uses an alternative investor disagreement measure (SUV). Column 2 shows the result for the primary measure of disagreement (DTO). Both specifications include industry- and year-fixed effects. Both specifications control for the non-price-based measure of a firm's investment opportunity set.

	(1) Investment	(2) Investment
Q_t	.048***	.045***
	(.013)	(.011)
CF_t	-.065	-.051
	(.066)	(.048)
SUV_t	.023*	
	(.012)	
$QxSUV_t$	-.036**	
	(.014)	
$CFxSUV_t$	.062	
	(.064)	
INV_AT_t	.621**	.497**
	(.237)	(.19)
$SIZE_t$	-.004	-.005
	(.004)	(.004)
DTO_t		5.643***
		(1.767)
$QxDTO_t$		-1.991**
		(.82)
$CFxDTO_t$		-2.546
		(4.06)
_cons	-.01	.007
	(.021)	(.019)
Observations	11203	11203
R-squared	.263	.261
Industry FE	YES	YES
Year FE	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 5: The probability of informed trading, disagreement, and learning from stock prices

Table 5 reports the linear regression results with the effects of the probability of informed trading. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is QxDTO for year *t* where DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover) and Q is the price-based measure of a firm's investment opportunity set. Controls include CF, INFO, QxINFO, CFxINFO, INV_AT, SIZE, SUV, CFxSUV, CFxINFOxSUV, DTO, CFxDTO, and CFxINFOxDTO. Column 1 uses an alternative investor disagreement measure (SUV). Column 2 shows the result for the primary measure of disagreement (DTO). Both specifications include industry- and year-fixed effects. Both specifications control for the non-price-based measure of a firm's investment opportunity set.

	(1)	(2)
	Investment	Investment
Q_t	.075***	.049**
	(.026)	(.018)
CF_t	-.308***	-.233***
	(.056)	(.054)
$INFO_t$	.075	-.093*
	(.087)	(.049)
$QxINFO_t$	-.116	-.017
	(.07)	(.045)
$CFxINFO_t$	.751***	.47***
	(.26)	(.107)
INV_AT_t	.325**	.267**
	(.122)	(.103)
$SIZE_t$	-.007	-.006
	(.007)	(.005)
SUV_t	.247**	
	(.112)	
$QxSUV_t$	-.165***	
	(.045)	
$INFOxSUV_t$	-.839**	
	(.393)	
$QxINFOxSUV_t$	.561***	
	(.184)	
$CFxSUV_t$	.78***	
	(.243)	
$CFxINFOxSUV_t$	-2.383***	
	(.837)	
DTO_t		6.96**
		(2.833)
$QxDTO_t$		-3.483***
		(1.115)
$INFOxDTO_t$		-29.188**
		(12.322)
$QxINFOxDTO_t$		10.708*
		(5.774)
$CFxDTO_t$		49.816**
		(19.671)
$CFxINFOxDTO_t$		-186.098**
		(79.255)
_cons	-.024	.018
	(.035)	(.034)
Observations	11454	11454
R-squared	.285	.281
Industry FE	YES	YES
Year FE	YES	YES

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 6: Analysts following, disagreement, and learning from stock prices

Table 6 reports the linear regression results with the effects of the number of analysts following. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is QxDTO for year *t* where DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover) and Q is the price-based measure of a firm's investment opportunity set. Controls include QxNum.Analyst, CF, CFxNum.Analyst, Num.Analyst, INV_AT, SIZE, DTO, DTOxNum.Analyst, CFxDTO, CFxDTOxNum.Analyst. The test includes industry- and year-fixed effects as well as a non-price-based measure of a firm's investment opportunity set.

