ESSAYS ON SELL-SIDE ANALYSTS

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ABSTRACT

Broadly, this study focuses on roles of sell-side analysts and examines the determinants and consequences of information discovery and stock timing roles by sell-side analysts. We also re-examine reiterations of prior recommendations by sell-side analysts.

In Chapter 1, the contribution is to document that analysts add value by engaging in discovery of private information and this value addition is greater than that due to interpretation of public news or stock timing. The innovation in this Chapter is to read over 3,700 analyst reports from *Investext* and explicitly identify whether the report contains discovery, interpretation, and/or timing. Analysts discover new information by talking to management sources (personal meetings, investor meetings, and conference calls) or non-management sources (such as channel checks). We find that information discovery is prevalent in 17% of the reports. The cumulative abnormal return (CAR) for reports containing discovery are 6.3% for upgrades and -10.6% for downgrades. The CARs are higher for reports containing discovery relative to those containing interpretation or timing. We find that economic determinants predict whether a report will contain discovery. Discovery from management sources is more likely for reports in the pre-Reg FD period and for reports by optimistic analysts. Discovery from non-management sources is more likely for reports written by All-Star analysts, and for firms that have high information asymmetry and those that are followed by more analysts.

In Chapter 2, the contribution is to introduce and document a third role that analysts play that is also valuable to investors, which we term “stock timing.”

Specifically, we define a timing report as one where the analyst revises his recommendation but does not revise the Price Target or any of the 23 fundamental drivers of stock price (such as EPS, FCF) tracked by I/B/E/S. Because the analyst maintains the same price target as in his prior report but still revises his recommendation, such timing calls are contrarian valuation calls. Analysts issue timing downgrades (upgrades) in response to price increases (declines) since the release of their prior report on the firm. 30% of all revisions are timing reports, indicating the importance of the timing role played by analysts. If analysts have timing ability, then markets should react to the release of the timing report and we should observe that economic determinants explain the cross-sectional variation in timing ability. We find the 3-day announcement return is over 2% in magnitude, 62% of the reports are winners (have announcement returns that have the correct sign), 10% of the reports are large enough to be considered influential, and 37% of the reports are persistent winners. These results suggest that analysts have timing ability. The ability to time is similar is magnitude to information interpretation but smaller compared to information discovery. We find considerable cross-sectional and time-series variation in timing ability. We find that the probability of issuing a timing report is positively related to the opportunities to time the stock provided by potential mispricing. Conditional on issuing a timing report, the probability of issuing a winner, an influential winner, or a persistent winner is positively related to analyst experience and negatively related to the costs associated with issuing a timing report.

In Chapter 3, we document that recommendation reiterations are not homogeneous and there is a large subset of reiterations that are as much valued by investors as recommendation revisions. We combine Detail History file containing the

measures tracked by I/B/E/S (Price Target, EPS, etc.) and Recommendation file to create the full time series of recommendations (initiations, reiterations, and revisions) made by each analyst for each firm for 14 years from 1999 to 2012. By adopting a modified version of "filling in the holes" method, we find that recommendation reiterations are prevalent, consisting of about 80% of recommendations for our 14-year sample period. Second, market response to recommendation reiterations increases monotonically from Reiteration: Strong Sell to Reiteration: Strong Buy. Third, reiterations coupled with contemporary changes in price targets and/or earning forecasts bring substantial absolute abnormal stock returns to investors. Lastly, when we replicate what Loh and Stulz (2011), we find that the number of reiterations which are influential is more than twice that of recommendation revisions that are influential.

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CHAPTER 1

INFORMATION DISCOVERY BY ANALYSTS

1.1. Introduction

A large literature in finance and accounting documents that sell-side analysts provide value to investors through their research reports.[1] The literature identifies two main ways in which analysts provide value. First, analysts aid in *information discovery*, where they generate new signals regarding firm fundamentals by talking to the management of the firm or its competitors, suppliers etc. Second, analysts aid in *information interpretation*, where they quantify the value implication of information events that affect the firm, such as earnings releases or other firm- and industry-level news. While discovery refers to the analyst generating private or proprietary information, interpretation refers to the analyst reacting to public information. A recent working paper (Daniel, Lee, and Naveen, 2014) proposes a third role for analysts, namely *stock timing*. Here, the analyst discerns that recent stock price movement is not due to a change in firm fundamentals and revises his recommendation to make a contrarian call. For example, following a price run-up, analysts may revise their recommendation downward even though they do not change their estimate of the firm's fundamentals. For brevity, we will henceforth refer to the three roles as discovery, interpretation, and timing.

[1] See Michealy and Womack (2005), Ramnath et al. (2008) and Bradshaw (2011) for recent reviews of this literature.

Our contribution is to provide *direct* evidence on the discovery role of analysts. We read over 3,700 research reports and classify what triggers the report. This novel research design allows us to exactly identify whether the report contains discovery, interpretation, and/or timing. In contrast, prior literature makes assumptions about which of the three roles are performed by the analyst in a given report.

The classification schemes adopted by prior research (Ivkovic and Jegadeesh, 2004; Asquith, Mikhail, and Au, 2005; Chen, Cheng, and Lo, 2010; Livnet and Zhang, 2012) all follow a similar pattern. These papers first identify a set of events (such as earnings) and then assume that reports issued within a window surrounding the event date contain analyst interpretation, while all other reports contain discovery. These papers do not consider timing because the concept of timing was introduced in a recent paper. The papers differ in the set of events and the event windows they consider. For example, Ivkovic and Jegadeesh (2004) consider earnings releases as the only event that analysts respond to and assume that all reports issued in weeks (+1, +6) relative to the earnings release date (excluding days 0 and 1) contain interpretation. Thus all reports issued in weeks (-6, -1) are assumed to contain discovery.[2] This is likely to lead to error in classification because (i) discovery is not limited to the weeks prior to the earnings release; it could happen in the 6 weeks after earnings, and (ii) there are many events other than earnings that analysts react to.

[2] Chen, Cheng, and Lo (2010) follow a similar classification scheme, though their main results assume that reports in days (+2,+6) contain interpretation, while those in days (-6, -2) contain discovery.

Asquith et al. (2005) identify 10 other events and consider all reports that are issued within (-4, +4) window surrounding these events to be interpretive in nature. This research design could also lead to misclassification because, by definition, reports issued on days (-4, -1) relative to an event cannot be in response to that event. Further, even though Asquith et al. read reports like we do, their focus is on coding the "strength of arguments" made by analysts to justify their recommendations. Additionally, they consider only reports issued by All-Star analysts, and are thus likely to overstate the pervasiveness of discovery.[3] Given the differences in research design, it is not surprising that there is no conclusive evidence on the importance of these analyst roles.

Using our data, we find that the misclassification is severe. For example, using the Ivkovic and Jegadeesh (2004) definition, 80% of the reports assumed by them as containing discovery do not, in fact, contain discovery. On the flip side, 16% of the reports assumed by them as containing interpretation contain discovery and 6% contain timing. Overall, as per our analysis, 17% of the reports contain discovery.

We address two broad questions. (i) How do markets react to reports containing discovery by analysts? A part of what we examine here has been addressed in prior work, though our results could differ from that in prior work given our cleaner identification strategy. (ii) What economic determinants predict whether a report contains discovery? This has not been explored in prior work because, given the classification scheme used in other papers, the only predictor of interpretation (and hence

[3] Livnat and Zhang (2012), similar to Asquith et al.(2005), consider a large set of events including 10K, 10Q, and 8K filings, but do not read the reports to identify correctly which report contains discovery.

discovery) is the event date. If we find that economic determinants explain the cross-sectional variation, then it provides further proof that analysts who engage in information discovery have a unique skill.

We test several hypotheses regarding the market reaction to reports containing discovery, in other words, the value of discovery. First, if discovery is valuable, then for reports with discovery, we expect that the market reaction to upgrades of recommendations, price targets, or EPS should be positive and the market reaction to downgrades should be negative. Second, if investors value discovery more than interpretation or timing, they will react more strongly to reports containing discovery relative to other reports. That is, for reports that contain discovery, the market reaction to upgrades will be more positive relative to other reports, and that for downgrades will be more negative. This is because investors will have greater confidence in the views expressed by the analyst if these views are backed by new information. Prior literature has found conflicting evidence on the importance of discovery versus interpretation, possibly because of the limitations in the identification schemes used. Our clean identification will help resolve this conflict. Third, we expect that the market reaction to discovery will be stronger if the discovery is due to information generated by talking to management. This has not been examined in the prior literature.

We also examine how broker, analyst, and firm characteristics affect discovery. We separately examine the determinants of discovery from both management and non-management sources. Section 1 develops our hypotheses.

To test our hypotheses, we assemble our data as follows. Since one of our hypotheses relates to the effect of Reg FD on discovery, we choose 1999 as our pre-Reg FD period (Reg FD was passed in October 2000). We expect that analysts will require some time to establish new non-management sources of information following Reg FD. Additionally, other regulatory events that impacted the analyst industry (such as NASD 2711, NYSE 472, the Sarbanes-Oxley Act, and the Global Research Settlement) were enacted in 2002. We therefore choose 2003 as our post-Reg FD period. We start with all firms on I/B/E/S that are covered by the same broker-analyst pair in both Jan 1999 and Dec 2003. We then group firms into 10 deciles each year based on the level of information asymmetry. We find 229 stocks that fall into the same information asymmetry decile in both years. For this sample of stocks, we download from *Investext* all the reports issued by those analysts who remained with the same broker as of January 1999 and December 2003. By ensuring that the broker-analyst pair and the information asymmetry remain the same across the two time periods, our research design helps isolate the effect of regulatory changes on how analysts discover information. Our final sample consists of 3,757 reports. Section I provides more details on data construction.

We read each report and classify whether the report contains discovery, interpretation, and/or timing. We also identify whether the discovery is based on management or non-management sources. The management sources we identify are personal meetings, conference calls, and investor meetings. Analysts also talk to non-management sources to generate new information. We identify the following non-management sources: survey of customers, discussions with executives in the supply chain (or ‘channel checks’), and contacts in the industry.[4] Table 1-1 provides several examples of reports that have information generated by the analyst using management as well as non-management sources. We estimate the market reaction to analyst reports using the cumulative abnormal returns (CARs) over the window (-1,+1) relative to the release of the analyst report.

Our main findings are consistent with our hypotheses. First, for reports containing discovery, the mean CAR is +6.3% for recommendation upgrades and –10.6% for recommendation downgrades. Second, for upgrades, the CARs for reports containing discovery are 4.0 percentage points higher than for reports containing interpretation and 3.8 percentage points higher than for reports containing timing. For downgrades, the CARs for reports containing discovery are -3.6 percentage points lower than for reports containing interpretation and -7.8 percentage points lower than for reports containing timing. Thus, reports containing discovery elicit a stronger market reaction compared to reports containing interpretation or timing. Third, we find the market reaction to discovery is stronger if the source of the new information is personal meeting with the management (+3.9% for upgrades and –4.0% for downgrades). All our results are robust if we consider revisions to price targets and revisions to EPS forecasts rather than revisions to recommendations.

[4] For example, in an April 2012 report on Apple, Canaccord Genuity noted that "Our monthly channel checks indicated strong sales trends for the iPhone 4S at all three U.S. carriers and strong overall iPhone sales in international markets, with particular strength driven by the iPhone 4S launch at China Telecom (NYSE: CHA) and Unicom (NYSE: CHU).”

Table 1-1

Examples of Reports

I. Information Discovery	
1. Management	A. Personal Meeting • We recently met with top management of HSY. • In meeting with senior management, 1Q03 trends appear to be tracking in-line with our expectations. B. Investor/Analyst Meetings • Today we are attending Motorola Analyst Day in Chicago. • Liberty Media's analyst day reinforced our belief that over the next 6–12 months, Liberty will transform itself from a holding to an operating company. C. Conference Calls • During the conference call, CMS indicated it anticipated 500 MW of peak. • Post earnings, Motorola held a conference call to discuss its Q1/03 results.
2. Non-Management	A. Surveys • Based on our internal room rate surveys, we believe that upside in the first quarter can exceed $0.30. • Based on results of our 2004 Health Benefit Survey, customers do not perceive CIGNA as bad, leading us to revise upward our estimate of enrollment loss in 2004 in late September 2003. B. Channel Checks • Our channel checks indicate that unit demand remains strong and customer inventories are low. • Based on our channel checks, we believe that recent demand trends have been solid and we expect Xilinx to at least meet expectations, with the potential for a positive revenue and EPS surprise. C. Industry Contacts/Sources • Our industry sources indicate that used aircraft values may have stabilized somewhat after large declines; • Several manufacturers we've talked to recently have noted that business picked up significantly in March, but while business is still up from the depressed levels of early 1999, it has not continued to accelerate in the second quarter.
II. News Interpretation • Yesterday's announcement by auto parts maker Gentex outlining its intention to produce automotive lighting products with high-brightness LEDs is further proof of the rapidly expanding demand for white light conversion LEDs. • Mid-day 11/19 AMC and Loews Cineplex confirmed they are in talks about a potential merger. • The recently released annual AF&PA capacity survey points to a solid outlook for uncoated free sheet in the United States	
III. Stock Timing • We are raising our rating to a Strong Buy from a Buy after the stock declined approximately 34% from its early May high of $25.94. • We see this recent weakness as a buying opportunity.	

Note. The table provides examples of contents in analysts' reports used when we define and categorize those reports into each source of value that analysts can generate and further into individual component of each source of value. For example, if analysts indicate in their reports that they met with management, then we classify those reports as "Personal Meetings" within sub-category "Management" of "Information Discovery" source of value. Similarly, analyst reports indicating that analysts performed survey are classified as "Surveys" within sub-category "Non-management" of "Information Discovery" source of value. Analysts' reports which are written based on firms' public announcements of events (e.g., earnings release, financing activities, M&A, management turnover, etc) are categorized to "News Interpretation" source of value. Lastly, when analysts recommend to take action, based on recent spike or weakness in stock price, we call those reports as "Stock Timing" source of value.

In terms of the economic determinants of information discovery, we find results generally consistent with our hypotheses. First, we find that information discovery from management sources is more likely in the pre-Reg FD period and if the analyst is more optimistic about the firm than the consensus. Second, we find that information discovery from non-management sources is more likely if the analyst is an All-Star Analyst, covers fewer stocks, has more experience, if the firm has greater information asymmetry, and if the firm is covered by more analysts.

Our contribution is to provide *direct* evidence that analysts add value by engaging in discovery of private information, and that this value addition is greater than that due to analyst interpretation of public news or short term stock timing by the analyst. Our paper answers Bradshaw's (2011) call for academics to perform rigorous "content analysis" of analyst reports to shed light on what analysts actually do in terms of adding value.

1.2. Hypotheses Development

In this section, we develop our hypotheses.

1.2.1. Hypotheses on Market Reaction to Discovery

If information discovery by analysts is important, we would expect this to be reflected in positive market reaction to reports containing discovery. Specifically, we have three predictions regarding the strength of market reaction to reports containing discovery. (i) For reports containing discovery, the market reaction to upgrades should be positive and the market reaction to downgrades should be negative. (ii) If investors value discovery more than interpretation or timing, we expect that relative to other reports, reports containing discovery will have a more positive market reaction for upgrades and a more negative reaction for downgrades. (iii) We expect that the market reaction to be stronger if the analyst discovery arises out of personal meeting with the management. The Introduction develops the rationale for our hypotheses, and we do not duplicate this here.

1.2.2. Hypotheses on Economic Determinants of Discovery

Acquiring information is costly to the analyst in terms of time and resources. There are benefits, however, in terms of obtaining more precise signals regarding firms' financials. We separately examine discovery from management sources and that from non-management sources. We do this because access to management is extremely important to analysts in terms of their ability to make reliable forecasts (Chen and Matsumoto, 2006; Brown et al., 2013). Information generated from management sources—from personal meetings in particular—is presumably more reliable, and therefore, more valuable than information generated from non-management sources.

We expect that discovery from management sources is more likely in the pre-Reg FD period because firms were free to give price-sensitive information to their favored analysts. In terms of broker characteristics, we expect reports from more prestigious brokers to contain discovery. Prestigious brokers may demand higher quality of reports, and hence analysts working for such brokers may have more incentives to engage in information discovery from both management as well as non-management sources. Also, prestigious brokers may have more resources to organize events such as investor conferences, conduct surveys, and do channel checks, thus facilitating discovery. On the other hand, prestigious brokers employ many analysts who cover a majority of the firms and industries. Thus, these analysts tap into the expertise of their colleagues who themselves engage in discovery in the firms they cover. For example, a steel analyst could use the information obtained by an iron-ore mining analyst at the same brokerage. Thus, we predict that analysts from prestigious brokers will have more discovery from management sources. It is not clear, however, whether these analysts will have more or less discovery from non-management sources.

In terms of analyst characteristics, we expect optimistic analysts, All-Star analysts, and experienced analysts will more likely engage in discovery, while busy analysts will be less likely to engage in discovery. Analysts who are optimistic in their forecasts for a firm will more likely receive favorable treatment from that firm's management (Francis and Philbrick, 1993; Chen and Matsumoto, 2006). Hence, reports from such analysts will more likely contain discovery from management sources. Optimism, however, should not have any effect on discovery from non-management sources. We expect All-Star analysts to engage in discovery from non-management sources rather than management sources. This is because while investors value All-Star analysts for their accuracy, firm management values optimism rather than accuracy. Thus, All-Star analysts need not have a comparative advantage over non-All-Star analysts with regard to management sources. Moreover, All-Star analysts are more likely to command greater resources from their employers and hence are able to engage in greater discovery from non-management sources. We expect experienced analysts—those with greater firm-specific and industry-specific knowledge—will have developed the network of contacts necessary to engage in discovery from both management and non-management sources. On the other hand, experienced analysts might believe they know everything there is to know about the firm and hence may not engage in costly discovery. Thus, it is not clear what the net impact would be. We expect busy analysts will not have the time required to engage in time-consuming surveys and channel checks and hence will be less likely to discover new information from non-management sources. Regardless of busyness, however, we expect that analysts will be willing to talk to management every chance they get due to the high quality of information they can get from the management.

