Analysts’ Incentives to Produce Firm-Specific versus Industry-Level Information: Theory and Evidence

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Abstract

This paper analyzes the incentives of financial analysts to produce firm-specific versus industry-level information. We first develop a theoretical model in which an analyst covering a stock produces information and sells it to an investor. The investor trades based on this private information and pays a fraction of the profit to the analyst. We show that, for firms in mature industries (which dominate the economy), the investment value of additional firm-specific information (conditional on the information already reflected in the firm’s current stock price) is greater than the investment value of additional industry-level information. This would give analysts an incentive to produce more firm-specific than industry-level information. In contrast, for firms in emerging industries, analysts have an incentive to produce more industry-level than firm-specific information. The model thus provides a rational explanation for “tunnel vision” among analysts (the popular notion that they pay too much attention to firm-specific issues and too little to broad industry and market conditions). We then empirically test the predictions of the model using analyst earnings forecasts from IBES. The evidence is strongly consistent with the predictions. In the overall sample (dominated by firms in mature industries), firm-specific information indeed has more investment value than industry-level information: stock prices react more to firm-specific earnings forecast changes and less to industry-level earnings forecast changes. Further, in split-sample tests, this relationship is reversed for firms in emerging industries: in this case, stock prices react more to industry-level information and less to firm-specific information in analyst earnings forecasts.

JEL Classification Code: D82, G14, G24
1 Introduction

Practitioners often accuse financial analysts of “tunnel vision.” They think analysts pay too much attention to firm-specific issues and too little to broad industry and market conditions. In academics, people have different views on whether the information financial analysts produce is mainly industry-level or firm-specific. Most empirical studies find that analysts have industry expertise. But some studies document that the information analysts produce is mainly firm-specific. Furthermore, there is no theory in the literature suggesting why the information produced by analysts should be mainly industry-level or firm-specific.

This raises the question of whether or not analysts produce more firm-specific than industry-level information? If, indeed, analysts produce more firm-specific information, is there a rational explanation? Or is it due to irrationality on the part of analysts? The answers to these questions should help investors understand analysts’ behavior better. More important, knowing what kind of information is in analysts’ research will help investors make better use of this information.

In this paper, we analyze financial analysts’ incentives to produce firm-specific versus industry-level information. We first develop a model in which an analyst covering a stock produces information and sells it to an investor. The investor trades based on this private information, and pays a fraction of the

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1 See, for example, Chopra (1998): “The finding ... suggests that analysts may focus too much on firm-specific issues and not enough on the overall macroeconomic environment...” In an article titled “tunnel vision” on Forbes, Dreman (2003) makes similar comments.

2 For example, Piotroski and Roulstone (2002) state: “...the results are consistent with the notion that... analysts and institutions have expertise in gathering, interpreting and disseminating industry-level information.” See, also, Boni and Womack (2003): “With few exceptions, the Wall Street analysts that write reports, estimate earnings, help underwrite new issues, and issue buy and sell recommendations are considered industry specialists...” Other examples include Gilson, Healy, Noe, and Palepu (2001), Chan and Hameed (2002), among others.

3 For example, Park and Stice (2000) find that individual analysts with superior past forecasting track record have a greater price impact on security price than other analysts do, while the price effects do not spill over to other firms followed by the same analyst. Demirtas (2003) find that analyst earnings forecasts for individual firms contain information about future stock returns, while earnings estimates aggregated in the same sector, industry, or group do not. Both findings suggest that analysts’ forecasting ability is firm-specific instead of industry-level.
profit to the analyst.\textsuperscript{4} \textsuperscript{5} We show that, for firms in mature industries (which dominate the economy), the investment value of additional firm-specific information (conditional on information already reflected in the firm’s current stock price) is greater than the investment value of additional industry-level information. Thus, we demonstrate that analysts have an incentive to produce more firm-specific rather than industry-level information in this case. For firms in emerging industries, however, analysts have an incentive to produce more industry-level than firm-specific information.

The intuition is as follows. Since analysts are compensated according to the investment value of the information they provide to investors, they have an incentive to devote more resources to producing the kind of information that has more investment value. In the case of firms in mature industries, the public information already available to investors about the prospects of the industry is sufficiently precise. Furthermore, since there is a large number of firms in mature industries, there are many additional signals available about the industry factor (since the public signals on every firm in the industry reflect information about this industry factor). Due to the above two reasons, a large fraction of the industry-level information is already reflected in the firm’s current stock price, so that the investment value of additional industry-level information is very small. Therefore, analysts are better off devoting more resources to producing firm-specific information.

In contrast, in emerging industries, the precision of the public information available to investors about the industry is low. Moreover, with fewer firms in such industries, there are fewer additional signals about the industry factor that investors can extract information from. Thus, the amount of industry-

\textsuperscript{4} Brokerage firms that analysts work for often have soft dollar arrangements with institutional investors, who pay higher commission fees in exchange for analysts’ research from brokerage firms. Conrad, Johnson, and Wahal (2001) document that institutional investors pay 29 (24) basis points more for small buyer- (seller-) initiated orders to soft dollar brokers than to other types of brokers. The differentials are even greater for large orders. Also, Brennan and Hughes (1991) show that brokerage firms have more incentives to produce information for stocks that bring them more commission fees.

\textsuperscript{5} There is a large literature documenting that analysts’ research is biased (overly optimistic) because of conflicts of interest, e.g., Carleton, Chen, and Steiner (1998), Easterwood and Nutt (1999), Michaely and Womack (1999), Lim (2001), and Chan, Karceski and Lakonishok (2003) among others. We do not model this aspect of analysts’ research in this paper. As long as the payoffs to analysts increase with the investment value of their research, the results in this paper hold.
level information already reflected in the stock price is small so that analysts are better off devoting more resources to producing industry-level rather than firm-specific information.

Since most firms are in mature industries, our model predicts that, in general, analysts produce more firm-specific information and less industry-level information. This provides a rational explanation for “tunnel vision” among analysts (the popular notion that they pay too much attention to firm-specific issues and too little to broader industry and market conditions). We also relate analysts’ incentives to produce industry versus firm-specific information to industry characteristics like the number of firms in the industry and the informativeness of public signals.

We then empirically test the predictions of the model using analyst earnings forecasts from the IBES database. The evidence is strongly consistent with the predictions. We find that, in the overall sample (dominated by firms in mature industries), firm-specific information does have more investment value than industry-level information: stock prices react more to firm-specific earnings forecast changes and less to industry-level earnings forecast changes. Further, in split-sample tests, this relationship is reversed for firms in emerging industries: in this case, stock prices react more to industry-level information and less to firm-specific information in analyst earnings forecasts.

We also examine the post-event drift to earnings forecast changes, even though our model does not have any prediction on this issue. Consistent with previous research, we find that stock return continues to drift in the direction of earnings forecast changes one month after the changes. Further, we find (for the first time in the literature) that the drift is mainly due to firm-specific earnings forecast changes, while industry-level earnings forecast changes do not have any predictive power for future returns.

There are several other possible interpretations for the result that, overall, the investment value of

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6 In our empirical tests, we define an industry as mature if it is more than five years old. As a result, on average, 74.12% of industries are classified as mature at any time in our sample. Since on average, a mature industry has more firms than an emerging industry, we find that 88.76% of firms are in mature industries.

7 Many studies find that the market reaction to analysts’ research is incomplete, see, e.g., Stickel (1991) and Womack (1996), among others.
analyst earnings forecasts is mainly firm-specific. It might be that it costs less to produce firm-specific information and more to produce industry-level information. If this is the case, however, more firm-specific information should be produced and the price should incorporate more firm-specific information, and this is contradicted by the empirical evidence that, overall, stock prices incorporate more industry-level information. Another possible explanation is that analysts covering one stock free-ride on the industry information produced by analysts covering other stocks in the same industry. Our theory encompasses that explanation. Our model assumes that there is one public signal about each stock, which could be the earnings forecasts provided by analysts covering that stock. This explanation is therefore a special case of our theory.

This paper is related to several strands of literature. The first is research on the incentives of market participants to acquire information about securities. Examples are Grossman and Stiglitz (1980), Verrecchia (1982), Boot and Thakor (1993), and Holden and Stuerke (2000). However, these studies do not differentiate between industry and firm-specific information, and do not address any of the issues we study here. The second is the micro-structure literature. The trading stage of our model is similar to a one-period Kyle (1985) model, although we focus on the information production decisions of analysts, which is not modeled in Kyle. Further, we differentiate the informed investor’s private information into industry-level and firm-specific, while Kyle does not make this distinction.

This paper is also related to the vast literature which examines the information content in analysts’ research. It is now widely accepted in finance and accounting literature that financial analysts’ research has investment value, be it stock recommendations, earnings forecasts, or target prices; see, e.g., Lys and Sohn (1990), Womack (1996), and Brav and Lehavy (2002). Our purpose is not to answer the question of whether analysts’ research has investment value, but to examine whether the investment value is industry-

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8 Barber et al. (2001) find that investors cannot benefit from trading on stock recommendations, assuming that investors do not have timely access to the recommendations. Many institutional investors, however, can obtain private information before announcement through soft dollar arrangements; see, e.g., Conrad, Johnson, and Wahal (2001), and Chen (2002).
level or firm-specific. Our research is also related to the empirical accounting literature documenting that industry earnings information is reflected in security prices earlier than firm-specific earnings information, see, e.g., Ayers and Freeman (1997). We go one step further, and examine analysts’ incentives to produce different kinds of information, given that different kinds of information are incorporated into price at different speeds.

This paper contributes to the literature in several ways. First, it is the first paper proposing a theory on why analysts should produce more industry-level or firm-specific information. Second, it is the first to undertake a systematic empirical comparison of industry-level and firm-specific information in analysts’ research, while previous studies draw inferences based on indirect evidence. Third, it is the first paper to document that the post-event drift to analyst earnings forecasts is mainly due to firm-specific rather than industry-level information.

The rest of the paper is organized as follows. Section 2 deals with the basic setup of the model. Section 3 derives the main theoretical results. Section 4 outlines some of the implications of the model. Section 5 presents the data, empirical methodologies, and results. Section 6 examines post-event drift. Section 7 concludes. The proofs of all lemmas and propositions are confined to the appendix.

2 The Model

The model consists of $2N + 1$ dates: time 0, 1, 2, ..., $2N$. There are $N$ risky assets (stocks) and one risk-free asset in the industry. For simplicity, we normalize the net return on the risk-free asset to 0. At time 0, investors receive a public signal on each of the $N$ stocks, and the market gives each stock a price based on those signals. At time 1, an analyst produces information about stock 1 and gives a forecast to investor 1. The investor then submits orders to the market maker. There are some noise traders in the economy submitting orders for stock 1, too. The market maker observes the total order flow and sets a

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9 For simplicity, we assume there is only one analyst covering each stock. However, we can treat the single forecast in the model as the consensus forecast given by all analysts covering that stock.
price for stock 1. At time 2, the private information produced by analyst 1 becomes public, and the market gives another valuation to stock 1. Investor 1 unwinds her positions and rewards analyst 1 for her private information. At times 3 and 4, similar things happen to stock 2 ... At times $2N - 1$ and $2N$, similar things happen to stock $N$. The time line of the model is given in Figure 1.

2.1 Fundamental Values of Stocks and Public Signals

The value of stock $n$ is $\tilde{v}_n$, and the expected value is $\tau_n$. The innovative part of $\tilde{v}_n$ consists of an industry component, $\tilde{I}$, and a firm-specific component, $\tilde{F}_n$. That is,

$$\tilde{v}_n = \tau_n + \tilde{I} + \tilde{F}_n, \quad n \in \{1, 2, ..., N\},$$

where $\tilde{I}$ and $\tilde{F}_n$ are independent, with the following distributions

$$\tilde{I} \sim N(0, \Sigma^I), \quad \tilde{F}_n \sim N(0, \Sigma^F_n).$$

Note that the industry component, $\tilde{I}$, is the same for all $N$ stocks. We can think of the industry component as a factor that affects all stocks in the industry.

