THE FLOW OF EARNINGS INFORMATION TO THE MARKET

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Prior to a firm's earnings announcement, the capital market receives earnings-relevant information from a wide array of sources. As such, the collective timeliness of the flow of earnings information to the market has large implications for the price path of a firm's stock. Despite this, our understanding of the timeliness of the flow of earnings information to the market and its economic determinants is limited, in part because prior work has focused on the timeliness of specific sources of information rather than the collective whole. In this study, I create a measure of the timeliness of the total earnings information flow – inspired by the price discovery literature – that captures how quickly the daily consensus analyst earnings forecast approaches the actual earnings as the quarter unfolds. I document wide within-firm variation in the timeliness of the earnings information flow and show that it is associated with the direction and magnitude of the news. Specifically, I show that the earnings information flow is significantly more timely for bad news than for good news. Perhaps more importantly, I show that while bad news becomes less timely as the magnitude of the earnings news increases, good news becomes more timely. This result is in direct contrast to the commonly cited litigation explanation for timelier bad news and is more consistent with a scenario where managers face a tradeoff between current stock price implications and future reporting reputation benefits.

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CHAPTER 1: INTRODUCTION

At least since Ball and Brown (1968), researchers have recognized that: (i) earnings news is an important driver of stock returns; (ii) much of the earnings-relevant information in a period precedes the actual earnings announcement itself; and (iii) earnings information arrives from a wide array of sources. As such, the timeliness of the flow of earnings information to the market (i.e., the broad set of information that investors can obtain to develop expectations for that quarter's earnings number) and its economic determinants have important implications for the price path of a firm's stock. In fact, prior research suggests that investors may value earnings news differentially depending upon its timing in the quarter (e.g., Bartov et al., 2002). In this study, I provide evidence on the timeliness of the flow of earnings information to the market and how it is influenced by the direction and magnitude of the news.

This study builds on prior work that explores the relation between the timeliness of earnings information and the direction and magnitude of the news, particularly on two important dimensions. First, unlike most of the work in this area that focuses on the timing of specific events, such as management forecasts or earnings announcements, I create and validate a measure of the *total* earnings information flow over a given quarter. Specifically, I draw from the price discovery literature to create a measure that captures how quickly the daily consensus analyst earnings forecast approaches the actual earnings as the quarter unfolds. This approach captures the interplay of numerous earnings information sources, which is particularly important because prior studies have focused on specific earnings news disclosure events (such as management forecasts or earnings announcements themselves), with conflicting results. For example, empirical evidence on the direction of the news documents timelier good news for earnings announcements (Chambers and Penman, 1984) and timelier bad news for management forecasts (Skinner, 1994). Second, my measure is distinct from prior research because it clearly identifies current quarter earnings news, whereas stock return-based proxies for timeliness have difficulty disentangling current earnings news from future earnings news and discount rate news. Additionally, these proxies cannot separate differential timeliness in earnings news from differential valuations of the news by investors.

I document wide between- and within-firm variation in the timeliness of the flow of earnings information to the market (i.e., differences in the timeliness with which analyst forecasts converge to the actual earnings number). Specifically, for the quartile in which earnings information flows fastest to the market, I find that the market has received 75 percent of the current quarter's earnings information by the last day of the quarter. In contrast, for the quartile in which earnings information flows slowest, the market has received none of the earnings information by that date. Further, I find that a larger proportion of the total variation in timeliness can be attributed to within-firm variation as opposed to between-firm variation. As such, I examine the extent to which this substantial within-firm variation is a consequence of the direction and magnitude of the news.

I first examine how the direction of the earnings news affects the timeliness of the earnings information flow. Prior theoretical work provides divergent predictions, suggesting timelier good news due to a standard agency problem (e.g., Dye, 1985; McNichols, 1984) or timelier bad news because of litigation or reporting reputation concerns (e.g., Beyer and Dye, 2012; Trueman, 1997). Also, empirical findings are mixed: studies examining earnings announcements document timelier good news (e.g., Chambers and Penman, 1984); studies examining management forecasts document timelier bad news (e.g., Skinner, 1994) and studies using stock returns as a proxy for disclosure document timelier good news (e.g., Kothari et al., 2009). Using the measure I develop in this study, which encompasses the timeliness of all information relevant to analysts' consensus earnings forecasts, I document that the earnings information flow is significantly more timely for bad news (by as much as 50 percent) than for good earnings news. This result suggests that litigation and reporting reputation concerns may be of particular importance in explaining the timeliness of the flow of earnings information, especially when the news is bad.

I next examine the role of the magnitude of the earnings news, and its interaction with the direction of the news, in explaining the timeliness of the earnings information flow. This analysis is important in understanding *why* bad news may be more timely than good news. I find that, as the magnitude of the news increases, bad news becomes less timely while good news becomes more timely. These findings on the timing of bad news are in direct contrast to the Ajinkya and Gift (1984) expectations-adjustment hypothesis and to the Skinner (1994) threat of litigation hypothesis, both of which predict bad news to become more timely as the magnitude of the news increases. Instead, my results are more consistent with a scenario where managers face a tradeoff between current stock price implications and reporting reputation benefits (e.g., Beyer and Dye, 2012; Graham et al., 2005). Specifically, managers may release bad news faster than good news to promote a reputation of transparent reporting; however, as the bad news gets large (and stock price implications increase), managers likely delay the news to allow for in-depth analysis, a positive interpretation, and/or consolidation into larger and potentially off-setting news releases (Graham et al., 2005).

I note that my primary analyses do not condition on the (unobservable) timing of shocks to earnings (i.e., when the firm learns whether the earnings news will be good or bad.) Thus, to distinguish between differential earnings information flow and differential timing of shocks to earnings, I exploit the exogenous shock of Hurricane Katrina to quarterly earnings for a sample of affected industries and examine factors that explain within-industry variation. This analysis enables me to examine the differential flow of earnings information, holding constant the date of the triggering event. Consistent with my primary results, I find that the earnings information flow is more timely for bad earnings news than for good earnings news. Importantly, I also find that as the magnitude of the earnings news increases, bad news becomes less timely while good news become more timely. This evidence suggests that the results of my primary analyses are not driven by differential timing in the shocks to earnings and further supports my prior inferences.

Because I rely on daily analyst consensus forecasts as my proxy for earnings information flow timeliness, my results may be susceptible to variation in the timing with which analysts impound earnings information into their forecasts. For example, prior work suggests that analysts are slower in revising earnings estimates when the news is unfavorable (e.g., Chan et al., 1996). This prior work makes my results – of timelier bad news – even more striking.[1] Further, prior work suggests that analysts have incentives to be more timely with large earnings news versus small earnings news because of the relation between forecast accuracy and job security (e.g., Mikhail et al., 1999). This result is in direct contrast with my finding that the timeliness of bad news decreases with its adversity.

Despite these striking differences, I want to ensure that analysts are not the driving force behind my results because my research question addresses motivations within the firm. As such I perform three analyses to demonstrate that my results are not attributable to analyst behavior. First, I examine the extent to which time-varying managerial disclosure incentives (which have

[1] Prior work also suggests that analysts underreact to negative information and overreact to positive information (Easterwood and Nutt, 1999), which is also contradictory to the evidence that I present of timelier bad news.

clear firm-specific directional predictions in prior literature) influence the relative timeliness of good versus bad news. As expected, I find that the timeliness of bad earnings news is increasing both in litigation risk and the extent of outside monitoring, whereas the timeliness of good earnings news is decreasing in those factors. I also find evidence that the timeliness of good news (bad news) is increasing (decreasing) in the level of sales growth, price momentum, and the amount of insider trading. Because the time-variant firm-specific factors behave as predicted in prior disclosure literature, the variation in earnings information flow timeliness is more likely attributed to time-varying firm factors, as opposed to analyst influences.

Second, I explore the within-firm association between my measure and the timing of observable firm disclosures. I find that earnings information flow timeliness is associated with the timing of management forecasts and the number of 8-K filings released in the period. Third, I perform an event-study analysis surrounding the release of management forecasts to examine whether my daily metric reflects the information on a timely basis. I provide results that my analyst-based measure impounds both good and bad news information from management forecasts within two trading days of the management forecast release. I also complete a number of additional tests to rule out other alternative explanations, such as earnings management, expectations management, prior quarter earnings surprises, and the timeliness of industry- or economy-wide earnings news. Collectively, my analyses suggest that time-varying firm factors drive the results, rather than analyst influences.

My study contributes to the literature by providing evidence on firms' aggregate flow of earnings information to the market. While prior work explores the timeliness of particular earnings-related disclosures, it is unclear how these disclosures (and their economic determinants) combine to form the total flow of earnings information. Using an analyst-based approach, I show that market participants obtain bad earnings news in a more timely manner than good earnings news. This result sheds light on how the direction of the news influences the total earnings information flow, which is particularly important because of conflicting results across individual disclosure events. Importantly, I also provide evidence that this relation is more complicated than prior research would suggest. For example, I show that as the magnitude of the earnings news increases, bad news becomes less timely while good news becomes more timely. In contrast to prior work that often assumes litigation concerns are the sole motivation for timelier bad news, this result suggests that the tradeoff between current stock price implications and future reporting reputation benefits is an important driver in the relative timeliness of bad versus good news. Additionally, I show that the relative timeliness of good versus bad news is influenced by the extent of outside monitoring, performance momentum, and insider trading.

My results also have implications for practice. Given that policy-makers are concerned with promoting timely firm disclosure in order to 'level the playing field' and promote market efficiency, my results can help regulators understand how the nature of the news influences within-firm timeliness of the flow of earnings information to the market. Specifically, my evidence of systematic variation with both the direction and magnitude of the earnings news is arguably inconsistent with regulators' objective of ensuring that investors receive a steady flow of timely, comprehensive, and accurate information (SEC, 2014).

I organize the remainder of this dissertation as follows: chapter 2 reviews prior literature and develops my hypotheses; chapter 3 describes my data and variable construction; chapter 4 describes my research design and provides the results of my primary empirical tests; chapter 5 provides robustness tests and additional analyses; chapter 6 concludes.

CHAPTER 2: BACKGROUND AND HYPOTHESIS DEVELOPMENT

The goal of this study is to provide insight into the within-firm variation in the timeliness of the flow of earnings-relevant information to the market. While sources outside the firm's control certainly have at least some influence on timeliness (e.g., analysts, industry reports, macroeconomic news), my study focuses on time-varying firm factors. As such, I base my analyses on two fundamental factors from prior literature – the direction of the earnings news (Ball and Brown, 1968) and the magnitude of the earnings news (Beaver et al., 1979) – and control for influences outside the firm's control. The next two sections discuss the potential links between earnings information flow timeliness and the direction/magnitude of the earnings news.

2.1 Direction of the Earnings News

Prior work has long recognized that the direction of the earnings news plays a role in the timing of specific disclosures, suggesting that it may be an important determinant for the timeliness of the total earnings information flow. It is difficult to extrapolate a directional prediction from this literature, however, because prior work offers conflicting predictions (at least partly due to its focus on specific pieces of the total earnings information flow).

On the one hand, prior literature predicts timelier disclosure of good news versus bad news. For example, the argument that managers have a tendency to withhold bad news due to a standard agency problem underlies many theoretical models explaining discretionary disclosure (e.g., Dye, 1985; McNichols, 1984). Specifically, managers have self-serving incentives (such as concerns about their careers, compensation packages, or stock-price-based wealth) that may cause them to withhold bad news until the last possible moment. The earnings announcement timeliness literature supports this good news early, bad news late hypothesis by documenting an association between the timing of earnings announcements and the direction of the news (e.g., Bagnoli et al., 2002; Begley and Fischer, 1998; Chambers and Penman, 1984; Givoly and Palmon, 1982; Kross, 1981; Kross and Schroeder, 1984). Relatedly, research using returns as a proxy for total disclosure also provides evidence in support of timelier good news relative to bad news (e.g., Kothari et al., 2009; McNichols, 1984, 1988).[2]

On the other hand, prior work also predicts timelier disclosure of bad news relative to good news. For example, Skinner (1994) and Trueman (1997) purport that managers report bad news early to alleviate or minimize lawsuit concerns. Relatedly, prior work also suggests that managers may report bad news on a timelier basis to enhance or promote a reputation for transparent and accurate reporting (Beyer and Dye, 2012; Graham et al., 2005).[3] The management guidance literature supports these hypotheses of timelier bad news through evidence that managers disclose bad news forecasts more often than good news forecasts (e.g., Anilowski et al., 2007; Skinner, 1994; Soffer et al., 2000).[4] Further, Kasznik and Lev (1995) examine the disclosure policies of firms facing large earnings surprises and find that bad news firms release more discretionary disclosures than good news firms, suggesting that firms may release bad earnings news more timely. Due to the conflicting predictions on the association between the direction of the news and earnings information flow timeliness, I present the following hypothesis (*stated in null form*):

> ***H1:*** *Earnings information flow timeliness is not associated with the direction of the earnings news.*

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[2] Further, Miller (2002) documents that firms expand voluntary disclosures during periods of increased earnings, which likely increases the timeliness of earnings news during good periods.

[3] Prior literature also presents other reasons to expect timelier disclosure of bad news. For example, Darrough and Stoughton (1990) show that managers may disclose bad news to discourage entry by competing firms. Additionally, Teoh and Hwang (1991) suggest that strategic behavior may lead to timelier disclosure of bad news.

[4] Early management forecast research provides opposite evidence, consistent with managers disclosing good news forecasts more often than bad news forecasts (e.g., Patell, 1976; Penman, 1980; Waymire, 1984). Further, Ajinkya and Gift (1984) also suggest a symmetric disclosure pattern for good news and bad news forecasts.