In terms of firm characteristics, we expect analysts to engage in discovery in firms with greater information asymmetry and in firms covered by more analysts. In firms with greater information asymmetry, an analyst could step in and provide better signals of firm fundamentals to the investors by engaging in discovery. Similarly, when there are more analysts covering a firm, an analyst may be more likely to engage in discovery to differentiate his report from that of other analysts to attract more brokerage business.

1.3. Data and Methodology

1.3.1. Sample Selection

We first identify the set of stocks covered by at least one analyst who covered it in the 1st quarter of 1999 and in the 4th quarter of 2003. We remove analysts coded as anonymous by I/B/E/S since it is not possible to track their forecast revisions. We identify 3,616 unique firm-analyst pairs, which exist in both periods using the unique stock and analyst identifiers. There are 1,511 unique firms and 749 unique analysts. Each year, we sort these 1,511 unique firms into 10 deciles, based on their level of information asymmetry, measured using dispersion of EPS forecasts.[5] We then choose firms which belong to the same decile in both years. This leaves us with 582 unique firm-analyst pairs, consisting of 229 unique firms and 357 unique analysts. For these firm-analyst pairs identified using I/B/E/S, we download from *Investext* all analyst reports published through the entire year, both in 1999 and in 2003. We download all reports issued by the analyst to ensure that we get an accurate sense for the frequency of discovery, interpretation, and timing for each firm covered.

1.3.2. Data Matching Between I/B/E/S and Investext

There are two differences between *Investext* and I/B/E/S databases: (i) the source of reports and (ii) the reports that are included. According to I/B/E/S representatives, I/B/E/S captures estimate information from *Investext* as well as from direct feeds from brokers. Thus, the coverage of brokers is larger in I/B/E/S compared to *Investext*. Even though *Investext* provides the most recent investment research reports authored by top analysts from more than 800 brokerage houses, investment banks, and consulting firms worldwide, some brokers do not contribute their analyst reports to *Investext* whereas they provide them to I/B/E/S. In such cases, we cannot locate reports written by analysts who

[5] Dispersion of EPS for a firm is obtained by dividing the standard deviation of EPS forecasts by the absolute value of the mean EPS forecast of all analysts following that firm. I/B/E/S provides mean and standard deviation of annual EPS forecasts for multiple fiscal years as well as quarterly and semi-annual EPS forecasts. As in Garfinkel (2009), we use annual EPS forecasts for the current fiscal year because these tend to be more accurate than EPS forecasts for later years. Also, I/B/E/S provides mean and standard deviation of EPS forecasts for the current fiscal year at a monthly frequency; we use the annual EPS forecasts as of January for 1999 and October for 2003 to compute the dispersion of EPS.

belong to such brokers. Because of this difference, the actual number of firm-analyst pairs we can identify from *Investext* (=365) is different from the firm-analysts we initially identify from I/B/E/S (=582).

Both databases also employ different internal policies in terms of keeping data in their database. I/B/E/S kept track of 17 measures (such as EPS, Revenue etc.) in 1999 and 22 measures in 2003. If a report does not contain a revision to any of these measures tracked by I/B/E/S, then that report is not kept as a separate record by I/B/E/S. The original record for that report is retained and only the review date (REVDATS) for all the I/B/E/S measures are updated to make them current. If an analyst report contains at least one change in the I/B/E/S measures, only then a new record is entered in the database with a new announcement date (ANNDATS). In contrast, *Investext* keeps all the reports issued by analysts regardless of whether or not the analysts revised their measures. Thus, for these 365 analyst-firm pairs, we are able to download 3,757 reports from Investext. Overall, we download 3,757 reports from 241 analysts issued on 176 firms from *Investext*.[6]

1.3.3. Classification of Reason for Release of New Report

After downloading the reports from *Investext* as described above, we read each report and manually code the main reason behind the release of the report. Then we

[6] We do not download analyst reports from *Investext* that are issued in the form of Morning Meeting Notes (MMN) because MMNs are mostly duplicates to full research reports that follow shortly. The MMN collection began as a subset of content from First Call Notes contributors. MMNs were geared toward real-time research users and were meant to provide a quick update of the analyst's opinion, typically followed by estimates changes or a full research report. Back in the early to mid-1990's, MMNs had very high value content. Over time, brokers moved onto full research reports and began to discontinue their MMNs as they were costly and duplicative. By 2007, the volume of MMNs had dwindled so much that *Investext* decided that MMNs were no longer a viable offering.

classify the justifications used by analysts into three categories: Discovery, Interpretation, and Timing. We classify a report as having "Discovery" if it contains private information generated by the the analyst by talking to the firm's management (either in personal meetings or in the context of conference calls or investor meetings) or non-management sources (supply chain or to other industry sources). We classify a report as containing "Interpretation" by the analyst if the report is in response to public corporate events such as earnings release/guidance, press/8-K release, financing through equity or debt issuance, management turnover, macro/industry updates. Last, we classify a report as "Timing" if the analyst explicitly recommends buying the stock citing a recent pull-back in price or selling the stock following a recent surge in price as justification for his or her recommendation.

Table 1-1 provides excerpts from the analyst reports as examples for each type of information source. For example, the analyst report may state that "we recently met with top management of HSY." We would classify these as personal meetings. In addition, the analyst may also interact with management during conference calls and investor meetings. For example, the analyst might note that "we attended Progressive's Investor Day in Cleveland yesterday." Similarly, examples for non-management sources are as follows: "our channel checks indicate that unit demand remains strong and customer inventories are low" and "our industry sources indicate that used aircraft values may have stabilized somewhat after large declines." Finally, we provide examples of interpretation ("the recently released annual AF&PA capacity survey points to a solid outlook for uncoated free sheet in the United States”) and timing (“we see this recent weakness as a buying opportunity”).

1.4. Results

1.4.1. Prevalence of New Information in Analyst Reports

We first document the prevalence of discovery in analyst reports. Table 1-2 presents the results. We find that 17% of reports contain new information, 6% contain timing, and the large majority of reports (89%) contain information interpretation. The total of discovery plus timing plus interpretation is more than 100% because these are not mutually exclusive; for example, analyst reports may contain interpretation as well as timing. Discovery is largely from management sources: of the reports containing discovery, 78% (=498/639) are due to management sources.

Examining discovery across the pre- and post-Reg FD periods reveals that analysts issued 889 more reports (=2,323–1,434) in the post-Reg FD period, but this is almost entirely due to increase in interpretive reports by 823 (=2,083–1,260). The number of timing reports remains roughly the same in both periods (116 vs. 113). The number of discovery reports has gone up from 274 to 365. We compare the number of reports across the two time periods rather than the percentage of reports that constitute discovery, interpretation, and timing because there were far more interpretive reports made in the post-Reg FD period and interpretive reports might require less effort.

For example, Amazon announced the launch of a smartphone on the afternoon of 6/19/2014 and analysts issued reports by the same evening in response to this news.

Table 1-2

Incidence of Discovery, Interpretation, and Timing in Analyst Reports

Year	Total		1999	2003
I. Information Discovery	639	17.0%	274	365
1. Management	498	13.3%	227	271
A. Personal Meetings	152	4.1%	88	64
B. Investor Meetings/Conference Calls	346	9.2%	139	207
2. Non-Management	141	3.8%	47	94
II. News Interpretation	3,343	89.0%	1,260	2,083
III. Stock Timing	229	6.1%	116	113
Total	3,757		1,434	2,323

Note..The table reports the number and frequency of reports that contain information related to each source of value that analysts can generate. Each source of value is also broken down further into individual component within each source. Total number of Investext Reports is not the same as summation of report in each source (I+II+III) of value because some reports are classified to multiple sources. For example, if analysts indicate in the reports that they had opportunities of having personal meetings with management after firms' M&A announcements, then their reports are classified under both "Information Discovery: Management (Personal Meetings)" and "News Interpretation."

Clearly, such interpretive reports would take less time relative to reports containing discovery, which involve surveys and channel checks. Another reason we can focus on the number of reports (rather than the percentage) is because we only examine reports by the same analyst covering the same firm in both years. Thus, we are able to infer that, in the post-Reg FD world, the analyst has more than doubled his efforts to obtain information from non-management sources (94 vs. 47). This may be because preferential information from management might have been curtailed post-Reg FD. We see that the analyst is less dependent on personal meetings with management (64 vs. 88) in the post-Reg FD period. It also seems that management responded to the regulation by participating in investor meeting and hosting conference calls (207 vs. 139). Overall, there seems to be some substitution away from personal meetings towards non-management sources of discovery.

1.4.2. Announcement Returns

1.4.2.1. Is Discovery More Valued Than Other Sources?

Table 1-3 shows descriptive statistics (panel A) and correlation (panel B) of key variables in our study. We estimate the market model over the window [-300, -46] using the CRSP equal-weighted market return as the benchmark. The cumulative abnormal return (CAR) over the event window [-1,1] is our proxy for announcement return. Table 1-4 presents the OLS regression results of announcement returns to the release of the analyst report.

We estimate the following regression to test our first two hypotheses:

$$\text{CAR} = b_0 + b_1\,\text{Up} + b_2\,\text{Down} + b_3\,\text{Up}\times\text{Discovery} + b_4\,\text{Down}\times\text{Discovery} +$$
$$b_5\text{Up}\times\text{Timing} + b_6\text{Down}\times\text{Timing} + b_7\text{Discovery} + b_8\text{Timing} + \text{Controls} + \varepsilon$$

The *Up* and *Down* indicator variables are defined differently depending on the specification. *Up* dummy takes the value 1 if the report contains an upgrade in recommendation (Column 1), upgrade in Price Target (Column 2), or upgrade in EPS (Column 3). *Down* dummy takes the value 1 if report contains a downgrade in recommendation (Column 1), downgrade in Price Target (Column 2), or downgrade in EPS (Column 3). *Discovery* takes the value 1 if an analyst report contains new information obtained either from management or from non-management sources. *Timing* takes the value 1 if an analyst issues a report in response to stock price movements that have occurred since the release of his previous report.

Table 1-3

Descriptive Statistics of Key Variables

Panel A. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
New Information	0.16	0.37	0.0	1.0
Personal Meetings	0.04	0.20	0.0	1.0
Non-Management	0.04	0.19	0.0	1.0
All-Star Analyst	1.1	1.5	0.0	4.0
Years Covering a Firm	5.9	4.3	0.0	19.8
Years Covering an Industry	9.0	5.1	0.3	21.6
Number of Firms Covered	19.0	9.9	5.0	66.0
Number of Industries Covered	4.0	2.2	1.0	10.0
Prestigious Broker (Dummy)	0.5	0.5	0.0	1.0
Firm-specific optimism	0.4	0.4	0.0	1.0
Information Asymmetry (Dummy)	0.6	0.5	0.0	1.0
Pre Reg-FD (Dummy)	0.6	0.5	0.0	1.0
Analysts Following	15.0	7.9	1.0	35.0

Note. Panel A presents descriptive statistics of variables of our interest used in our tests. New Information has a value of 1 if an analyst report contains new information obtained either from personal meeting with managements or from non-management sources (i.e., survey of customer, channel checks or industry contacts/sources). Personal Meetings has a value of 1 if an analyst report contains new information obtained from personal meetings with managements only and Non-Management has a value of 1 if an analyst report contains new information obtained from non-management sources only. All Star Analyst has values ranging from 1 (for runner up) to 4 (first all-star) at the time of reports. When an analyst issued a report between January and October of year *t*, then his rank of previous year *t-1* was assigned while if a report was published in November and December of year *t*, then rank of current year *t* was assigned. Years Covering a Firm represents the number of years since an analyst began covering a firm. Years Covering an Industry represents the number of years since an analyst began covering an industry where a stock the analyst covers at the time of report. Number of Firms (Industries) Covered is the number of firms (industries) an analyst is identified in I/B/E/S to issue earnings forecasts, target prices or recommendations in each sample year. Prestigious Broker has a value of 1 if a report is issued by an analyst who works for the top 10 rated brokerage houses by institutional investors (Hong and Kubik, 2003) at the time of report. Firm-specific Optimism is an average score of indicators (which have a value of 1 when a recommendation revision is above the most recent consensus recommendation) across all recommendation made on a given firm an analyst follows during two (2) years prior to each sample year. Information Asymmetry has a value of 1 if a report was issued to a firm which belongs to upper five (5) dispersion groups in terms of dispersion of annual EPS forecasts. Dispersion of each firm is obtained by dividing standard deviation of annual EPS forecasts by absolute value of mean annual EPS forecasts of all analysts following each firm. Pre Reg-FD has a value of 1 if an analyst report issued in 1999. Analysts Following is the number of annual earnings forecasts used by IBES to calculate monthly earnings consensus. All continuous variables are winsorized at upper and lower 1% to control for extreme values. Panel B reports the correlation of those variables with *** representing for $p<0.01$, ** for $p<0.05$ and * for $p<0.1$.

Panel B. Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	New Information	1												
(2)	Personal Meetings	0.46***	1											
(3)	Non-Management	0.45***	-0.01	1										
(4)	All-Star Analyst	0.04**	-0.01	0.03**	1									
(5)	Years Covering a Firm	-0.04**	-0.01	-0.06***	0.15***	1								
(6)	Years Covering an Industry	-0.02	-0.01	-0.01	0.04**	0.18***	1							
(7)	Number of Firms Covered	-0.03*	-0.06***	-0.01	0.19***	-0.01	0.05***	1						
(8)	Number of Industries Covered	-0.08***	-0.06***	-0.06***	0.20***	0.08***	-0.00	0.65***	1					
(9)	Prestigious Broker (Dummy)	0.02	-0.01	-0.00	0.54***	-0.06***	-0.15***	0.28***	0.24***	1				
(10)	Firm-specific optimism	0.01	0.04**	0.02	-0.11***	-0.06***	0.00	0.02	-0.02	-0.12***	1			
(11)	Information Asymmetry (Dummy)	-0.00	-0.03*	0.04**	-0.06***	-0.14***	-0.06***	-0.09***	0.03**	-0.00	0.00	1		
(12)	Pre Reg-FD (Dummy)	0.04**	0.08***	-0.02	-0.15***	0.09***	0.16***	-0.35***	-0.36***	-0.32***	0.16***	-0.04**	1	
(13)	Analysts Following	0.08***	-0.00	0.03*	0.02	-0.21***	-0.31***	0.11***	0.03*	0.10***	-0.06***	0.08***	0.07***	1

Table 1-4

Stock Market Reaction to Information Discovery

Panel A

		Recommendation	Price Target	EPS
		(1)	(2)	(3)
Intercept	b_0	0.211	0.197	0.387
		(0.6)	(0.6)	(1.1)
Up (Dummy)	b_1	2.740***	1.282***	0.797**
		(3.7)	(3.2)	(2.5)
Down (Dummy)	b_2	-6.555***	-2.593***	-2.203***
		(-4.0)	(-3.7)	(-5.8)
Up × Discovery	b_3	4.190***	2.753***	2.643***
		(3.1)	(3.2)	(3.0)
Down × Discovery	b_4	-3.435*	-4.006**	-1.912**
		(-1.8)	(-2.3)	(-2.1)
Up × Timing	b_5	0.143	-1.291	-0.809
		(0.1)	(-1.3)	(-0.8)
Down × Timing	b_6	4.100**	1.944	1.947*
		(2.3)	(1.1)	(1.8)
Discovery	b_7	-0.150	-0.131	-0.067
		(-0.6)	(-0.5)	(-0.2)
Timing	b_8	0.143	0.346	0.117
		(0.4)	(0.8)	(0.3)
All-Star Analyst		-0.030	-0.007	-0.009
		(-0.4)	(-0.1)	(-0.1)
Price Runup		1.126	-0.143	-0.382
		(1.3)	(-0.2)	(-0.5)
Price Rundown		-4.556***	-3.725***	-3.829***
		(-5.2)	(-4.2)	(-4.3)
Earnings guidance		-4.192***	-4.015***	-3.547***
		(-4.2)	(-4.2)	(-3.7)
Years Covering a Firm		-0.005	-0.005	-0.023
		(-0.2)	(-0.2)	(-0.8)
Years Covering an Industry		-0.003	-0.003	0.012
		(-0.1)	(-0.1)	(0.4)
Number of Firms Covered		-0.014	-0.011	-0.009
		(-1.4)	(-1.1)	(-1.0)
Number of Industries Covered		-0.023	-0.054	-0.045
		(-0.4)	(-1.1)	(-0.9)
Prestigious Broker (Dummy)		0.050	0.033	0.056
		(0.2)	(0.1)	(0.2)
Observations		2,419	2,419	2,419
R-square		0.090	0.078	0.085

Table 1-4

(Continue)

	(1) Recommendation	(2) Price Target	(3) EPS forecast
Tests of Hypothesis 1			
Upgrades: CARs to Discovery ($b_0 + b_1 + b_3 + b_7 + \sum \hat{\beta}\overline{Control}$)	6.3***	3.3***	3.1***
Downgrades: CARs to Discovery ($b_0 + b_2 + b_4 + b_7 + \sum \hat{\beta}\overline{Control}$)	-10.6***	-7.3***	-4.5***
Tests of Hypothesis 2			
Upgrades: CARs to Discovery Minus CARs to Interpretation ($b_3 + b_7$)	4.0***	2.6***	2.6***
Downgrades: CARs to Discovery Minus CARs to Interpretation ($b_4 + b_7$)	-3.6*	-4.1**	-2.0**
Upgrades: CARs to Discovery Minus CARs to Timing ($b_3 + b_7$) – ($b_5 + b_8$)	3.8*	3.6***	3.3***
Downgrades: CARs to Discovery Minus CARs to Timing ($b_4 + b_7$) – ($b_6 + b_8$)	-7.8***	-6.4***	-4.0***