At time 0, there is one public signal for each firm. The public signal could be either an earnings announcement, a stock recommendation, an earnings forecast, or any other public news. A price is formed

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10 The value of the stock may also be influenced by market factors. We assume market factors are constant and are part of $\tau_n$. 

for each stock after that. The public signal about firm \( n \) is informative about the total value of the firm and takes the form:\(^{11}\)

\[
\bar{y}_n = \bar{v}_n + \bar{e}_yn, \quad (3)
\]

where \( \bar{e}_yn \) is normally distributed and independent of all other variables:

\[
\bar{e}_yn \sim N(0, \Sigma_{eyn}). \quad (4)
\]

### 2.2 Market Valuation

We assume all agents are risk-neutral. We also assume the market is semi-strong form efficient so that the price of a stock is its expected value, given all publicly available information. At time \( t \), the price of stock \( n \in \{1, 2, \ldots, N\} \) is given by

\[
P_{n,t} = E[\bar{v}_n | \Omega_t], \quad (5)
\]

where \( \Omega_t \) is the set of all public information available at time \( t \).

Since all \( N \) risky assets are symmetric ex ante, we concentrate on the information production decision of one analyst on one stock, namely, that of analyst 1 on stock 1. For algebraic simplicity, we assume the variances on the firm-specific components for the other \( N - 1 \) assets are the same. Also, the public signals for the other \( N - 1 \) firms are as precise:

\[
\Sigma_2^F = \Sigma_3^F = \ldots = \Sigma_N^F = \Sigma^F, \quad \Sigma_{ey} = \Sigma_{ey3} = \ldots = \Sigma_{eyN} = \Sigma_{ey}. \quad (6)
\]

### 2.3 Analyst’s Information Production and Informed Trading

At time 1, analyst 1 decides how much information to produce about stock 1. Since there is a public signal for each stock at time 0, some of the uncertainty regarding the stock’s value is resolved. Investors and

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\(^{11}\) We assume the signal is informative about the total firm value. In reality, the signal may contain more industry information or firm-specific information. As long as the public signal is informative about the industry factor, all the results hold.
analysts are interested in only the residual uncertainty about firm value. Therefore, we define:

\[
\tilde{v}_n' = \tilde{v}_n|\Omega_0, \quad \tilde{I}' = \tilde{I}|\Omega_0 - E\{\tilde{I}|\Omega_0\}, \quad \tilde{F}_n' = \tilde{F}_n|\Omega_0 - E\{\tilde{F}_n|\Omega_0\},
\]

(7)

where \(\tilde{v}_n'\) is the firm value based on the public information at time 0, \(\tilde{I}'\) and \(\tilde{F}_n'\) are the residual innovative part of the industry factor and firm \(n\)'s firm-specific component. Each analyst covers one stock and produces information about the industry factor as well as firm-specific information about the stock covered. At time 1, analyst 1 acquires two signals, one about the industry factor (\(\tilde{s}'\)) and one about firm 1’s firm-specific component (\(\tilde{s}_1'\)), which take the following forms:

\[
\tilde{s}' = \tilde{I}' + \tilde{e}'_s, \quad \tilde{s}_1' = \tilde{F}_1' + \tilde{e}_{s1}',
\]

(8)

where

\[
\tilde{e}'_s \sim N(0, \frac{1}{h_I}), \quad \tilde{e}_{s1}' \sim N(0, \frac{1}{h_{F1}}).
\]

(9)

Note \(h_I\) and \(h_{F1}\), the precision of the industry signal and the firm-specific signal, measure how much information analyst 1 produces about the industry factor and stock 1’ firm-specific component, respectively.

The costs for the industry and firm-specific signals are \(C(h_I)\) and \(C_n(h_{F1})\) respectively, as functions of the precision of the signals. We make the following assumption about information production costs:

**Assumption 1** \(C'(.) > 0, C'_n(.) > 0, C''(.) > 0, C''_n(.) > 0, C'(0) = C'_n(0) = \infty, \text{ and } C'(\infty) = C'_n(\infty) = 0.\)

Assumption 1 says that information production cost increases with the precision of the signal, and marginal productivity decreases with the precision. The last two parts of the assumption \((C'(0) = C'_n(0) = \infty, \text{ and } C'(\infty) = C'_n(\infty) = 0)\) guarantee interior solutions.

Analyst 1 gives a forecast \(f_1\) to investor 1, who trades on the basis of the forecast. Specifically, the investor submits an order of \(\tilde{x}\) to a market maker. The informed investor pays a fraction \(\rho \in (0, 1]\) of the profit to the analyst as compensation for the information. The analyst rationally anticipates how much
profit the informed investor will make and decides how much industry-level and firm-specific information to produce.\footnote{We do not consider the contract between the investor and the analyst, which is an interesting research topic but not our focus. As long as the investor’s payment to the analyst increases with the profits made, all the results hold.} In summary, analyst 1’s objective is as follows:

\[
\text{Max}_{h^I, h^F} \quad \rho \times \pi(h^I, h^F) - C(h^I) - C_1(h^F)
\]  

(10)

where \(\pi(h^I, h^F)\) is the profit earned by investor 1 using information provided by analyst 1.

2.4 Noise Traders and the Market Maker

There are noise traders at time \(2n - 1\) who trade stock \(n \in \{1, 2, \ldots, N\}\). In particular, there are noise traders at time 1 who trade stock 1. Their order flow is

\[
\tilde{u} \sim N(0, \Sigma_u),
\]

(11)

which is independent of all other variables. The market maker observes the total order flow and sets a price depending on that. We assume the market is semi-strong form efficient so that

\[
P_{1,1} = E\{\tilde{v}_1'x + \tilde{u} = y\}
\]

(12)

The informed investor submits the order strategically, knowing that the order partly reveals her private information. The setup is similar to the Kyle (1985) model.

3 Market Equilibrium

We concentrate on the first three periods of the model. From the fourth period onward, what happens to stock 1 will happen to other stocks, so we can focus on one stock only without loss of generality. The equilibrium consists of: (1) the price of stock 1 at times 0, 1 and 2; (2) analyst 1’s information production and forecast decision at time 1; (3) investor 1’s trading decision at time 1, given the analyst’s forecast; (4) the market maker’s pricing decision at time 1, depending on total order flow; and (5) a system of beliefs.
formed by each party about other parties’ decisions. These prices, beliefs, and decisions must be such that:

(a) the price of stock $1$ in each period is its expected value conditional on all publicly available information;
(b) the analyst’s information production and forecasting decisions maximize her utility given the pricing rules and other agents’ actions; (c) the informed investor’s trading strategy maximizes her utility, given the market maker’s pricing rule and the noise trader’s trading rule; and (d) the beliefs of all parties are consistent with the equilibrium choices of others.

### 3.1 Time 0 Price of Stock 1 and Its Properties

At time $0$, the market receives one signal for each stock and gives each stock a valuation based on all publicly available information. The exact form of stock $1$’s price is given in the following proposition.

**Proposition 1 (Stock Price as A Function of Public Signals)** The price of asset $1$ at time $0$ is a linear combination of the public signals on the $N$ stocks:

$$P_{1,0} = \bar{p}_1 + \frac{\Sigma^I(\Sigma^F + \Sigma_{ey})}{(\Sigma_1^I + \Sigma_{ey})}(y_1 - \bar{p}_1) + \frac{\Sigma^I(\Sigma^F + \Sigma_{ey})}{(\Sigma_2^I + \Sigma_{ey})}(y_2 - \bar{p}_2) + \cdots + \frac{\Sigma^I(\Sigma^F + \Sigma_{ey})}{(\Sigma_N^I + \Sigma_{ey})}(y_N - \bar{p}_N) + \frac{\Sigma^F(y_1 - \bar{p}_1)}{\Sigma_1^F + \Sigma^I + \Sigma_{ey}}. \tag{13}$$

Furthermore, the sensitivity of the above price to the public signal about stock $1$ decreases with the noise of stock $1$’s signal, $\Sigma_{ey1}$, and the total number of stocks in the industry, $N$. It increases with the noise of other stocks’ signals, $\Sigma_{ey}$, and the variance of other stocks’ firm-specific components, $\Sigma^F$. The sensitivity of the price to other stocks’ public signal increases with $\Sigma^I$, $\Sigma_{ey1}$, and decreases with $\Sigma^F$, $\Sigma_{ey}$. That is,

$$\frac{\partial^2 P_{1,0}}{\partial y_1 \partial \Sigma_{ey1}} < 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_1 \partial y_N} < 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma_{ey}} > 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma^F} > 0; \text{ and for } n \in \{1, 2, \ldots, N\}, \quad \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma^I} > 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma_{ey1}} > 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma_{ey}} < 0, \text{ and } \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma^F} < 0.$$

The price of stock $1$ at time $0$ is a function of stock $1$’s public signal since the signal is informative about the stock’s value. It is also a function of other stocks’ public signals. This is because all stocks are affected by the same industry factor. The public signal on every stock is informative about the industry factor, and in turn, informative about other stocks’ value (since other stocks’ values are also affected by the industry factor). Therefore, the price of stock $1$ is affected not only by the public signal on stock $1$, but also by public signals on other stocks.
Since $\Sigma_{ey1}$ measures the noise in stock 1’s public signal, a large $\Sigma_{ey1}$ means the signal is not that accurate, and thus, the market gives less weight to the public signal on stock 1. If there are many stocks in the industry, the market can learn a lot about the industry factor from other stocks, and, as a consequence, the price of stock 1 gives less weight to the public signal on stock 1. When $\Sigma_{ey}$ is large, or the variance of other stock’s firm-specific component, $\Sigma^F$, is large, public signals of other stocks are not very informative about the industry factor. As a result, the price of stock 1 gives more weight to stock 1’s signal and less weight to other stocks’ signals. The sensitivity of stock 1’s price to other stocks’ public signals increases with $\Sigma^I$, since a high $\Sigma^I$ means other stocks’ public signals are more informative about the industry factor, so the market can learn more from other stocks’ signals when it values stock 1.

Since the public signal on each stock is informative about the industry factor, how much industry information is incorporated into the price of stock 1 depends on the public signals on all the $N$ stocks. The firm-specific component of stock 1 only has one signal, however, i.e., stock 1’s public signal. Other stocks’ public signals are independent of stock 1’s firm-specific component. How much firm-specific information is incorporated into stock 1 depends only on the public signal on stock 1. Let us define the fraction of industry information and firm-specific information incorporated into the stock price as follows:

$$
\delta^I \equiv 1 - \frac{\text{Var}(\hat{I} | \hat{P}_{1,0})}{\text{Var}(\hat{I})}, \quad \delta^F_1 \equiv 1 - \frac{\text{Var}(\hat{F}_1 | \hat{P}_{1,0})}{\text{Var}(\hat{F}_1)}. \tag{14}
$$

Lemma 1 tells us exactly how much industry information and firm-specific information is impounded into the price of stock 1:

**Lemma 1** At time 0, a fraction $\delta^I = \frac{\Sigma^I[(N-1)(\Sigma^F_1 + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]}{(\Sigma^I_1 + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I[(N-1)(\Sigma^F_1 + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]}$ of industry information, and a fraction $\delta^F_1 = \frac{\Sigma^F}{\Sigma^I_1 + \Sigma^F + \Sigma_{ey1}}$ of firm-specific information is incorporated into the price of stock 1, $P_{1,0}$. Furthermore, $\delta^I$ increases with the variance of the industry factor $\Sigma^I$ and the total number of stocks $N$ and decreases with $\Sigma^F_1$, $\Sigma_{ey1}$, $\Sigma^F$, and $\Sigma_{ey}$. Also, $\delta^F_1$ increases with $\Sigma^F_1$, decreases with $\Sigma^I$ and $\Sigma_{ey1}$, and is independent of $N$.

The fraction of industry information incorporated into price, $\delta^I_1$, increases with $N$ and $\Sigma^I$. The reason is that when there are more stocks in the industry, there are more public signals about the industry factor.
Therefore, more industry information is incorporated into the price of stock 1. When the variance of the industry factor, $\Sigma^I$, increases, all the public signals are more informative about the industry factor, and thus, more industry information is incorporated into price. When $\Sigma^F_1, \Sigma_{ey1}, \Sigma^F$, or $\Sigma_{ey}$ increase, the public signal becomes less informative about the industry factor. Therefore, less industry information is incorporated into price.