2.2 Magnitude of the Earnings News

Prior work also provides reasons to expect (potentially opposite) associations between the magnitude of bad or good earnings news and earnings information flow timeliness. First, Ajinkya and Gift (1984) present the expectations-adjustment hypothesis, which suggests that the likelihood of a manager preempting an earnings announcement is increasing in the size of the earnings surprise, regardless of its sign. Second, the litigation hypothesis in Skinner (1994) purports that managers are more likely to preempt large negative earnings than other earnings announcements. This hypothesis suggests a positive association between timeliness and the magnitude of the news, but only for bad news surprises.

Third, Beyer and Dye (2012) demonstrate that managers may trade off future reporting reputation benefits against current stock price implications. In this reporting reputation hypothesis, managers release bad news in a timely manner to build a reputation for being forthcoming up to a certain threshold where current stock price implications overwhelm the potential reputation benefits. Thus, this reporting reputation hypothesis suggests a negative association between the magnitude of the news and earnings information flow timeliness for bad news and a positive relation for good news (since stock price and reputation incentives are aligned). Relatedly, Graham et al. (2005) suggest that as bad news gets large, managers become more concerned with stock price implications and delay the release of the news to: (i) allow for in-depth analysis and interpretation; (ii) seek offsetting news with which to consolidate the bad news; or (iii) put a positive spin on the news.

Because prior work presents conflicting predictions regarding the association between the magnitude of bad earnings news and earnings information flow timeliness (i.e., the expectations adjustment hypothesis and the litigation hypothesis predict a positive association, whereas the reporting reputation/stock price implication hypotheses predict a negative association), I present the following hypothesis *(in null form*):

> ***H2a:*** *Earnings information flow timeliness is not associated with the magnitude of bad earnings news.*

In contrast to bad news, prior work presents consistent predictions for the relation between the magnitude of good earnings news and earnings information flow timeliness. Therefore, I present the following hypothesis *(in alternative form):*

> ***H2b:*** *Earnings information flow timeliness is positively associated with the magnitude of good earnings news.*

CHAPTER 3: VARIABLE CONSTRUCTION AND SAMPLE SELECTION

3.1 Earnings Information Flow Timeliness ("EIFT")

My research question requires a proxy for earnings information flow timeliness. Isolating the flow of earnings information presents at least three fundamental challenges. First, the proxy should be comprehensive and ideally capture earnings news from all of the sources used by capital market participants. Second, the proxy should account for the speed with which the earnings news helps capital market participants develop expectations prior to the actual earnings announcement realization. Third, the proxy must be refined to capture only news relevant for expectations for the upcoming quarterly earnings announcement, and avoid capturing all of the other news available about a firm during the quarter (such as future quarters' earnings news). These three challenges limit the applicability of traditional disclosure proxies (see chapter 1). For example, management forecasts are not comprehensive in that they likely omit earnings information from other sources, whereas return-based proxies are not refined enough to disentangle current earnings news from future earnings news and discount rate news. Specifically, Richardson et al. (2010) note that the returns-based measures of earnings news and discount rate news are quite noisy, especially at the security level.

I adopt a new approach using the trajectory of daily consensus analyst earnings forecasts to overcome these challenges and identify the overall flow of earnings information to the market. Specifically, I calculate and plot the daily consensus earnings forecast revisions as a percent of the total earnings news within each firm-quarter, holding the analyst pool constant, and apply area-under-the-curve technology, typical of the price discovery literature, to create a measure that captures the speed of convergence to the ultimate earnings realization ("earnings information flow timeliness" or "*EIFT*").[5]

Using analyst forecasts to develop a proxy for earnings information flow timeliness is beneficial for at least four reasons. First, analyst forecast revisions are broad-based, as they reflect information in a multitude of firm-specific disclosures. For example, prior research shows that analyst forecasts reflect management earnings forecasts (Hassell et al., 1988; Jennings, 1987), conference calls (Bowen et al., 2002; Frankel et al., 1999), product-related and business expansion press releases (Nichols and Wieland, 2009), and other nonfinancial disclosures (Dhaliwal et al., 2012). This provides a distinct advantage relative to proxies exploring isolated events, such as management forecasts, which omit information from other disclosures.

Second, analyst forecast revisions are refined enough to only reflect current quarter earnings news (i.e., the evolution of forecast revisions is mostly unaffected by future quarter earnings news and discount rate news). This is in direct contrast to stock returns, which encompass earnings news related to all future quarters, along with discount rate news. Third, analyst forecast revisions are useful in translating soft disclosures into earnings implications because the market values analysts' interpretive role in assessing earnings implications of disclosures (Altinkiliç et al., 2013; Livnat and Zhang, 2012). This alleviates the aggregation challenge that researchers commonly face when gathering a broad set of disclosures. Further, it

[5] This measure builds on prior work that identifies the advantages of inferring the timeliness of information flows through the lens of analyst forecasts (e.g., Aboody and Kasznik, 2000; Donelson et al., 2012). *EIFT* is most closely related to work in Donelson et al. (2012), which examines the timeliness of bad earnings news in a litigation context. I extend their work by: (i) applying area-under the curve (AUC) methods, typical of the price discovery literature; (ii) holding the analyst pool constant to limit selection concerns; (iii) standardizing the period length from the beginning of the quarter to encompass all earnings news events, especially the prior quarter's earnings announcement; and (iv) examining and validating the measure across a large panel dataset. AUC methods provide theoretical support to the measure, as price discovery measures have a long history in accounting research, including Alford et al., 1993; Ball and Brown, 1968; Bushman et al., 2010; Butler et al., 2007; and McNichols, 1984.

increases the likelihood that the inferred earnings implications from soft disclosures are aligned with investors. Finally, analyst earnings forecast revisions are timely, as 90 percent of analyst earnings forecast revisions follow disclosures within three trading days (Altinkiliç et al., 2013).[6]

To create my earnings information flow timeliness proxy, I first identify the population of active analyst forecasts in the I/B/E/S unadjusted detail file on the first trading day of each firm-quarter. I begin the window on the first trading day to ensure that the initial expectation precedes the quarter's operations and to ensure that the window encompasses all important earnings news events in the quarter, particularly the prior quarter's earnings announcement that often includes forward-looking bundled information (Rogers and Van Buskirk, 2013) and conference call discussion (Matsumoto et al., 2011). Specifically, I select all quarterly earnings forecasts for the firm quarter that are announced prior to day one of the quarter and then filter as follows: (i) remove forecasts that are more than 90 days old (unless the analyst confirmed the forecast to still be accurate for that date range) to limit the effect of stale forecasts; (ii) remove stopped estimates; and (iii) retain only the latest earnings forecast for each brokerage firm.

Second, for each trading day until the earnings announcement, I identify the most recent forecast from each of the analysts identified in step one.[7] Third, I adjust the identified detail forecasts for stock splits (if any) that occurred between day one and the earnings announcement, using the CRSP adjustment factor. Fourth, I calculate daily mean, median, number of forecasts, and standard deviation of the identified forecasts.

Next, I construct a curve that plots the consensus (median) forecast revision, scaled by the consensus forecast error (relative to the forecast at the beginning of the period) over a

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[6] I provide additional support on the timeliness of analyst forecast revisions in Table 10.
[7] Holding the analyst pool constant limits any concerns of analyst selection effects (McNichols and O'Brien, 1997).

standardized time period. The ratio must equal one on or after the earnings announcement date, as by definition the forecast will be revised to the actual value at the earnings announcement. I standardize the window length by examining the 115 trading day-period following the first day of the quarter. This window encompasses the longest regulatory requirement for earnings disclosure (i.e., 75 calendar days following the end of the fiscal year, or roughly 50 trading days). Finally, I calculate *EIFT* as an estimated area-under-the-curve metric. *EIFT* is therefore a measure of earnings information flow timeliness that incorporates the trajectory of the forecast revisions (holding the analyst pool constant), relative to the firm's actual earnings announcement for the quarter, where greater areas indicate timelier earnings information flow.

Specifically, I construct a curve over the time period, where a point on the curve is generated for each trading day by computing the forecast revision from the first trading day up to and including the given trading day m, FR_m, divided by the forecast error for the entire time period, FE.[8] Thus, the curve, which is based on 115 distinct trading days, reflects the sequencing of the forecast revisions over the entire time interval. Then, from this curve, I compute the area-under-the-curve based on the following equation:

$$EIFT = \frac{1}{2}\sum_{m=1}^{115}(FR_{m-1} + FR_m)/FE = \sum_{m=1}^{114}(FR_m/FE) + \frac{1}{2}, \qquad (1)$$

where FR_m is the forecast revision on trading day m, calculated as the difference between the day m consensus forecast and the consensus forecast at the beginning of the time period; FE is the total forecast error for the entire time period, calculated as the difference between the

[8] For example, to calculate the point on trading day m, I calculate the difference between the consensus analyst forecast on trading day m and the consensus analyst forecast on the first trading day of the quarter, and scale that difference by the total forecast error over the entire period (calculated as the difference between the actual earnings per share according to I/B/E/S and the consensus forecast at the beginning of the quarter).

actual earnings for the quarter less the consensus forecast at the beginning of the time period. This formula represents the calculation of the area under a given curve as the sum of the areas of the series of trapezoids computed for each trading day.

3.2 Industry-Level Earnings Information Flow Timeliness

I also create a measure of earnings information flow timeliness for industry earnings (*IND_EIFT*). I follow the same methodology that I describe for firm-level *EIFT*, but use daily industry-level earnings forecasts and actuals. To calculate an industry-level earnings revision series, I follow prior research (e.g., Kothari et. al. 2006) and calculate cross-sectional sums of unscaled earnings forecasts for each trading day.[9] I then apply the area-under-the-curve formula to each industry series to calculate *IND_EIFT*. Finally, I set *IND_EIFT* to zero for quarters that have industry forecast errors of less than two percent. This alleviates interpretation problems when there is 'no news' and the small denominator problem of scaling by 'no news'.[10]

3.3 Sample Selection

I begin the sample selection for my primary sample (the "Primary Sample") by selecting all firm-quarters from 2003 to 2013 in the intersection of Compustat, CRSP, and I/B/E/S. I start in 2003 to ensure that my inferences are based on the current institutional and regulatory landscape (i.e., after Regulation Fair Disclosure and the Global Settlement). From this subsample of firm-quarter observations, I make four other requirements: (i) the firm has a calendar-quarter fiscal year end (i.e., FYE month = 3, 6, 9, or 12); (ii) the earnings announcement date is after the

[9] Specifically, my population of firms for the cross-sectional sums begins with all calendar quarter firms in the intersection of Compustat, CRSP, and I/B/E/S with analyst coverage and normal earnings announcement dates. I then exclude extreme observations (based on the ratios of FR/FE or FE to book value). I provide the specifics of the truncation process in the variable definitions within Appendix A.

[10] Results throughout the paper are not sensitive to the 2 percent cutoff, as inferences are unchanged with alternative cutoff points (e.g., 1 percent or 5 percent).

fiscal-quarter-end and in accordance with regulatory requirements; (iii) there is at least one active analyst forecast on the first day of the quarter; and (iv) the total forecast error for the period is at least five percent of the consensus at the beginning of the time period and more than $0.02 per share. These four requirements standardize the time period and ensure that there is earnings news.[11] These sample procedures yield a sample of 68,678 firm quarters (4,584 firms), which I use for my portfolio-level analyses in chapter 4. I require additional control variables for my regression analyses, which reduces the sample to 54,017 firm quarters (3,952 firms).

I note that the timing of earnings shocks is unknown for the Primary Sample. To further distinguish between differential earnings information flow and differential timing of earnings shocks, I create a second sample to directly examine a known economic shock to performance. Specifically, I exploit the exogenous shock of Hurricane Katrina on a number of industries to create a subsample of affected firms (i.e., the "Katrina Sample") in order to examine the differential flow of earnings information, holding constant the date of the triggering event. Hurricane Katrina is a unique economic event because the timing of the economic impact is known and it negatively impacted some firms, while positively impacting others. For example, within the petroleum refining industry, many firms lost significant capacity due to hurricane damages, while others benefited from increasing margins due to rising oil and natural gas prices.

For the Katrina Sample, I follow similar selection procedures as the Panel Sample only I begin with a set of December 2005 quarter end observations in industries that were expected to be impacted by Hurricane Katrina (see Appendix B for the specific industries and how they were

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[11] Prior work uses a variety of mechanisms to ensure that there is earnings news in the sample. For example, Kasznik and Lev (1995) select only the firms with earnings surprises that are larger than one percent of the firm's stock price. For comparison, my sample reduction is much less restrictive as the average ratio of earnings surprise to price for the firms that I exclude is 0.18 percent.

expected to be impacted).[12] Additionally, rather than beginning the observation window at the beginning of the quarter, I begin the window one week before landfall.[13] These sample procedures yield a sample of 570 firms. I provide further detail on the sample selection procedures for the Primary Sample and the Katrina Sample in Table 1.

[Insert Table 1 Here]

3.4 Flow of Earnings Information

Figure 1 and Table 2 show the cross-sectional distribution of the flow of earnings information to the market over the 115 trading day period starting with the beginning of the quarter. Specifically, on each trading day *m*, I calculate the ratio FR_m/FE for each firm quarter where FR_m is the forecast revision on day *m* and *FE* is the forecast error for the entire period.[14] I then provide descriptive statistics of the distribution of this ratio on sequential trading days throughout the period. Figure 1 summarizes the distribution graphically, whereas Table 2 presents distributional detail for select trading days throughout the window.