	Investment
Q $_t$	.031***
	(.004)
CF $_t$	-.057
	(.036)
CFxNum. Analyst $_t$	.003
	(.005)
Num. Analyst $_t$	.002*
	(.001)
INV_AT $_t$	.871*
	(.444)
SIZE $_t$	-.006***
	(.002)
DTO $_t$	3.737***
	(1.153)
DTOxNum. Analyst $_t$	-.047
	(.135)
QxDTO $_t$	-1.828***
	(.372)
QxDTOxNum. Analyst $_t$	.071**
	(.034)
CFxDTO $_t$	9.988
	(8.115)
CFxDTOxNum. Analyst $_t$	-.139
	(.659)
_cons	.015
	(.036)
Observations	9944
R-squared	.444
Industry FE	YES
Year FE	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 7: Short interest, disagreement, and learning from stock prices

Table 7 reports the linear regression results with the effects of the underlying stock's short interest. The dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is QxDTO for year *t* where DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover) and Q is the price-based measure of a firm's investment opportunity set. Controls include CF, CFxlog_short, log_short, INV_AT, SIZE, DTO, and DTOxlog_short. The test includes industry- and year-fixed effects as well as a non-price-based measure of a firm's investment opportunity set.

	Investment
Q t	.019***
	(.002)
CF t	.48**
	(.203)
CFxlog_short	-.042*
	(.023)
log_short	.002
	(.002)
INV_AT t	1.652
	(1.16)
SIZE t	-.001
	(.002)
DTO t	15.915***
	(4.656)
DTOxlog_short t	-1.381***
	(.457)
QxDTO t	-8.334***
	(2.289)
QxDTOxlog_short t	.809***
	(.221)
CFxDTO t	36.128**
	(13.642)
CFxDTOxlog_short t	-2.9**
	(1.194)
_cons	.017
	(.039)
Observations	6411
R-squared	.441
Industry FE	YES
Year FE	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 8: Reg SHO pilot program, disagreement, and learning from stock prices

Table 8 reports regressions results with a differences-in-differences setting using Reg SHO pilot program. For Panel A, the dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is duringxQxDTO for year *t* where during equals one during the pilot period, DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover), and Q is the price-based measure of a firm's investment opportunity set. Controls for Panel A include CF, INV_AT, SIZE, shortint, during, duringxQ, duringxCF, duringxINV_AT, duringxSIZE, duringxshortint, DTO, and duringxDTO. The test includes industry- and year-fixed effects as well as a non-price-based measure of a firm's investment opportunity set. For Panel B, the dependent variable is investment in year t+1 (defined as the sum of capital expenditures and R&D divided by total assets), and the main independent variable of interest is regshoxduringxQxDTO for year *t* where regsho and during are dummy variables, DTO is a measure of investor disagreement (unexplained volume; specifically, I use change in turnover), and Q is the price-based measure of a firm's investment opportunity set.

Panel A: Learning channel during the pilot period

	Investment
Q $_t$	.029***
	(.003)
QxDTO $_t$	-2.571**
	(1.024)
CFxDTO $_t$	4.94
	(2.983)
duringxQxDTO $_t$	1.06**
	(.514)
duringxCFxDTO $_t$	-2.907
	(4.097)
Observations	5123
R-squared	.468
Controls	YES
Industry FE	YES
Year FE	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel B: Differences-in-differences regression with pre, during, and post periods

	Investment
Q $_t$	.018**
	(.007)
CF $_t$	-.014
	(.023)
INV_AT $_t$	.412***
	(.087)
SIZE $_t$	-.002*
	(.001)
during $_t$	-.019
	(.011)
post $_t$	-.02
	(.02)
regsho $_t$	.006
	(.009)
duringxQ $_t$	.009***

	(.002)
postxQ $_t$	.01*
	(.005)
duringxregsho $_t$	-.001
	(.006)
postxregsho $_t$	-.003
	(.004)
duringxINV_AT $_t$	-.243
	(.231)
postxINV_AT $_t$	-.034
	(.185)
duringxSIZE $_t$	.001
	(.001)
postxSIZE $_t$	0
	(.003)
regshoxQ $_t$	-.005
	(.005)
DTO $_t$	2.24
	(1.492)
QxDTO $_t$	.362
	(.821)
duringxDTO $_t$	-2.728
	(2.097)
postxDTO $_t$	-1.397
	(1.284)
duringxQxDTO $_t$	.533
	(.878)
postxQxDTO $_t$	-.66
	(.678)
regshoxQxDTO $_t$	-.892
	(1.316)
regshoxduringxQxDTO $_t$	1.976**
	(.845)
regshoxpostxQxDTO $_t$	1.894
	(1.081)
_cons	.038**
	(.013)
Observations	2324
R-squared	.29
Industry FE	YES
Year FE	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

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