Note. Panel A reports the OLS regression results where the dependent variable is the announcement return to the release of the analyst report. The announcement return is given by CAR[-1,1], which are obtained from Eventus where we estimate a market model with CRSP equal-weighted market return as the benchmark. We exclude analyst reports released in the [-2,+2] window surrounding the firms' quarterly earnings announcements. The *Up* and *Down* indicator variables are defined differently depending on the specification. *Up* dummy takes the value 1 if the report contains an upgrade in recommendation (Column 1), upgrade in Price Target (Column 2), or upgrade in EPS (Column 3). *Down* dummy takes the value 1 if report contains a downgrade in recommendation (Column 1), downgrade in Price Target (Column 2), or downgrade in EPS (Column 3). *Discovery* takes the value 1 if an analyst report contains new information obtained either from management or from non-management sources. *Timing* takes the value 1 if an analyst issues a report in response to stock price movements that have occurred since the release of his previous report. In Panel B, we replace *Up* and *Down* indicator variables with the change in recommendation (or price target or EPS, depending on the specification) compared to those measures indicated in the prior report by the same analyst. b0, b1, etc. are the coefficients of the regressions from the corresponding tables, $\sum \hat{\beta}\ \overline{Control}$ is a summation of the regression coefficients multiplied by mean value of each control variable used in the regressions, and σ_m is the standard deviation of the relevant change in measure (standard deviation of recommendation level, price target, and EPS respectively). For the definitions of variables used here, please refer to table 1-3. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 1-4

(Continue)

Panel B

		Measure =		
		Recommendation	Price Target	EPS
		(1)	(2)	(3)
Intercept	b_0	0.132	0.135	0.296
		(0.4)	(0.4)	(0.8)
Discovery	b_1	-0.073	-0.328	0.196
		(-0.3)	(-1.2)	(0.8)
Timing	b_2	0.210	0.326	0.299
		(0.5)	(0.8)	(0.8)
Change in Measure	b_3	4.363***	0.135***	3.434**
		(4.7)	(3.5)	(2.1)
Change in Measure × Discovery	b_4	2.628**	0.237***	1.999**
		(2.4)	(4.1)	(2.0)
Change in Measure × Timing	b_5	-1.499	-0.009	-0.882*
		(-1.4)	(-0.2)	(-1.7)
All-Star Analyst		-0.022	0.022	-0.024
		(-0.3)	(0.3)	(-0.3)
Price Runup		1.489*	-0.367	-0.234
		(1.8)	(-0.5)	(-0.3)
Price Rundown		-4.459***	-3.690***	-3.868***
		(-5.2)	(-4.3)	(-4.5)
Earnings guidance		-4.229***	-4.231***	-4.079***
		(-4.2)	(-4.3)	(-4.2)
Years Covering a Firm		-0.005	-0.002	-0.015
		(-0.2)	(-0.1)	(-0.5)
Years Covering an Industry		-0.002	-0.003	-0.002
		(-0.1)	(-0.1)	(-0.1)
Number of Firms Covered		-0.014	-0.012	-0.011
		(-1.5)	(-1.2)	(-1.2)
Number of Industries Covered		-0.024	-0.046	-0.053
		(-0.5)	(-0.9)	(-1.1)
Prestigious Broker (Dummy)		0.031	-0.087	0.031
		(0.1)	(-0.3)	(0.1)
Observations		2,419	2,419	2,419
R-square		0.090	0.078	0.085
Tests of Hypothesis 1				
CARs to Discovery: $(b_0 + b_1) + (b_3 + b_4)\sigma_m + \sum \hat{\beta}\overline{Control}$		1.3***	1.5***	1.5**
Tests of Hypothesis 2				
CARs to Discovery Minus CARs to Interpretation $b_1 + b_4\,\sigma_m$		0.7*	1.5***	0.9
CARs to Discovery Minus CARs to Timing $(b_1 - b_2) + (b_4 - b_5)\,\sigma_m$		0.9	1.6**	1.7*

Our first hypothesis is that for reports containing discovery, CARs will be positive for upgrades and negative for upgrades. For upgrades containing discovery, the CAR is given by ($b_0 + b_1 + b_3 + b_7 + \sum \hat{b}\,\overline{Control}$) and for downgrades containing discovery, the CAR is given by ($b_0 + b_2 + b_4 + b_7 + \sum \hat{b}\,\overline{Control}$). The panel at the bottom of the table 1-4 gives these results. Column 1 shows that the predicted CARs to upgrades is 6.3% and to downgrades is -10.6%, which are statistically and economically significant.

Our second hypothesis is that if the market views reports containing discovery to be more valuable than reports containing interpretation and timing, then the market reaction to such reports should be stronger. The difference in CAR between discovery and interpretation is given by ($b_3 + b_7$) for upgrades and ($b_4 + b_7$) for downgrades. The difference in CAR between discovery and timing is given by (($b_3 + b_7$) – ($b_5 + b_8$)) for upgrades and (($b_4 + b_7$) – ($b_6 + b_8$)) for downgrades. As can be seen from the table 1-4 (bottom panel), the CARs to reports containing discovery are stronger than the CARs to reports containing interpretation: 4.0% more positive for upgrades and 3.6% points more negative for downgrades. Similarly, the CARs to reports containing discovery are stronger than the CARs to reports containing timing: 3.8% more positive for upgrades and 7.83% points more negative for downgrades. All the differences are statistically and economically significant, consistent with hypothesis 2.

In Column 2, we examine CARs to upgrades and downgrades to Price Targets rather than upgrades and downgrades to recommendations. In Column 3 we examine CARs to upgrades and downgrades to EPS. In both cases, we find qualitatively similar results to those in Column 1.

In Panel B, we replace *Up* and *Down* indicator variables with the continuous variable. That is, depending on the specification, we use change in recommendation levels (Column 1), change in price target (Column 2), and change in EPS (Column 3). The changes are relative to the measures indicated in the prior report by the same analyst. Specifically, we estimate the following regression:

CAR = b_0 + b_1 Discovery + b_2 Timing + b_3 Change in Measure +

b_4 Change in Measure×Discovery + b_5 Change in Measure×Timing +

Controls + ε

Because the specification includes continuous variables (rather than dummy variables as in the earlier specification), we test our hypotheses for a one standard deviation change in the measure. For reports containing discovery, the predicted CAR for a one standard deviation increase in the measure is given by: b_0 + b_1 + (b_3 + b_4)×Standard Deviation of the Measure+$\sum \hat{b}\,\overline{Control}$. As per hypothesis 1, this should be positive. We find this to be 1.3% (see bottom of Panel B). Moreover, as per hypothesis 2, reports containing discovery will be more valuable than reports containing interpretation (that is, b_1 + b_4×Standard Deviation of the Measure should be positive) and reports containing discovery will be more valuable than reports containing timing (that is, (b_1 – b_2) + (b_4 – b_5)×Standard Deviation of the Measure should be positive). We find these numbers to be 0.7% and 0.9% respectively (see bottom of Panel B).

Column 2 reports the results for CARs to changes in Price Targets rather than changes to recommendations, and Column 3 reports the results for CARs to changes in EPS. Again, the results are qualitatively similar to those in Column 1.

Overall, the results in Table 2-4 strongly support hypotheses 1 and 2. Investors value discovery both in absolute terms and relative to interpretation or timing.

1.4.2.2. Is Discovery from Personal Meetings with Management More Valued?

As per hypothesis 3, we expect that CARs to reports containing discovery will be higher if the source of discovery is management. Even within management sources, analysts are more likely to discover unique information during their personal meetings with management, rather than during conference calls or analyst days where there are multiple analysts competing for management time. We therefore repeat the regressions in Table 1-5, but we separate out the Discovery from Personal Meetings and Discovery from all sources other than Personal Meetings. We estimate the following regression:

$$\begin{aligned}
CAR = {} & b_0 + b_1\,Up + b_2\,Down + b_3\,Up \times Discovery\ (Personal\ Meetings) \\
& + b_4\,Up \times Discovery\ (Other\ Sources) + b_5\,Down \times Discovery\ (Personal\ Meetings) \\
& + b_6\,Down \times Discovery\ (Other\ Sources) + b_7\,Up \times Timing + b_8\,Down \times Timing \\
& + b_9\,Discovery\ (Personal\ Meetings) + b_{10} Discovery\ (Other\ Sources) + b_{11} Timing \\
& + Controls + \varepsilon
\end{aligned}$$

The predicted CAR for an upgrade report containing Discovery from Personal Meetings is given by $b_0 + b_1 + b_3 + b_9 + \sum \hat{b}\,\overline{Control}$. Similarly, the predicted CAR for a downgrade report containing discovery from personal meetings is given by $b_0 + b_2 + b_5 + b_9 + \sum \hat{b}\,\overline{Control}$. For upgrades containing discovery, the difference between CARs for discovery from Personal Meetings and discovery from Other Sources is given by $(b_3 + b_9) - (b_4 + b_{10})$.

Table 1-5

Stock Market Reaction to Information Discovery: Personal Meetings versus Other Sources

		Recommendation	Price Target	EPS
		(1)	(2)	(3)
Intercept	b_0	0.194	0.202	0.389
		(0.6)	(0.6)	(1.1)
Up (Dummy)	b_1	2.744***	1.289***	0.795**
		(3.7)	(3.2)	(2.4)
Down (Dummy)	b_2	-6.630***	-2.592***	-2.203***
		(-4.0)	(-3.6)	(-5.8)
Up × Discovery (Personal Meetings)	b_3	7.271**	1.127	1.400
		(2.3)	(0.7)	(0.8)
Up × Discovery (Other Sources)	b_4	3.133**	3.081***	2.948***
		(2.5)	(3.3)	(2.9)
Down × Discovery (Personal Meetings)	b_5	-6.651***	-3.420	-1.767
		(-7.6)	(-1.6)	(-1.3)
Down × Discovery (Other Sources)	b_6	-2.968	-4.094**	-1.956*
		(-1.4)	(-2.1)	(-1.8)
Up × Timing	b_7	0.140	-1.323	-0.803
		(0.1)	(-1.4)	(-0.8)
Down × Timing	b_8	4.102**	1.935	1.929*
		(2.2)	(1.1)	(1.8)
Discovery (Personal Meetings)	b_9	-0.357	0.008	0.052
		(-0.9)	(0.0)	(0.1)
Discovery (Other Sources)	b_{10}	-0.066	-0.193	-0.120
		(-0.2)	(-0.7)	(-0.4)
Timing	b_{11}	0.146	0.341	0.115
		(0.4)	(0.8)	(0.2)
Control Variables (as in Table 2-4)		Yes	Yes	Yes
Observations		2,419	2,419	2,419
R-square		0.091	0.078	0.086
Tests of Hypothesis 3				
Upgrades: CARs to Discovery (Personal Meeting) $(b_0 + b_1 + b_3 + b_9 + \sum \hat{\beta}\overline{Control})$		9.2***	1.9	2.0
Downgrades: CARs to Discovery (Personal Meeting) $(b_0 + b_2 + b_5 + b_9 + \sum \hat{\beta}\overline{Control})$		-14.1***	-6.6***	-4.2***
Upgrades: CARs to Discovery (Personal Meetings) – CARs to Discovery (Other Sources) $(b_3 + b_9) – (b_4 + b_{10})$		3.9	-1.8	-1.4
Downgrades: CARs to Discovery (Personal Meetings) – CARs to Discovery (Other Sources) $(b_5 + b_9) – (b_6 + b_{10})$		-4.0*	0.9	0.4

*Note.*The table reports the OLS regression results where we replicate table 1-4, but this time we separate out discovery from personal meetings and discovery from other discovery sources. b0, b1, etc. are the coefficients of the regressions from the corresponding tables, and $\sum \hat{\beta}\overline{Control}$ is a summation of the regression coefficients multiplied by mean value of each control variable used in the regressions. For the definitions of variables used here, please refer to Table 1-3. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Finally, for downgrades containing discovery, the difference between CARs for discovery from Personal Meetings and discovery from Other Sources is given by (b_5 + b_9) – (b_6 + b_{10}). Table 1-5 presents the results. The bottom panel of the Table 1-5 presents the tests of our hypotheses. Consistent with our hypothesis, we find that the predicted CARs for reports containing an upgrade based on discovery from personal meetings are significantly positive. Similarly the predicted CARs for reports containing downgrades based on discovery from Personal Meetings are significantly negative. Moreover, discovery from personal meetings has a bigger impact on CAR relative to discovery from other sources.

Overall, the results to this point show that Discovery by analysts is valued by investors, and is more valuable than interpretation and timing. Moreover, Discovery from management sources, particularly from personal meetings, is more valued by investors relative to discovery from other sources.

1.4.3. Economic Determinants of Information Discovery

Our second line of enquiry examines the characteristics of brokers, analysts, and firms associated with reports that contain discovery. Section II describes our hypotheses, which we test in this section.

1.4.3.1. Dependent Variables

We identify personal meetings with management, investor meetings, and conference calls as potential sources of information from management. Incremental discovery by the analyst, however, is unlikely to be the same across all three sources. Solomon and Soltes (2012) point to survey evidence suggesting that 97% of CEOs of publicly traded firms meet privately with investors. Using data on all personal meetings between top management and investors for one NYSE firm, they find that private meetings with management help investors to make informed trading decisions. Similarly, Brown et al. (2013) find that such one-on-one personal meetings with the management are highly sought after. Participating in investor meetings and conference calls, on the other hand, confer less advantages to the analyst. For example, Mayew et al. (2012) find that even analysts who ask questions to management during conference calls receive no information advantage. Additionally, Green et al. (2013) argue that only analysts associated with brokers who host the investor meeting get an informational advantage. Thus, for our base-case analysis, we use only personal meetings as a source of information from management. We define an indicator variable *Personal Meetings*, which equals 1 if the report mentions a personal meeting with the management and equals 0 otherwise. We then estimate logistic regressions using *Personal Meetings* as the dependent variable. We also consider an alternative dependent variable, *Management*, which equals 1 if the report mentions any interaction with the management and equals 0 otherwise. We expect all our results to be stronger with *Personal Meetings* rather than with *Management*.

To test our hypothesis regarding information discovery using non-management sources, we define an indicator variable *Non-Management*, which equals 1 if the report mentions discovery through non-management sources (such as surveys, channel checks, industry contacts), and equals 0 otherwise. Finally, we also use the indicator variable *Discovery*, defined earlier.

1.4.3.2. Independent Variables

To test our hypothesis about the impact of Reg FD, we form an indicator variable, *Pre-Reg FD*, which equals 1 if the year is 1999, and equals 0 if the year is 2003. To test our hypothesis relating to broker characteristics, we use an indicator variable, *Prestigious Broker*, which equals 1 if a report is issued by an analyst who works for the top 10 rated brokerage houses by institutional investors (Hong and Kubik, 2003) at the time of report

To test the hypotheses relating to analyst characteristics, we define the following variables. (i) *Firm-specific Optimism*: this captures the distance of the analyst's forecast from the consensus. First, we assign the value 1 when an analyst's recommendation is above the most recent consensus recommendation and 0 otherwise. We then average this variable across all recommendations made on an individual firm by the analyst in the two years prior to the sample year. (ii) *All Star Analyst*: this equals 1 if the analyst is an All-Star analyst as rated by Institutional Investor, and equals 0 otherwise (see Clarke et al. 2007) for details on this variable) (iii): *Years covering Firm* and *Years covering Industry*: these two variables are meant to capture analyst experience in covering the firm and the industry to which the firm belongs. (iv) *Number of Firms Covered* and *Number of Industries Covered*: these two variables are meant to capture analyst busyness.

To test the hypotheses relating to firm characteristics, we define the following variables. (i) *Information Asymmetry*: this is an indicator variable that equals 1 if the firm covered by the analyst report is above median in terms of dispersion of annual EPS forecasts. (ii) *Analysts Following*: this is the number of annual earnings forecasts used by IBES to calculate monthly earnings consensus.

1.4.3.3. Logistic Results

Table 1-6 presents the logistic results. The Table 1-6 also presents the predicted sign for each of the variables based on our hypotheses. We do not have any unique predictions for the determinants of *Discovery*. Because *Discovery* is the sum of *Management* and *Non-Management*, we give the predicted sign only when the determinants have the same predicted effect on both *Management* and *Non-Management*. For example, the predicted effect of information asymmetry is positive for both *Management* and *Non-Management*, and therefore, the predicted effect on *Discovery* would have to be positive. We, nevertheless, present the results for *Discovery* for the sake of completeness.

For column 1, the dependent variable is *Personal Meetings*. Because our hypotheses are based on whether there will be discovery in a report relative to interpretation and timing, we exclude from the regressions observations where there is discovery from sources other than personal meetings with the management.

The results are generally consistent with our expectations. The coefficient on *Pre-Reg FD* is positive, implying that, pre-Reg FD, analysts were more likely to meet with management to obtain information. Analysts who are optimistic about the prospects of the firms are more likely to engage in discovery through personal meetings with management. This is consistent with several studies that show that management favors analysts who provide more optimistic forecasts (for example: Chen and Matsumoto, 2006). Indeed the Brown et al. (2013) survey of analysts state that a big concern for analysts is being “frozen out” by the management. Analyst experience (number of years covering firm and industry) is not related to information discovery.