[Insert Figure 1 Here]

[Insert Table 2 Here]

Figure 1 and Table 2 provide evidence that firms exhibit wide variation in the timeliness of the flow of earnings information to the market. For example, Figure 1 (Panel A of Table 2) shows that the market does not receive any of the earnings news for the lower quartile by the

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[12] I identify the industries that were expected to be impacted by Hurricane Katrina by searching analyst industry reports, press releases, conference calls, and other news articles around the time that Katrina made landfall. I choose to select 12/31/2005 quarter end observations because this is the first full quarter impacted by Hurricane Katrina.
[13] Hurricane Katrina made landfall on August 29, 2005. To avoid omitting anticipatory effects, I examine the trajectory of forecast revisions for quarters ending in December 2005 from August 22, 2005 to the earnings announcement date.
[14] This calculation is analogous to the ratio that I use on each trading day within my *EIFT* measure. FR_m is calculated as the difference between the consensus forecast on day *m* and the consensus forecast at the beginning of the quarter. *FE* is calculated by taking the difference between the actual earnings per share and the consensus forecast at the beginning of the quarter.

time the prior quarter's earnings announcement is released (i.e., 25 trading days into the quarter), whereas the market receives 41 percent of the earnings news for the upper quartile by this time. Similarly, by the end of the quarter (65 trading days) the market continues to receive none of the earnings information for the lower quartile, whereas the market receives 75 percent for the upper quartile. Due to the large number of studies focusing on management guidance, I also separately present descriptive statistics on the distribution of firm-quarters that do not contain management guidance (Panel B) and those that do contain guidance (Panel C).[15] While the management guidance subsample shows an overall increase in timeliness, there is still substantial variation in the subsample without explicit management guidance. Thus, my results suggest that earnings information flow timeliness is affected by both management forecasts and other sources.

3.5 Descriptive Statistics

I next present descriptive statistics for my measure of earnings information flow timeliness in Table 3.[16] Specifically, in Panel A I report summary statistics of my earnings information flow timeliness measure calculated at both the firm-level *(EIFT)* and the industry-level (*IND_EIFT*) for select industries; in Panel B, I compare descriptive statistics across *high-* and *low-EIFT* quarters; and in Panel C I report correlation coefficients among the variables used in this study. I define all variables in Appendix A.

Panel A of Table 3 reveals substantial variation in earnings information flow timeliness across industries. Industries such as Metal Mining, Lumber, Paper, Primary Metals, and Nonmetallic Minerals appear to be among the most timely, whereas Tobacco, Hotels, Real

[15] I differentiate between firm-quarters with (without) management guidance using the I/B/E/S guidance database. Any management forecasts not included in the guidance database would be included in the no management forecast subsample.
[16] Because the Katrina Sample is essentially a subset of firm-quarters within the Primary Sample, I do not tabulate descriptive statistics for this subsample for brevity.

Estate, Utilities, and Insurance Carriers appear to be among the least timely earnings information flow industries. Additionally, there appears to be substantial variation in the industry-level *EIFT*, as demonstrated by the interquartile range. This descriptive evidence suggests that the industry-level *EIFT* may play at least some role in the variation of *EIFT*. As such, I control for the timeliness of industry earnings news in my regression analyses in chapter 4.

In Panel B of Table 3, I provide descriptive statistics for *high-EIFT* quarters and *low-EIFT* quarters (based on a median split). Results show that the direction of the news may play an important role in earnings information flow timeliness because 62 percent of the good news firm quarters are in my *low-EIFT* group. I also note, however, that this table demonstrates the need to control for analyst forecasting environment variables (e.g., *DISPERSION, FOLLOWING, MTB*) as many of the variables show significant differences across the *high-* and *low-EIFT* subgroups. Additionally, the prior quarter's earnings announcement lag is shorter for *high-EIFT* firm quarters than for *low-EIFT* quarters. As such, I also control for *PRQ_EALAG* in my regression analyses, which I discuss in chapter 4.

I provide correlation coefficients in Panel C of Table 3. Similar to Panel B, Panel C provides univariate evidence suggesting that the flow of earnings information is timelier for bad news than for good news (negative correlation between *EIFT* and *GOOD_NEWS*). I also document positive correlations between *EIFT* and analyst following and industry timeliness (*IND_EIFT*) and a negative correlation between *EIFT* and the prior quarter's earnings announcement lag (*PRQ_EALAG*), further emphasizing the importance of controlling for these variables in my regression analyses. Panel C also shows a positive correlation between *EIFT* and my proxy for litigation risk (institutional ownership), suggesting that as litigation risk (outside monitoring) increases, *EIFT* increases. Similarly, I document negative correlations between

EIFT and financial distress (*OSCORE*) and forecasting uncertainty (*PR_FE*). These results suggest that as financial distress (or forecasting uncertainty) increases, earnings information flow timeliness decreases. No other correlations with *EIFT* exceed five percent.

[Insert Table 3 Here]

Up to this point, I have presented cross-sectional descriptive statistics. However, the primary emphasis of my study is on firm forces and therefore *within-firm* variation in *EIFT*. As such, Table 4 presents a breakdown of the between- and within-firm variation in *EIFT* and compares the characteristics of firms with high within-firm variation to those with low within-firm variation in *EIFT*. Panel A presents two estimates of the relative between- versus within-firm variation. Somewhat surprisingly, results show that more than 75 percent of the variation can be attributed to within-firm variation. This provides further motivation for my focus on within-firm tests. Panel B presents the distribution of the within-firm standard deviation in *EIFT*. Additionally, to remove concerns that within-firm variation is driven by small firms or weak information environments, I also present the characteristics of high- versus low-variance firms. Results show no significant differences in firm size and, if anything, the high-variance firms tend to be those with stronger information environments.

[Insert Table 4 Here]

CHAPTER 4: RESEARCH DESIGN AND EMPIRICAL RESULTS

I begin exploring my hypotheses through a series of portfolio analyses to maintain consistency with the methodology employed in the price discovery literature (e.g., Bushman et. al. 2010). Next, I formally test the hypotheses in a regression framework that explores within-firm variation of earnings information flow timeliness, controlling for the analyst forecasting environment and the timeliness of industry and economy earnings news.

4.1 Portfolio Analyses

For my first examination of *H1*, I partition firm-quarter observations into good versus bad news portfolios and compare the earnings information flow timeliness. Specifically, I plot equal-weighted forecast revisions (as a percent of the total forecast error) across each trading day for both the good and bad news portfolios. I provide this evidence in Figure 2 and show that the trajectory for the bad news portfolio is consistently above the trajectory for the good news portfolio. For example, the market has received 33 percent of the earnings news for the bad news portfolio by the time the prior earnings announcement is released, whereas the market has only received 11 percent for the good news portfolio. Further, by the end of the fiscal quarter, the market has received 61 percent of the earnings news for the bad news portfolio, but only 18 percent of the earnings news for the good news portfolio.

[Insert Figure 2 Here]

Similarly, I also examine my second hypothesis graphically. Specifically, I partition firms into good and bad news portfolios within each decile of earnings magnitude (calculated as the absolute value of the forecast error, scaled by price at the beginning of the quarter). Figure 3 summarizes the results for small (bottom three deciles), medium (middle four deciles), and large (top three deciles) levels of earnings magnitude across good news and bad news portfolios. I continue to show that the bad news portfolios are consistently above the good news portfolios, however the curves are converging as the magnitude of the news increases (i.e., as magnitude increases, bad news becomes less timely whereas good news becomes more timely).

[Insert Figure 3 Here]

I formally test the differences across the direction and magnitude of the news portfolios in Table 5. Specifically, I estimate *EIFT* for each good and bad news portfolio (i.e., for the full sample and within each magnitude decile) and compute a test statistic equal to the difference, *ΔEIFT*. I use permutation analysis to test whether the test statistic, *ΔEIFT*, is statistically different from zero.[17]

[Insert Table 5 Here]

Table 5 first documents that earnings information flow timeliness is significantly more timely for bad news (by more than 50 percent), relative to the information flow for good earnings news (i.e., the area under the curve for the bad news portfolio is significantly greater than the area under the curve for the good news portfolio). This evidence rejects my first null hypothesis in favor of a negative association between the direction of news and earnings information flow timeliness. Table 5 also presents *EIFT* measures and test statistics for each of the earnings magnitude deciles. These results show that the area under the curve for bad news portfolios is significantly greater than the area under the curve for good news portfolios curve for all earnings magnitudes, based on permutation analysis. Importantly, the difference between the timeliness of

[17] Specifically, I construct a distribution under the null hypothesis that the order of arrival of the forecast revisions does not matter because there is no difference in earnings information flow timeliness for one portfolio relative to the other. To compute the distribution of test statistics under the null, I randomly scramble the order of the forecast revision pairs (i.e., one forecast revision for each portfolio for each time increment), recalculate the *ΔEIFT* test statistic, repeat the process 1,000 times, and count the number of times the magnitude (i.e., absolute value) of the outcome is equal to or greater than the magnitude of my actual test statistic. This process compares my actual test statistic to the distribution of the test statistic under the null that the order of forecast revisions does not matter.

the earnings information flow for bad news and good news is converging in the magnitude of the news (i.e., as the magnitude of the news increases, bad news becomes less timely, whereas good news becomes more timely). In fact, Table 5 shows that the difference between bad news and good news is decreasing monotonically from the smallest decile to the largest decile of earnings magnitude. These results provide initial evidence to reject my null hypothesis *H2a*, in favor of a negative association between the magnitude of bad earnings news and *EIFT*, and to support my hypothesis *H2b*.

4.2 Regression Analyses

I note that the price discovery literature generally uses a portfolio specification as its primary methodology, due to the concern that random news arrivals may render firm-period measures based on returns extremely noisy (e.g., Bushman et. al. 2010). In contrast to returns, however, analyst earnings forecast revisions display much smoother trajectories, partly due to the fact that they are not confounded by other news arrivals (e.g., future earnings news and discount rate news). Thus, a regression specification is not only possible, but seemingly more effective and applicable, because I can run *within-firm* analyses that control for the analyst forecasting environment. Thus, I formally explore the direction and magnitude of the earnings news with the following regression specifications (firm and time subscripts suppressed):

$$\begin{aligned} EIFT = \alpha + \beta_1 GOOD\_NEWS + Control\,Variables + Firm\,Fixed\,Effects \\ + Time\,Fixed\,Effects + \varepsilon, \end{aligned} \tag{2}$$

$$\begin{aligned} EIFT = \alpha + \beta_1 GOOD\_NEWS + \beta_2 GOOD\_NEWS * ABSFE + \beta_3 BAD\_NEWS \\ * ABSFE + Control\,Variables + Firm\,Fixed\,Effects \\ + Time\,Fixed\,Effects + \varepsilon, \end{aligned} \tag{3}$$

where, *EIFT* is a firm-quarter-specific measure of earnings information flow timeliness; *GOOD_NEWS* is an indicator variable set to one if the forecast error (i.e., *FE* or the difference between the actual earnings and the consensus analyst forecast at the beginning of the time period) is positive, zero otherwise; *BAD_NEWS* is one minus *GOOD_NEWS;* and *ABSFE* is the scaled decile rank (between zero and one) of the absolute forecast error scaled by the quarter beginning stock price. I winsorize continuous variables at the one percent level.[18]

Control variables include scaled decile ranks of analyst forecasting environment variables, an indicator variable for *Q4,* a variable to control for the timing of the prior quarter's earnings announcement, and measures to control for the timeliness of industry earnings information. Specifically, I control for analyst following and forecast dispersion because higher analyst following and higher levels of forecast dispersion are likely correlated with a more timely response by analysts to disclosures. I also control for analyst optimism with the market-to-book ratio (*MTB*) to account for prior research that documents that analysts may overreact to positive information and underreact to negative information (e.g., Easterwood and Nutt 1999).[19] Next, I control for a fourth quarter effect because regulatory filing requirements are longer for *Q4* and prior literature notes that the *Q4* is inherently different from the other quarters (e.g., Beaver et. al. 2008; Bradshaw and Sloan 2002). Additionally, I control for the timing of the prior quarter's earnings announcement (*PRQ_EALAG*) to ensure that my results are distinct from the earnings announcement lag literature (e.g., Chambers and Penman 1984). Finally, I control for the timeliness of industry (economy) earnings information with *SS*IND_EIFT*, *OS*IND_EIFT*, and *NO_IND_NEWS* (time fixed effects) to account for differential timing in the industry (economy) component of earnings. *IND_EIFT* is an industry-level *EIFT* measure, *SS* (*OS*) are set to one if the firm forecast error is the same sign (opposite sign) as the industry forecast error, and

[18] For robustness, I also examine specifications where I truncate *EIFT* at the 1 percent and 5 percent levels. I draw similar inferences from these alternative analyses.
[19] I also examine an analyst-based measure of optimism (long-term earnings growth forecasts) and find similar results. I tabulate the results using the *MTB* ratio because *MTB* is more widely available than *LTG* forecasts.

NO_IND_NEWS is set to one if the absolute value of the industry forecast error is less than two percent of the industry consensus forecast at the beginning of the quarter.

Table 6 presents the results of equations (2) and (3), along with an estimation of equation (2) by earnings magnitude decile. My results are consistent with the portfolio analyses that I present in the prior section. Specifically, I document that the earnings information flow is significantly more timely for bad news than for good news, as evidenced by the significantly negative coefficient on *GOOD_NEWS* in column (1). Further, as the earnings magnitude increases, firms exhibit timelier good news but less timely bad news. This can be seen with both the significantly positive (negative) coefficient on *GOOD_NEWS*ABSFE* (*BAD_NEWS*ABSFE*) in column (2) and the monotonically increasing coefficient on *GOOD_NEWS* in column (3).