The fraction of firm-specific information incorporated into the price of stock 1, $\delta^F_1$, increases with $\Sigma^F_1$ and decreases with $\Sigma^I$ and $\Sigma_{ey1}$. The intuition is as follows. When the variance of the firm-specific component, $\Sigma^F_1$, is higher, stock 1’s value is more affected by the firm-specific component, so its public signal is more informative about its firm-specific component and a greater fraction of firm-specific information is incorporated into price. Similarly, a higher value of $\Sigma^I$ or $\Sigma_{ey1}$ means stock 1’s public signal is less informative about its firm-specific component. Therefore, less firm-specific information is incorporated into price.

Proposition 2 compares the fraction of industry versus firm-specific information incorporated into price:

**Proposition 2 (Information in the Stock Prices of Firms in Mature and Emerging Industries)** Suppose $\Sigma^I \leq \Sigma^F_1$ and conditions (A.8) and (A.9) hold. In mature industries where there are many firms and public signals are informative, more industry than firm-specific information is incorporated into stock prices. In emerging industries where there are fewer firms and public signals are not very informative, more firm-specific than industry information is incorporated into stock prices. That is, there exist critical values $N^*$ and $\Sigma^*$ such that for $N > N^*$ and $\Sigma_{ey} \leq \Sigma^*$, we have $\delta^I > \delta^F_1$, and for $N \leq N^*$ and $\Sigma_{ey} > \Sigma^*$, we have $\delta^I \leq \delta^F_1$.

The intuition for Proposition 2 is as follows. For firms in mature industries, the public information available to investors about the prospects of the industry is sufficiently precise. Furthermore, since there are many firms in mature industries, there are many additional signals available about the industry factor. This is because the public signal on every firm in the industry reflects information about this industry factor. Therefore, a large fraction of industry-level information is incorporated into price. The fraction of firm-specific information reflected in price is not affected by the number of firms in the industry nor the
precision of public signals on other stocks. This is why more industry-level than firm-specific information is incorporated into price in mature industries.

In emerging industries, however, the public information available to investors about the industry is less precise. Further, since there are fewer firms in such industries, there are fewer additional signals about the industry factor that investors can extract information from. Thus, only a small fraction of industry-level information is reflected in price, and more firm-specific than industry-level information is incorporated into price in emerging industries.

3.2 Analysts’ Forecasting and Information Production Decisions

At time 1, because of the public signals at time 0, part of the uncertainty about the stock’s value is already resolved. Define:

\[ \tilde{v}_1 = \tilde{v}_1|P_{1,0}, \]

\[ \bar{I} = \bar{I}|P_{1,0} \]

\[ \bar{F}_1 = \bar{F}_1|P_{1,0} \]

we have

\[ \tilde{v}_1 = P_{1,0} + \bar{I} + \bar{F}_1, \]

where

\[ \bar{I} \sim N(0, \Sigma^{I}(1 - \delta^{I})), \quad \bar{F}_1 \sim N(0, \Sigma^{F}_{1}(1 - \delta^{F}_1)). \]

That is, the value of stock 1 conditional on the publicly available information is its price at time 0, plus the residual uncertainty on the industry factor and on the firm-specific component.

Analyst 1 gives a forecast according to two sources of information: the public information in the stock’s price, and the private signals she acquires. Proposition 3 gives the analyst’s forecast decision:
Proposition 3 (Analyst’s Forecast Decision) Analyst 1 makes a forecast of

\[ f_1 = P_{1,0} + \frac{\Sigma^I (1 - \delta^I) s^I}{\Sigma^I (1 - \delta^I) + 1/h^I} + \frac{\Sigma^F (1 - \delta^F) s^F}{\Sigma^F (1 - \delta^F) + 1/h^F} \]  

(20)

for stock 1 and this is also the price of stock 1 at time 2:

\[ P_{1,2} = P_{1,0} + \frac{\Sigma^I (1 - \delta^I) s^I}{\Sigma^I (1 - \delta^I) + 1/h^I} + \frac{\Sigma^F (1 - \delta^F) s^F}{\Sigma^F (1 - \delta^F) + 1/h^F}. \]  

(21)

Analyst 1’s forecast is informative about both the industry factor and stock 1’s firm-specific component.

We define the fraction of the industry information and the firm-specific information incorporated in the analyst’s forecast as follows:

\[ \eta^I \equiv 1 - \frac{\text{Var}(\tilde{I}|\tilde{f}_1)}{\text{Var}(I)}, \quad \eta^F \equiv 1 - \frac{\text{Var}(\tilde{F}_1|\tilde{f}_1)}{\text{Var}(F_1)}. \]  

(22)

Proposition 4 tells us the amount of industry information and firm-specific information incorporated in the analyst’s forecast for firms in mature and emerging industries.

Proposition 4 (Information in the Analyst’s Forecast for Firms in Mature and Emerging Industries) Suppose \( \Sigma^I \leq \Sigma^F, C(h^F) = C(h^I) \), and conditions (A.8) and (A.9) hold. In mature industries where there are many firms and public signals are informative, more industry than firm-specific information is incorporated into the analyst’s forecast. In emerging industries where there are fewer firms and public signals are not very informative, more firm-specific than industry information is incorporated into the analyst’s forecast. That is, there exist critical values \( N' \) and \( \Sigma' \) such that for \( N > N' \) and \( \Sigma_{ey} \leq \Sigma' \), we have \( \eta^I > \eta^F \), and for \( N \leq N' \) and \( \Sigma_{ey} > \Sigma' \), we have \( \eta^I \leq \eta^F \).

The intuition for Proposition 4 is as follows. For firms in mature industries, most of the industry-level information is already reflected in price. The analyst can simply copy the information in the firm’s stock price, and form a very accurate forecast about the industry-level information. Therefore, the forecast incorporates more industry-level than firm-specific information. For firms in emerging industries, however, very little industry-level information is reflected in price. The analyst’s forecast incorporates less industry-level information and more firm-specific information.

After receiving the forecast from the analyst, the investor submits an order to the market maker, knowing that the size of her order partly reveals her private information. Lemma 2 gives the informed investor’s trading strategy and the market maker’s pricing rule:
Lemma 2 At time 1, the informed investor's trading strategy, based on the analyst's forecast, \( f_1 \), is given by

\[
X(f_1) = \alpha + \beta f_1
\]

(23)

and the market maker sets the price, based on the observed order flow \( x + u \), as

\[
P_{1,1}(x + u) = \mu + \lambda(x + u),
\]

(24)

where:

\[
\alpha = -P_{1,0}\sqrt{\frac{\sum_u [\Sigma^I(1 - \delta^I) + 1/h^I] \Sigma^F(1 - \delta^F) + 1/h^F]}{(\Sigma^I)^2(1 - \delta^I)^2[\Sigma^F(1 - \delta^F) + 1/h^F] + (\Sigma^F)^2(1 - \delta^F)^2[\Sigma^I(1 - \delta^I) + 1/h^I]}}
\]

(25)

\[
\beta = \sqrt{\frac{\sum_u [\Sigma^I(1 - \delta^I) + 1/h^I] \Sigma^F(1 - \delta^F) + 1/h^F]}{(\Sigma^I)^2(1 - \delta^I)^2[\Sigma^F(1 - \delta^F) + 1/h^F] + (\Sigma^F)^2(1 - \delta^F)^2[\Sigma^I(1 - \delta^I) + 1/h^I]}}
\]

(26)

\[
\mu = P_{1,0},
\]

(27)

\[
\lambda = \sqrt{\frac{1}{4\sum_u [\Sigma^I(1 - \delta^I) + 1/h^I] \Sigma^F(1 - \delta^F) + 1/h^F]}(\Sigma^I)^2(1 - \delta^I)^2 + (\Sigma^F)^2(1 - \delta^F)^2\Sigma^F(1 - \delta^F) + 1/h^F]
\]

(28)

Proposition 5 gives the profit earned by the informed investor, unconditional on the analyst’s forecast.

We can think of it as investor 1’s expected profit before learning the forecast:

**Proposition 5 (Investor’s Trading Profit)** The expected profit earned by investor 1, unconditional on the analyst’s forecast, is

\[
\pi = \sqrt{\frac{\sum_u [\Sigma^I(1 - \delta^I)^2 + (\Sigma^F)^2(1 - \delta^F)^2\Sigma^F(1 - \delta^F) + 1/h^F]}{4\sum_u [\Sigma^I(1 - \delta^I) + 1/h^I] \Sigma^F(1 - \delta^F) + 1/h^F]}}
\]

(29)

which increases with \( \sum_u, h^I \), and \( h^F_1 \) and decreases with \( \delta^I \) and \( \delta^F_1 \).

The expected profit of the informed investor increases with the precision of the analyst’s signals, \( h^I \) and \( h^F_1 \): when the analyst produces more information, the informed investor has more information than the market maker, and therefore, the more profit she can make. The expected profit also increases with the variance of the noise trader’s order, \( \sum_u \): when the order flow from the noise trader is very volatile, it is very easy for the informed investor to hide her order and make more profit. The expected profit decreases with the proportion of industry-level and firm-specific information incorporated into the market price, \( \delta^I \).
and $\delta^F_1$: when most of the information is already incorporated into price, it is very hard for the informed investor to profit from private information.

Now, let us consider the analyst’s information production decision. Suppose the information production functions have standard properties so that Assumption 1 holds. Lemma 3 gives the analyst’s information production decision:

**Lemma 3** 
The amount of industry information produced by the analyst, $h_I$, is uniquely determined by the following equation:

$$C'(h^I) = \frac{\rho(\Sigma^I)^2 (1 - \delta^I)^2 \Sigma_u}{4[\Sigma^I (1 - \delta^I) h^I + 1]^2 \sqrt{\Sigma_u [\frac{(\Sigma^I)^2 (1 - \delta^I)^2}{\Sigma^I(1 - \delta^I) + 1/h^I} + \frac{(\Sigma^F_1)^2 (1 - \delta^F_1)^2}{\Sigma^F_1(1 - \delta^F_1) + 1/h^F_1}]}},$$

The amount of firm-specific information produced by the analyst, $h^F_1$, is uniquely determined by the following equation:

$$C'_1(h^F_1) = \frac{\rho(\Sigma^F_1)^2 (1 - \delta^F_1)^2 \Sigma_u}{4[\Sigma^F_1 (1 - \delta^F_1) h^F_1 + 1]^2 \sqrt{\Sigma_u [\frac{(\Sigma^F_1)^2 (1 - \delta^F_1)^2}{\Sigma^F_1(1 - \delta^F_1) + 1/h^F_1} + \frac{(\Sigma^F_1)^2 (1 - \delta^F_1)^2}{\Sigma^F_1(1 - \delta^F_1) + 1/h^F_1}]}},$$

The amount of industry information produced increases with $\rho, \Sigma_u, \Sigma^I, h^I$, but decreases with $\delta^I$. The amount of firm-specific information produced increases with $\rho, \Sigma_u, \Sigma^F_1, h^F_1$ and decreases with $\delta^F_1$.

The analyst knows it costs more to produce more precise information. At the same time, more precise information results in a more valuable forecast, and the informed investor can make more profit. Since the analyst’s payoff is proportional to the informed investor’s profit, there is a benefit to the analyst from producing more precise information. The analyst weighs the costs and benefits, and produces information so that the marginal cost of information production equals the marginal benefit.

Proposition 6 compares the amount of industry versus firm-specific information the analyst produces:

**Proposition 6 (Analyst Information Production About Firms in Mature and Emerging Industries)** Suppose $\Sigma^I \leq \Sigma^F_1$, $C(h^I) = C_1(h^F_1)$, and conditions (A.8) and (A.9) hold. For firms in mature industries, the analyst produces more firm-specific than industry-level information. For firms in emerging industries, the analyst produces more industry-level than firm-specific information. That is, there exist critical values $\bar{N}$ and $\bar{\Sigma}$ such that for $N \geq \bar{N}$ and $\Sigma \leq \bar{\Sigma}$, we have $h^F_1 \geq h^I$, and for $N < \bar{N}$ and $\Sigma > \bar{\Sigma}$, we have $h^F_1 < h^I$. 