Table 1-6

Break-up of New Information into Different Sources of Information

	Predicted Sign	Personal Meetings	Predicted Sign	Management	Predicted Sign	Non-Management	Predicted Sign	Discovery
		(1)		(2)		(3)		(4)
Pre Reg-FD	+	0.776***	+	0.219	NA	-0.589*	NA	0.061
		(3.6)		(1.6)		(-1.9)		(0.5)
Prestigious Broker	+	0.448	+	0.156	+/-	-0.604**	NA	0.009
		(1.6)		(1.1)		(-2.4)		(0.1)
Firm-specific Optimism	+	0.403*	+	0.002	NA	0.306	NA	0.109
		(1.7)		(0.0)		(1.1)		(0.8)
All Star Analyst	NA	-0.020	NA	0.073	+	0.272***	NA	0.113***
		(-0.2)		(1.6)		(3.6)		(2.7)
Number of Firms Covered	NA	0.009	NA	0.004	-	-0.008	NA	0.002
		(0.8)		(0.6)		(-0.7)		(0.4)
Number of Industries Covered	NA	-0.089*	NA	-0.006	-	0.008	NA	-0.002
		(-1.9)		(-0.2)		(0.2)		(-0.1)
Years Covering the Firm	+/-	-0.013	+/-	0.017	+/-	0.097**	+/-	0.030*
		(-0.4)		(0.9)		(2.1)		(1.8)
Years Covering the Industry	+/-	-0.021	+/-	-0.031*	+/-	-0.141***	+/-	-0.047***
		(-0.7)		(-1.9)		(-3.8)		(-3.2)
Analysts Following	+	-0.007	+	0.024***	+	0.022*	+	0.024***
		(-0.6)		(3.1)		(1.7)		(3.5)
Information Asymmetry	+	-0.030	+	-0.043	+	0.906***	+	0.095
		(-0.2)		(-0.4)		(3.4)		(0.9)
Constant		-3.273***		-2.337***		-3.453***		-2.104***
		(-8.2)		(-9.1)		(-7.1)		(-8.9)
Observations		2,563		2,824		2,553		2,910
Pseudo R-square		0.0295		0.0117		0.0624		0.0139

Note..The table reports logit regression results where the dependent variable takes various forms of discovery. The dependent variable in column 1 is Personal Meetings, in column 2 is Management, in column 3 is Non-Management, and column 4 is Discovery. For the definitions of variables used here, please refer to Table 1-3. Robust z-statistics is in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

While experience helps build networks that can aid discovery, it could also mean that the analyst has greater knowledge of the firms he is covering and hence has less need to talk to others to obtain information. Given our results, it appears that these two countervailing effects cancel each other out. Analyst competition (proxied by number of analysts following the firm) and information asymmetry are not significantly related to discovery. Overall, our results are consistent with our hypotheses.

In Column 2, we use *Management* as the dependent variable. Therefore, we exclude from the regressions observations where there is discovery from sources other than management. As expected, results are weaker. We do not find any effect of Reg FD and prestigious broker on discovery from management sources. The analyst's industry experience is negatively related to discovery, which is consistent with the idea that the analyst expertise attenuates the dependence on management.

In Column 3, we use *Non-Management* as the dependent variable. We, therefore, exclude observations where there is discovery from management sources. We find that analysts associated with prestigious brokers are less likely to engage in discovery from non-management sources. This is consistent with such analysts acquiring information about the firms and industries they cover from their colleagues who follow related firms in the supply chain. These analysts, therefore, do not have to do external surveys or channel checks because they get the relevant information in-house. We find that, consistent with our hypothesis, All-Star analysts are more likely to discover new information by talking to non-management sources. Contrary to our prediction, we do not find that busy analysts (i.e., analysts who follow a large number of firms and industries) are less likely to engage in discovery from non-management sources. Selfselection could explain this counterintuitive result, wherein only analysts who can handle the workload are given the responsibility of covering more firms and industries. We find that experience has both a positive and negative effect. The years covering the firm is positively related to discovery from non-management sources while years covering the industry is negatively related to discovery from non-management sources. Consistent with our expectations, analysts following is positively related to discovery from non-management sources. It seems that analysts try to stay above the competition by generating new information. Lastly, consistent with our expectations, discovery from non-management sources is more likely in firms with greater information asymmetry. Thus, analysts try to bridge the information gap between management and investors by collecting information from non-management sources.

1.5. Conclusion

A large literature on the role of equity analysts finds that analyst reports are valued by capital market participants. The vast majority of previous studies document that analysts add value through information discovery and through interpretation of public information. But this result is based on assumptions regarding which reports contain discovery and which reports contain interpretation. For example, most of these studies typically assume that reports within a certain time frame (for example, within a week) following certain events (for example, earnings releases) contain interpretation while all other reports contain discovery. In contrast we make no such assumptions. Instead, we read the contents of over 3,700 analyst reports to classify which reports have discovery, interpretation, and/or stock timing. This unique research design allows us to contribute to the analyst literature by providing direct evidence on the value of the discovery role.

We have three main findings. First, we find that about 17% of reports contain new information generated by the analysts. About 13% of reports contain information discovery from management sources (such as personal meetings or conversations with management, conference calls, and analyst meetings) and about 4% contain information discovery from non-management sources (such as surveys, channel checks, talking to industry contacts).

Second, the market reaction to discovery is strongly positive for upgrades (of recommendation levels, target prices, and EPS) and strongly negative for downgrades. Further, this reaction is stronger than that for reports containing discovery than for reports containing timing and interpretation.

Third, in terms of economic determinants, we find that information discovery from management sources is more likely for reports issued in the pre-Reg FD period and for analysts that are more optimistic (those that have a record of issuing more favorable recommendations about the firm). Information discovery from non-management sources is less likely for reports in the pre-Reg FD period, for reports by analysts that are employed by more prestigious brokers. It is more likely for reports by All-Star analysts, when the analyst has more years covering the firm, when the firm has higher information asymmetry and when the firm is followed by more analysts.

Our findings have implications for several strands of research that deal with the role of equity analysts: (i) In terms of consequences to investors, we expect that post-revision drift will be higher for reports that contain more information generation. If an analyst includes new information, then other analysts covering the same stock will, in all likelihood, attempt to verify this information, which generates more reports confirming the original analyst's discovery. This in turn will cause a drift in stock price post-revision. (ii) In terms of consequences to analysts, we expect that analysts that engage in more discovery will make bolder, more timely, more accurate, and more influential forecasts. Additionally, we expect that analysts who engage in more discovery are more likely to exhibit persistent skill, more likely to move up the career ladder to a better-reputation broker, and more likely to become an All-Star analyst.

CHAPTER 2

STOCK TIMING BY ANALYSTS

2.1. Introduction

Revisions in recommendations by sell-side analysts are associated with positive abnormal returns for upgrades and negative abnormal returns for downgrades. Several studies (Ivkovic and Jegadeesh, 2004; Asquith, Mikhail, and Au, 2005; Chen, Cheng, and Lo, 2010) have attempted to answer the specific question: what do analysts do to create this value? These studies document two sources for this value addition. First, the analyst may revise his recommendation after generating new signals regarding firm fundamentals by talking to management, competitors, suppliers, customers, or industry contacts. This is termed as information discovery. Second, the analyst may revise his recommendation following information release (such as earnings, industry data). This is termed as information interpretation. The innovation in our paper is to propose a third source of value addition: we hypothesize that analyst possess what we term as "stock timing" ability. This is the ability to discern that the recent stock price movement is not due to a change in firm fundamentals, and then issue an upgrade if the price has fallen or issue a downgrade if the price has risen.

We define a timing report as one where, in relation to his prior report, the analyst revises his recommendation but does not revise his estimate of fundamental value of the firm (i.e., Price Target) or any of the 23 fundamental drivers of firm value (such as

Revenue, EPS etc.) for any of the 28 future time periods tracked by I/B/E/S.[7] Though an analyst could revise a maximum of 672 (=24×28) I/B/E/S measures, the maximum number of changes made by an analyst in a single report is 414. Because the analyst maintains the same price target as in his prior report, but still revises his recommendation, it must be because the stock price, subsequent to the release of his prior report, has either moved up warranting a downgrade or moved down warranting an upgrade. Thus, we are able to capture the essence of stock timing with our definition. Moreover, one may regard a timing report as a short-term contrarian call rather than a long-term valuation call because, by definition, the analyst is not changing his view on firm fundamentals. Using a methodology described in detail in the next section, we classify all reports as timing, discovery, and interpretation. Any reports that are not obviously identifiable as one of these three groups is classified as "others."

If analysts possess stock timing ability as we hypothesize, then (i) markets should react to the release of the timing reports and (ii) economic determinants should explain the cross-sectional and time-series variation in timing ability. To test these predictions, we combine I/B/E/S data from Detail History file and Recommendation file to create the full time series of recommendations made by each analyst over the period 1999–2012. We first identify all revisions and, within this group, we then identify the reports that are timing reports by comparing the Price Target and the 23 I/B/E/S measures in the revision with that in the prior report. Having identified the timing revisions, we then exclude initiations and reiterations. We then exclude revisions issued in the 2 days before and 2

[7] I/B/E/S keeps track of 10 annual forecasts, 12 quarterly forecasts, and 6 semi-annual forecasts. See Appendix for the full list of 24 measures (including price target) tracked by I/B/E/S.

days after earnings announcement date as given in I/B/E/S. We also exclude pseudo revisions issued in 2002 when many brokers, made revisions as they switched to a 3-tier rating scale, but these were not true revisions to comply with a series of regulations (e.g., NASD 277 & NYSE 472). Our final sample consists of 130,729 revisions.

Before we examine our research questions, we provide some validity for our identification strategy. For non-timing reports, we find the stock return between the release of the revision report and the release of the prior report on the same stock by the same analyst is positive for both downgrades and upgrades. By contrast, for timing reports, the return is positive for downgrades and negative for upgrades. Thus, timing reports seem to be in response to short-term price movement and represent contrarian calls. This provides some confidence to our identification of timing reports.

To get a sense for the importance of timing reports, we first estimate the frequency with which analysts issue timing reports. We find that almost a third of the reports are timing revisions. Moreover, we find that 34% of the downgrades and 26% of the upgrades are timing calls. The higher frequency for downgrades is consistent with the idea that analysts, who are typically reluctant to downgrade stocks, could more easily justify a downgrade to the management if it is a timing downgrade. Analysts could point out to management that their expectations of the fundamentals of the firm have not changed. This way they could continue to be on favorable terms with the management of the firms they track.

Having established the importance of timing reports in terms of their frequency, we turn to our first test of timing ability. We examine the market reaction to timing reports by estimating the cumulative abnormal return (CAR) over the interval [–1, +1] where day 0 refers to the report date. Abnormal return is the stock return less return from a market model estimated over the interval [–300, –46]. The benchmark return is the equal-weighted CRSP returns. We find that timing revisions are associated with mean market reaction of over 2% (CARs = –2.4% for downgrades and +2.2% for upgrades). This is statistically and economically significant, and compares well with the CARs for interpretation reports (–2.6% for downgrades and +2.1% for upgrades). Consistent with Daniel, Lee, and Naveen (2014), however, the CARs for timing are smaller than the CARs for discovery (–4.1% for downgrades and +3.7% for upgrades).

If timing revisions are short-term calls, we expect most of the investor reaction to occur on announcement. It is still possible that the announcement return is incomplete in the sense that it captures only part of the market reaction to the release of timing reports. Therefore, we examine the post-revision abnormal returns (sometimes referred to as "drift" in the literature) to timing reports. We consider CARs over 1-month [+2, +22], 2-month [+2, +43], and 3-month [+2, +64] intervals following the report date. We find a 1-month post-revision drift in the same direction as the initial reaction (–1.3%) for downgrades but a reversal (–0.5%) for upgrades. The magnitude becomes larger as the drift period extends to 3 months (–2.9% for downgrades and –2.7% for upgrades). Thus, it seems that timing upgrades are short-term contrarian calls because the price corrects itself completely: total abnormal return (announcement return + drift) equals –0.5% over the [–1, +64] period. To the contrary, timing downgrades appear to be true downgrades disguised as timing downgrades, perhaps to keep the management happy (total abnormal return equals –5.3% over the [–1,+64] period).

While the average market reaction indicates timing ability, on average, it does not indicate whether the analyst exhibits ability in any given timing report. We construct three proxies of timing ability at the report level: *Winner*, *Influential Winner*, and *Persistent Winner*. *Winner* is an indicator variable that equals 1 if the announcement CAR has the correct sign (positive for upgrades and negative for downgrades), and equals 0 otherwise. We find the mean of *Winner* to be 60% (significantly greater than 50%), implying that timing ability is widespread and mean announcement CARs are not driven by a few observations.

We then define an indicator variable, *Influential Winner* (as in Lo and Stulz (2011)), which equals 1 if the announcement return has the expected sign (i.e., *Winner* = 1) and is statistically significant at the 5% level. We find that 9–10% of the announcement abnormal returns associated with timing reports are large enough to be influential. In comparison, Loh and Stulz (2011) find that 13% of the reports in their study are influential as per their definition. Thus, some analyst possess significant timing ability.

We next examine whether analysts exhibit persistence in timing ability using a simple 2×2 classification. We put all timing revisions into four bins based on whether the current timing report is a *Winner* and whether the prior timing report on the same firm by the same analyst is also a *Winner*. We then define *Persistent Winner*, which equals 1 if the current timing report and the prior timing report are both *Winners*, and equals 0 otherwise. We find the mean of *Persistent Winner* to be 37%. Statistically, we are able to reject the null hypothesis of no persistence in ability. The collective evidence on market reaction suggests that analysts have timing ability.

As a second test of our hypothesis that analysts have stock timing ability, we examine the economic forces that can explain the variation in timing ability. Our proxies for timing ability are *Winner*, *Influential Winner*, and *Persistent Winner*. Because we observe whether the analyst has timing ability only if he or she issues a timing report, we estimate bivariate probit regressions of *Timing* and our proxies for timing ability. *Timing* is an indicator variable that equals 1 if the revision is a timing report, and equals 0 otherwise.

At the univariate level, we find that 28.8% of the 7,487 analysts in our sample issue no timing reports (i.e., *Timing* = 0) through their entire career. At the other extreme, about 7.3% of the analysts issue timing reports over 90% of the time. Even analysts who issue timing reports do not issue timing reports on all the firms they cover. About 11.2% of analysts issue at least one timing report on all the firms they cover. Only a third of analysts issue timing reports on half the firms they cover. These results provide some preliminary evidence that there is cross-sectional variation in timing, which is both analyst and stock-specific. At the aggregate level, we find that timing revisions are more frequent in the months when mispricing is more likely, as proxied by high levels of market volatility (*VIX*). This result indicates that there is also time series variation in timing.

Timing depends on opportunities available to the analyst to issue a timing report. The opportunities are likely to be higher when VIX and stock volatility are higher, and when the potential for stock to be mispriced is higher. Firms with lower institutional ownership, smaller analyst following, and those that are hard-to-value (as per Baker and

Wurgler (2006)) are more likely to be mispriced. Consistent with our hypothesis, we find that *Timing* is indeed related to the five proxies.

We have two broad categories of hypotheses regarding the firm and analyst characteristics that predict timing ability: (i) analyst experience and (ii) costs to the analyst to issuing a timing report. We expect analyst experience, in terms of years being an analyst, years following the industry to which the stock belongs and the number of stocks in the same industry, and years following the stock to be positively related to timing ability. Such experience enables the analyst to disentangle stock price movements due to fundamentals and stock price movements due to mispricing. The first timing report comes after 4.3 years after being an analyst, 3.4 years after following the industry, and 2.9 years after following the stock, implying that experience matters.

In terms of costs, we expect that analysts who cover more firms and industries will find it harder (because of the significant time costs involved) to capitalize on any temporary mispricing that affects the stocks in their portfolio. On the other hand, given the heavy workload associated with covering multiple stock across many industries, it might be harder for such analysts to engage in costly information discovery and hence they may resort to timing as a way to distinguish themselves. Thus, it is not clear how coverage universe affect the analyst ability to exhibit timing ability. Consistent with our hypotheses, we find that timing ability is positively related to experience. We find mixed evidence when it comes to the costs of timing.

To sum up, prior papers have proposed and examined two important roles of analysts, namely information discovery and information interpretation. We propose a third role: stock timing, which is the ability to time short-term price moves. Our contribution is to document that stock timing is both pervasive and valuable. Our paper provides a first step to understanding this significant role of analysts.

2.2. Data

Our sample period is from 1999 to 2012. We start with 1999 because I/B/E/S has availability of price targets only from 1999. We combine data from Detail History file containing the measures tracked by I/B/E/S (Price Target, EPS, etc.) and Recommendation file to create the full time series of recommendations (initiations, reiterations, and revisions) made by each analyst for each firm. This is required in order to identify which of the revisions are timing reports. Because our idea of timing rests on the analyst making a comparison of price target with current price, we throw out the reports on firms for which the analyst has never issued a price target.

2.2.1. Definitions of Timing

Our idea of timing is one where the analyst revises his recommendation but does not revise his estimate of the fundamental value of the stock (Price Target) or his estimate of 23 firm fundamentals (Sales, EPS, etc.) tracked by I/B/E/S.[8] Of course, there can be different definitions of what it means to say that the analyst has not changed his fundamental view of the firm. We consider an alternative definition of timing, which is less strict than our base case.

[8] We handle missing I/B/E/S data in the following way. If a fundamental measure is not available in the both the revision and the previous report, then it implies that the analyst does not think that measure is relevant to estimate his price target and hence only the non-missing measures are compared to identify the timing revisions. If a fundamental measure is available in only one of the two reports (either the revision or the prior report), then we exclude that revision from the final sample. If a fundamental measure has a non-missing value in both the revision report and the prior report, only then are we able to make a comparison to determine whether the revision is a timing report or not.

Our alternative definition of timing is one where the analyst revises his recommendation but does not revise his estimate of fundamental value of the stock, namely the price target.[9] That is, we do not examine whether the analyst has changed his forecast of the fundamentals of the firm (such as Sales or EPS). One could think of the other 23 measures such as EPS as providing signals of price target. For example, one could think of the analyst arriving at the price target by forecasting, say, future EPS and an appropriate future P/E multiple. Because price target could not have changed as per our definition, if the EPS was increased, the analyst must be implicitly reducing the P/E multiple in order to keep the price target the same.[10] Thus, the analyst estimates of various aspects of the fundamentals offset each other. For example if NFLX entered the content business, the analyst could raise his forecasted EPS while at the same time using a lower P/E multiple to reflect the competitiveness of the content business, leaving the price target the same.

2.2.2. Classification of Reports as Discovery, Interpretation, and Timing

Prior research (Ivkovic and Jegadeesh (2004), Asquith, Mikhail, and Au (2005), Chen, Cheng, and Lo (2010), Livnat and Zhang (2012)) generally follows the same broad pattern for identifying discovery and interpretation reports. These papers first identify a set of events (such as earnings) and then assume that reports issued within a window surrounding the event date contain analyst interpretation, while all other reports contain

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[9] This alternative definition of timing has a close parallel to the definition of market timing in the investments literature. The market timer compares his forecast of, say, the S&P500 index (his timing benchmark) to the current index level to decide whether to invest and, if so, how much to invest in the S&P 500 index. In the case of the analyst, he compares his forecast of the stock price—the price target—to the current stock price to decide on his recommendation.