[Insert Table 6 Here]

4.3 Hurricane Katrina Analyses

To distinguish between differential earnings information flow and differential timing of shocks to earnings, I next exploit the exogenous shock of Hurricane Katrina to quarterly earnings for a sample of affected industries. Specifically, I estimate equations (2) and (3) for this subsample using industry-fixed effects in lieu of the firm fixed effects because there is only one observation per firm. I also use scaled quintile rankings, rather than scaled decile rankings for *ABSFE* and the analyst forecasting control variables due to the limited number of observations. I present the results in Table 7.

[Insert Table 7 Here]

The results for Hurricane Katrina support my primary analyses in Tables 5 and 6. For example, in column (1) the good news indicator variable is negative and significant, suggesting timelier earnings information flow for bad news versus good news. Further, column (2) shows a positive and significant coefficient for *GOOD_NEWS*ABSFE*, and a negative and significant coefficient for *BAD_NEWS*ABSFE*, suggesting that the relative timeliness for bad and good earnings news converges in the magnitude of the earnings news. This evidence suggests that the results of my primary analyses are not driven by differential timing in the shocks to earnings and further supports my prior inferences.

4.4 Validation Tests

Because I rely on daily analyst consensus forecasts as my proxy for *EIFT*, my results may be susceptible to variation in the timing with which analysts impound earnings information into their forecasts. While analysts are certainly one component of the information flow, I want to ensure that they are not the driving force behind my results because my research question addressers motivations within the firm. As such, I perform three analyses to validate my measure and show that results are not attributed to analyst behavior.

First, I examine the extent to which time-varying managerial disclosure incentives influence the relative timeliness of good versus bad news. While these incentive variables have clear predictions in the literature on how they might affect the timeliness of firm-specific disclosure, there is no reason to expect these variables to influence the timeliness with which analysts impound information into their forecasts. As such, this analysis helps to rule out the analyst timing explanation and also aids in our understanding of how firm-specific motivations influence timeliness. Specifically, I estimate the following regression in Table 8 (firm and time subscripts suppressed):

$$
\begin{aligned}
EIFT = \alpha + \beta_1 GOOD\_NEWS + \beta_2 GOOD\_NEWS * ABSFE + \beta_3 BAD\_NEWS \\
* ABSFE + GOOD\_NEWS * LITIG\_MON \sum_{j=4}^{6} \beta_j \\
+ GOOD\_NEWS * INCENT \sum_{k=7}^{15} \beta_k + LITIG\_MON \sum_{l=16}^{18} \beta_l \\
+ INCENT \sum_{m=19}^{27} \beta_m + Control\ Variables \\
+ Firm\ Fixed\ Effects + Time\ Fixed\ Effects + \varepsilon,
\end{aligned}
\tag{4}
$$

where variables and controls are as defined in equation (3). *LITIG_MON* is a vector of time-varying scaled tercile variables to reflect litigation risk and the extent of outside monitoring; *INCENT* is a vector of time-varying scaled tercile variables to reflect capital market incentives. I define each of the variables and provide rationale for the predictions in Appendix A.

I present the results of equation (4) in Table 8 and show that the timeliness of bad earnings information is increasing both in litigation risk and the extent of outside monitoring, whereas the timeliness of good news earnings information is decreasing in those proxies. I also find evidence that capital market incentives are associated with a differential timeliness of earnings information between bad and good news. Specifically, the timeliness of good news (bad news) is increasing (decreasing) in the amount of insider trading, level of sales growth, the amount of price momentum, and the level of capital intensity. Because these time-variant factors behave as predicted in prior disclosure literature, the variation in earnings information flow timeliness is more likely attributed to time-varying firm factors, as opposed to analyst influences.

[Insert Table 8 Here]

Second, I explore the association between my measure and the timing of observable firm disclosures. To accomplish this objective, I follow Anilowski et. al. (2007) and divide each fiscal quarter into four subperiods and then examine how observable firm disclosures within each subperiod associate with *EIFT*.[20] I expect that disclosures in the early subperiods will associate positively, whereas the disclosures in the later subperiods will associate negatively. Specifically, I present the results of the following regression (time and firm subscripts suppressed) in Table 9:

$$\begin{aligned} EIFT = \alpha &+ \beta_1 PD1\_MF + \beta_2 PD2\_MF + \beta_3 PD3\_MF + \beta_4 PD4\_MF \\ &+ \beta_5 PD1\_8k + \beta_6 PD2\_8k + \beta_7 PD3\_8k + \beta_8 PD4\_8k \\ &+ Controls + Firm\ Fixed\ Effects + Time\ Fixed\ Effects \\ &+ \varepsilon, \end{aligned} \quad (5)$$

where *PDN* represents subperiod 1, 2, 3, or 4; *MF* indicates the presence of a management forecast for the quarter of interest in the subperiod; *8k* is the natural log of one plus the number of days with 8-K filings in the subperiod; *Controls* is the series of control variables that I include in my primary regressions summarized in equation (3).[21]

[Insert Table 9 Here]

As predicted, the management forecast variables have a positive association with *EIFT* in subperiods 1 and 2, and a negative association in subperiods 3 and 4. Further, the 8-K filing measures also display a similar pattern.

Finally, I perform an event-study analysis surrounding the release of management forecasts to examine whether my metric reflects the information on a timely basis. For each firm quarter, I calculate the ratio of forecast revisions to total forecast error (FR_m/FE) on each of the eight trading days surrounding the release of a management forecast.[22] I then separately examine eight partitions based on the direction of the overall news for the quarter and the magnitude of

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[20] The four subperiods are as follows: (i) the period from the end of the previous fiscal quarter to 50 calendar days before the end of the fiscal quarter; (ii) the period from 50 days before the end of the fiscal quarter to 25 days before the end of that quarter; (iii) the period from 25 days before the end of the fiscal quarter to the end of the quarter; and (iv) the period from the end of the fiscal quarter to the earnings announcement date.

[21] I obtain management forecast disclosures from the I/B/E/S guidance database and 8-K filing information from the SEC's EDGAR database.

[22] FR_m and *FE* are defined similarly to early derivations in this study. Specifically, FR_m is the difference between the consensus forecast at trading day *m* and the consensus forecast at the beginning of the quarter; *FE* is the difference between the actual earnings per share and the consensus forecast at the beginning of the period.

the revision suggested by the management forecast. I present the results in Table 10, which shows that my measure impounds good and bad news information from management forecasts in the proper magnitude within two trading days of the management forecast release.

[Insert Table 10 Here]

In addition to the above analyses, I also perform an analysis to directly address analyst incentives. Specifically, O'Brien et al. (2005) document that affiliated analysts downgrade (upgrade) more slowly (quickly) than non-affiliated analysts both at the analyst and issuer level. As such, I identify the subsample of firm quarters with upcoming or recent seasoned equity offerings (i.e., SEO in the next quarter or within the last year) and estimate equation (3) separately for these quarters and those that are unaffected by SEOs. Using my *EIFT* measure, I am able to replicate the finding from O'Brien et al. (2005), showing that good news (bad news) is more (less) timely for firm-quarters impacted by SEOs. More importantly, I continue to find that bad news is more timely than good news and that bad news becomes less timely as the magnitude of the news increases in both of the subsamples (SEO and non-SEO quarters). This provides further assurance that analyst optimism and/or other biases are not driving my results.

[Insert Table 11 Here]

CHAPTER 5: ROBUSTNESS TESTS AND ADDITIONAL ANALYSES

5.1 Management Guidance versus No Management Guidance

As described above, a vast literature explores the relation between the direction of the news and the timing (or presence) of management forecasts. To further distinguish my study (and emphasize the importance of considering other sources of earnings information), I re-estimate equations (2) and (3) separately for firm-quarters that contain management guidance and for those that do not contain management guidance. I present the results in Table 12 and show that the effects described in this study are perpetuated both through explicit management guidance and through other sources. For example, coefficient estimates for equation (3) are -55.35 for *GOOD_NEWS*, 7.27 for *GN*ABSFE*, and -26.93 for *BN*ABSFE* for firm quarters that contain explicit guidance, compared to -36.13, 1.28, and -27.06, respectively, for firm quarters that do not contain explicit guidance. These results also suggest that the observed effects are likely driven by firm-specific news and managerial incentives because the relative differences in timeliness are even more pronounced in quarters with explicit managerial guidance.

[Insert Table 12 Here]

5.2 Earnings Management

My approach to estimating earnings information flow timeliness requires an 'actual' measure of earnings to benchmark the timeliness with which analyst forecasts reflect final earnings news. As such, I implicitly assume that the announced earnings number is the true earnings number. Prior work, however, suggests that the announced earnings may actually be managed, at least at some level, to meet specific targets (e.g., Burgstahler and Dichev 1997). To ensure that my results are not driven by differential earnings management, I estimate performance-matched abnormal accruals for each firm-quarter and perform the following analyses in Table 13: (i) include a scaled tercile variable of abnormal accruals, interacted with good and bad news indicators, in the equation (3) model; and (ii) estimate equation (3) separately for each tercile of abnormal accruals. Additionally in Table 14, I also estimate equation (3), excluding meet-or-beat observations (i.e., non-negative earnings surprises less than $0.02), which may be indicative of earnings management. Under all specifications, I continue to find that bad news is more timely than good news and that bad news becomes less timely as the magnitude of the news increases. This suggests that my results are not driven by the extent of earnings management.

[Insert Table 13 Here]

[Insert Table 14 Here]

5.3 Expectations Management

Prior work suggests that managers may engage in a practice of expectations management, which suggests that managers walk-down optimistic analyst forecasts to a level that can be beat or met at the earnings announcement (e.g., Cotter et al. 2006; Matsumoto 2002; Richardson et al. 2004). Although I consider this practice to be a component of the overall flow of earnings information to the market, I explore its pervasiveness in my sample. I identify all firm quarters where the direction of the news switches when comparing the consensus analyst forecast at the beginning of the quarter to the forecast five trading days prior to the earnings announcement (e.g., a positive (negative) forecast error at the beginning of the quarter and a negative (positive) forecast error preceding the earnings announcement). I find that this practice is only descriptive for roughly 15 percent of my sample. Further in Table 15, I re-run my regression analyses with an indicator variable set to one for observations that switched from bad news at the beginning of the quarter to good news at the end of the quarter and document similar results. Additionally, I estimate equation (2) across each decile of *ABSFE*, excluding all observations that switched direction and continue to document that bad earnings news is consistently more timely than good earnings news and that the difference in timeliness between bad and good news is decreasing in the magnitude of the earnings news.

[Insert Table 15 Here]

5.4 Prior Quarter's Earnings News

Rogers and Van Buskirk (2013) provide evidence that firms are more likely to bundle guidance with positive earnings surprises following Reg FD. As such, the association between *EIFT* and the direction/magnitude of the news may vary depending upon the prior quarter's earnings surprise. In Table 16, I partition my sample into four groups based on the direction and magnitude of the prior quarter's earnings surprise (i.e., small-good, large-good, small-bad, large-bad) and re-estimate equation (3) for each subgroup. Consistent with my primary findings, I find that bad news is more timely than good news in each subgroup, and that bad news becomes less timely as the magnitude of the news becomes larger, suggesting that my results are not dependent on the prior quarter's earnings surprise.

[Insert Table 16 Here]

5.5 Relative Importance of Firm Earnings News vs. Industry or Economy Earnings News

Although I control for the timeliness of industry- and economy-wide earnings news in my primary regressions, I also explore the relative importance of firm-specific news compared to economy- or industry-news in explaining the variation in earnings information flow timeliness. In Table 17, I document that each type of news (i.e., firm, economy, and industry) explains a significant portion of the variation in *EIFT*. More importantly, I find that firm-earnings news explains significantly more of the timeliness than economy- or industry-news.

[Insert Table 17 Here]

CHAPTER 6: CONCLUSION

This study provides evidence on the timeliness of the flow of earnings information to the market and how it is influenced by the direction and magnitude of the news. I draw from the price discovery literature to create a measure of earnings information flow timeliness that captures how quickly the daily consensus analyst earnings forecast approaches the actual earnings as the quarter unfolds. This is distinct from prior work that focuses on the timing of specific events in isolation (e.g., earnings announcements, management forecasts) but largely ignores the interplay of numerous earnings news sources. I document wide within-firm variation in the timeliness of the earnings information flow (i.e., differences in the timeliness with which analyst forecasts converge to the actual earnings number) and show that it is associated with the direction and magnitude of the news.

First, I show that the earnings information flow is significantly more timely for bad news than for good news. This result sheds light on how the direction of the news influences the total earnings information flow, which is particularly important because of conflicting results across individual disclosure events. Second, I show that as the magnitude of the news increases, bad news becomes *less* timely whereas good news becomes *more* timely. This result is in direct contrast to the commonly cited litigation explanation for timelier bad news and is more consistent with a scenario where managers face a tradeoff between current stock price implications and reporting reputation benefits. Specifically, managers may release bad news faster than good news to promote a reputation of transparent reporting; however as the bad news gets large (and stock price implications increase), managers likely delay the news to allow for in-depth analysis, a positive interpretation, and/or consolidation into larger and potentially offsetting news releases. Finally, I also show that the relative timeliness of good versus bad news is influenced by the extent of outside monitoring, performance momentum, and insider trading.

Collectively, this study provides some of the first evidence on the timeliness of the total flow of earnings information to the market. While prior work examines the economic determinants of the timeliness of particular disclosures, it is potentially more important to understand the economic forces that shape the collective timeliness of all earnings news sources because of the price path implications. My study takes a first step toward understanding the timeliness of this total earnings information flow.