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The intuition behind proposition 6 is as follows. Since the analyst is compensated according to the investment value of the information she provides to the investor, she has an incentive to devote more resources to producing information that has greater investment value. In the case of firms in mature industries, as we have shown earlier, most of the industry-level information is already reflected in the stock price so that the investment value of additional industry-level information is very low. As a result, the analyst is better off devoting more resources to producing firm-specific information. In contrast, in emerging industries, very little industry-level information is already reflected in the stock price so that the investment value of additional industry-level information is very high. As a result, the analyst is better off devoting more resources to producing industry-level rather than firm-specific information.

4 Testable Implications

We highlight some of the model’s testable implications here. The model assumes analysts provide forecasts on the value of stocks. In the real world, however, “fundamental values” of stocks are not readily observable, and analysts generally forecast earnings instead of values. Since, under reasonable assumptions, current earnings are proportional to stock value, we discuss testable implications in terms of earnings forecasts.13

(i) Accuracy of industry versus firm-specific information in analyst forecasts. We can see from Proposition 4 that there is more industry than firm-specific information incorporated in analysts’ forecasts for firms in mature industries where there are many firms in the industry and public signals are informative, and there is more firm-specific than industry information incorporated in analysts’ forecasts in emerging industries where there are fewer firms in the industry and public signals are not very informative. Since most industries are mature industries, we expect that, overall, more industry than firm-specific information is incorporated into analyst earnings forecasts.

Therefore, the first hypothesis (Hypothesis 1) is that, overall, and for firms in mature industries,

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13 For example, in a constant-growth dividend discount model, if we assume the dividend payout ratio is constant over time, the market value of the stock is linear with its current earnings.
analyst earnings forecasts are more accurate with regard to industry-level information and less accurate with regard to firm-specific information; for firms in emerging industries, analyst earnings forecasts are more accurate about firm-specific than industry-level information.

(ii) Market reaction to industry-level versus firm-specific information in analyst research. Proposition 6 states that in mature industries, where there are many stocks and public signals are informative, analysts are expected to produce more incremental firm-specific than industry-level information, and in emerging industries, where there are fewer stocks and public signals are not very informative, analysts are expected to produce more incremental industry-level than firm-specific information. Since the incremental information produced by analysts is not yet reflected in price, once analyst earnings forecasts become public, the market is expected to react to the information, and the more incremental information produced by analysts, the stronger the predicted market reaction.

Therefore, the second hypothesis (Hypothesis 2) is that, overall, and for firms in mature industries, the market reacts more to firm-specific information and less to industry-level information in analyst earnings forecasts; for firms in emerging industries, the market reacts more to industry-level than firm-specific information.

(iii) Cross-industry comparison of market reaction to industry-level information in analyst research. Since the amount of incremental industry information produced by analysts decreases with the number of stocks in the industry and the informativeness of public signals, we predict that analysts produces more industry-level information for firms in emerging industries and less industry-level information for firms in mature industries. Therefore, the third hypothesis (Hypothesis 3) is that the market reacts more to industry-level information in emerging industries and less to industry-level information in mature industries.

(iv) Effect of public news about one stock on the price of other stocks in the same industry. From
Proposition 1, we can see that the price of stock 1 increases not only with its own public signal, but also with the public signals on other stocks in the same industry. This implies that if there is good (bad) news on one stock, the prices of stocks with similar factor loadings, on average, increase (decrease).

(v) Relationship between information production cost and the information produced by analysts. Since the information (both industry-level and firm-specific) produced by analysts is negatively related to the information production cost, we expect that when information production cost is high (low), less (more) information is produced. The findings of Morck, Yeung, and Yu (2000) are consistent with this prediction. They find that security analysts produce less firm-specific information in emerging markets because it is harder for analysts to access firm-specific information in these countries.

(vi) Noise trading and analysts’ incentives to produce information. Analysts’ incentives to produce information (both industry and firm-specific) increase with the amount of noise trading (see Lemma 3). Since more noise trading confounds informed trading and makes informed trading more profitable, this encourages analysts to produce more information in the first place. In reality, we expect larger and more liquid stocks to be more informationally efficient since analysts have more incentive to produce information for those stocks.

5 Empirical Evidence

In this section, we empirically test some of the testable implications of the model. Specifically, we test the three hypotheses developed in Section 4. We first describe data and variables for empirical tests. Then, we describe methodologies and report results.

5.1 Data and Variable Descriptions

We obtain mean analyst forecasts of quarterly earnings per share (EPS) for US companies from Institutional Brokers Estimate System (IBES) Summary Statistics data. Stock prices, shares outstanding, dividend
payments, and firm sectors are also obtained from IBES.\textsuperscript{14} We obtain book values from the COMPUSTAT dataset, and monthly returns and three-digit SIC codes from the Center for Research in Security Prices (CRSP).

Each month for each firm, there is a mean earnings forecast for the coming quarter. We include only firms with fiscal-year endings in March, June, September, or December, to match the quarter endings. There are normally three monthly mean forecasts for each firm quarter: one in the month before the month of quarter ending, one in the month of quarter ending, and one in the month after. We use only the first forecast, i.e., the forecast in the month before the quarter ending month.\textsuperscript{15}

Realized earnings per share are also obtained from the IBES Summary file. We obtain the latest available book value for each firm from COMPUSTAT, and divide it by the shares outstanding in IBES to obtain book value per share (BPS). Firm-quarters missing any data are dropped from the sample. The resulting sample includes observations from 1985Q1 through 2001Q2.

First, we define firm $n$’s earnings forecast changes, $\Delta FNE_{nt}$, as the increase between earnings forecast per share from quarter $t-1$ to quarter $t$ divided by book value per share in quarter $t-1$. Similarly, we define firm $n$’s actual earnings changes, $\Delta NE_{nt}$, as the increase between realized earnings per share from quarter $t-1$ to quarter $t$ divided by book value per share in quarter $t-1$. Then, we decompose earnings

\textsuperscript{14} We use the price and shares outstanding data from IBES instead of CRSP/COMPUSTAT because the two datasets treat stock splits differently. To make sure that earnings forecasts and realized earnings use the same numbers of shares outstanding, we obtain the data from IBES.

\textsuperscript{15} In some cases, the first forecast is not one month before the quarter ending month, and we exclude those cases. We also use last earnings forecast of each quarter, i.e., the earnings forecasts one month after the quarter ending month, and the results are qualitatively the same.
forecast changes ($\Delta FNE_{nt}$) into industry ($\Delta FNE^I_{nt}$) and firm-specific ($\Delta FNE^F_{nt}$) components:

$$\Delta FNE^I_{jt} \equiv \Delta FNE^S_{jt} - \Delta FNE^M_t$$

$$\Delta FNE^F_{nt} \equiv \Delta FNE_{nt} - \Delta FNE^S_{jt}$$

$$\Delta FNE^S_{jt} \equiv median\{\Delta FNE_{nt}\} \text{ of all firms sharing firm } n \text{'s three-digit SIC in quarter } t$$

$$\Delta FNE^M_t \equiv median\{\Delta FNE^S_{jt}\} \text{ in quarter } t.$$

Similarly, we decompose $\Delta NE_{nt}$ into industry, $\Delta NE^I_{nt}$, and firm-specific, $\Delta NE^F_{nt}$, components:

$$\Delta NE^I_{jt} \equiv \Delta NE^S_{jt} - \Delta NE^M_t$$

$$\Delta NE^F_{nt} \equiv \Delta NE_{nt} - \Delta NE^S_{jt}$$

$$\Delta NE^S_{jt} \equiv median\{\Delta NE_{nt}\} \text{ of all firms sharing firm } n \text{'s three-digit SIC in quarter } t$$

$$\Delta NE^M_t \equiv median\{\Delta NE^S_{jt}\} \text{ in quarter } t.$$

Firm $n$’s cumulative abnormal return in quarter $t$ ($CAR_{nt}$) is the product of monthly abnormal returns ($AR^I_{mt}$) from the third month in quarter $t - 1$ to the second month in quarter $t$.\(^{16}\) For example, for the quarter ending June 1997, the earnings forecast is given in May 1997, and the cumulative abnormal return spans March, April, and May of 1997. Specifically, $CAR_{nt}$ is calculated as follows:

$$CAR_{nt} = \prod_{m=-3}^{-1} (1 + AR_{nm}) - 1,$$

$$AR_{nm} = R_{nm} - R_{gm},$$

where

$$R_{nm} = \text{ actual return on firm } n \text{'s common stock in month } m; \text{ and}$$

$$R_{gm} = \text{ the average monthly return of securities in firm } n \text{'s SIZE/PB group.}$$

\(^{16}\) We calculate $CAR_{nt}$ this way to capture the abnormal return from the previous forecast to the current forecast, to be consistent with the time span of earnings forecast changes. See Figure 2 for the exact time span of $CAR_{nt}$. 

21
Specifically, $R_{gm}$ is calculated by dividing firms into 25 groups according to market capitalization and price-to-book ratio and calculating the average monthly return in each group. Figure 2 shows the timing of the key variables.

Table 1 provides the summary statistics for the variables: $\Delta NE^I_{jt}$, $\Delta NE^F_{nt}$, $\Delta FNE^I_{jt}$, and $\Delta FNE^F_{nt}$. Both the range and standard deviations of the earnings forecasts are below those of the realized earnings, which means that analyst forecasts may underreact to real earnings changes.

### 5.2 Empirical Methodology and Results

#### A. Test of Hypothesis 1

Hypothesis 1 states that, overall, and for firms in mature industries, analyst earnings forecasts are more accurate with regard to industry-level information and less accurate with regard to firm-specific information; for firms in emerging industries, analyst earnings forecasts are more accurate about firm-specific than industry-level information.

To test Hypothesis 1, we compare the forecast errors for the industry and firm-specific components. We normalize the mean of the absolute value of the forecast errors on the industry $[Mean(|\Delta FNE^I_{jt} - \Delta NE^I_{jt}|)]$ and firm-specific $[Mean(|\Delta FNE^F_{nt} - \Delta NE^F_{nt}|)]$ components by the standard deviations of the
actual industry earnings changes $[\text{St.Dev.}(\Delta NE_{jt}^I)]$ and firm-specific earnings changes $[\text{St.Dev.}(\Delta NE_{nt}^F)]$, respectively, and compare them. We first compare them in the whole sample. Then, we go to split-sample tests. We divide the whole sample into two subsamples: firms in emerging industries and firms in mature industries. We define emerging industries as those industries whose three-digit SIC code has been in CRSP for less than or equal to 5 years. Otherwise, we define an industry as mature at that time.

Table II shows that, for the whole sample, the forecast error on the industry part (0.23) is smaller than that on the firm-specific part (0.30). This is also true for firms in mature industries (0.20<0.31). However, in emerging industries, the relation is reversed: the forecast error on the industry part (0.35) is larger than that on the firm-specific part (0.28). The empirical evidence is consistent with hypothesis 1.

**B. Test of Hypothesis 2**

Hypothesis 2 states that, overall, and for firms in mature industries, the market reacts more to firm-specific information and less to industry-level information in analyst earnings forecasts; for firms in emerging industries, the market reacts more to industry-level than firm-specific information.

To test Hypothesis 2, we first perform a preliminary test of the market reaction to industry-level versus firm-specific earnings forecast changes. In each quarter, we form ten decile portfolios based on the magnitude of industry-level earnings forecast changes ($\Delta FNE_{jt}^I$), and compare the average abnormal cumulative quarterly returns ($CAR_{nt}$) for these portfolios over time. Similarly, we form ten portfolios based on the magnitude of firm-specific earnings forecast changes ($\Delta FNE_{nt}^F$), and compare the average abnormal cumulative quarterly returns ($CAR_{nt}$) for these portfolios over time.

Figure 3 shows the average cumulative abnormal returns by portfolios ranked on the basis of the magnitudes of industry versus firm-specific analyst forecast changes. For the industry forecast change portfolios, the average quarterly abnormal returns of top and bottom decile are not very different: 1.06%

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17 We treat an industry as not present at all in CRSP if there are only one or two firms in the industry at any time.
versus −1.35%. For firm-specific analyst forecast change portfolios, the average quarterly abnormal returns of top and bottom decile are much more different: 1.50% versus −5.33%. This preliminary result shows a much greater market reaction for firm-specific analyst forecast changes than for industry analyst forecast changes.