[10] It is also possible that the increase in his earnings forecast is so small that it has a negligible impact on price target, and hence the analyst decides to leave the price target unchanged.

discovery. The papers differ in the set of events and the event windows they consider. For example, Jegadeesh and Ivkovic (2004) consider earnings releases as the only event that analysts respond to and assume that all reports issued in weeks (+1, +6) relative to the earnings release date (excluding days 0 and 1) contain interpretation. Thus all reports issued in weeks (-6, -1) are assumed to contain discovery. Similarly, Chen, Cheng, and Lo (2010) assume in their main results that reports in days (+2, +6) contain interpretation, while those in days (-6, -2) contain discovery.

Based on these papers, we adopt the following classification. We define all reports that are issued in days (+3, +7) following an earnings release as interpretation reports.[11] To be conservative, we include in this group reports that we would normally have classified as timing as per our definition above. We define as discovery all reports that are issued in days (-3, -7) and that are not timing reports as per our definition. The logic here is discovery refers to new information production by the analyst—a report that does not have any change in any of the fundamental estimates (as in timing revisions) cannot, therefore, constitute discovery. Any remaining reports are classified as "Others." These reports are a mix of interpretation and discovery, which cannot be separately identified unless we read through the contents of each report as in Daniel, Lee, and Naveen (2014).

[11] We ignore day –2 and day +2 relative to the earnings date. We do this because when we estimate the cumulative abnormal returns (CARs) to the report, we use a window (–1, +1) relative to the report date. Thus, when we calculate CARs for a report issued on day +2 relative to earnings, day –1 relative to this report would actually refer to day +1 relative to earnings. This would therefore contaminate our CAR results because the CAR window overlaps with the market reaction to earnings. For the same reason, we also ignore day –2 relative to the earnings announcement.

2.2.3. Timing Frequency Around Earnings

We compute the timing frequency in the 6 weeks surrounding earnings week. We obtain the earnings announcement date from I/B/E/S. Week 0 is the 5-day interval surrounding the earnings announcement date, week –1 is days (–7, –3), and week +1 is days (+3, +7) relative to the earnings announcement date. Figure 2-1 plots the frequency.

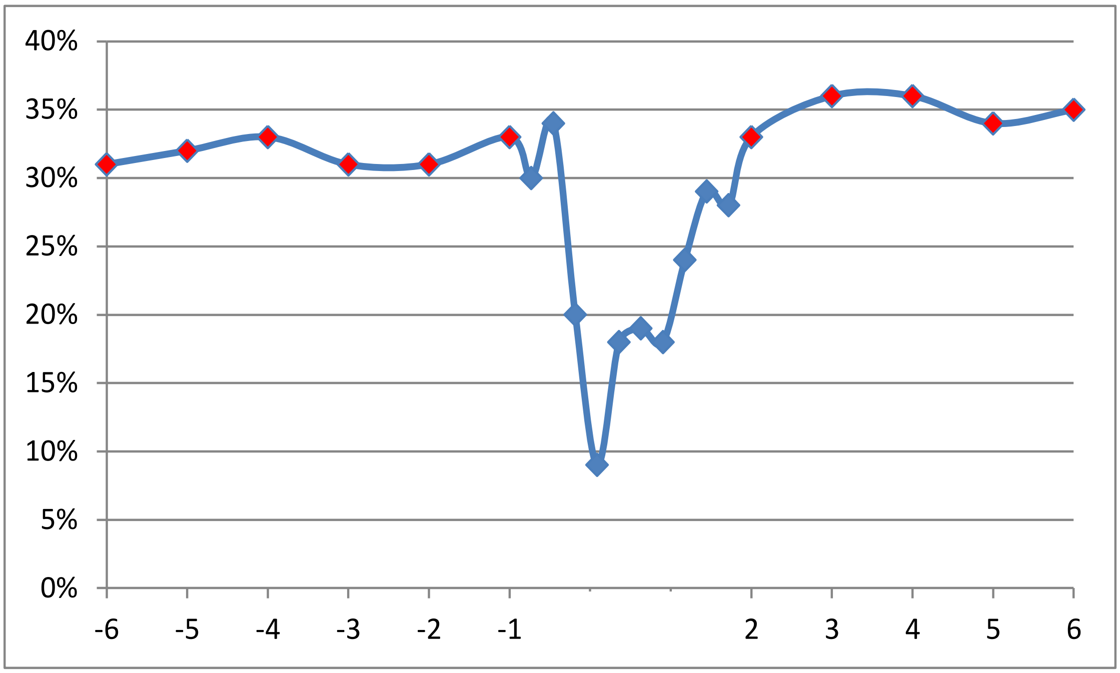


Figure 2-1. Timing Surrounding Earnings.

The figure plots the mean of *Timing* over weeks -6 to -1 and weeks +2 to +6 surrounding earnings. In the middle 2 weeks (10 trading days), it plots the daily frequency of *Timing*. Earning announcement day is in the middle of week 0. *Timing* equals 1 if the recommendation revision is a timing report, and equals 0 otherwise. A timing report is one where the analyst revises his recommendation but does not revise the price target or any of the 23 fundamental measures of firm value.

We find that the frequency is between 30 to 35% (overall mean = 30%) in all *weeks* except week 0 and 1. For these 10 *days* alone, we plot the frequency on a daily basis. We find the frequency to be above 30% for *day* -2 and *day* -1 relative to earnings. It falls to 20% on day 0 and to its lowest level of 9% on day 1. It climbs back over the next 6 days and hits the normal level of just above 30% on the first day of week 2, and maintains the same frequency over *weeks* 2 to 6. The evidence suggests that timing is not related to data interpretation, at least with respect to earnings.

2.2.4. Are These Truly Timing Reports?

Before we examine our research questions, we first document that timing reports are indeed in response to stock price. We report the mean stock returns between the release of the timing report and the release of the "prior report" by the same analyst on the same firm when his fundamental view is exactly same as that in the timing report. The "prior report," thus, depends on our definition of timing. For our base case definition, the prior report for the timing report is the one where all the I/B/E/S measures are exactly same as in the timing report. Because our announcement CARs are estimated over the [–1,+1] window, the prior price change is estimated from day 0 of the release of the prior report to day –2 of the release of the timing report. For timing reports, we expect to find positive returns before downgrades and negative returns before upgrades.

Panel A of Table 2-1 reports the results for our base case timing definition. For timing revisions, as expected, we find a positive return (+3.9%) before downgrades and a negative return (–1.4%) before upgrades. In contrast, for non-timing revisions, we find positive returns for both upgrades and downgrades.[12] These numbers are not large because the number of days that elapses between the timing report and the prior report is only 57 days.

[12] We report the values for non-timing reports only to draw the comparison with timing reports. We have no hypothesis regarding the difference in returns between timing and non-timing reports. We report the difference for those who might be curious.

We follow a similar procedure for examining the validity of our alternative definition of timing described in Section I.A. As per our first alternative definition, the analyst has not changed his fundamental view if he maintains the same price target. Therefore, we start with the timing report, go back in time, and identify the first report where the price target is different from that in the timing report. The report following this identified report contains the same price target as that in the timing report, and this is the "prior report." On average, there are 139 days between the timing report and the prior report. We compute the return between these two reports. Panel B of Table 2-1 reports the results. We find that prior to release of timing reports, the price has run up 6.1% before downgrades and the price has stayed the same before upgrades. For non-timing reports, once again it is positive for both downgrades and upgrades. As final proof, we use the sample of analyst reports downloaded from Investext in 1999 and 2003 (see, Daniel, Lee, and Naveen (2014)). Of the 213 revisions, 67 are timing reports as per our definition. We read these reports and code whether the analyst mentions that the reason for his revision is due to either price run up (in the case of downgrades) or price fall (in the case of upgrades). We find that in 43% of the timing reports, the analysts mention price change as the reason for the revision. Thus, we are confident we have identified timing reports correctly.

Table 2-1

Are Timing Reports in Response to Price Movement?

Panel A: Return Since Prior Report for Base Case Definition of Timing

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	3.9%***	2.3%***	1.9%***	2.1%***
Upgrade	-1.4%***	1.2%***	0.9%*	1.0%***

Panel B: Return Since Prior Report for Alternative Definition of Timing

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	6.1%***	4.0%***	0.5%	1.9%***
Upgrade	0.1%	4.1%***	5.9%***	5.2%***

Note.. The table examines whether timing reports are indeed in response to stock price movement. We report the mean stock returns between the release of the timing report and the release of the "prior report" on the same firm by the same analyst in which his fundamental view is exactly same as that in the timing report. The "prior report," thus, depends on our definition of timing. In Panel A, a timing report is one where the analyst revises his recommendation but does not revise any of the 24 measures tracked by IBES for any of the future time periods. Thus the prior report is the one where all the 24 IBES measures are exactly the same as in the timing report. In Panel B, a timing report is one where the analyst revises his recommendation but does not revise his price target. Therefore, we start with the timing report, go back in time, and identify the first report where the price target is different from that in the timing report. The report following this identified report contains the same price target as that in the timing report, and this is the "prior report." We exclude reports (contaminated reports) issued five days around quarterly earnings announcement dates. We also exclude reports issued during 2002 to take care of mere rating system changes to comply with regulatory rules.

2.2.5. Prevalence of Timing Reports

We examine the frequency of timing reports to get a sense for the importance of this issue. Table 2-2 reports the results. Panel A reports the frequency for our base case definition of timing. Overall, 30% of revisions are timing reports. Thus, a substantial fraction of the reports is timing reports. We find the frequency to be higher in the case of downgrades compared to upgrades (34% vs. 26%).

Table 2-2

How Frequent Are Timing Reports?

Panel A: Base Case Definition of Timing

Recommendation	Timing	Interpretation	Discovery	Others	Total	Timing/Total
Downgrade	22,927	6,025	2,301	36,181	67,434	34%
Upgrade	16,726	6,478	2,287	37,804	63,295	26%
Total	39,653	12,503	4,588	73,985	130,729	30%

Panel B: Alternative Definition of Timing

Recommendation	Timing	Interpretation	Discovery	Others	Total	Timing/Total
Downgrade	40,095	6,025	1,313	20,001	67,434	60%
Upgrade	30,017	6,478	1,524	25,276	63,295	47%
Total	70,112	12,503	2,837	45,277	130,729	54%

Note. The table reports the fraction of recommendation revisions that are defined as timing reports. Thus, the sample consists of only revisions in recommendations. The different panels correspond to different definitions of timing. In Panel A, a revision is defined as a timing report if the analyst revises his recommendation but does not revise any of the 24 measures tracked by IBES. In Panel B, a revision is defined as a timing report if the analyst revises his recommendation but does not revise the price target. We exclude reports (contaminated reports) issued five days around quarterly earnings announcement dates. We also exclude reports issued during 2002 to take care of mere rating system changes to comply with regulatory rules.

The higher number for downgrades is to be expected because analysts are typically reluctant to downgrade stocks in order to keep their management contacts happy (Chen and Matsumoto, 2006; Mayew, 2006; Brown et al., 2013). An analyst could more easily justify a downgrade to the management if it is a timing downgrade because they could point out that their expectations of the fundamentals of the firm have not changed and that they downgraded only because of movement in stock price.

Panel B reports the frequency for our alternative definition of timing report, which is one where the analyst revises his recommendation but does not revise the price target (but could revise any of the other fundamental measures such as EPS). We find

54% of the revisions to be timing reports, which, as expected, is higher than the number in Panel A because the only condition we impose is that the price target has to be the same. Here again, the frequency of timing downgrades is higher than the frequency of timing upgrades (60% vs. 47%). Overall, timing revisions are a big subset of overall revisions, and hence deserve a closer look.

2.3. Main Results

First, we examine the market reaction to the release of timing reports ability. Second, we examine the factors that can explain the variation in timing ability.

2.3.1. Do Analysts Have Timing Ability?

2.3.1.1. Announcement Returns

We examine if timing reports are a reflection of analyst skill by estimating market reaction to the release of timing reports. As with all event studies that examine whether announcement returns are significantly different from zero, this is a test of the joint hypotheses that analysts have ability and that the markets react accordingly. For brevity, we will simply interpret market reaction as a reflection of analyst timing ability. That is, if market reaction is negative to a timing downgrade or positive to a timing upgrade, we will interpret the result to mean that analysts have timing ability.

We estimate the cumulative abnormal returns over the [–1, +1] period, where day 0 is the report date. We choose day –1 to account for potential tipping of the recommendation by the analyst to his clients and day +1 to account for the fact that the report could have been released after market close on day 0.[13] We estimate the market model using CRSP equal-weighted returns as the market proxy over the interval [–300,–46]. Table 2-3 presents the results. We provide data for non-timing reports for the purpose of comparison only, because we have no prediction that timing reports will be significantly different from non-timing reports.

We first report the mean CARs in Panel A of Table 2-3. We find significant negative return (–2.4%) for timing downgrades and significant positive returns (+2.2%) for timing upgrades. This implies that analysts have timing ability.[14] This is of the same magnitude as the CARs for *Interpretation* (-2.6% and 2.1% respectively for downgrades and upgrades), but lower than those for *Discovery* (-4.1% and 3.7% respectively). The CARs being highest for discovery is consistent with Daniel, Lee, and Naveen (2014) who argue that investors react more strongly to reports that contain discovery because the report is backed by private information generated by the analyst. Note that we have no hypothesis for whether the announcement CARs for timing reports should be bigger or smaller than that for all other reports. We report the CARs for the other categories purely for comparison purpose.

To examine whether this ability is widespread, we define *Winner* = 1 if the announcement return to the timing report has the predicted sign (negative for downgrades and positive for upgrades), and 0 otherwise.

[13] Kecskes et al. also consider day 1 return but use the open price instead of the closing price. Given low volumes during pre-open trading and after-close trading on days other than big-news days such as earnings release, institutional investors who follow analysts may not have had a chance to trade on the report before open on day 1. That is why we use day 1 closing price.
[14] The median CARs are is lower: –1.4% for timing downgrades +1.2% for timing upgrades.

Panel B of Table 2-3 reports the mean of *Winner*. We find 63% of timing downgrades have negative CARs and 60% of the timing upgrades have positive CARs. These numbers are significantly greater than 50% implying that a substantial number of analysts have timing ability. Again, these numbers are comparable to those for *Interpretation* (64% and 64% respectively for downgrades and upgrades) but slightly lower than those for *Discovery* (70% and 70% respectively).

Next, we examine whether some of the announcement returns are economically large. Specifically, as in Lo and Stulz (2011), we define an indicator variable *Influential Winner*, which equals 1 if the CAR[–1, +1] has the correct expected sign (i.e., *Winner* = 1) and is statistically significant at the 5% level, and equals 0 otherwise. CAR[–1, +1] is significant if the absolute value of CAR[–1,+1] > $1.96\times\sqrt{3}\times\sigma_e$, where σ_e is the standard deviation of residuals in the estimation interval. Panel C reports the mean of *Influential Winner*. We find that between 9-10% of the timing revisions are influential. This is comparable with Loh and Stulz (2011) who find that 12% of their sample reports have influential CARs, and indicates that some analysts seem to have the ability to predict big short-term moves in stock price.

In untabulated results, for these influential timing reports, the mean announcement CARs are –15.3% for downgrades and +13.9% for upgrades. These numbers are comparable to the mean CARs for influential non-timing reports.

Table 2-3

Announcement CARs

Panel A: Announcement CARs

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	-2.4%***	-2.6%***	-4.1%***	-4.6%***
Upgrade	2.2%***	2.1%***	3.7%***	3.2%***

Panel B: Winner

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	63%***	64%***	70%***	70%***
Upgrade	60%***	64%***	71%*	70%***

Panel C: Influential Winner

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	9%***	13%***	16%***	15%***
Upgrade	10%***	13%***	14%*	14%***

Note. The table reports results of tests examining the initial market reaction to the release of timing reports. A timing report is one where the analyst revises his recommendation but does not revise any of the 24 measures tracked by IBES. The sample consists of only revisions in recommendations. We obtain the cumulative abnormal returns (CARs) to the announcements from Eventus. This is the stock return minus the return predicted from the market model cumulated over the interval [–1,+1], where day 0 is the day of the report. We estimate market model parameters using CRSP equal-weighted returns as the market proxy over the interval [–300,–46]. Panel A reports the mean of announcement CARs. Panel B reports the mean of *Winner*, which equals 1 if the announcement CAR has the expected sign (positive for upgrades, negative for downgrades), and equals 0 otherwise. Panel C reports the mean of *Influential Winner*, which equals 1 if the announcement CAR has the expected sign (i.e., *Winner* = 1) and is statistically significant at the 5% level, and equals 0 otherwise. Announcement CAR is statistically significant if the absolute value of the announcement CAR > $1.96\times\sqrt{3}\times\sigma_e$, where σ_e is the standard deviation of residuals in the estimation interval. For Panel C, as in Lo and Stulz (2011), we also exclude revisions of firms followed by less than 4 analysts or revisions having multiple recommendations on the same date. We exclude reports (contaminated reports) issued five days around quarterly earnings announcement dates. We also exclude reports issued during 2002 to take care of mere rating system changes to comply with regulatory rules.

2.3.1.2. Post-Revision Returns

If timing revisions are short-term valuation calls, we expect most of the investor reaction to occur on announcement. It is still possible that the announcement return is incomplete in the sense that it captures only part of the market reaction to the release of timing reports. The magnitude of the post-revision drift depends on how quickly the announcement returns impound the information in the report is impounded. Therefore, we examine the post-revision abnormal returns computed as the CARs over the 1-month [+2,+22], 2-month [+2,+43], and 3-month [+2,+64] periods. As in Keskes et al. (2014), we use a 21-day trading interval to represent a 1-month calendar interval.