My study also contributes across a methodological dimension by developing a strategy to assess earnings information flow timeliness across all earnings-relevant sources. Specifically, I build on prior work that identifies the advantages of inferring the timeliness of information flows through the lens of analyst forecasts (e.g., Aboody and Kasznik, 2000; Donelson et al., 2012) by incorporating the theoretical underpinnings from the price discovery literature, removing analyst selection concerns, and emphasizing the importance of the information releases around the prior quarter's earnings announcement. My strategy can be used in future research to assess the collective timeliness of earnings-relevant information to investors.

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APPENDIX A: VARIABLE DEFINITIONS

Variable	***Definition of Variable***
EIFT	Earnings information flow timeliness, calculated as the area under the curve that plots the sequencing of forecast revisions (holding the analyst pool constant) from the beginning of the quarter to the earnings announcement. Specifically, I apply the following formula: $EIFT = \frac{1}{2}\sum_{m=1}^{115}(FR_{m-1} + FR_m)/FE = \sum_{m=1}^{114}(FR_m/FE) + \frac{1}{2}$, where FR_m is the forecast revision on trading day *m* (calculated as the difference between the consensus forecast on day *m* and the consensus forecast at the beginning of the period); *FE* is the forecast error for the time period (calculated by taking the difference between the actual earnings per share and the consensus forecast at the beginning of the period).
IND_EIFT	Industry earnings information flow timeliness, calculated in a similar fashion as *EIFT* using an estimate of the forecast revisions and actual earnings for each 2-digit SIC industry. Specifically, for each quarter in my sample, I calculate cross-sectional sums of the daily consensus analyst forecasts of unscaled earnings for all firms in each 2-digit SIC code. Prior to calculating the cross-sectional sums, I perform two truncation steps to minimize the influence of outliers and better isolate the industry news: (i)delete the top and bottom five percent based on the maximum or minimum ratio of *FR* / *FE*; (ii)delete the top and bottom one percent based on the ratio of *FE* to total book value per share. I then apply the *EIFT* formula using the 'industry' *FR* and *FE* measures. If the industry forecast error for the quarter is less than 2 percent, I set *IND_EIFT* to zero because there is minimal news.
GOOD_NEWS	Indicator variable set to one if the difference between the actual earnings per share and the consensus forecast at the beginning of the period is positive, zero otherwise.
ABSFE	Absolute value of the difference between the actual earnings per share and the consensus analyst forecast at the beginning of the period, scaled by stock price at the beginning of the period.
DISPERSION	Average daily dispersion over from the beginning of the quarter to the earnings announcement, where dispersion is calculated as the standard deviation of analyst forecasts, scaled by the quarter beginning stock price.
FOLLOWING	Average number of analysts providing quarterly earnings forecasts for the company from the beginning of the quarter to the earnings announcement.
Q4	Indicator variable set to one if the observation corresponds to fourth quarter earnings for the firm, zero otherwise.
MTB	Market-to-book ratio as of the beginning of the quarter.

<table>
<tr><td>PRQ_EALAG</td><td>The earnings announcement lag for the prior quarter, calculated as the difference between the announcement date of the prior quarter’s earnings and the first day of the quarter of interest (or the beginning of the analysis period for the Katrina sample).</td></tr>
<tr><td colspan="2">Unless specified otherwise, all variables below are calculated as of the beginning of the quarter of interest.</td></tr>
<tr><td colspan="2">LITIG_MON (Litigation Risk and the Extent of Outside Monitoring)</td></tr>
<tr><td>LITRISK</td><td>The lagged probability of litigation derived from a logit regression using the specification in Rogers and Stocken (2005). Specifically, I regress the incidence of a class action lawsuit on the following independent variables: Size, Turnover, Beta, Returns, Std_Ret, Skewness, Min_Ret, and a series of High Risk Industry indicator variables. I follow the variable definitions in Rogers and Stocken (2005) and estimate the model only for firms with I/B/E/S coverage.

Rationale: Following Skinner (1994), I expect the timeliness of bad (good) earnings information to increase (decrease) as litigation concerns for the firm increase.</td></tr>
<tr><td>INST_OWN%</td><td>The percentage of shares owned by institutional investors, calculated using data from Thomson Reuters.

Rationale: I use the level of institutional ownership as a proxy for outside monitoring. I expect the timeliness of bad (good) earnings information to increase (decrease) as outside monitoring increases because managers are less likely to withhold bad news when scrutiny increases.</td></tr>
<tr><td>SHORT_INT%</td><td>The number of short sale positions in the company, scaled by the number of shares outstanding.

Rationale: Same as for institutional ownership, as I consider an increase in short sellers to be indicative of an increase in sophisticated investors.</td></tr>
<tr><td colspan="2">INCENT (Capital Market Incentives)</td></tr>
<tr><td>INSIDER_SALES</td><td>The total dollar value of insider sales during the calendar quarter, scaled by the market value of equity. I define insider sales as all sales made by officers and directors of the firm. I gather insider sale information from Thomson Reuters.

Rationale: I use this measure to proxy for the wealth incentives of management. I expect timelier good news (and less timely bad news) as wealth implications increase.</td></tr>
<tr><td>INSIDER_OWN%</td><td>The percentage of shares owned by officers and directors of the firm (either directly or indirectly), calculated using data from Thomson Reuters.

Rationale: Same as INSIDER_SALES.</td></tr>
</table>

OSCORE	A measure of financial distress, calculated using the coefficient estimates from model (1) in Ohlson (1980). Specifically, the *OSCORE* is calculated as: -1.32 – 0.41 log(total assets) + 6.03(total liabilities/total assets) – 1.43(working capital/total assets) + 0.08(current liabilities/current assets) – 1.72(1 if total liabilities > total assets, else 0) – 2.37(net income/total assets) – 1.83(funds from operations/total liabilities) + 0.285(1 if net loss for last two years, else 0) – 0.52(net income_t – net income_{t-1})/(|net income_t| + |net income_{t-1}|). *Rationale: Gilson (1989) suggests that managers experience large personal costs when their firms default. Therefore, as the level of financial distress increases, managers have incentives to delay bad earnings information to avoid or delay turnover. I use OSCORE as a measure of financial distress to proxy for manager career concerns.*
SALE_GRQ	Quarterly sales growth, calculated as the ratio of the quarterly sales prior to the quarter of interest to the quarterly sales for the same quarter from the prior year. *Rationale: I use prior sales growth to capture performance momentum, which can create differential incentives for management. For example, managers are under increasing pressure to maintain earnings and/or other performance momentum, since breaking the momentum streak results in severe capital market consequences (Barth et al., 1999; Myers et al., 2007). Therefore, I expect the timeliness of good (bad) earnings information to increase (decrease) with high prior sales growth.*
PR12_RET	Stock price momentum, calculated as the buy-and-hold return for the 12 months preceding the quarter of interest. *Rationale: I use stock price momentum as an alternative proxy for performance momentum. See rationale for SALE_GRQ.*
ABS_ACC	The absolute value of the total accruals for the quarter of interest. Accruals are calculated as the difference between earnings (*IBQ*) and cash flows adjusted for extraordinary items (quarterly *OANCF* – quarterly *XIDOC*). *Rationale: I use the absolute value of total accruals to capture reporting discretion, since Kasznik (1999) suggests that managers can use accounting discretion to reduce voluntary disclosure costs. Specifically, managers with accounting discretion can avoid forecasting errors that may result in litigation or reputation costs. Therefore, I expect good news to become more timely (and bad news to become less timely) as reporting discretion increases.*

CAP_INTEN	Sum of depreciation, amortization and depletion expenses, scaled by sales, for the fiscal year preceding the quarter of interest. *Rationale: I use capital intensity as a proxy for the volatility of the business or forecasting environment. I expect the timeliness of good news to increase and the timeliness of bad news to decrease as capital intensity increases because managers are less likely to be held responsible for forecasting inaccuracies in volatile business environments. Capital intensity is a proxy for earnings expected earnings volatility because firms with higher capital intensity face higher adjustment costs when faced with demand shocks (Lev 1983). Higher operating leverage translates to higher earnings volatility (Lev 1974, 1983).*
STDRET	The standard deviation of daily returns over the year preceding the quarter of interest. *Rationale: I use STDRET as an alternative proxy for the volatility of the business environment and expect a similar relation as that described for capital intensity.*
PR_FE	The average forecast error (or unsigned earnings surprise) from the eight quarters preceding the quarter of interest. Forecast error is calculated as the absolute value of the difference between actual earnings and the consensus forecast as of the I/B/E/S calculation date immediately preceding the earnings announcement, scaled by stock price as of the quarter end. *Rationale: I use PR_FE as a measure of the inherent uncertainty in the forecasting environment and expect a similar relation as that described for capital intensity.*

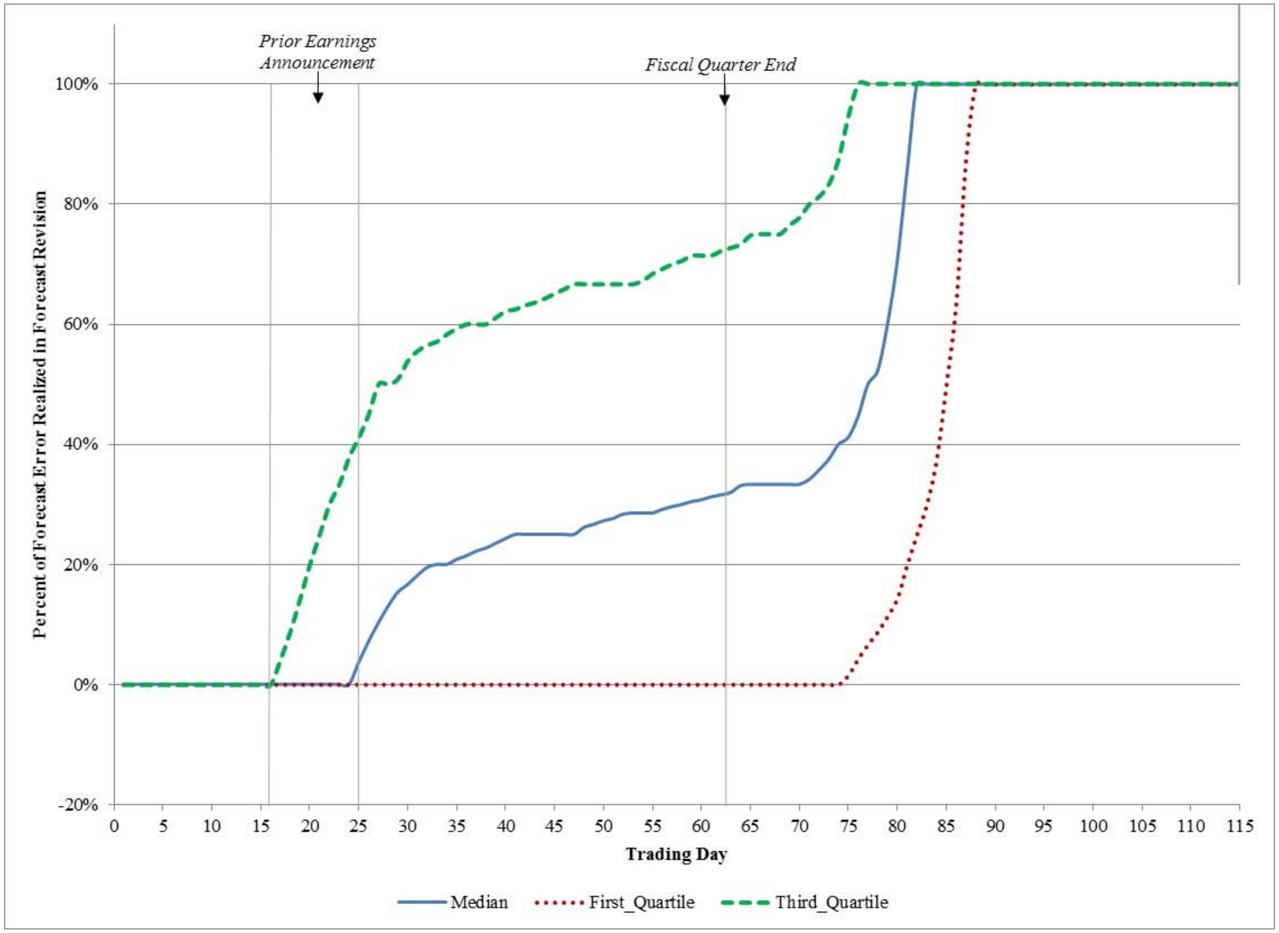
APPENDIX B:

INDUSTRIES EXPECTED TO BE IMPACTED BY HURRICANE KATRINA

Industry	***Examples of Expected Impact from Analyst Industry Reports, Press Releases, Conference Calls, and News Articles***
Oil Extraction and Refining	
Oil Extraction (13XX)	-Katrina's impact on production and infrastructure will be felt for many months due to lost production, widening price differentials, and the potential for higher operating costs. -Katrina exacerbated a low spare capacity situation, suggesting EPS increases, however Gulf-of-Mexico operators could show EPS declines due to Katrina damages.
Petroleum Refining (291X)	-Expect record earnings due to the benefits from rising oil and natural gas prices and refining margins. -Average refining margins have doubled relative to a year prior. -Loss of capacity due to damages.
Transport	
Oil Tankers (44XX)	-Loss of refinery capacity and low inventory spawned dramatic increase for imports. -Record rates for the product segment, with spot rates on the Europe-US route tripling.
Other Transport (40XX, 42XX, 45XX)	-Lower EPS due to sharp acceleration in fuel costs because the best surcharge programs are only covering approximately 80% of increase. -Some direct operational impacts from Hurricane Katrina.
Utilities	
Utilities (49XX)	-Higher natural gas and energy prices leads to increased earnings. -Higher energy prices also equals higher values on underlying assets (i.e., drilling prospects that weren't viable at lower prices are now attractive). -Some gas utility stocks have unregulated production subsidiaries that directly benefit from higher energy prices.
Rebuild Efforts	
Building Materials (140X, 24XX, 32XX, 505X)	-Wood product prices surged in the wake of Katrina, as it is used in 100% of reconstruction applications. -Increased cement usage for reconstruction.
Construction (15XX, 16XX, 17XX)	-Due to devastating damage from Hurricane Katrina, a number of companies will benefit from the enormous restructuring and rebuilding efforts. -Additionally, other firms will benefit indirectly due to tighter national market conditions.
Machinery (352X, 353X, 508X)	-Significant heavy infrastructure projects for reconstruction will increase demand. -Rising energy prices could have offsetting effect.