After the preliminary test, we run the following pooled regression:

\[
CAR_{nt} = \beta_0 + \beta_1 \Delta FNE_{jt}^I + \beta_2 \Delta FNE_{nt}^F + \beta_3 \ln(cap_{nt})
\]

\[
+ \beta_4 DIV_{nt-1} + \beta_5 PB_{nt} + \beta_6 beat_{nt-1} + \sum_{k=1}^{11} \beta_{k+6} SEC_{knt} + \epsilon_{nt},
\]

where \(beat_{nt-1}\) is a dummy variable indicating that firm \(n\)’s earnings meet or exceed the consensus forecast during last quarter, with values of 1 if yes and 0 otherwise; \(\ln(cap_{nt})\) is the natural logarithm of firm \(n\)’s market capitalization in quarter \(t\);\(^{18}\) \(DIV_{nt-1}\) is firm \(n\)’s dividend payment during the previous year divided by book value per share in the previous quarter; \(PB_{nt}\) is firm \(n\)’s price-to-book ratio; and \(SEC_{knt}\) is the sector dummy, with a value of 1 when firm \(n\) is in sector \(k\) in quarter \(t\), and 0 otherwise.\(^{19}\)

Hypothesis 2 says that \(\beta_2\) should be significantly larger than \(\beta_1\). To test this hypothesis, we see if we can reject the null hypothesis: \(H_0: \beta_2 - \beta_1 = 0\). Table III reports the results of regression (32). Panel A gives the results of the panel data regression. The market reacts more to firm-specific analyst forecast changes than to industry analyst forecast changes. When the firm-specific earnings forecast changes by one unit, the market return in that quarter changes by \(\beta_2 = 23\%\). When the industry analyst forecast changes by one unit, however, the market return changes by \(\beta_1 = 7.1\%\), a much lower response. We can also compare the economic significance of the market reaction to industry-level versus firm-specific analyst forecast changes. When the industry-level analyst forecast changes by one standard deviation, the return on that stock changes by \(0.016 \times 7.1\% = 0.11\%\). When the firm-specific analyst forecast changes by one

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\(^{18}\) Market capitalization is obtained in the second month of the quarter, when the earnings forecast is also obtained.

\(^{19}\) Some people may argue that, by definition, the excess return excludes industry component. To address this problem, we use raw returns as a robustness check and find similar results.
standard deviation, the return on that stock changes by \(0.033 \times 23\% = 0.76\%\). The t-statistic associated with \(H_0 : \beta_2 - \beta_1 = 0\) is 3.12, which means we strongly reject the null hypothesis that the coefficients on \(\Delta FNE_{jt}^I\) and \(\Delta FNE_{nt}^F\) are the same.

Panel B of table III shows the time series properties of the coefficients from the cross-sectional regressions for each quarter (Fama and MacBeth (1973) type regression). The results are very similar: \(\bar{\beta}_1 = 13.0\%\) and \(\bar{\beta}_2 = 32.899\%\). The average adjusted \(R^2\) of the cross-sectional regressions is much higher than the adjusted \(R^2\) of the pooled regression (11.68% versus 3.70%). Unreported coefficients on the sector dummies, in most cases, are not significantly different from zero. The t-statistic associated with \(H_0 : \beta_{2t} - \beta_{1t} = 0\) is 2.392, which indicates rejection of the null hypothesis that the coefficients on \(\Delta FNE_{jt}^I\) and \(\Delta FNE_{nt}^F\) are the same. The empirical results are in support of hypothesis 2 that, in the whole sample, the market reacts more to firm-specific analyst forecast changes than to industry-level analyst forecast changes.

During the course of a quarter, the market return and earnings forecasts may influence each other, we need to overcome the endogeneity problem. To address this question, we use a simultaneous equations method. Beaver, McAnally, and Stinson (1997) use simultaneous equations to estimate the relationship between realized earnings and market prices; they find that price and earnings coefficients increase from an ordinary least square (OLS) to a joint estimation approach.

We first run the joint regression:

\[
\begin{align*}
CAR_{nt} & = \beta_0 + \beta_1 \Delta FNE_{nt} + \beta_3 \ln(cap_{nt}) + \beta_4 \text{beat}_{nt-1} \\
& \quad + \beta_5 \text{DIV}_{nt-1} + \beta_6 PB_{nt} + \sum_{j=1}^{11} \beta_{j+6} \text{SEC}_{jnt} + \epsilon_{nt}, \\
\Delta FNE_{nt} & = b_0 + b_1 CAR_{nt} + b_2 \Delta FNE_{nt-1} + \epsilon_{nt},
\end{align*}
\]

where \(\Delta FNE_{nt-1}\) is the earnings forecast change in the last quarter for firm \(n\), and all other variables are as defined. We use a two-stage least square (2SLS) regression to estimate the joint regression. The first stage provides an estimate of both endogenous variables (\(\Delta FNE_{nt}\) and \(CAR_{nt}\)) by regressing each of them
on the exogenous variables \((ln(\text{cap}_{nt}), \text{DIV}_{nt-1}, \text{PB}_{nt}, \text{beat}_{nt-1}, \text{SEC}_{jnt}, \text{and } \Delta FNE_{nt-1})\). We denote \(y_{nt}\) and \(w_{nt}\) as the residuals from the first-stage regressions of \(\Delta FNE_{nt}\) and \(CAR_{nt}\) on the exogenous variables, respectively. In the second stage, we add \(y_{nt}\) and \(w_{nt}\) to equations (33) and (34), respectively, and use OLS to estimate the coefficients.

Table IV reports the results. Panels A and B report the coefficients estimated by OLS for (33) and (34). Panels C and D report the coefficients estimated by 2SLS for joint regression of (33) and (34). The coefficients on both \(CAR_{nt}\) and \(\Delta FNE_{nt}\) increase from OLS to joint estimation. The coefficient on \(\Delta FNE_{nt}\) increases from 0.2 (in OLS) to 0.25 (in 2SLS), and that on \(CAR_{nt}\) increases from 0.0086 to 0.018.

We then use a simultaneous equation approach to estimate equations (32) and (34) jointly. Using 2SLS to estimate the coefficients is equivalently to adding \(y_{nt}\) to equation (32) and using OLS to estimate the coefficients. The coefficients estimated by 2SLS for equation (32) are reported in panel E of table IV. A comparison with the coefficients estimated by OLS reported in panel A of table III indicates a reduction for industry forecast change \((\Delta FNE_{Ij}^I)\) from \(\beta_1 = 0.071\) by OLS to \(\beta_1 = 0.048\) by 2SLS, and an increase for firm-specific forecast change \((\Delta FNE_{F}^F)\) from \(\beta_2 = 0.23\) by OLS to \(\beta_2 = 0.33\) by 2SLS. The result is strengthened if we take into consideration the effect of price change on earnings forecast changes.

For a split-sample test, we run separate pooled regressions of equation (32) for firms in mature industries and in emerging industries. Panel A of table V reports the results for firms in emerging industries, and Panel B those for mature industries. For firms in emerging industries, the market reacts more to industry earnings forecast changes than to firm-specific earnings forecast changes. When industry earnings forecasts change by one unit, stock return changes by 29.1%. When firm-specific earnings forecasts change by one unit, stock return changes by only 11.5%. We have to reject the null that \(\beta_1 - \beta_2 = 0\). The associated t-statistic is 1.92. This is consistent with the prediction that, for firms in emerging industries, the market responds more to industry than firm-specific information in analyst earnings forecasts.
The results also show that, for firms in mature industries, the market reacts more to firm-specific earnings forecast changes than to industry earnings forecast changes. When industry earnings forecasts change by one unit, stock return changes by only 3.5% (not statistically significant). When firm-specific earnings forecasts change by one unit, stock return changes by 24.4%. We have to reject the null that $\beta_2 - \beta_1 = 0$. The associated t-statistic is 2.86. This is consistent with the prediction that, for firms in mature industries, market responds more to firm-specific than industry information in analyst earnings forecasts.

In summary, we find strong support for hypothesis 2.

C. Test of Hypothesis 3

Hypothesis 3 states that the market reacts more to industry-level information in emerging industries and less to industry-level information in mature industries.

We have seen how the market reacts to industry-level information in analyst earnings forecasts in emerging industries and in mature industries. Panels A and B of table V show that, for firms in emerging industries, when industry earnings forecasts change by one unit, stock return changes by 29.1%. For firms in mature industries, when industry earnings forecasts change by one unit, stock return changes by only 3.5%.

The evidence shows that the market reacts more strongly to industry-level information in analyst earnings forecasts in emerging industries than to industry-level information in analyst earnings forecasts in mature industries. The evidence is consistent with Hypothesis 3.

6 Post-event Drift

Previous studies have found that the market reaction to analysts’ research is incomplete. Stickel (1991) finds that prices continue to drift in the direction of the earnings forecast revisions for about six months after the revisions. Womack (1996) finds similar price drifts after stock recommendation changes. Given
these findings, we try to explore whether there is post-event drift after earnings forecast changes. Note that the post-event drift is not a prediction of the theoretical model in this paper. We test it empirically to see if there is post-event drift for analyst earnings forecast changes, and if there is, we want to see if it is caused by firm-specific or industry-level information.

To see if earnings forecast changes have any predictive power for future stock returns, we first conduct a preliminary test. We compare the predictive power (return drift) of industry and firm-specific earnings forecast changes by constructing three different self-financing portfolios based on different components of analyst earnings forecast changes.

1) At the beginning of the third month of each quarter (the month after earnings forecast changes are calculated), we sort firms according to total earnings forecast changes, \( \Delta FNE_{nt} \), and buy stocks in the top decile (highest \( \Delta FNE_{nt} \)) and short stocks in the bottom decile (lowest \( \Delta FNE_{nt} \)). We then hold the portfolio for one month (i.e., look at the return of the portfolio in the third month of that quarter).

2) At the beginning of the third month of each quarter, we sort firms according to industry-level earnings forecast changes, \( \Delta FNE_{jt} \), and buy stocks in the top decile and short stocks in the bottom decile. We also hold this portfolio for one month.

3) At the beginning of the third month of each quarter, we sort firms according to firm-specific earnings forecast changes, \( \Delta FNE_{Fnt} \), and buy stocks in the top decile and short stocks in the bottom decile. We hold the portfolio for one month.

We then look at the returns on these three portfolios over time. Denote the return on the portfolio in quarter \( t \) as \( r_t \). The average return of each portfolio over time and the t-statistic are:

\[
m_r = \frac{1}{T} \sum_{t=1}^{T} r_t, \quad \sigma_r^2 = \frac{1}{T} \sum_{t=1}^{T} (r_t - m_r)^2, \quad t_r = \frac{\sqrt{T \times m_r}}{\sigma_r}.
\]

Table VI reports the results for the predictive power of industry-level versus firm-specific earnings forecast changes. The first row reports the results for the whole sample period, from the first quarter
of 1985 to the second quarter of year 2001. The average profit using total earnings forecast changes ($\Delta FNE_{nt}$) is 7.27%/year, with a t-statistic of 1.85, which is significant at the 10% level. The average profit using industry earnings forecast changes ($\Delta FNE^I_{jt}$) is only 2.5%/year and the t-statistic is only 0.62, not statistically significant. The profit using firm-specific earnings forecast changes ($\Delta FNE^F_{nt}$) is 10.02%/year, with a t-statistic of 3.35, significant at the 1% level. These results indicate that the predictive power (return drift) comes mainly from firm-specific instead of industry earnings forecast changes.

To see if the results are robust, we look at the trading profits in sub periods. We divide the whole sample period into 2 or 3 equally-length sub periods, and the results are qualitatively the same in each sub period.