Table 2-4 reports the results. From Panel A, we find that for timing downgrades, the mean 1-month drift is –1.3%. This implies that there is continuation of the announcement reaction in the same direction. Such a continuation is consistent with analysts masking their true long-term downgrades as timing downgrades. In contrast, for timing upgrades, however, there seems to be a mild reversal of the initial reaction (–0.5%).[15] Thus, upgrades seem to be much more of a short-term valuation call. Examination of the longer-term drift (Panels B and C) provides further validation. The continuation for downgrades and reversal for upgrades strengthens further to –2.9% for downgrades and an identical –2.7% for upgrades. Thus, for upgrades, the initial market reaction of +2.2% completely reverses over the next 3 months.

[15] As with announcement CARs, we have no hypothesis whether the post-revision CARs for timing reports should be bigger or smaller than that for non-timing reports. We therefore report the post-revision CAR for non-timing reports purely for comparison purpose.

Table 2-4

Post-Revision CARs and Total CARs

Panel A: Post-Revision CAR[+2,+22]

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	-1.3%***	-0.8%***	0.1%	-0.9%***
Upgrade	-0.5%***	0.4%***	0.6%**	0.0%

Panel B: Post-Revision CAR[+2,+43]

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	-2.1%***	-1.6%***	-0.3%	-1.2%***
Upgrade	-1.5%***	-0.2%	0.4%	0.0%

Panel C: Post-Revision CAR[+2,+64]

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	-2.9%***	-2.2%***	-1.0%	-1.6%***
Upgrade	-2.7%***	-0.5%	-0.8%	-0.3%**

Panel D: Mean Total CAR[–1,+64]

Recommendation	Timing (A)	Interpretation (B)	Discovery	Others
Downgrade	-5.3%***	-4.8%***	-5.2%***	-6.2%***
Upgrade	-0.5%**	1.7%***	2.8%***	3.0%***

Note. The table reports results of tests examining the return that investors could earn by buying after the release of the timing report. The post-revision CAR is the stock return minus the return predicted from the market model cumulated over various intervals. Given approximately 21 trading days per month, we estimate 1-month, 2-month, and 3-month post-revision CARs over the intervals [+2,+22], [+2,+43] and [+2,+64] respectively, where day 0 is the day of the report. We estimate market model parameters using CRSP equal-weighted returns as the market proxy over the interval [–300,–46]. Panels A, B, and C reports the mean post-revision CARs. Panel D reports the mean of total CAR over the interval [–1,+64], which is the sum of announcement CAR[–1,+1] and post-revision CAR[+2,+64]. We exclude reports (contaminated reports) issued five days around quarterly earnings announcement dates. We also exclude reports issued during 2002 to take care of mere rating system changes to comply with regulatory rules.

In comparison, for *Interpretations*, there is continuation of the announcement reaction for downgrades, but less reversal for upgrades. For *Discovery*, there is little drift in either direction for both upgrades and downgrades.

Panel D reports the mean of total abnormal return over the interval [–1,+64], which is the sum of announcement abnormal return[–1,+1] and post-revision abnormal return[+2,+64]. We find the total CAR is -5.3%% for downgrades and -0.5% for upgrades. The total CARs for downgrades are comparable across *Timing*, *Interpretation*, and *Discovery*, but for upgrades, the CARs are higher for *Interpretation* and *Discovery* compared to *Timing*.

2.3.1.3. Persistence

Next, we examine whether analysts exhibit persistence in timing ability using a simple 2×2 classification used in the literature on portfolio performance evaluation (for example: Brown and Goetzmann, 1995). We put all timing revisions into four bins based on whether the current timing report is a *Winner* and whether the prior timing report on the same firm by the same analyst is also a *Winner*. We refer to our four groups as WW ($Winner_t$, $Winner_{t-1}$), WL ($Winner_t$, $Loser_{t-1}$), LW ($Loser_t$, $Winner_{t-1}$), and LL ($Loser_t$, $Winner_{t-1}$). Here *Loser* is simply 1-*Winner*. Because timing ability could be stock-specific (we provide evidence for this in Section II.F.1), we do not attempt to characterize an analyst as persistent timer by aggregating data across all stocks covered by the analyst (as in Mikhail, Walther, and Willis 2004).

Table 2-5 reports the result. We report the number of observations that belong to each of the four groups. For each cell, we also report the mean announcement abnormal return (in parentheses), the mean post-revision abnormal return over the interval [+2,64] {in braces}, and the mean total abnormal return [in square brackets]. Because the observations within a group include both upgrades and downgrades, we present the returns to an investor who takes a long position in upgrades and a short position in downgrades.

We find that, of the total of 11,981 reports, 7,219 (or 60%) are *Winners* at time *t-1* and a similar fraction (7,172/11,981 = 60%) are *Winners* at time *t* (see "Overall" row). This is also the aggregate of the numbers reported in Panel B of Table 2-3.[16]

To test the null of no persistence, we define the Cross-Product Ratio (CPR) as in Brown and Goetzmann (1995). This is the odds ratio of the number of repeat performers to the number of those that do not repeat, and is given by (#WW×#LL)/ (#WL×#LW), where # indicates the number of reports in each group. As per the numbers shown in Table 2-5, CPR = 1.26. The standard error of the natural log of the CPR is given by $\sqrt{\frac{1}{\#WW}+\frac{1}{\#WL}+\frac{1}{\#LW}+\frac{1}{\#LL}}$. The test statistic is logarithm of CPR divided by the standard error and this is 6.0. Therefore, we reject the null of no persistence.

We also find the returns (announcement, post-revision, and total) to be higher for timing reports that are persistent winners. Announcement CARs for WW are +6.2% and those for WL are 5.8%. CARs for persistent losers are -5.0%. We observe similar pattern in both post-revision CARs and Total CARs, suggesting that persistent timing ability is recognized by the market place.

[16] The numbers are slightly different from those in Table II because to define persistent *Winner*, we need to have the same analyst issue two timing reports on the same firm during our time-period. This causes attrition in the sample size in Table IV.

Table 2-5

Do Analysts Exhibit Persistence in Timing Ability?

		Winner$_t$ Yes	Winner$_t$ No	Overall
Winner$_{t-1}$	Yes	4,479 (6.20%) {0.80%} [6.80%]	2,740 (-4.70%) {0.31%} [-4.38%]	7,219 (1.95%) {0.62%} [2.56%]
	No	2,693 (5.80%) {1.07%} [6.87%]	2,069 (-5.01%) {0.21%} [-4.32%]	4,762 (1.70%) {0.74%} [2.63%]
	Overall	7,172 (5.92%) {0.90%} [6.83%]	4,809 (-4.81%) {0.27%} [-4.36%]	11,981 (1.85%) {0.66%} [2.59%]

Note. The table reports results from tests that examine whether analysts exhibit persistence in timing ability. Using a 2×2 classification, we put all timing revisions into four bins based on whether the current timing report is a *Winner* and whether the prior timing report on the same firm by the same analyst is a *Winner*. We exclude the first timing revision made by the analyst on a given firm because there cannot be a prior timing report issued on the same firm by the same analyst employed by the same broker. *Winner* equals 1 if the announcement CAR has the expected sign (positive for upgrades, negative for downgrades), and equals 0 otherwise. We report the number of timing reports that belong to each group, the mean announcement abnormal return (in parentheses), the mean post-revision abnormal return {in braces}, and the mean total abnormal return [in square brackets]. Announcement CAR is the stock return minus the return predicted from the market model cumulated over the interval [–1,+1], where day 0 is the day of the report. We estimate market model parameters using CRSP equal-weighted returns as the market proxy over the interval [–300,–46]. Post-revision CAR is the stock return minus the return predicted from the market model cumulated over the interval [+2,+22]. Total CAR is the sum of announcement CAR and post-revision CAR. We exclude reports (contaminated reports) issued five days around quarterly earnings announcement dates. We also exclude reports issued during 2002 to take care of mere rating system changes to comply with regulatory rules.

2.3.2. What Factors Explain The Variation In Timing Ability?

Having established that analysts have timing ability, we then explore the factors that explain the cross-sectional and time-series variation in timing ability. First, we develop our hypotheses regarding factors that explain the variation in timing and timing ability. Second, we present univariate evidence on this variation. Finally, we present regression results that explain the variation in both timing frequency and timing ability.

2.3.2.1. Hypotheses Development And Variable Construction

In this section, we develop hypotheses regarding firm, analyst, and broker characteristics predict variation in timing as well as in timing ability. *Timing* depends on opportunities available to the analyst to issue a timing report. Stock price moves must provide sufficient opportunities for the analyst to issue timing revisions. First, we expect analysts to issue timing reports when market volatility, proxied by monthly average of the daily closing values of volatility of the S&P500 index (*VIX*), is high. Second, we expect a volatile stock to provide more opportunities for the analyst to issue timing reports. For example, when volatility is high, stocks are more likely to reach the price target issued by the analyst, giving a chance for the analyst to issue a timing downgrade opportunistically. High volatility could also result in stock price moving much below the price target, giving the analyst a chance to issue a timing upgrade. We estimate *Stock Volatility* as the standard deviation of daily stock returns in the 21 trading days (roughly corresponds to a calendar month) prior to the issue of the timing report. Third, opportunities are more likely where stock mispricing is more likely. Firms with high institutional ownership (*Institutional Ownership*) are less likely to be mispriced. Similarly, if there are many analysts following the stock, then uncertainty associated with the prospect of the firm will be lower, providing less mispricing opportunity for analysts to time their calls. To test this hypothesis, we use *Analyst Following*, which is the number of analysts' annual earnings forecasts used by I/B/E/S to calculate the consensus estimate for the firm for the month that is prior to the month in which the analyst issues his timing report on that firm.

Finally, we follow Baker and Wurgler (2006) to identify a set of firms who are likely to exhibit wider swings in price away from fundamentals. They argue that stocks of smaller, younger, unprofitable, high-volatility, non–dividend paying, growth firms, and firms in financial distress are likely to be harder to value and also harder to arbitrage, and hence likely to be subject to mispricing. Thus, we use the factor score derived from firm size (proxied by natural logarithm of market capitalization), firm age (years trading on CRSP), profitability (EBITDA/Sales), Dividend Payer dummy, Market-to-Book of Equity, and Altman Z-Score. We do not include volatility because we consider it separately. Only one factor has an eigen value greater than 1. The factor loadings have the correct sign except for market-to-book ratio: we find younger, unprofitable, non–dividend paying, and firms in financial distress have a lower factor score. Hence, we term the factor score *Low-Likelihood-of-Mispricing Factor Score*.

We have two broad categories of hypotheses regarding firm and analyst characteristics that predict timing ability: (i) analyst experience and (ii) costs to the analyst to issuing a timing report.

While opportunities are a necessary condition to issuing a timing report, it is not sufficient to issue a winning timing report. The analyst must have the experience to decipher if the price move is due to change in fundamentals or due to mispricing. We define three different types of relevant experience. (i) *Market Experience*, which is the number of months the analyst has spent covering at least one stock. (ii) *Industry Experience*. We have two proxies: the number of months the analyst has been covering the industry to which the stock belongs and the number of stocks covered by the analyst in the same industry in that year. (iii) *Stock Experience*, which is the number of months the analyst has been covering the stock. We compute the experience values in the year before the analyst issues his timing report. The first timing revision issued by an analyst on a given firm follows 3.4 revisions issued by the same analyst on the same firm and the first timing report comes after 2.9 years of following the stock. This implies that analyst experience matters. We also estimate a factor score for each analyst-firm-year observation using our three experience measures because the correlations among the experience measures are high: 86% between market and industry experience, 52% between market and stock experience, and 58% between industry and stock experience. We term the factor score *Analyst Experience Factor Score*.

Even if opportunities arise and the analyst has the experience to disentangle stock price movements that arise from changes in fundamental versus mispricing, the analyst has to make a tradeoff between the benefits and costs of issuing a timing report. The benefits of issuing a prescient timing call to the analyst's clients are just the same as the benefits from issuing a revision in recommendation following information discovery or interpretation. Thus, the costs associated with timing might play a bigger role.

In terms of costs to issuing a timing report, we identify only type of costs: time costs. To issue a timing report, the analyst has to be opportunistic to take advantage of, sometimes, fleeting mispricing opportunities. Thus, the analyst has to keep up with what is going on with all the stocks that he covers. This job becomes harder as his coverage universe expands. Thus, we expect that greater the number of industries (*Number of Industries*) and greater the number of stocks (*Number of Stocks*) the analyst covers, the less the likelihood of issuing a timing report. We compute the values of the variables in the year when the analyst issues his timing report. Once again, we compute a factor score, for each analyst-year observation using our two proxies because the correlation is high at 56%. We term the factor score *Analyst Costs Factor Score*.

Table 2-6 reports the descriptive statistics of these variables.

2.3.2.2. Univariate Results

If timing ability is uncommon, we should find that not all analysts issue timing reports. To explore this hypothesis we first estimate the frequency with which analysts issue timing reports over their entire career. That is, we estimate the analyst-level mean of *Timing*, which we term *Analyst Frequency*. Because this variable is a continuous number, we place the 7,487 analysts in the sample in 12 bins depending on the frequency with which they issue timing reports: exactly 0%, between 0 and 10%,…,, between 90 and 100%, and exactly 100%. Panel A of Figure 2-2 presents the bar chart of the distribution of *Analyst Frequency*, where each bar represents the proportion of the 7,487 analysts in the sample who belong to each of the 12 bins. We find that 28.8% of the analysts never issue a timing report. We exclude analysts who work for less than a year from our sample before we perform this analysis. Thus, short-tenured analysts who have not yet faced market conditions conducive to issuing a timing report do not drive our results. Moreover, the average tenure of the analysts who never issue a timing report is 3.9 years. Thus, it is not that these analysts are in the database for a short period.

Table 2-6

Descriptive Statistics of Key Variables

Panel A: Summary Statistics

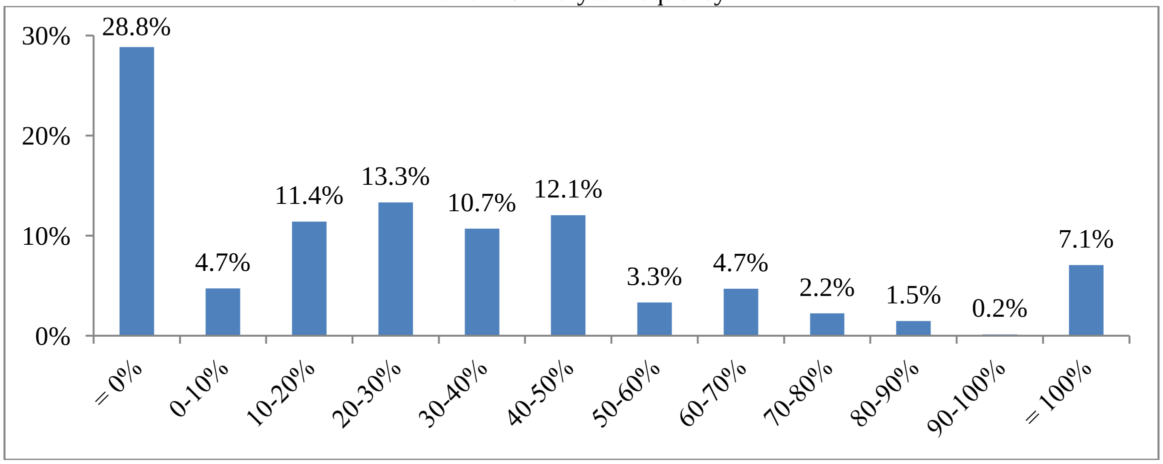
Variable	Mean	SD	Median	p25	p75
Market Volatility	22.4	9.4	20.7	16.2	25.6
Stock Volatility	54.7	40.0	42.6	28.4	67.1
Institutional Ownership	0.6	0.3	0.7	0.5	0.9
Analyst Following	12.1	8.2	10.0	5.0	17.0
Low-likelihood-of-Mispricing Factor	0.0	0.8	-0.1	-0.6	0.6
Opportunities Factor Score	0.0	0.8	0.1	-0.5	0.6
Market Experience	7.7	5.5	6.8	3.5	10.6
Industry Experience: Years covering industry	6.4	5.2	5.3	2.3	9.2
Industry Experience: Number of stocks covered in the same industry	10.2	8.5	8.0	3.0	14.0
Stock Experience	3.1	3.2	2.0	0.8	4.2
Analyst Experience Factor Score	0.0	1.0	-0.2	-0.7	0.5
Number of Industries	4.1	2.9	3.0	2.0	5.0
Number of Stocks	18.0	10.9	16.0	12.0	22.0
Analyst Costs Factor Score	0.0	0.7	-0.1	-0.5	0.3

Note. Panel A reports the descriptive statistics of key variables that explain the variation in timing ability while Panel B reports the correlations among these variables. The sample includes all recommendation revisions issued between 1999 and 2012. A recommendation revision is defined as a timing report if the analyst revises his recommendation but does not revise any of the 24 measures tracked by IBES for any of the future time periods. Market Volatility is monthly average of VIX. Stock Volatility is the annualized standard deviation of daily stock returns in the 21 days (roughly corresponds to a month) prior to the issue of the revision. Institutional Ownership is a percentage of shares owned by institutional investors at the quarter of revision. Analyst Following is the number of annual earnings forecasts used by IBES to calculate the consensus estimate for the firm for the month prior to which the analyst issues revisions on that firm. Market Experience is the number of years working as an analyst at the time of revision. Stock Experience represents the number of years since an analyst began covering a firm at the time of revision. Number of Industries represents the number of industries the analyst covers in the year of revision. Number of Firms represents the number of firms the analyst covers in the year of revision. We exclude reports (contaminated reports) issued five days around quarterly earnings announcement dates. We also exclude reports issued during 2002 to take care of mere rating system changes to comply with regulatory rules. Panel B reports the correlation of those variables with *** representing for $p<0.01$, ** for $p<0.05$ and * for $p<0.1$.