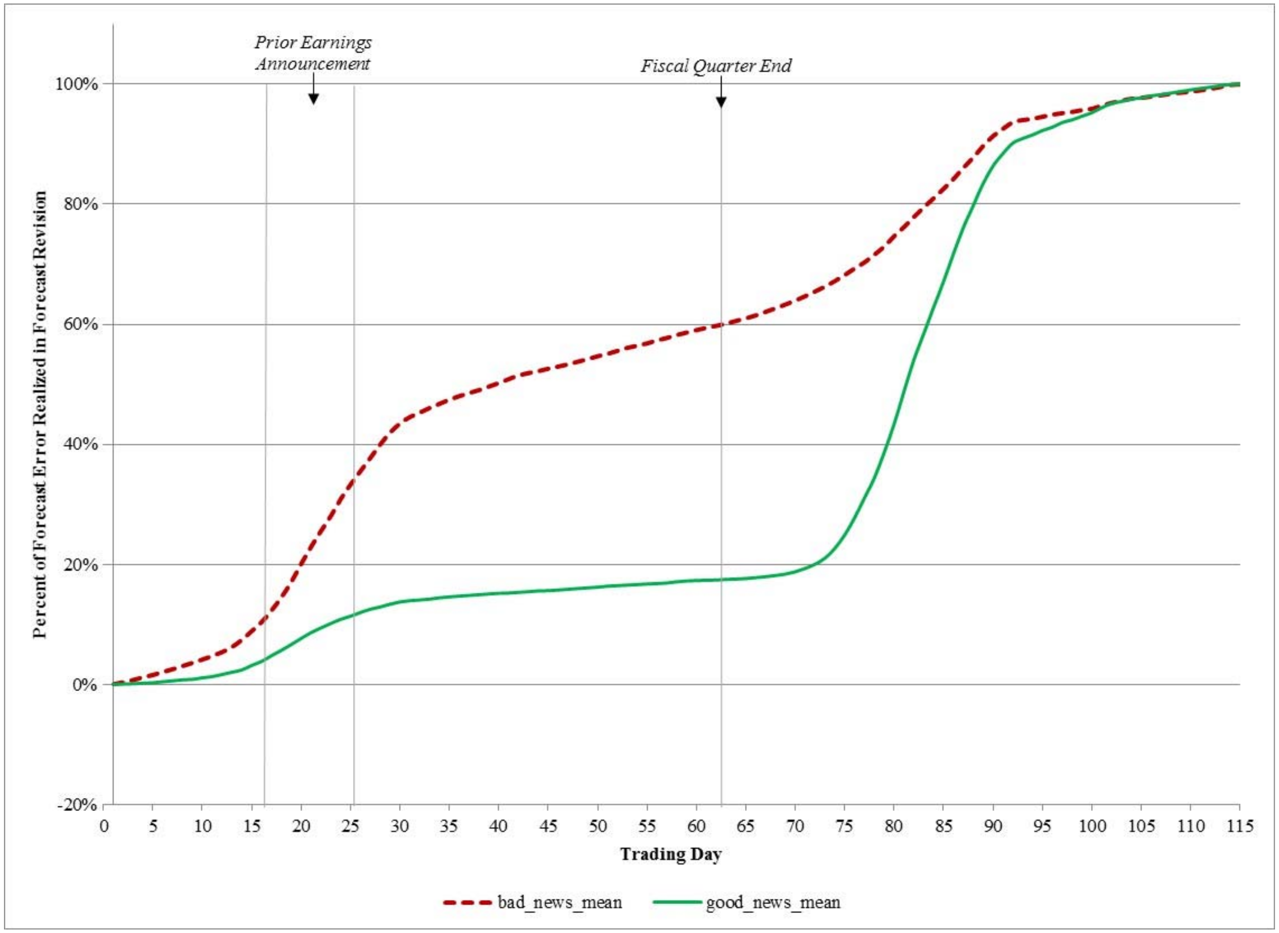
Insurance	
Insurance (63XX)	-Hurricane losses reduce earnings; -Some are impacted directly, whereas others are impacted from damage to autos, property, and business interruption.
Chemicals	
Specialty Chemicals (28XX, 516X)	-Rise in crude and natural gas put upward pressure on raw materials and energy costs, leading to decreased margins and/or lower sales volumes.
Food and Restaurants	
Food Products (20XX)	-As price of fuel increases, so does the cost to deliver the food. -Food products are also seeing a rise in packaging costs. -Katrina's dark clouds will likely linger for Food Manufacturers in the form of higher energy prices and packaging costs.
Restaurants (58XX)	-Increasing oil prices impact both the top and gross margin lines. -Gross margins are affected by food price increases from suppliers. -Consumers are feeling the pinch via a decrease in discretionary spending due to spending more on gas for the car; thus, there's an indirect affect at the top line as well. -Many restaurant closings due to damage.

Figure 1
Cross-Sectional Earnings Information Flow Timeliness Distribution Plots



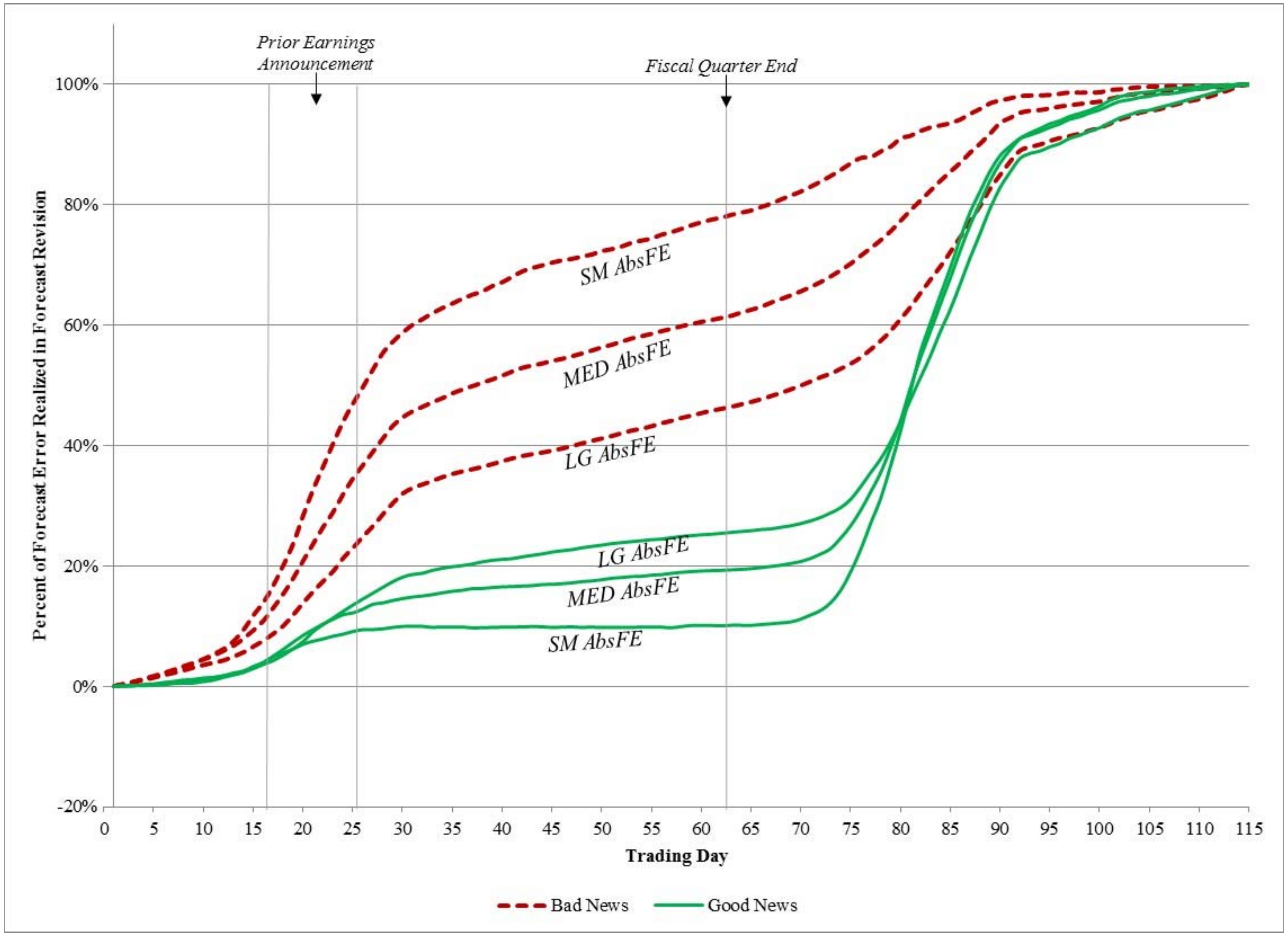
Notes: This figure plots the percentage of the consensus forecast error realized in the consensus forecast revision by trading day (relative to the beginning of the quarter) for the median, first, and third quartiles of the Primary Sample distribution. The plotted percentage is equal to the ratio of FR_m to FE, where m represents a trading day from 1 to 115. FR_m is the forecast revision at trading day m, calculated as the difference between the consensus analyst forecast on trading day m and the consensus analyst forecast at the beginning of the quarter. FE is the forecast error for the quarter, calculated as the difference between the actual earnings per share and the consensus analyst forecast at the beginning of the quarter.

Figure 2
Earnings Information Flow Timeliness By Direction of the Earnings News



Notes: This figure plots the percentage of the consensus forecast error realized in the consensus forecast revision for each trading day (from 1 to 115, relative to the beginning of the quarter) for equal-weighted good news and bad news portfolios from the Primary Sample. The plotted percentage is equal to the ratio of FR_m to *FE*, where *m* represents the trading day from 1 to 115. FR_m is the forecast revision on day *m*, calculated as the difference between the consensus analyst forecast on day *m* and the consensus analyst forecast at the beginning of the quarter. *FE* is the forecast error for the quarter, calculated as the difference between the actual earnings per share and the consensus analyst forecast at the beginning of the quarter.
In Table 5, I formally test whether the areas under the bad news and good news curves are significantly different using permutation analysis.

Figure 3
Earnings Information Flow Timeliness By Direction and Magnitude of the Earnings News



Notes: This figure plots the percentage of the consensus forecast error realized in the consensus forecast revision for each trading day (from 1 to 115, relative to the beginning of the quarter) for equal-weighted portfolios partitioned on the direction and the magnitude of the earnings news. The plotted percentage is equal to the ratio of FR_m to *FE*, where *m* represents the trading day from 1 to 115. FR_m is the forecast revision on day *m*, calculated as the difference between the consensus analyst forecast on day *m* and the consensus analyst forecast at the beginning of the quarter. *FE* is the forecast error for the quarter, calculated as the difference between the actual earnings per share and the consensus analyst forecast at the beginning of the quarter. *SM AbsFE*, *MED AbsFE*, and *LG AbsFE* reflect the bottom three, middle four, and top three deciles, respectively, of the ratio of the unsigned forecast error for the quarter to the stock price of the firm at the beginning of the quarter.

In Table 5, I formally test whether the areas under the bad news and good news curves for each earnings magnitude decile are significantly different using permutation analysis.

Table 1
Sample Selection

Panel A: Primary Sample

	Sample Reductions	*Cumulative Sample Total*
Intersection of Compustat and CRSP (2003-2013)	170,872	
Require I/B/E/S Coverage	(38,717)	132,155
Include Only Calendar Quarter Firms	(14,892)	117,263
Remove Invalid EA dates	(8,378)	108,885
Require at least 1 'active' forecast at beg of Qtr	(12,112)	96,773
Subtotal for Aggregate Measures	96,773	
Require Earnings News (>5% of fcst & > $0.02)	(28,095)	68,678
Subtotal for Portfolio Level Analyses	68,678	
Less: Observations with missing DISPERSION	(11,943)	56,735
Less: Observations with Negative BV or missing MTB	(1,610)	55,125
Less: Observations from Industry-Quarters with < 5 firms	(1,108)	54,017
Total For Regression Specification	54,017	

Notes: This table presents an overview of the sample selection procedure. Panel A summarizes the procedure for the Primary Sample, whereas Panel B summarizes the procedure for the Katrina Sample. Both of the samples following similar selection procedures. For the Primary Sample, I begin by selecting all firm-quarters in the intersection of Compustat, CRSP and I/B/E/S. I then require only calendar quarter firms (i.e., quarter end month in 3, 6, 9, or 12) to ensure a consistent time pattern. I remove firm quarters with invalid earnings announcement dates (i.e., those with earnings announcements that are prior to the fiscal quarter end, or those that occur after regulatory filing requirements: 40 days after quarter end for interim quarters and 75 days after quarter end for fiscal year ends). To complete my sample for portfolio analyses, I also require at least one 'active' analyst forecast and some level of earnings news (i.e., greater than 5 percent of the original forecast or $0.02). For each of my regression specifications, I also require a series of control variables and limit my sample to only observations from industry quarters with at least 5 firms.