Then, we run the regression:

$$R_{nt+1} = \beta_0 + \beta_1 \Delta FNE^I_{jt} + \beta_2 \Delta FNE^F_{nt} + \beta_3 \ln(cap_{nt}) + \beta_4 beat_{nt-1} + \beta_5 DIV_{nt-1} + \beta_6 PB_{nt} + \sum_{k=1}^{11} \beta_{k+6} SEC_{knt} + e_{nt}, \quad (35)$$

where $R_{nt+1}$ is one-month-ahead raw return, i.e., the stock return in the month after the earnings forecast changes are issued. Results for a pooled regression are reported in panel A of table VII. The coefficient on $\Delta FNE^F_{nt}$ is positive and statistically significant ($\beta_2 = 0.0296$ with $t = 2.1$), while that on $\Delta FNE^I_{nt}$ is not ($\beta_1 = -0.00158$ with $t = 0.52$). This implies that firm-specific earnings forecast changes have predictive power for one-month ahead stock returns, while industry earnings forecast changes do not.

The results for a cross-sectional regression of equation (35) each quarter are reported in panel B of table VII. The results are similar to those from the pooled regression.

For a robustness check, we use one-month-ahead abnormal returns instead of raw returns in the same regression, calculating abnormal returns the same way as before. The results reported in panels C and D of table VII are qualitatively the same.

All the empirical evidence points in the direction that firm-specific earnings forecast changes predicts
one-month-ahead return, while industry earnings forecast changes do not. This means the post-event drift in analyst earnings forecasts is caused mainly by firm-specific instead of industry-level information.

7 Conclusion

We have analyzed financial analysts’ incentives to produce firm-specific versus industry-level information. In our theoretical model, an analyst covering a stock produces information and sells it to an investor. The investor trades on the basis of this private information, and pays a fraction of the profit to the analyst. We show that, for firms in mature industries (which dominate the economy), the investment value of additional firm-specific information (conditional on the information already reflected in the current price) is greater than the investment value of additional industry-level information. Thus, we demonstrate that analysts have an incentive to produce more firm-specific than industry-level information in this case. In contrast, for firms in emerging industries, analysts have an incentive to produce more industry-level than firm-specific information. Therefore, our model provides a rational explanation for “tunnel vision” among analysts (the popular notion that they pay too much attention to firm-specific issues and too little to broader industry and market conditions).

We then empirically test the predictions of our model using analyst earnings forecasts from IBES. The evidence is strongly consistent with the predictions of the model. In the overall sample (dominated by firms in mature industries), firm-specific information indeed has higher investment value than industry-level information: stock prices react more to firm-specific earnings forecast changes and less to industry-level earnings forecast changes. Split-sample tests indicate this relationship is reversed for firms in emerging industries: in this case, stock prices react more to industry-level information in analyst earnings forecasts and less to firm-specific information.

We also explore whether the market reaction to earnings forecasts changes is incomplete, although this is not a prediction of the model. We find that stock return continues to drift in the direction of earnings
forecast changes one month after forecast changes. This drift is due mainly to firm-specific earnings forecasts, while industry earnings forecast changes do not have any predictive power for future returns.
Appendices

A Proofs of Propositions

Proof of Proposition 1:
The price of stock 1 at time 0 is the expected value of the stock conditional on all the publicly available information:

\[ P_{1,0} = E[y_1, ..., y_N | y_1 = y_1, ..., y_N = y_N] \]

\[ = E[y_1 + \bar{a}_N + \bar{\epsilon}_y = y_1, ..., \bar{a}_N + \bar{\epsilon}_y = y_N] \]

Since all variables are normally distributed, application of the projection theorem yields equation (13).

The sensitivity of stock 1’s price, \( P_{1,0} \), to stock 1’s public signal, \( y_1 \), is

\[
\frac{\partial P_{1,0}}{\partial y_1} = \frac{\Sigma^I(\Sigma^F + \Sigma_{ey})}{(\Sigma^I + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I[(N-1)(\Sigma^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]} + \frac{\Sigma^F}{\Sigma^I + \Sigma^F + \Sigma_{ey1}}, \tag{A.1}
\]

which increases with \( \Sigma^F \) and \( \Sigma_{ey} \), and decreases with \( \Sigma_{ey1} \) and \( N \). The sensitivity of \( P_{1,0} \) to other stock’s signal is

\[
\frac{\partial^2 P_{1,0}}{\partial y_1 \partial \Sigma_{ey1}} = -\frac{\Sigma^I[(\Sigma^F + \Sigma_{ey}) + \Sigma^I(N-1)]}{[(\Sigma^I + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I[((N-1)(\Sigma^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]^2
\]

\[
- \frac{\Sigma^I}{(\Sigma^I + \Sigma^F + \Sigma_{ey1})^2} < 0. \tag{A.2}
\]

Similarly, we can show that

\[
\frac{\partial^2 P_{1,0}}{\partial y_1 \partial N} < 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_1 \partial \Sigma_{ey}} > 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_1 \partial \Sigma^F} > 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma_{ey1}} > 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma^F} < 0, \quad \frac{\partial^2 P_{1,0}}{\partial y_n \partial \Sigma_{ey}} < 0.
\]

Proof of Lemma 1:
We can show that

\[
Var(\bar{I} | \bar{P}_{1,0}) = \Sigma^I(1 - \frac{\Sigma^I[(N-1)(\Sigma^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]}{(\Sigma^I + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I[(N-1)(\Sigma^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]}, \tag{A.3}
\]

which means a fraction

\[
\delta^I = \frac{\Sigma^I[(N-1)(\Sigma^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]}{(\Sigma^I + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I[(N-1)(\Sigma^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]} \tag{A.4}
\]

of industry information is incorporated into the price.

Similarly, we can show that

\[
Var(\bar{F}_1 | \bar{P}_{1,0}) = \Sigma^I(1 - \frac{\Sigma^F}{\Sigma^I + \Sigma^F + \Sigma_{ey1}}), \tag{A.5}
\]

which means a fraction of

\[
\delta^F = \frac{\Sigma^F}{\Sigma^I + \Sigma^F + \Sigma_{ey1}} \tag{A.6}
\]
of firm-specific information is incorporated into the price.

It is easy to see that

$$\frac{\partial \delta^I}{\partial \Sigma^I} = \frac{(\Sigma_1^F + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey})[(N-1)(\Sigma_1^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]}{\{\Sigma_1^F + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I[(N-1)(\Sigma_1^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]\}^2} > 0. \quad (A.7)$$

Similarly, we can show $\frac{\partial \delta^I}{\partial N} > 0$, $\frac{\partial \delta^I}{\partial \Sigma_{ey1}} < 0$, $\frac{\partial \delta^I}{\partial \Sigma^F} < 0$, $\frac{\partial \delta^I}{\partial \Sigma^F} > 0$, and $\frac{\partial \delta^I}{\partial \Sigma_{ey1}} < 0$.

**Proof of Proposition 2:**
For any given value of $\Sigma_{ey}$, let us assume $\Sigma_{ey1}$ is not too small, and $\Sigma^I$ is not too large compared to $\Sigma_1^F$, so that the condition holds:

$$\frac{\Sigma^I[(\Sigma_1^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]}{(\Sigma_1^F + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I(\Sigma_1^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]} \leq \frac{\Sigma_1^F}{\Sigma_1^F + \Sigma^I + \Sigma_{ey1}}. \quad (A.8)$$

From lemma 1, we can see that $\delta^I$ increases with $N$, while $\delta_1^F$ is independent of $N$. When $N$ is small, say, $N = 2$,

$$\delta^I = \frac{\Sigma^I[(\Sigma_1^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]}{(\Sigma_1^F + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I[(\Sigma_1^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]} \leq \frac{\Sigma_1^F}{\Sigma_1^F + \Sigma^I + \Sigma_{ey1}} = \delta_1^F,$$

and when $N$ is large, say $N \to \infty$, $\delta^I = 1 > \delta_1^F$. Therefore, there must exist an integer $N^*$ such that for all $N \leq N^*$, we have $\delta^I \leq \delta_1^F$, and for all $N > N^*$, we have $\delta^I > \delta_1^F$.

For any given value of $N$, let us assume $\Sigma_{ey1}$ is not too small, and $\Sigma^I$ is not too large compared to $\Sigma_1^F$, so that the conditions hold:

$$\frac{\Sigma^I[(N-1)(\Sigma_1^F + \Sigma_{ey1}) + \Sigma^F]}{(\Sigma_1^F + \Sigma_{ey1})\Sigma^F + \Sigma^I[(N-1)(\Sigma_1^F + \Sigma_{ey1}) + \Sigma^F]} > \frac{\Sigma_1^F}{\Sigma_1^F + \Sigma^I + \Sigma_{ey1}}, \quad (A.9)$$

and $\Sigma^I \leq \Sigma_1^F$. From lemma 1, we can see that $\delta^I$ decreases with $\Sigma_{ey}$, while $\delta_1^F$ is independent of $\Sigma_{ey}$. When $\Sigma_{ey} \to \infty$, $\delta^I \to \frac{\Sigma^I}{\Sigma_1^F + \Sigma^F + \Sigma_{ey1}} \leq \frac{\Sigma_1^F}{\Sigma_1^F + \Sigma^F + \Sigma_{ey1}} = \delta_1^F$, and when $\Sigma_{ey} \to 0$,

$$\delta^I = \frac{\Sigma^I[(N-1)(\Sigma_1^F + \Sigma_{ey1}) + \Sigma^F]}{(\Sigma_1^F + \Sigma_{ey1})\Sigma^F + \Sigma^I[(N-1)(\Sigma_1^F + \Sigma_{ey1}) + \Sigma^F]} \geq \frac{\Sigma_1^F}{\Sigma_1^F + \Sigma^I + \Sigma_{ey1}} = \delta_1^F.$$

Therefore, there must exist a critical value $\Sigma_1^*$ such that for $\Sigma_{ey} > \Sigma_1^*$, we have $\delta^I < \delta_1^F$, and for $\Sigma_{ey} \leq \Sigma_1^*$, we have $\delta^I \geq \delta_1^F$.

**Proof of Proposition 3:**
Analyst 1's forecast is the expected value of stock 1 based on all publicly available information and her private signals:

$$f_1 = E[\overline{v}_1|\overline{I}_1 + \overline{c}_n = s^I, \overline{F}_1 + \overline{c}_{sn1} = s_{sn1}^F] = P_{1,0} + \frac{\Sigma^I(1-\delta^I)s^I}{\Sigma^I(1-\delta^I) + 1/h^I} + \frac{\Sigma_1^F(1-\delta_1^F)s_{sn1}^F}{\Sigma_1^F(1-\delta_1^F) + 1/h_1^F}.$$

At time 2, the analyst’s forecast becomes public and the market price of stock 1 at time 2 is the same as the time 1 forecast.
Proof of Proposition 4:
For any given value of $\Sigma_{cy}$ and other parameter values, note that $\eta^I$ increases with $N$, while $\eta^F$ is independent of $N$. From proposition 2, we can see that when $N = 2$, we have $\delta^I \leq \delta^F_1$. When $C(h^I) = C_1(h^F_1)$, this means $\eta^I \leq \eta^F_1$. When $N$ is large enough, the price would become very informative about the industry component, as shown in proposition 2. The forecast incorporates even more information than $P_{1,0}$, so we have $\eta^I \rightarrow 1 > \delta^F_1$ as $N \rightarrow \infty$. Therefore, there must exist an integer $\bar{N}$ such that for all $N > \bar{N}$, we have $\eta^I > \eta^F_1$, and for $N \leq \bar{N}$, we have $\eta^I \leq \eta^F_1$.

For any given value of $N$ and other parameter values, note that $\eta^I$ decreases with $\Sigma_{cy}$, while $\eta^F_1$ is independent of $\Sigma_{cy}$. From proposition 2 we can see that when $\Sigma_{cy} \rightarrow \infty$, $\delta^I \leq \delta^F_1$. Together with $C(h^I) = C_1(h^F_1)$, this means $\eta^I \leq \eta^F_1$. When $\Sigma_{cy} \rightarrow 0$, we proved in proposition 2 that $\delta^I > \delta^F_1$. Together with $C(h^I) = C_1(h^F_1)$, this means $\eta^I > \eta^F_1$. Therefore, there must exist a critical value $\Sigma$ such that for $\Sigma_{cy} > \Sigma$, we have $\eta^I < \eta^F_1$, and for $\Sigma_{cy} \leq \Sigma$, we have $\eta^I \geq \eta^F_1$.