Panel B: Correlations

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Market Volatility	1								
(2)	Stock Volatility	0.42***	1							
(3)	Institutional Ownership	-0.00	-0.14***	1						
(4)	Analyst Following	-0.01***	-0.13***	0.24***	1					
(5)	Market Experience	0.03***	-0.06***	0.13***	0.06***	1				
(6)	Industry Experience: Years covering industry	0.03***	-0.07***	0.12***	0.08***	0.86***	1			
(7)	Industry Experience: Number of stocks covered in the same industry	0.02***	-0.05***	0.01***	0.02***	0.10***	0.25***	1		
(8)	Number of Industries	0.02***	-0.12***	0.14***	0.14***	0.52***	0.58***	0.07***	1	
(9)	Number of Stocks	0.04***	-0.01**	0.10***	-0.09***	0.16***	0.05***	-0.14***	0.07***	1

Panel A: Analyst Frequency



Panel B: Stock Frequency

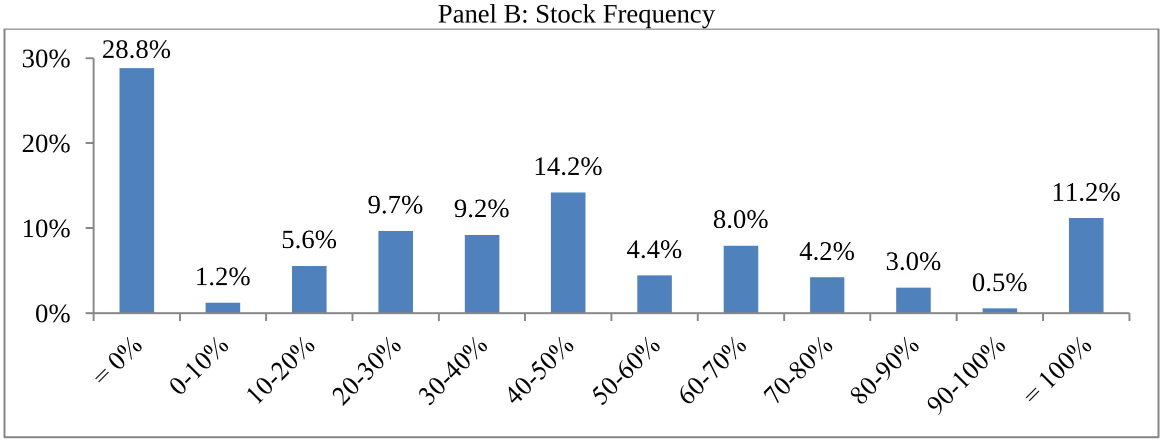


Figure 2-2. Cross-Sectional Variation in Timing Frequency

The figure documents the cross-sectional variation in timing. We estimate the frequency with which analysts issue timing reports over our sample periods from 1999 to 2012 (*Analyst Frequency*). This is the analyst-level mean of *Timing*, which equals 1 if the recommendation revision is a timing report, and equals 0 otherwise. We place the 7,487 analysts in the sample in 12 bins depending on *Analyst Frequency*: exactly 0%, between 0 and 10%,…, between 90 and 100%, and exactly 100%. We exclude analysts who work for less than twelve months at the time of recommendation revisions or who did not make any recommendation revision during their careers as analysts from our sample before we perform this analysis. Panel A presents the bar chart of the distribution of *Analyst Frequency*, where each bar represents the proportion of the 7,487 analysts in the sample who belong to each of the 12 bins. Panel B presents the bar chart of the distribution of *Stock Frequency*, which is the fraction of stocks in the analyst's coverage on which the analyst has issued at least one timing report during the time he has covered the stock. To estimate this frequency, we first sum up *Timing* for each analyst for each stock the analyst covers over the entire time period during which he has covered the stock. If the sum of *Timing* ≥ 1, it implies that the analyst has issued at least one timing revision on that firm. *Stock Frequency* is the fraction of stocks in the analyst's coverage whose sum of *Timing* ≥ 1. We put each analyst into 12 bins depending on: exactly 0%, between 0 and 10%,…, between 90 and 100%, and exactly 100%. The bar chart plots the proportion of the total of 7,487 analysts who belong to each of the 12 bins.

At the other extreme, some analysts issue timing reports at a very high frequency: 7.1% of the analysts issue timing reports 100% of the time.

The results above do not tell us whether analysts issue timing reports on all the stocks they cover. It is likely that analysts are not equally skilled at detecting short-term tops and bottoms in all the stocks they cover. To explore this, we first identify whether the analyst has issued at least one timing report on a given firm (on average, an analyst covers 14 firms). We first sum up *Timing* for each analyst for each stock the analyst covers over the entire time during which he has covered the stock. If the sum of *Timing* ≥ 1, it implies that the analyst has issued at least one timing revision on that firm. We then define *Stock Frequency*, which is the fraction of stocks in the analyst's coverage whose sum of *Timing* ≥ 1. As before, we place analysts in 12 bins depending on the frequency: exactly 0%, between 0 and 10%,…, between 90 and 100%, and exactly 100%. Panel B of Figure 2-2 presents the bar chart of the distribution of *Stock Frequency*, where each bar represents the proportion of the 7,487 analysts in the sample who belong to each of the 12 bins. In addition to excluding from our sample analysts who work for less than a year, we also exclude analysts who did not make any revision during our sample period from 1999 to 2012. This ensures that we are only including analysts who can time the stocks they cover, but choose not to.

As before, we find that 28.8% of analysts do not have a timing report in any of the stocks they cover. It is not because these analysts cover just a few stocks; the average number of stocks these analysts cover is 8.3. In untabulated results, we find that the median analyst issues timing reports in 17% of the firms. We find (by counting the frequencies for bins > 50%) that about a third of the analyst issue timing reports on more than half their coverage universe. About 11% of the analysts issue timing reports in all of the stocks they cover. Overall, the results imply that issuing timing reports is not pervasive and timing ability might not only be analyst specific but also specific to the stock they cover.

Next, we explore the time series variation in timing reports. When markets are volatile, prices are likely to deviate from fundamental values, giving opportunities for the analyst to step in and issue timing reports. To explore this, we compute the monthly average of the daily closing of *VIX*. We compare this with the monthly mean of *Timing*. Figure 2-3 plots the time series of average *VIX* and average *Timing*. As shown in Figure 2-3, both seem to move in tandem during our sample period, except for 4th quarter of 2008 when Lehman Brothers filed for bankruptcy. Consistent with our hypothesis, we find a statistically significant correlation of 0.22 (p-value < 0.01), implying there is time series variation in timing.[17]

2.3.2.3. Multivariate Analysis

We first present logistic regression results for *Timing*. Table 2-7 reports the results. We winsorize all the variables at the 1st and 99th percentile values. We estimate the p-values using standard errors clustered at the analyst-firm level. Given that *VIX* is the same for all observations within a month, we do not include time fixed effects. In Column 1, we use the *Opportunities Factor Score* as the independent variable.

[17] When excluding the 4th quarter of 2008 when the VIX shot to an all-time high, the correlation increases to 0.30 with p-value of 0.0001.

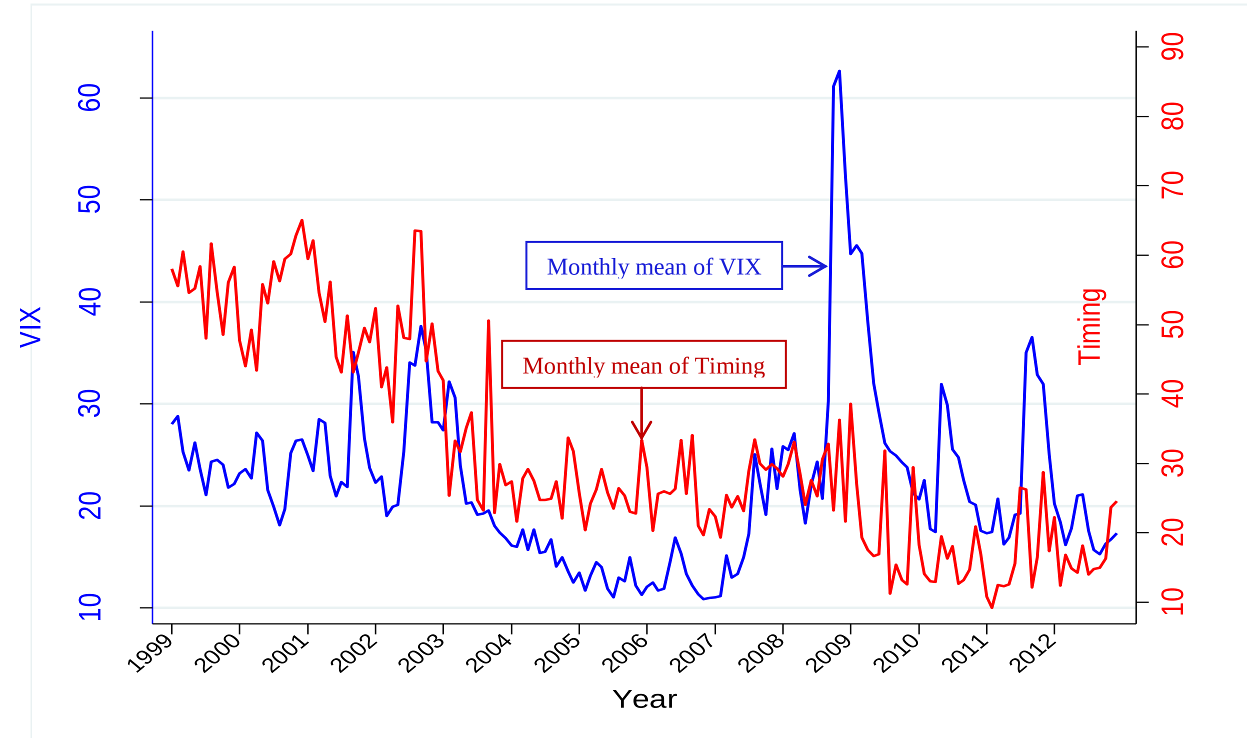


Figure 2-3.Time-Series Variation in Timing Frequency

The figure plots the month-by-month mean of daily closing values of *VIX* and mean of *Timing*. The overall mean of *VIX* and *Timing* are also plotted in the graph. *VIX* is the implied volatility of S&P500 index options. *Timing* equals 1 if the recommendation revision is a timing report, and equals 0 otherwise.

Table 2-7

What Explains the Variation in Timing?

Variable	Dependent Variable = Timing		
Opportunities Factor Score	0.141***		
	(0.007)		
VIX		0.006***	0.006***
		(0.001)	(0.001)
Stock Volatility		0.001***	0.001***
		(0.000)	(0.000)
Institutional Ownership		-0.468***	-0.459***
		(0.035)	(0.036)
Analyst Following		-0.004***	-0.006***
		(0.001)	(0.002)
Low-Likelihood-of-Mispricing Factor Score		-0.009	
		(0.013)	
Firm Size			0.003
			(0.009)
Firm Age			-0.001**
			(0.001)
Profitability			0.008
			(0.010)
Dividend Payer			0.028
			(0.019)
Market-to-Book			0.011***
			(0.002)
Z-Score			0.009***
			(0.001)
Observations	82,034	82,034	82,034

Note. The table presents logistic regressions results with *Timing* as the dependent variable. *Timing* equals 1 if the revision is a timing report, and equals 0 otherwise. *Market Volatility* is based on S&P's volatility index (VIX). *Stock Volatility* is the standard deviation of daily stock returns in the 21 trading days (roughly corresponds to a calendar month) prior to the issue of the timing report. *Analyst Following* is the number of analysts covering the stock. *Low-Likelihood-of-Mispricing Factor Score* is based on Firm Size (natural log of firm market capitalization), Profitability (EBITDA/Assets), Dividend Payer (indicator variable that equals 1 if firms pays dividend), market-to-book ratio of equity, and Z-score. Standard errors are clustered at both firm-analyst pair level. p-values are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

As expected, we find the coefficient to be positive, consistent with the idea that analysts try to time the stocks when the opportunities are high for the stock to deviate temporarily from its fundamentals.

In Column 2, we replace the factor score with its individual components. We find that, as hypothesized, *Timing* is more likely when market volatility and stock volatility are high. Also, as expected, *Timing* is negatively related to institutional ownership and analyst following. Contrary to our expectation of a negative coefficient on *Low-Likelihood-of-Mispricing Factor Score*, we find the factor has no explanatory power.

In Column 3, we replace the *Low-Likelihood-of-Mispricing Factor Score* by its underlying components. Firm size, profitability, and dividend status do not affect the likelihood of *Timing*. Consistent with our hypothesis, we find timing is more likely in younger firms, growth firms, and firms in financial distress. This is consistent with the conjecture of Baker and Wurgler that younger firms, high-growth firms, and firms in financial distress are hard to value and hard to arbitrage, which gives rise to higher probability of being mispriced, which in turn provides greater opportunities for the analyst to engage in stock timing.

We finally report the results for regressions of timing ability. Our three proxies for timing ability are *Winner*, *Influential Winner*, and *Persistent Winner*. Since we observe timing ability only when there is a timing report in the first place, we estimate Heckman probit regressions of *Timing* and timing ability. In the interest of brevity, and because the results on *Timing* are very similar to those in Table 2-7, we only report the results for the timing ability measures. Table 2-8 reports the 2nd stage results.

Table 2-8

What Explains the Variation in Timing Winners?

	Dependent Variable =					
Variable	Winner	Influential Winner	Persistent Winner	Winner	Influentia l Winner	Persistent Winner
Analyst Experience Factor Score	0.029***	0.024**	0.086***			
	(0.009)	(0.010)	(0.012)			
Analyst Costs Factor Score	-0.055***	-0.030***	0.129***			
	(0.009)	(0.011)	(0.021)			
Analyst Experience						
Market Experience				-0.001	-0.005	0.001
				(0.003)	(0.005)	(0.005)
Industry Experience: Years Covering the Industry				0.002	-0.004	0.001
				(0.004)	(0.005)	(0.005)
Industry Experience: Number of Stocks Covered in Same Industry				-0.001	0.014***	-0.003*
				(0.001)	(0.003)	(0.002)
Stock Experience				0.008**	0.047***	0.006
				(0.003)	(0.004)	(0.004)
Analyst Costs						
Number of Industries				-0.015***	0.022***	-0.017***
				(0.004)	(0.007)	(0.006)
Number of Stocks Covered				0.000	0.001	0.003
				(0.001)	(0.003)	(0.002)
Observations	24,445	14,944	24,445	24,445	14,944	24,445

Note. The table presents the second stage heckman probit regression results wherein the first stage we predict Timing, and in the second stage, we predict timing ability. We consider three proxies for timing ability: *Winner*, *Influential Winner*, and *Persistent Winner*. For brevity, we do not report the first stage results, which are similar to the results presented in Table 2-7. In models 1–3, where we use the *Analyst Experience Factor Scores* and *Analyst Costs Factor Scores*, we use the *Opportunities Factor Score* to predict *Timing*. In models 4–6, where we use the underlying components of the experience and cost factor scores, we similarly use the underlying components of the opportunities factor score. In models for Influential Winner, we additionally exclude both observations of firms followed by less than 4 analysts and observations having multiple recommendations on the same date just like Loh & Stulz (2011) do. Standard errors are clustered at both firm-analyst pair level. p-values are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Column 1–3 reports the regression results using the *Analyst Experience Factor Score* and *Analyst Costs Factor Score*. In all three cases, as expected, *Analyst Experience Factor Score* is significantly positive. This implies that more experienced analysts are more likely to exhibit timing ability. We find that, as expected, *Analyst Costs Factor Score*, is significantly negative but in only two out of three specifications.

Column 4–6 reports the regression results using the underlying components of the two factor scores. Not all components have a statistically significant impact. *Market Experience* and *Industry Experience* in terms of years covering the industry to which the stock belongs does not predict timing ability. *Industry Experience* in terms of number of same-industry stocks covered by the analyst has an uncertain impact on timing ability. While the coefficient is positive (as expected) when it comes to predicting *Influential Winner*, the coefficient is negative when it comes to predicting *Persistent Winner*. *Stock Experience*, as expected, is positively related to timing ability.

In terms of time costs as captured by the busyness of the analyst, we find that the number of stocks covered by the analyst has no bearing on his timing ability. As expected, the number of industries covered has a negative impact on timing ability, but in only two of the three specifications.

Overall, economic determinants appear to explain the variation in timing ability, though there are certain results that go contrary to our expectations. The finding that economic determinants predict timing ability provides further validation that analysts indeed possess timing ability.

2.4. Robustness

Table 2-9 reports the results of the various robustness tests we conduct. Our first set of tests examines alternative definitions of *Timing*. Our second set of tests examines alternative windows for announcement returns and post-revision returns.

Table 2-9

Robustness

		Downgrades			Upgrades		
		Timing (A)	Non-Timing (B)	(A) - (B)	Timing (C)	Non-Timing (D)	(C) - (D)
		A. Alternative Definitions of Timing					
1.	Only ΔPT=0						
	a. Announcement CAR	-3.4%***	-4.6%***	1.2%***	2.1%***	3.7%***	-1.6%***
	b. Post-revision CAR	-0.9%***	-0.6%***	-0.3%**	-0.0%	0.3%***	-0.3%***
2.	48 hours prior to earnings						
	a. Announcement CAR	-3.4%***	-4.7%***	1.3%***	3.9%***	3.3%***	-0.6%
	b. Post-revision CAR	-0.3%	-0.6%***	0.3%	0.9%***	0.2%***	0.7%**
		B. Alternative Windows for Announcement Returns					
3.	Announcement CAR[–2,+2]	-2.6%***	-4.9%***	2.3%***	1.9%***	3.3%***	-1.4%***
4.	Announcement CAR[–3,+3]	-2.7%***	-5.1%***	2.4%***	1.6%***	3.3%***	-1.7%***

Note. The table provides results from several robustness tests. Panel A considers alternative definitions of *Timing*. Panel B considers alternative estimation windows for announcement returns and post-revision drift.