The Katrina Sample follows similar procedures.

Table 1 (Continued)

Panel B: Katrina Sample

	Total
Intersection of Compustat and CRSP for Select Industries	1,128
Require I/B/E/S Coverage	(209)
Include Only Calendar Quarter Firms	(33)
Remove Invalid EA dates	(19)
Require at least 1 'active' forecast at beg of Qtr	(123)
Require Earnings News (>5% of fcst & > $0.02)	(155)
Subtotal	589
Less: Observations with missing Controls	(19)
Total For Regression Specification	570

Notes: This table presents an overview of the sample selection procedure. Panel A summarizes the procedure for the Primary Sample, whereas Panel B summarizes the procedure for the Katrina Sample. Both of the samples following similar selection procedures. For the Primary Sample, I begin by selecting all firm-quarters in the intersection of Compustat, CRSP and I/B/E/S. I then require only calendar quarter firms (i.e., quarter end month in 3, 6, 9, or 12) to ensure a consistent time pattern. I remove firm quarters with invalid earnings announcement dates (i.e., those with earnings announcements that are prior to the fiscal quarter end, or those that occur after regulatory filing requirements: 40 days after quarter end for interim quarters and 75 days after quarter end for fiscal year ends). To complete my sample for portfolio analyses, I also require at least one 'active' analyst forecast and some level of earnings news (i.e., greater than 5 percent of the original forecast or $0.02). For each of my regression specifications, I also require a series of control variables and limit my sample to only observations from industry quarters with at least 5 firms.

The Katrina Sample follows similar procedures.

Table 2
Flow of Earnings Information by Trading Day

Panel A: Full Sample (n=68,678)

Trading Days from Beginning of Quarter	Percent of Forecast Error Reflected in Consensus: Mean	Median	First Quartile	Third Quartile	Std Dev
15 Trading Days	6.1%	0.0%	0.0%	0.0%	36.0%
25 Trading Days	**22.6%**	**3.7%**	**0.0%**	**41.2%**	**66.3%**
35 Trading Days	31.4%	20.8%	0.0%	59.3%	78.3%
45 Trading Days	34.5%	25.0%	0.0%	65.1%	80.6%
55 Trading Days	37.2%	28.6%	0.0%	68.4%	82.8%
65 Trading Days	**39.8%**	**33.3%**	**0.0%**	**74.8%**	**83.9%**
75 Trading Days	47.1%	41.2%	1.6%	94.7%	83.8%
85 Trading Days	75.1%	100.0%	50.0%	100.0%	65.6%
95 Trading Days	93.5%	100.0%	100.0%	100.0%	37.7%
105 Trading Days	97.7%	100.0%	100.0%	100.0%	20.6%
115 Trading Days	100.0%	100.0%	100.0%	100.0%	0.0%

Notes: This table provides descriptive statistics on the flow of earnings information by trading day. Panel A presents results for the entire sample; Panel B excludes firm-quarters that contain management forecasts; and Panel C reports results for only the quarters that contain management forecasts.

At each trading day m, I calculate the ratio FR_m/FE for each firm-quarter, where FR_m is the forecast revision on trading day m (calculated as the difference between the consensus forecast on day m and the consensus forecast at the beginning of the quarter) and FE is the forecast error for the full quarter calculated by taking the difference between the actual earnings per share and the consensus forecast at the beginning of the quarter). I then provide descriptive statistics on the distribution of this ratio on sequential trading days throughout the 115-trading day period following the beginning of the quarter.

Table 2 (Continued)

Panel B: Firm-Quarters Without Management Forecasts (n=55,125)

Trading Days from Beginning of Quarter	Percent of Forecast Error Reflected in Consensus: Mean	Median	First Quartile	Third Quartile	Std Dev
15 Trading Days	5.7%	0.0%	0.0%	0.0%	37.0%
25 Trading Days	**20.2%**	**0.0%**	**0.0%**	**36.7%**	**66.2%**
35 Trading Days	28.7%	18.2%	0.0%	54.5%	79.1%
45 Trading Days	31.8%	22.2%	0.0%	60.0%	81.6%
55 Trading Days	34.3%	25.0%	0.0%	65.5%	84.2%
65 Trading Days	**36.6%**	**28.6%**	**0.0%**	**67.6%**	**85.7%**
75 Trading Days	43.5%	36.4%	0.0%	85.7%	85.8%
85 Trading Days	72.3%	100.0%	38.5%	100.0%	68.8%
95 Trading Days	92.6%	100.0%	100.0%	100.0%	40.4%
105 Trading Days	97.3%	100.0%	100.0%	100.0%	22.4%
115 Trading Days	100.0%	100.0%	100.0%	100.0%	0.0%

Notes: This table provides descriptive statistics on the flow of earnings information by trading day. Panel A presents results for the entire sample; Panel B excludes firm-quarters that contain management forecasts; and Panel C reports results for only the quarters that contain management forecasts.

At each trading day m, I calculate the ratio FR_m/FE for each firm-quarter, where FR_m is the forecast revision on trading day m (calculated as the difference between the consensus forecast on day m and the consensus forecast at the beginning of the quarter) and FE is the forecast error for the full quarter calculated by taking the difference between the actual earnings per share and the consensus forecast at the beginning of the quarter). I then provide descriptive statistics on the distribution of this ratio on sequential trading days throughout the 115-trading day period following the beginning of the quarter.

Table 2 (Continued)

Panel C: Firm-Quarters With Management Forecasts (n=13,553)

Trading Days from Beginning of Quarter	Percent of Forecast Error Reflected in Consensus: Mean	Median	First Quartile	Third Quartile	Std Dev
15 Trading Days	7.8%	0.0%	0.0%	0.0%	31.6%
25 Trading Days	**32.7%**	**18.5%**	**0.0%**	**60.0%**	**65.8%**
35 Trading Days	42.3%	33.3%	0.0%	75.0%	74.0%
45 Trading Days	45.6%	38.1%	5.5%	81.5%	75.4%
55 Trading Days	49.1%	42.9%	9.1%	87.5%	75.9%
65 Trading Days	**52.7%**	**50.0%**	**11.7%**	**95.0%**	**75.0%**
75 Trading Days	61.4%	63.6%	20.0%	100.0%	73.3%
85 Trading Days	86.3%	100.0%	100.0%	100.0%	49.1%
95 Trading Days	97.2%	100.0%	100.0%	100.0%	23.9%
105 Trading Days	99.4%	100.0%	100.0%	100.0%	10.1%
115 Trading Days	100.0%	100.0%	100.0%	100.0%	0.0%

Notes: This table provides descriptive statistics on the flow of earnings information by trading day. Panel A presents results for the entire sample; Panel B excludes firm-quarters that contain management forecasts; and Panel C reports results for only the quarters that contain management forecasts.

At each trading day *m*, I calculate the ratio FR_m/FE for each firm-quarter, where FR_m is the forecast revision on trading day *m* (calculated as the difference between the consensus forecast on day *m* and the consensus forecast at the beginning of the quarter) and *FE* is the forecast error for the full quarter calculated by taking the difference between the actual earnings per share and the consensus forecast at the beginning of the quarter). I then provide descriptive statistics on the distribution of this ratio on sequential trading days throughout the 115-trading day period following the beginning of the quarter.

Table 3
Descriptive Statistics and Correlations

Panel A: EIFT Descriptive Statistics for Select Industries

		Firm-Level EIFT					*Industry-Level EIFT*		
	Avg Num Firms	Mean	Median	First Quartile	Third Quartile	Std Dev	Median	First Quartile	Third Quartile
Top-10 Industries by Median Firm-Level EIFT									
SIC2=10: Metal Mining	*6*	63.65	65.15	42.99	86.58	44.56	71.08	54.75	79.23
SIC2=24: Lumber and Wood	*6*	67.80	64.84	44.18	88.89	45.51	70.23	53.76	84.52
SIC2=26: Paper	*18*	66.44	64.41	41.02	89.15	45.35	76.28	45.98	95.97
SIC2=33: Primary Metal Industries	*25*	65.15	64.35	41.50	87.34	46.67	72.18	45.20	82.03
SIC2=14: Nonmetallic Minerals	*5*	57.05	62.88	33.01	80.44	37.08	68.02	53.62	94.30
SIC2=44: Trucking and Warehousing	*8*	66.31	62.33	37.71	87.13	45.80	72.36	48.06	95.17
SIC2=40: Railroads	*6*	59.82	62.25	40.20	77.33	34.16	64.52	21.52	82.42
SIC2=25: Furniture and Fixtures	*11*	64.96	62.24	42.44	85.53	35.67	64.31	27.45	103.01
SIC2=36: Electronic Equipment	*144*	63.70	61.63	41.38	83.16	38.83	63.14	38.71	93.52
SIC2=29: Petroleum and Coal Products	*14*	61.10	61.50	41.56	78.45	43.51	63.02	48.15	76.63
Bottom-10 Industries by Median Firm-Level EIFT									
SIC2=21: Tobacco	*5*	33.51	33.66	17.71	41.50	19.33	0.00	0.00	0.00
SIC2=70: Hotels and Lodging	*6*	45.14	36.84	20.90	63.50	47.22	52.18	30.99	93.58
SIC2=65: Real Estate	*7*	41.80	37.52	20.90	60.77	39.80	48.75	26.60	64.17
SIC2=49: Utilities	*73*	45.74	40.37	26.95	62.59	38.12	23.27	0.00	56.12
SIC2=63: Insurance Carriers	*71*	44.09	40.83	29.34	56.00	33.00	35.31	21.01	43.27
SIC2=48: Communication	*59*	45.33	41.25	24.50	65.01	38.65	45.08	2.40	71.11
SIC2=78: Motion Pictures	*7*	45.11	41.36	25.03	68.00	43.51	44.60	15.46	74.18
SIC2=67: Other Investment Offices	*13*	46.55	43.08	26.36	65.72	40.95	35.01	0.00	56.42
SIC2=16: Heavy Construction	*8*	47.55	43.79	27.29	67.41	39.95	41.00	25.40	69.58
SIC2=80: Health Services	*35*	50.34	44.50	31.17	67.30	36.07	47.73	29.69	74.38
Largest 5 Industries by Number of Firms (not listed above)									
SIC2=60: Depository Institutions	*221*	56.13	52.89	38.66	71.50	33.83	46.95	14.74	61.39
SIC2=73: Business Services	*201*	54.57	50.25	32.50	73.77	39.23	39.07	0.00	71.26
SIC2=28: Chemicals	*161*	50.84	47.09	28.50	70.81	42.79	33.03	9.76	80.47
SIC2=38: Instruments	*109*	55.18	50.72	33.00	76.33	41.13	35.05	0.00	79.98
SIC2=35: Industrial Machinery	*94*	60.15	58.50	37.38	80.92	41.39	50.26	13.52	76.03
Smallest 5 Industries by Number of Firms (not listed above)									
SIC2=56: Apparel Stores	*5*	58.89	56.58	41.51	72.63	24.07	51.35	24.64	65.59
SIC2=72: Personal Services	*5*	53.96	50.90	31.22	67.65	39.76	27.61	8.71	86.51
SIC2=57: Furniture Stores	*5*	55.86	58.85	40.44	72.31	25.58	28.79	-42.64	60.54
SIC2=17: Special Trade Contractors	*5*	51.79	44.93	30.28	72.50	33.40	61.46	40.00	90.91
SIC2=22: Textile Mill Products	*6*	60.59	57.70	39.50	85.72	34.49	58.12	25.39	74.67
Remaining 28 Industries	*18*	55.71	53.00	34.00	76.17	40.62	52.57	25.20	76.29
Full Sample	*32*	57.94	55.94	36.79	78.21	39.17	53.63	20.19	80.54

Notes: This Panel of Table 3 presents summary statistics of my earnings information flow timeliness (*EIFT*) measure, calculated at the firm and industry-level, for select industries. 'Avg Num Firms' reflects the average number of firms for the industry during my sample period.