Proof of Lemma 2:
Suppose that for constants $\mu, \lambda, \alpha,$ and $\beta$, linear function $X$ and $P$ are given by

$$X(f_1) = \alpha + \beta f_1.$$  \hfill (A.10)

Given the linear rule $P$, profits can be written as

$$E\{[\bar{P}_{12} - P(x + \bar{u})]x|\bar{P}_{12} = f_1\} = (f_1 - \mu - \lambda x)x.$$  \hfill (A.11)

Profit maximization gives us that $x = \frac{h_1 \mu - \lambda \mu}{2\lambda}$. Since we assume that $X(f_1) = \alpha + \beta f_1$, we have

$$\alpha = \frac{\mu}{2\lambda}, \beta = \frac{1}{2\lambda}$$  \hfill (A.12)

Given linear $X$ and $P$, the market efficiency condition is equivalent to

$$\mu + \lambda y = E\{\bar{v}_1^I|\alpha + \beta f_1 + \bar{u} = y\}$$  \hfill (A.13)

We need a solution to $E\{\bar{v}_1^I|\alpha + \beta f_1 + \bar{u} = y\}$.

We define

$$\phi^I = \frac{\Sigma^I(1 - \delta^I)}{\Sigma^I(1 - \delta^I) + 1/h^I}, \phi^F_1 = \frac{\Sigma^F_1(1 - \delta^F_1)}{\Sigma^F_1(1 - \delta^F_1) + 1/h^F_1}$$  \hfill (A.14)

and we can see that

$$E\{\bar{v}_1^I|\alpha + \beta f_1 + \bar{u} = y\}$$

$$= E\{P_{1,0} + \bar{P} + \bar{F}_1^I|\alpha + \beta[\bar{P}_{1,0} + \phi^I(\bar{P} + \bar{c}_s) + \phi_F^I(\bar{F}_1^I + \bar{c}_{s_01})] + \bar{u} = y\}$$

$$= P_{1,0} + \frac{\beta(\phi_1^I(\Sigma^I(1 - \delta^I) + 1/h^I) + \phi^F_1(\Sigma^F_1(1 - \delta^F_1) + 1/h^F_1) + \Sigma_u)}{(\phi^I)^2(\Sigma^I(1 - \delta^I) + 1/h^I) + (\phi^F_1)^2(\Sigma^F_1(1 - \delta^F_1) + 1/h^F_1) + \Sigma_u}$$
We have
\[ \lambda = \frac{\beta[\phi^I \Sigma^I (1 - \delta^I) + \phi^F \Sigma^F (1 - \delta^F)]}{\beta^2[\phi^I (1 - \delta^I) + \phi^F (1 + 1/h^I)] + \Sigma_u} \]
\[ \mu = P_{1,0} - \frac{\beta[\phi^I \Sigma^I (1 - \delta^I) + \phi^F \Sigma^F (1 - \delta^F)](\alpha + \beta P_{1,0})}{\beta^2[\phi^I (1 - \delta^I) + \phi^F (1 + 1/h^I)] + \Sigma_u} \]

After solving we have equations (25) to (28). This completes the proof.

**Proof of Proposition 5:**
From the proof of lemma 2, we can see that for a given value of \( f_1 \), the informed investor’s profit is
\[ \pi(f_1) = (f_1 - \mu - \lambda(f_1 - \mu))(f_1 - \mu) = \frac{(f_1 - \mu)^2}{4\lambda} \] (A.15)

Then the profit earned by the investor, unconditional on analyst’s forecast, is
\[ \pi = E[\pi(f_1)] = E[\frac{(f_1 - \mu)^2}{4\lambda}], \] (A.16)

Since \( \mu = P_{1,0} = E(f_1) \), we have
\[ \pi = \frac{Var(f_1)}{4\lambda} = \frac{1}{4\lambda} \frac{\Sigma^I (1 - \delta^I)^2}{\Sigma^I (1 - \delta^I) + 1/h^I} + \frac{(\Sigma^F)^2(1 - \delta^F)^2}{\Sigma^F (1 - \delta^F) + 1/h^F} \] (A.17)

Plug in the value of \( \lambda \), we can see that the unconditional profit is given by equation 29. It is easy to see that \( \pi \) is increasing in \( \Sigma_u, h^I, \) and \( h^F \), and decreasing in \( \delta^I \) and \( \delta^F \).

**Proof of Lemma 3:**
The analyst’s problem is as follows
\[ \max_{h^I, h^F} \rho \pi(h^I, h^F) - C(h^I) - C_1(h^F). \] (A.18)

Plug in the value of \( \pi(h^I, h^F) \), equations (30) and (31) follow from the first-order conditions directly. Now we have to prove the existence and uniqueness of the solutions. Note that the LHS of equation (30) strictly increases with \( h^I \) and has value 0 when \( h^I \to 0 \) and value \( \infty \) when \( h^I \to \infty \), and the RHS of equation (30) strictly decreases with \( h^I \) and has value \( \infty \) when \( h^I \to 0 \) and value 0 when \( h^I \to \infty \). Therefore, if we plot both the LHS and RHS of equation (30), there must be one and only one crossing for the two plots, which is the solution to equation (30). In other word, there is one and only one solution to equation (30). Similarly, we can prove the existence and uniqueness of the solution to equation (31).

**Proof of Proposition 6:**
Since \( \delta^F \) is independent of \( N \), while \( \delta^I \) increases with \( N \), from equations (30) and (31), we can see that \( h^F \) is independent of \( N \), while \( h^I \) decreases with \( N \). When \( N \) is small, say, \( N = 2 \), and
\[ \frac{\Sigma^I(\Sigma^F + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey})}{(\Sigma^F + \Sigma_{ey1})(\Sigma^F + \Sigma_{ey}) + \Sigma^I[\Sigma^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma_{ey})]} \leq \frac{\Sigma^F(\Sigma^I + \Sigma_{ey1})}{\Sigma^F + \Sigma^I + \Sigma_{ey1}}, \]
we can see from equation (29) that there is less profit from firm-specific information than from industry information if equal amounts of industry and firm-specific information are produced. Since \( C(h^I) = C_1(h^F) \), we have \( h^I < h^F \) when \( N = 2 \).
As $N \to \infty$, we have $\delta^I \to 1$, so that the right-hand side of equation (30) goes to zero. From assumption 1, we have $h^I \to 0 < h^F_1$. Hence, there exists a finite integer $\bar{N}$ such that for $N > \bar{N}$, we have $h^F_1 > h^I$, and for $N \leq \bar{N}$, we have $h^F_1 \leq h^I$.

Since $\delta^F_1$ is independent of $\Sigma_{ey}$, while $\delta^I$ decreases with $\Sigma_{ey}$, from equations (30) and (31), we can see that $h^F_1$ is independent of $\Sigma_{ey}$, while $h^I$ increases with $\Sigma_{ey}$. When $\Sigma_{ey} \to 0$, and

$$\frac{\Sigma^I (\Sigma^F + \Sigma_{ey1}) (\Sigma^F)}{(\Sigma^F + \Sigma_{ey1}) (\Sigma^F + \Sigma^I) + \Sigma^I [(N - 1) (\Sigma^F + \Sigma_{ey1}) + (\Sigma^F + \Sigma^I)]} < \frac{\Sigma^F (\Sigma^I + \Sigma_{ey1})}{\Sigma^F + \Sigma^I + \Sigma_{ey1}},$$

we can see from equation (29) that there is a higher profit from firm-specific information than from industry information if equal amounts of industry and firm-specific information are produced. Since $C(h^I) = C_1(h^F_1)$, we have $h^I < h^F_1$ when $\Sigma_{ey} \to 0$.

When $\Sigma_{ey} \to \infty$, and $\Sigma^I \geq \Sigma^F$, we can see from equation (29) that there is less profit from firm-specific information than from industry information if equal amounts of industry and firm-specific information are produced. Since $C(h^I) = C_1(h^F_1)$, we have $h^I < h^F_1$ when $\Sigma_{ey} \to \infty$. Hence, there exists a value $\bar{\Sigma}$ such that for $\Sigma_{ey} \geq \bar{\Sigma}$, we have $h^I \geq h^F_1$, and for $\Sigma_{ey} < \bar{\Sigma}$, we have $h^I < h^F_1$. 

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References


Figure 3: Average cumulative quarterly abnormal returns of portfolios ranked according to industry-level versus firm-specific analysts earnings forecast changes
Table I: Summary Statistics

Descriptive statistics for the key variables in the empirical part of the paper.

<table>
<thead>
<tr>
<th></th>
<th>$\Delta NE^I_{jt}$</th>
<th>$\Delta NE^F_{nt}$</th>
<th>$\Delta FNE^I_{jt}$</th>
<th>$\Delta FNE^F_{nt}$</th>
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<tbody>
<tr>
<td>Mean</td>
<td>0.000099</td>
<td>−0.00043</td>
<td>0.0011</td>
<td>0.000091</td>
</tr>
<tr>
<td>St.Dev.</td>
<td>0.023</td>
<td>0.06</td>
<td>0.016</td>
<td>0.033</td>
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<tr>
<td>Minimum</td>
<td>−1.31</td>
<td>−1.47</td>
<td>−0.8</td>
<td>−1.41</td>
</tr>
<tr>
<td>Median</td>
<td>.00076</td>
<td>0</td>
<td>.00092</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.32</td>
<td>1.44</td>
<td>1.09</td>
<td>1.16</td>
</tr>
<tr>
<td># of Observations</td>
<td>10687</td>
<td>97646</td>
<td>10687</td>
<td>97646</td>
</tr>
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</table>
Table II: Comparison of Forecast Accuracy of Industry-Level vs. Firm-Specific Earnings

This table compares the forecast accuracy of industry-level earnings as opposed to firm-specific earnings, in the overall sample, in emerging industries, and in mature industries. Mean (|ΔFNE_{jt}^{I} − ΔNE_{jt}^{I}|) is the mean value of the absolute value of the forecast error on the industry component, and Mean (|ΔFNE_{nt}^{F} − ΔNE_{nt}^{F}|) is the value of the firm-specific company. St.Dev. (ΔNE_{jt}^{I}) is the standard deviation of the actual industry earnings, and St.Dev. (ΔNE_{nt}^{F}) is the standard deviation of the actual firm-specific earnings. The number of observations (# of obs.) is also reported.

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>Overall</td>
<td>Mean(</td>
<td>ΔFNE_{jt}^{I} − ΔNE_{jt}^{I}</td>
<td>) = 0.23</td>
<td>10687</td>
</tr>
<tr>
<td>Emerging Industries</td>
<td>Mean(</td>
<td>ΔFNE_{jt}^{I} − ΔNE_{jt}^{I}</td>
<td>) = 0.35</td>
<td>2761</td>
</tr>
<tr>
<td>Mature Industries</td>
<td>Mean(</td>
<td>ΔFNE_{jt}^{I} − ΔNE_{jt}^{I}</td>
<td>) = 0.20</td>
<td>7926</td>
</tr>
</tbody>
</table>
Table III: Market Reaction to Industry-Level vs. Firm-Specific Earnings Forecast Changes

This table reports results for the regression

\[ CAR_{nt} = \beta_0 + \beta_1 \Delta FNE^I_{jt} + \beta_2 \Delta FNE^F_{nt} + \beta_3 \ln(cap_{nt}) \]
\[ + \beta_4 \text{DIV}_{nt-1} + \beta_5 \text{PB}_{nt} + \beta_6 \text{beat}_{nt-1} + \sum_{k=1}^{11} \beta_{k+6} \text{SEC}_{knt} + e_{nt}. \]

Panel A reports results of the pooled regression and panel B results of cross-sectional regressions for each quarter.