2.4.1. Alternative Definitions Of Timing

Our base case definition of timing is one where the analyst revises his recommendation but does not revise any of the other I/B/E/S measures such as EPS, price target etc. Our alternative definition of timing, also mentioned in Section I.A, is a recommendation revision where the analyst does not revise his price target even though he could revise any of the 23 fundamental drivers of stock price. Row 1a and Row 1b of Table 2-9 reports the mean announcement CARs and post-revision CARs. Once again, the numbers are similar to that for our base case definition of timing.

Our second alternative definition of timing report is one in which the analyst issues a recommendation revision in the 48 hours prior to earnings release. Clearly, the analyst is making a bold call.[18] In untabulated results, we find that only 2% of recommendation revisions are issued 2 days prior to earnings release. Row 2a and Row 2b of Table 2-9 reports the mean announcement CARs and post-revision CARs respectively. We find that the mean announcement CARs are -3.4% for downgrades and +3.9% for upgrades. These numbers are higher in magnitude to the base case (-2.0% and +2.5%). Thus, the markets seem to respond to these bold analysts more strongly.

[18] It is also possible that the earnings information leaked out and the analyst capitalizes on the information to issue a revision in advance of the earnings release. This seems unlikely because a timing report is one where the analyst does not revise any of the fundamental measures but only the recommendation. Thus if the information leaked out was above (below) expectations, then the analyst should have revised his outlook for the fundamental upwards (downwards), which would make it a regular revision and not a timing revision.

2.4.2. Alternative Estimation Windows

Our base case announcement CARs are over the window [-1,+1]. Panel B of Table 2-9 reports the announcement CARs over the windows [-2,2] and [-3,+3]. Results are similar to our base case results.

2.5. Conclusions

What do analysts do and how do they add value? The literature has documented that analysts engage in information discovery and data interpretation, and both these activities add value. The contribution of our paper is to document a third dimension, what we term as stock timing. This is the ability of the analyst to discern that the recent stock price movements are not due to fundamentals and revise their recommendation to reflect potential mispricing. Specifically timing is defined as the change in recommendation regarding a stock by an analyst without a corresponding change in any of the fundamental estimates of the firm. We show that timing reports are a significant fraction of total reports (30%). Timing is valuable to investors as evidenced by stock returns around the date of a timing report. We find that firm-specific, analyst-specific, and market-specific factors predict both the probability of timing as well as the timing ability. Specifically, timing is more likely at time periods when markets are more volatile, for more volatile stocks, as well as for stocks that are more likely to be mispriced. Timing ability is higher for more experienced analysts and for analysts covering fewer industries.

CHAPTER 3

RECOMMENDATION REITERATIONS

3.1. Introduction

Current literature on sell-side analysts generally ignores reiterations of prior recommendations by sell-side analysts, but argues that recommendation revisions are all that matters (Womack, 1996). This is partly because market responses to reiterations are close to zero. Given the findings that the majority of analysts' reports reiterate prior recommendations (Brav and Lehavy, 2003; Asquith et al, 2005), why do analysts expend their valuable time and resources just to reiterate if reiterations are not valuable? In fact, the Buy-reiteration could not be the same as the Sell-reiteration because one is saying buy and the other is saying sell. Buy-reiteration is expected to generate positive abnormal return while the sell-reiteration is expected to generate negative abnormal return. Therefore, it is not surprising to see market response which is close to zero, on average. In addition, when the current recommendation is already a Strong Buy (Strong Sell), the analyst has no way to increase (decrease) his prior recommendation even if he becomes more optimistic (pessimistic).

In this chapter, we argue that reiterations are not homogeneous and there is a large subset of reiterations which are as much valued by investors as recommendation revisions. For this study, starting with I/B/E/S, we break up recommendation reiterations into 5 different categories: Reiteration: Strong Buy, Reiteration: Buy, Reiteration: Hold, Reiteration: Sell, and Reiteration: Strong Sell. We then develop several hypotheses to support our arguments. First, if reiterations are valuable, we should see a monotonic increase in announcement CARs from the Reiteration: Strong Sell to the Reiteration: Strong Buy because market should extract differing level of information contents from different categories of reiterations. In other words, Reiteration: Strong Buy will bring more positive market response than Reiteration: Strong Sell. Second, if reiterations are valuable, for each of the 5 categories, we expect to see a monotonic increase in CARs from reiterations with contemporary downgrades in both earnings forecasts and price targets to reiterations with contemporary upgrade in both earnings forecasts and price targets. Lastly, if reiterations are valuable, then we should find a significant proportion of reiterations to be influential (Loh and Stulz, 2011) and this proportion will also be similar to that for upgrades and downgrades of recommendations. To test these hypotheses, we separate each type of reiteration into different groups based on certain observable characteristics (e.g., accompanying revision to earnings forecast and/or price targets). The sample is obtained from I/B/E/S for 14 years from 1999 to 2012. We choose 1999 as a starting year because I/B/E/S began to track price targets from 1999. We adopt a modified version of "filling in the holes" method used by Conrad et al. (2006) and combine Detail History file containing the measures tracked by I/B/E/S (Price Target, EPS, etc.) and Recommendation file to create the full time series of recommendations (initiations, reiterations, and revisions) made by each analyst for each firm during our sample period. More detailed discussion on how to construct our sample will follow in section 3.3 (Data and Methodology).

Our main finding are generally consistent with our hypotheses. First, we find that recommendation reiterations are prevalent, re-confirming prior findings (Brav and Lehavy, 2003; Asquith et al, 2005).

Second, as hypothesized, market response to recommendation reiterations increase monotonically from Reiteration: Strong Sell to Strong Buy. As prior literature suggests, CARs of reiterations is only -0.14% on average, but CARs increase monotonically from -0.63% for Reiteration: Strong Sell to 0.00% for Reiteration: Strong Buy. Third, reiterations coupled with contemporary changes in price targets and/or earning forecasts bring substantial abnormal stock returns to investors. Lastly, when we replicate what Loh and Stulz (2011), we find that the number of reiterations which are influential is more than twice that of recommendation revisions. Our contribution in this chapter is to provide convincing evidence that there are a substantial subset of reiterations that are as much valued by investors as recommendation revisions and to suggest that researchers should include recommendation reiterations in their future studies on sell-side analysts.

3.2. Hypotheses Development

In this section, we develop our hypotheses. The premise behind all our hypotheses is that the reiterations are not a homogenous group. When we divide the reiterations into separate groups based on certain observable characteristics, we expect to find that some reiterations are valuable to investors. We first do this by separating reiterations into 5 different categories: Reiteration: Strong Buy, Reiteration: Buy, Reiteration: Hold, Reiteration: Sell, and Reiteration: Strong Sell. We expect that we should see a monotonic increase in announcement CARs from the Reiteration: Strong Sell to the Reiteration: Strong Buy. Second, recommendation changes, which by definition are discrete, are made only when the expectation of the analyst changes substantially. For smaller changes, analysts may revise either of two other key summary measures (i.e., earnings forecasts and price targets) or both, but not their recommendation. Thus, we expect to see market to respond stronger to reiterations with upgrades in two other key measures than to those with downgrades in two other key measures. Lastly, we expect to find a significant proportion of reiterations to be influential and this proportion will be similar to that for upgrades and downgrades.

3.3. Data and Methodology

Our sample period is from 1999 to 2012. We start with 1999 because I/B/E/S has availability of price targets only from 1999. We combine Detail History file containing the measures tracked by I/B/E/S (Price Target, EPS, etc.) and Recommendation file to create the full time series of recommendations (initiations, reiterations, and revisions) made by each analyst for each firm. This is required in order to identify which of the recommendations are reiterations given the fact that IBES only adds new observation to each file only when analysts change their estimates. For this study, we focus only on annual EPS in the Detail history file and merged files using unique "firm-analyst-announcement date" pairs. If an analyst changed earnings forecast, price target and recommendation on the same date for the same firm he covers, then the pair will have data for all three measures. However, if an analyst changed only either earnings forecast or price target or BOTH, but not recommendation, then the pair will have data for earnings forecast or price target, but not for recommendation. In this case we "fill in the hole" using the most recent prior recommendation issued on the same firm by the same analyst. An illustration in Table 3-1 is presented to help better understand how we fill in the holes to identify reiterations. Suppose that an analyst, named Tom initiated his coverage on a firm, XX on January 5th of 1999 with BUY recommendation. Soon after the initiation, on January 19th, the analyst revised his earnings forecast from \$1.5 to \$1.7, but did not change either prior price target or recommendation on the firm XX. On April 19th, the analyst revised up price targets from \$24 to \$26 without changing his prior recommendations. On July 19th, the analyst downgraded his recommendation to HOLD from BUY. In this case, we fill in the hole of each observation 2 and 3 under assumption that the previous recommendation still holds.

Table 3-1

How To Fill-In-Holes

Observation	ticker	analyst	date	EPS	PT	Recommendation	Category
1	XX	Tom	5-Jan-99	1.5	24	buy	Initialization
2	XX	Tom	19-Jan-99	1.7		**buy**	**Reiteration**
3	XX	Tom	19-Apr-99		26	**buy**	**Reiteration**
4	XX	Tom	19-Jul-99			hold	Downgrade
5	XX	Tom	22-Jul-99	1.4	22	buy	Upgrade

3.4. Main Results

First, we examine how prevalent the recommendation reiterations are. As shown in Table 3-2, about 80% of recommendations are reiterations, which is consistent with prior findings (Brav and Lehavy, 2003; Asquith et al, 2005), suggesting that researchers are missing out a significant portion of recommendations in their studies. Second, we examine how market responds differently to each level of recommendation reiterations. For this test, we break reiterations into 5 different categories: Reiteration: Strong Buy, Reiteration: Buy, Reiteration: Hold, Reiteration: Sell, and Reiteration: Strong Sell.

Table 3-2

Distribution of Recommendations By Year

Year	Reiterations	Initial Recommendations	Revisions	Total	Reiterations/Total
1999	54,205	12,075	10,677	76,957	70%
2000	65,327	10,529	9,924	85,780	76%
2001	82,225	9,413	9,978	101,616	81%
2002	81,990	10,718	14,037	106,745	77%
2003	77,091	9,305	11,652	98,048	79%
2004	81,291	10,200	11,174	102,665	79%
2005	82,667	9,282	10,748	102,697	80%
2006	82,425	9,637	10,809	102,871	80%
2007	84,672	9,028	11,502	105,202	80%
2008	100,751	10,019	13,082	123,852	81%
2009	93,660	9,469	11,791	114,920	82%
2010	101,882	9,917	9,894	121,693	84%
2011	107,397	9,268	11,020	127,685	84%
2012	107,484	8,336	10,056	125,876	85%
Total	1,203,067	137,196	156,344	1,496,607	80%

Note. We exclude observations occurring 3 days around quarterly earnings announcement dates. we also exclude observations having multiple recommendation on the same date.

We use 2-day cumulative abnormal returns (CARs) over the window (0,+1) relative to the release of recommendation reiterations. As expected, we observe a monotonic increase in CARs from the Reiteration: Strong Sell (-0.63%) to the Reiteration: Strong Buy (0.00%) as shown in Table 3-3. The results suggest that just like upgrade and downgrade of recommendations, investors react more positively (negatively) to positive (negative) reiterations.

Next, we examine whether there are reiterations which are as much valued by investors as recommendation revisions. For this test, we form 5 subgroups based on two other summary measures (i.e., earnings forecasts and price target) within each of the 5 categories of reiterations.

Table 3-3

Returns around Recommendations

1-Day CAR [0, +1]	Recommendation		
	Reiteration of	Downgrade to	Upgrade to
Strong Sell	-0.63*** (16,416)	-3.75*** (5,920)	NA
Sell	-0.43*** (47,148)	-3.63*** (10,908)	0.65* (354)
Hold	-0.26*** (472,456)	-3.41*** (56,866)	2.30*** (11,980)
Buy	-0.05*** (368,836)	-2.66*** (12,375)	2.78*** (27,232)
Strong Buy	0.00 (298,121)	NA	2.83*** (30,665)
Overall	-0.14*** (1,202,977)	-3.36*** (86,069)	2.71*** (70,231)

Note. we break reiterations into 5 different categories: Reiteration: Strong Buy, Reiteration: Buy, Reiteration: Hold, Reiteration: Sell, and Reiteration: Strong Sell. We exclude observations occurring 3 days around quarterly earnings announcement dates. we also exclude observations having multiple recommendation on the same date.

Group 1 (both EPS and price target are down) consists of reiterations with contemporary downgrades in both summary measures. Group 2 (one measure is down, but the other remains the same as before) consists of reiterations with contemporary downgrade in one key measure and no change in the other measure. Group 3 (no changes in both measures) consists of reiterations with no change in both key measures. Group 4 (one measure is up, but the other remains the same as before) consists of reiterations with contemporary upgrade in one key measure and no change in the other measure. Group 5 (both measures are up) consists of reiterations with contemporary upgrades in both summary measures. As correctly hypothesized, we find that CARs increase monotonically from Group 1 to Group 5 for each of the 5 categories in Table 3-4, providing confirming evidence that reiterations are not homogeneous and there are substantial number of reiterations which bring as much value to investors as revisions.

Lastly, we replicate what Loh and Stulz (2011) do by identifying influential reiterations in 5 categories and compare to upgrade and downgrade of recommendation. Surprisingly, we observe in Table 3-5 that the number of influential reiterations is 44,799, which is more than twice the number of influential revisions (sum of downgrade and upgrade).

Table 3-4

Returns around Changes in Earnings Forecasts and Price Targets

	△EPS and △PT				
2-Day CAR [0, +1]	**Group 1 (Both < 0)**	**Group 2 (Only 1 < 0)**	**Group 3 (Both = 0)**	**Group 4 (Only 1 > 0)**	**Group 5 (Both > 0)**
Reiteration of:					
Strong Sell	-2.97^{***}	-1.46^{***}	-0.20	0.35^{***}	0.40^{**}
	(1,267)	(4,949)	(983)	(4,007)	(1,086)
Sell	-2.28^{***}	-0.98^{***}	-0.17^{**}	0.48^{***}	0.52^{***}
	(3,946)	(15,093)	(3,990)	(11,980)	(2,858)
Hold	-2.03^{***}	-0.79^{***}	-0.07^{**}	0.61^{***}	0.80^{***}
	(35,977)	(139,862)	(30,550)	(117,951)	(30,698)
Buy	-1.71^{***}	-0.52^{***}	0.06^{*}	0.59^{***}	1.12^{***}
	(31,111)	(109,117)	(30,286)	(108,364)	(31,371)
Strong Buy	-1.86^{***}	-0.57^{***}	0.17^{***}	0.73^{***}	1.34^{***}
	(21,805)	(79,128)	(19,217)	(80,278)	(23,954)
Reiteration: Overall	-1.91^{***}	-0.67^{***}	0.03	0.62^{***}	1.04^{***}
	(94,106)	(348,149)	(85,026)	(322,580)	(89,967)
Upgrade	2.19^{***}	2.53^{***}	2.27^{***}	3.23^{***}	3.28^{***}
	(2,200)	(6,140)	(19,022)	(13,458)	(10,659)
Downgrade	-5.86^{***}	-5.35^{***}	-2.05^{***}	-1.09^{***}	-1.07^{***}
	(11,381)	(16,048)	(30,237)	(6,527)	(1,984)

Note. we form 5 subgroups based on two other summary measures (i.e., earnings forecasts and price target) within each of the 5 categories of reiterations. We exclude observations occurring 3 days around quarterly earnings announcement dates. we also exclude observations having multiple recommendation on the same date.

Table 3-5

Influential Recommendations

	Recommendation		
1-Day CAR [0, +1]	**Reiteration of**	**Downgrade to**	**Upgrade to**
Strong Sell	-12.44*** (1,187)	-12.56*** (851)	NA
Sell	-11.45*** (3,101)	-11.40*** (1,571)	7.81** (25)
Hold	NA	-11.79*** (7,160)	11.09*** (1,332)
Buy	10.07*** (21,880)	-7.07*** (1,312)	9.66*** (4,097)
Strong Buy	10.40*** (18,631)	NA	10.71*** (4,598)
Overall	8.12*** (44,799)	-11.23*** (10,894)	10.32*** (10,052)

Note. We exclude observations occurring 3 days around quarterly earnings announcement dates. we also exclude observations having multiple recommendation on the same date. Announcement CAR is influential if the absolute value of the announcement CAR > $1.96\times\sqrt{2}\times\sigma_e$, where σ_e is the standard deviation of residuals in the estimation interval.

3.5. Conclusions

The literature has documented that recommendation reiterations are basically non-event because market response to reiterations is close to zero. By dividing each type of reiteration into different groups based on certain observable characteristics, we find that the number of reiterations that are valued by investors are greater than the number of recommendation revisions that are valued. The contribution of this chapter is to document that reiterations are not homogeneous and there is a large subset of reiterations which are valued by investors.

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APPENDIX

FUNDAMENTAL MEASURES TRACKED BY I/B/E/S

Variable	Description	Forecast Period
(EPS)	Earnings Per Share	▪ 10 Annuals ▪ 12 Quarters ▪ 6 Semi-Annuals
(BPS)	Book Value Per Share	
(CPS)	Cash Flow Per Share	
(Non per share, CPX)	Capital Expenditure	
(CSH)	Cash Earnings Per Share	
(DPS)	Dividend Per Share	
(EBG)	Earnings Per Share - Before Goodwill	
(Non Per Share, EBI)	EBIT	
(EBS)	EBITDA Per Share	
(Non Per Share, EBT)	EBITDA	
(Non Per Share, ENT)	Enterprise Value	
(EPX)	Earnings Per Share - Alternate	
(FFO)	Funds From Operations Per Share	
(GPS)	GAAP/Earnings Per Share - Fully Reported	
(Percent, GRM)	Gross Margin	
(Non Per Share, NAV)	Net Asset Value	
(NDT)	Net Debt	
(Non Per Share, NET)	Net Income	
(Non Per Share, OPR)	Operating Profit	
(Non Per Share, PRE)	Pre-tax Profit	
(Percent, ROA)	Return on Assets	
(Percent, ROE)	Return on Equity	
(Non Per Share, SAL)	Revenue	
(PTG)	Price Target	Mostly 6, 12 and 18 Month Horizons