Panel A: Pooled regression

<table>
<thead>
<tr>
<th>Coef</th>
<th>(t-stat)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.016</td>
<td>3.37</td>
</tr>
<tr>
<td>0.071</td>
<td>1.52</td>
</tr>
<tr>
<td>0.23</td>
<td>10.22</td>
</tr>
<tr>
<td>-0.0074</td>
<td>-16.20</td>
</tr>
<tr>
<td>0.067</td>
<td>44.57</td>
</tr>
<tr>
<td>-0.067</td>
<td>-9.91</td>
</tr>
<tr>
<td>0.00081</td>
<td>4.18</td>
</tr>
</tbody>
</table>

\[ Adj. R^2 \] 3.70%

\[ \# of observations \] 69417

\[ t(\beta_2 - \beta_1 = 0) \] 3.121

Panel B: Cross-sectional regression for each quarter

<table>
<thead>
<tr>
<th>Average Coef</th>
<th>(t-stat)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>1.96</td>
</tr>
<tr>
<td>0.13</td>
<td>3.19</td>
</tr>
<tr>
<td>0.33</td>
<td>12.31</td>
</tr>
<tr>
<td>-0.0064</td>
<td>-7.73</td>
</tr>
<tr>
<td>0.066</td>
<td>51.46</td>
</tr>
<tr>
<td>-0.21</td>
<td>-8.65</td>
</tr>
<tr>
<td>0.0025</td>
<td>5.8</td>
</tr>
</tbody>
</table>

\[ Average Adj. R^2 \] 11.68%

\[ \# of quarters \] 66

\[ Average \# of firms per quarter \] 1052

\[ t(\beta_{2t} - \beta_{1t} = 0) \] 2.392
Table IV: Simultaneous Equations Approach to Estimate Market Reaction to Industry-Level vs. Firm-Specific Earnings Forecast Changes

Simultaneous equations estimation of the joint regressions:

\[
\begin{align*}
(1) \quad \text{CAR}_{nt} &= \beta_0 + \beta_1 \Delta FNE_{nt} + \beta_3 \ln(\text{cap}_{nt}) + \beta_4 \text{beat}_{nt-1} \\
&\quad + \beta_5 \text{DIV}_{nt-1} + \beta_6 \text{PB}_{nt} + \sum_{j=1}^{11} \beta_{j+6} \text{SEC}_{jnt} + \epsilon_{nt}, \\
(2) \quad \Delta FNE_{nt} &= b_0 + b_1 \text{CAR}_{nt} + b_2 \Delta FNE_{nt-1} + \epsilon_{nt}.
\end{align*}
\]

Panels A and B report the OLS regressions of the two equations, and panels C and D report the results of 2SLS estimations. Panel E reports the results of 2SLS estimations of the joint regression when we change the first equation to

\[
(1') \quad \text{CAR}_{nt} = \beta_0 + \beta_1 \Delta FNE_{jt}^I + \beta_2 \Delta FNE_{nt}^F + \beta_3 \ln(\text{cap}_{nt}) \\
&\quad + \beta_4 \text{DIV}_{nt-1} + \beta_5 \text{PB}_{nt} + \beta_6 \text{beat}_{nt-1} + \sum_{k=1}^{11} \beta_{k+6} \text{SEC}_{knt} + \epsilon_{nt}.
\]

Panel A: OLS regression of equation (1)

<table>
<thead>
<tr>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.016</td>
<td>0.2</td>
<td>-0.0074</td>
<td>0.067</td>
<td>-0.067</td>
<td>0.00081</td>
</tr>
</tbody>
</table>

(t-stat) 3.35 9.63 -16.18 44.49 -9.90 4.20

Adj. $R^2$ =3.68%

Panel B: OLS regression of equation (2)

<table>
<thead>
<tr>
<th>$b_0$</th>
<th>$b_1$</th>
<th>$b_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0016</td>
<td>0.0086</td>
<td>-0.14</td>
</tr>
</tbody>
</table>

(t-stat) 10.20 14.07 -39.51

Adj. $R^2$ =2.46%

Panel C: 2SLS regression of equation (1)

<table>
<thead>
<tr>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0079</td>
<td>0.25</td>
<td>-0.0059</td>
<td>0.065</td>
<td>-0.051</td>
<td>-0.00064</td>
</tr>
</tbody>
</table>

(t-stat) 1.43 4.73 -11.27 37.76 -6.91 -2.17

Adj. $R^2$ =3.64%
Panel D: 2SLS regression of equation (2)

<table>
<thead>
<tr>
<th></th>
<th>$b_0$</th>
<th>$b_1$</th>
<th>$b_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef</td>
<td>0.0014</td>
<td>0.018</td>
<td>-0.18</td>
</tr>
<tr>
<td>(t-stat)</td>
<td>10.24</td>
<td>9.55</td>
<td>-43.69</td>
</tr>
</tbody>
</table>

Adj. $R^2 = 4.01\%$

Panel E: 2SLS regression of equation (1')

<table>
<thead>
<tr>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Coef</td>
<td>0.008</td>
<td>0.048</td>
<td>0.33</td>
<td>-0.0059</td>
<td>0.065</td>
<td>-0.051</td>
</tr>
<tr>
<td>(t-stat)</td>
<td>1.46</td>
<td>0.69</td>
<td>5.87</td>
<td>-11.19</td>
<td>37.71</td>
<td>-6.91</td>
</tr>
</tbody>
</table>

Adj. $R^2 = 3.68\%$
Table V: Comparison of Market Reaction to Industry-Level vs. Firm-Specific Earnings Forecast Changes in Emerging and Mature Industries

This table reports results for the regression:

\[
CAR_{nt} = \beta_0 + \beta_1 \Delta FNE^I_{jt} + \beta_2 \Delta FNE^F_{nt} + \beta_3 \ln(cap_{nt}) + \\
\beta_4 DIV_{nt-1} + \beta_5 PB_{nt} + \beta_6 beat_{nt-1} + \sum_{k=1}^{11} \beta_k SEC_{knt} + \epsilon_{nt}
\]

for emerging and mature industries. Panel A reports results for emerging industries, and panel B reports results for mature industries.

<table>
<thead>
<tr>
<th>Panel A: Regression for emerging industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Intercept )</td>
</tr>
<tr>
<td>Coef</td>
</tr>
<tr>
<td>(t-stat)</td>
</tr>
<tr>
<td>Adj. ( R^2 )</td>
</tr>
<tr>
<td># of observations</td>
</tr>
<tr>
<td>( t(\beta_1 - \beta_2 = 0) )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Regression for mature industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Intercept )</td>
</tr>
<tr>
<td>Coef</td>
</tr>
<tr>
<td>(t-stat)</td>
</tr>
<tr>
<td>Adj. ( R^2 )</td>
</tr>
<tr>
<td># of observations</td>
</tr>
<tr>
<td>( t(\beta_2 - \beta_1 = 0) )</td>
</tr>
</tbody>
</table>
Table VI: Preliminary Test of Predictive Power of Firm-Specific versus Industry-Level Earnings Forecast Changes on One-Month-Ahead Stock Returns (Post-event Drift)

This table examines the returns of stocks one month after earnings forecast changes, for the whole sample, and different sub periods. The first column is the average portfolio returns (annualized) using total earnings forecast changes (\(\Delta FNE_{nt}\)). In the second and third column, stocks are sorted according to the extent of industry earnings forecast changes (\(\Delta FNE^I_{jt}\)) and firm-specific earnings forecast changes (\(\Delta FNE^F_{nt}\)) respectively. T-statistics are in parentheses.

<table>
<thead>
<tr>
<th>Period</th>
<th>(1) Return Using (\Delta FNE_{nt})</th>
<th>(2) Return Using (\Delta FNE^I_{jt})</th>
<th>(3) Return Using (\Delta FNE^F_{nt})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1985Q1-2001Q2</td>
<td>7.27%(t = 1.85)</td>
<td>2.5%(t = 0.62)</td>
<td>10.02%(t = 3.35)</td>
</tr>
<tr>
<td>1985Q1-1990Q2</td>
<td>6.21%(t = 0.96)</td>
<td>-0.77%(t = -0.14)</td>
<td>10.56%(t = 2.76)</td>
</tr>
<tr>
<td>1990Q3-1995Q4</td>
<td>3.70%(t = 0.76)</td>
<td>-0.63%(t = 0.10)</td>
<td>6.7%(t = 1.37)</td>
</tr>
<tr>
<td>1996Q1-2001Q2</td>
<td>11.91%(t = 1.37)</td>
<td>8.91%(t = 1.0)</td>
<td>12.80%(t = 1.94)</td>
</tr>
<tr>
<td>1985Q1-1993Q1</td>
<td>4.92%(t = 1.02)</td>
<td>-1.7%(t = -0.36)</td>
<td>10.16%(t = 3.09)</td>
</tr>
<tr>
<td>1993Q2-2001Q2</td>
<td>9.63%(t = 1.54)</td>
<td>6.7%(t = 1.02)</td>
<td>9.88%(t = 1.95)</td>
</tr>
</tbody>
</table>
Table VII: Predictive Power of Firm-Specific versus Industry-Level Earnings Forecast Changes on One-Month-Ahead Stock Returns (Post-event Drift)

First, we use one-month-ahead raw returns \( R_{nt+1} \) and run the following pooled regression

\[
R_{nt+1} = \beta_0 + \beta_1 \Delta FNE_{jt}^I + \beta_2 \Delta FNE_{nt}^F + \beta_3 \ln(\text{cap}_n) \\
+ \beta_4 \text{beat}_{nt-1} + \beta_5 \text{DIV}_{nt-1} + \beta_6 \text{PB}_{nt} + \sum_{k=1}^{11} \beta_{k+6} \text{SEC}_{knt} + \epsilon_{nt}.
\]

Results are reported in panel A. Then, we run cross-sectional regressions of the above equation each quarter, and look at the coefficients overtime. The results are reported in panel B. We also run regressions using abnormal returns instead of raw returns, and the results are reported in panels C and D.

Panel A: Pooled Regression Using Raw Returns

<table>
<thead>
<tr>
<th>Coef</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( \beta_5 )</th>
<th>( \beta_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.0016</td>
<td>-0.034</td>
<td>0.03</td>
<td>0.00039</td>
<td>0.013</td>
<td>0.0022</td>
<td>-0.000044</td>
</tr>
<tr>
<td>(t-stat)</td>
<td>-0.52</td>
<td>-1.16</td>
<td>2.10</td>
<td>0.14</td>
<td>13.95</td>
<td>0.52</td>
<td>-0.36</td>
</tr>
</tbody>
</table>

Adj. \( R^2 = 0.41\% \)

Panel B: Cross-sectional Regression Using Raw Returns

<table>
<thead>
<tr>
<th>Avg Coef</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( \beta_5 )</th>
<th>( \beta_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0026</td>
<td>-0.047</td>
<td>0.024</td>
<td>-0.00042</td>
<td>0.012</td>
<td>0.0018</td>
<td>0.00018</td>
</tr>
<tr>
<td>(t-stat)</td>
<td>0.56</td>
<td>-2.11</td>
<td>1.84</td>
<td>-0.82</td>
<td>19.33</td>
<td>0.23</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Avg Adj. \( R^2 = 8.2\% \)

Panel C: Pooled Regression Using Abnormal Returns

<table>
<thead>
<tr>
<th>Coef</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( \beta_5 )</th>
<th>( \beta_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.00047</td>
<td>-0.07</td>
<td>0.021</td>
<td>-0.0015</td>
<td>0.011</td>
<td>-0.0017</td>
<td>-0.00036</td>
</tr>
<tr>
<td>(t-stat)</td>
<td>-0.17</td>
<td>-2.53</td>
<td>1.62</td>
<td>-5.51</td>
<td>11.83</td>
<td>-0.43</td>
<td>-3.19</td>
</tr>
</tbody>
</table>

Avg Adj. \( R^2 = 0.33\% \)

Panel D: Cross-sectional Regression Using Abnormal Returns

<table>
<thead>
<tr>
<th>Coef</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( \beta_5 )</th>
<th>( \beta_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.00047</td>
<td>-0.051</td>
<td>0.032</td>
<td>-0.0015</td>
<td>0.011</td>
<td>0.0089</td>
<td>-0.0003</td>
</tr>
<tr>
<td>(t-stat)</td>
<td>-0.18</td>
<td>-2.25</td>
<td>2.45</td>
<td>-4.8</td>
<td>18.4</td>
<td>1.15</td>
<td>-1.75</td>
</tr>
</tbody>
</table>

Adj. \( R^2 = 5.83\% \)