Table 3 (Continued)

Panel B: Descriptive Statistics – High EIFT vs. Low EIFT

	High EIFT Firm Quarters		Low EIFT Firm Quarters		Difference (High-Low)	
	Mean	Median	Mean	Median	Mean	Median
IND_EIFT	53.0711	52.8507	46.7522	44.6945	6.3189 ***	8.1562 ***
GOOD_NEWS	0.3691	0.0000	0.6202	1.0000	-0.2511 ***	-1.0000 ***
ABSFE	0.0096	0.0042	0.0129	0.0044	-0.0033 ***	-0.0001 ***
DISPERSION	0.0035	0.0016	0.0037	0.0015	-0.0002 ***	0.0001 ***
FOLLOWING	6.8423	5.0000	5.9698	5.0000	0.8725 ***	0.0000 ***
MTB	3.0113	2.0464	3.0603	1.9823	-0.0490 *	0.0641 ***
PRQ_EALAG	19.7726	19.0000	21.3641	21.0000	-1.5915 ***	-2.0000 ***
LITRISK	0.0324	0.0232	0.0268	0.0198	0.0056 ***	0.0034 ***
INST_OWN%	0.7139	0.7659	0.6841	0.7324	0.0298 ***	0.0335 ***
SHORT_INT%	0.0601	0.0420	0.0566	0.0386	0.0035 ***	0.0034 ***
INSIDER_SALES	0.0018	0.0001	0.0018	0.0001	0.0000	0.0000
INSIDER_OWN%	0.1058	0.0469	0.1162	0.0532	-0.0104 ***	-0.0063 ***
OSCORE	-1.5375	-1.4154	-1.0935	-1.0427	-0.4439 ***	-0.3728 ***
SALE_GRQ	1.1583	1.0838	1.1580	1.0851	0.0003	-0.0013
PR12_RET	0.1385	0.0600	0.1423	0.0806	-0.0038	-0.0206 ***
ABS_ACC	0.0272	0.0176	0.0283	0.0174	-0.0011 ***	0.0002
CAP_INTEN	0.0688	0.0411	0.0721	0.0394	-0.0033 ***	0.0017 ***
STDRET	0.0294	0.0263	0.0293	0.0261	0.0001	0.0003 ***
PR_FE	0.0115	0.0022	0.0163	0.0029	-0.0048 ***	-0.0007 ***

Notes: This Panel of Table 3 presents descriptive statistics for *high-EIFT* and *low-EIFT* quarters, where high and low earnings information flow timeliness are determined based on a median split. I define each of the variables in Appendix A. I winsorize all continuous variables at the one percent level.

***/**/* indicate whether the means (medians) are significantly different across the *high-EIFT* and *low-EIFT* samples at the 1 percent, 5 percent, and 10 percent levels, respectively, based on t-tests (Wilcoxon signed rank tests).

Table 3 (Continued)

Panel C: Univariate Correlations (Spearman coefficients in the upper triangle; Pearson coefficients in the lower triangle)

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**
(1) EIFT	*1*	**0.08**	**-0.31**	**-0.02**	**0.02**	**0.10**	**0.01**	**-0.14**	**0.12**	**0.06**	**0.04**	0.00	**-0.04**	**-0.11**	-0.01	**-0.03**	-0.01	0.01	0.01	**-0.12**
(2) IND_EIFT	**0.05**	*1*	**-0.09**	**0.07**	**0.07**	**0.02**	**-0.04**	**0.01**	**0.04**	**0.03**	**0.03**	-0.01	0.00	**-0.05**	**-0.02**	**-0.08**	**0.04**	**0.04**	**0.10**	0.00
(3) GOOD_NEWS	**-0.31**	**-0.08**	*1*	**-0.18**	**-0.18**	**0.06**	**0.11**	**-0.08**	**-0.02**	0.00	**-0.08**	**0.14**	**-0.05**	**-0.02**	**0.12**	**0.20**	**-0.05**	0.00	**-0.05**	**-0.03**
(4) ABS_FE	**-0.06**	**0.04**	**-0.14**	*1*	**0.70**	**-0.19**	**-0.35**	**0.16**	**-0.12**	**-0.16**	**0.07**	**-0.22**	**0.11**	**0.26**	**-0.18**	**-0.33**	**0.16**	**0.03**	**0.44**	**0.58**
(5) DISPERSION	0.00	**0.04**	**-0.10**	**0.69**	*1*	**-0.07**	**-0.35**	**0.22**	**-0.06**	**-0.13**	**0.11**	**-0.23**	**0.07**	**0.31**	**-0.20**	**-0.33**	**0.17**	**0.13**	**0.45**	**0.64**
(6) FOLLOWING	**0.08**	**0.03**	**0.06**	**-0.11**	**-0.09**	*1*	**0.13**	**-0.20**	**0.51**	**0.30**	**0.13**	**0.09**	**-0.23**	**-0.20**	**0.03**	**0.03**	0.00	**0.07**	**-0.12**	**-0.24**
(7) MTB	**-0.01**	**-0.03**	**0.07**	**-0.11**	**-0.09**	**0.07**	*1*	-0.01	**0.28**	**0.07**	**0.11**	**0.21**	**-0.02**	**0.01**	**0.30**	**0.38**	**0.16**	**0.07**	**-0.09**	**-0.31**
(8) PRQ_EALAG	**-0.10**	**0.03**	**-0.08**	**0.07**	**0.12**	**-0.21**	**0.02**	*1*	**-0.08**	**0.00**	**0.07**	**-0.03**	**0.09**	**0.17**	**0.04**	**-0.05**	**0.16**	**0.11**	**0.16**	**0.22**
(9) LITRISK	**0.09**	**0.02**	**-0.07**	**0.05**	**0.06**	**0.36**	**0.17**	**-0.06**	*1*	**0.29**	**0.20**	**0.04**	**-0.31**	**-0.14**	**0.09**	**0.11**	**0.05**	**0.09**	**-0.04**	**-0.17**
(10) INST_OWN%	**0.06**	**0.03**	**0.01**	**-0.16**	**-0.18**	**0.26**	**0.02**	**-0.02**	**0.17**	*1*	**0.33**	**0.12**	**-0.27**	**-0.14**	-0.01	**0.05**	**0.05**	**-0.02**	**-0.12**	**-0.19**
(11) SHORT_INT%	**0.03**	**0.03**	**-0.08**	**0.08**	**0.11**	**0.06**	**0.12**	**0.06**	**0.20**	**0.27**	*1*	**0.05**	**0.10**	**-0.02**	**0.05**	**-0.09**	**0.15**	**0.03**	**0.25**	**0.05**
(12) INSIDER_SALES	**-0.01**	0.00	**0.10**	**-0.07**	**-0.07**	**-0.04**	**0.11**	**0.02**	**-0.04**	**-0.01**	**0.04**	*1*	**0.06**	**-0.12**	**0.16**	**0.24**	**0.01**	**-0.03**	**-0.09**	**-0.19**
(13) INSIDER_OWN%	**-0.03**	0.00	**-0.02**	**0.05**	**0.04**	**-0.16**	**0.01**	**0.09**	**-0.12**	**-0.29**	0.00	**0.11**	*1*	0.01	**0.03**	**-0.04**	**0.07**	**-0.07**	**0.21**	**0.15**
(14) OSCORE	**-0.08**	**-0.04**	-0.01	**0.20**	**0.27**	**-0.21**	**0.17**	**0.15**	**-0.08**	**-0.17**	**-0.02**	**-0.05**	**-0.02**	*1*	**-0.07**	**-0.07**	**0.01**	**0.10**	**0.14**	**0.35**
(15) SALE_GRQ	-0.01	**-0.01**	**0.07**	**-0.07**	**-0.05**	0.00	**0.17**	**0.07**	**0.09**	**-0.06**	**0.07**	**0.11**	**0.03**	**0.05**	*1*	**0.31**	**0.05**	**0.05**	**-0.09**	**-0.17**
(16) PR12_RET	**-0.02**	**-0.06**	**0.18**	**-0.23**	**-0.24**	0.01	**0.25**	**-0.03**	**0.09**	**0.03**	**-0.05**	**0.16**	0.00	**-0.04**	**0.23**	*1*	**-0.04**	0.00	**-0.27**	**-0.11**
(17) ABS_ACC	**-0.01**	**0.02**	**-0.06**	**0.21**	**0.16**	**-0.03**	**0.14**	**0.10**	**0.06**	**-0.02**	**0.14**	**0.03**	**0.06**	**0.06**	**0.06**	**-0.03**	*1*	0.11	**0.21**	**0.10**
(18) CAP_INTEN	**-0.02**	**0.03**	0.00	**0.06**	**0.12**	**0.06**	**0.07**	**0.15**	**0.06**	**-0.07**	**0.06**	**-0.02**	0.00	**0.23**	**0.17**	**0.01**	**0.11**	*1*	**0.08**	**0.06**
(19) STDRET	0.00	**0.07**	**-0.04**	**0.38**	**0.45**	**-0.12**	0.00	**0.14**	**0.08**	**-0.16**	**0.19**	0.00	**0.11**	**0.22**	**-0.02**	**-0.13**	**0.18**	**0.14**	*1*	**0.46**
(20) PR_FE	**-0.03**	-0.01	**-0.03**	**0.39**	**0.42**	**-0.10**	**-0.03**	**0.06**	**0.01**	**-0.17**	**0.04**	**-0.04**	**0.05**	**0.21**	**-0.02**	**-0.04**	**0.05**	**0.10**	**0.30**	*1*

Notes: This Panel of Table 3 presents univariate correlations. Spearman correlations are in the upper triangle and Pearson correlations are in the lower triangle. I define all variables in Appendix A. I winsorize all continuous variables at the one percent level. Bolded coefficients are statistically significant at the 5 percent level or better.

Table 4
Between- Versus Within-Firm Variation in EIFT

Panel A: Estimates of Between- and Within-Firm Variation in EIFT

	Variance		Estimated Standard Dev. From Anova	
	Between-Firm	Within-Firm	Between-Firm	Within-Firm
Earnings Information Flow Timeliness	404.70	1,392.11	10.08	38.76
	23%	*77%*	*21%*	*79%*

Panel B: Distribution of Within-Firm Variation in EIFT

	Mean	Median	First Quartile	Third Quartile
Standard Deviation of EIFT by Firm	34.6047	33.1781	24.0897	43.8929

Panel C: Characteristics of High- Versus Low-EIFT Variation Firms

	High EIFT Variance Firms		Low EIFT Variance Firms		Difference (High-Low)	
	Mean	Median	Mean	Median	Mean	Median
Log of Market Value of Equity	6.6055	6.4493	6.6461	6.4067	-0.0406	0.0426
Log of Total Assets	6.7623	6.6383	6.8768	6.7642	-0.1145 *	-0.1259
MTB	3.2215	2.1594	3.3186	2.2666	-0.0490	0.0641
DISPERSION	0.0043	0.0026	0.0036	0.0018	0.0007 ***	0.0008 ***
FOLLOWING	5.5249	4.6000	5.4495	4.1818	0.0754	0.4182 ***
INST_OWN%	0.6680	0.7142	0.6154	0.6504	0.0526 ***	0.0638 ***
LITRISK	0.0276	0.0230	0.0261	0.0211	0.0015 ***	0.0020 ***
INSIDER_OWN%	0.1259	0.0634	0.1276	0.0678	-0.0017	-0.0045
OSCORE	-1.0393	-1.0616	-0.9798	-1.0510	-0.0595	-0.0106
SALE_GRQ	1.1876	1.1060	1.1853	1.1118	0.0023	-0.0058
STDRET	0.0313	0.0308	0.0302	0.0284	0.0011 ***	0.0024 ***

Notes: This Table presents descriptive statistics on the amount of between- versus within-firm variation in *EIFT*. Panel A presents estimates of the relative proportion of between- versus within-firm variation; Panel B presents the distribution of within-firm variation throughout my sample; Panel C present firm characteristics of high- versus low-*EIFT* variation firms.

In panel A, I first adopt the terminology conventionally employed by panel studies by using "between-firm" to refer to differences in firm-specific averages across firms, where the averages are computed over time. The term "within-firm" is used to refer to deviations of variables from these firm-specific means. Alternatively, the second set of estimates utilizes a one-way anova of *EIFT* on firm to estimate the relative proportion of between- versus within-firm variation.

In Panel B, I calculate the standard deviation of *EIFT* by firm and present the distribution of this variable across my sample.

In Panel C, I present descriptive statistics for *high-EIFT Variation Firms* and *low-EIFT Variation Firms*, where high and low refer to the above- and below-median points of the firm-specific standard deviation in earnings information flow timeliness. Variables represent firm averages over the entire sample period. I provide specific details on the firm-quarter calculations of each variable in Appendix A. I winsorize all continuous variables at the one percent level.

***/**/* indicate whether the means (medians) are significantly different across the *high-* and *low-* groups at the 1 percent, 5 percent, and 10 percent levels, respectively, based on t-tests (Wilcoxon signed rank tests).

Table 5
Portfolio Level Analyses on the Association Between Earnings Information Flow Timeliness and the Direction and Magnitude of the Earnings News

	Bad News EIFT	Good News EIFT	Δ EIFT	*p-value*
Full Sample Analyses				
Full Sample	65.5617	41.3026	24.2591	*0.00* ***
By ABSFE Decile				
Decile 1 (Smallest)	83.7081	38.1725	45.5356	*0.00* ***
Decile 2	75.0769	37.5286	37.5483	*0.00* ***
Decile 3	74.9239	39.6557	35.2682	*0.00* ***
Decile 4	71.0425	40.7876	30.2549	*0.00* ***
Decile 5	67.6543	42.1062	25.5481	*0.00* ***
Decile 6	64.6475	43.0966	21.5509	*0.00* ***
Decile 7	65.4114	43.5851	21.8263	*0.00* ***
Decile 8	61.3146	43.2749	18.0397	*0.00* ***
Decile 9	58.1957	44.7329	13.4628	*0.00* ***
Decile 10 (Largest)	48.8927	43.9849	4.9079	*0.00* ***

Notes: This table tests whether *EIFT* values for good news and bad news portfolios within the Primary Sample are significantly different for the full sample and across a series of earnings magnitude deciles. A firm-quarter is allocated to the good news (bad news) portfolio if the difference between the actual earnings per share and the consensus analyst forecast at the beginning of the period is positive (negative). *ABSFE* deciles are calculated annually, where *ABSFE* is the forecast error scaled by price at the beginning of the period. *ΔEIFT* is my test statistic, calculated as the difference between the *EIFT* measure for the equal-weighted bad news portfolio and the *EIFT* measure for the equal-weighted good news portfolio.

I use permutation analysis to test whether the test statistic, *ΔEIFT*, is statistically different from zero. Specifically, I construct a distribution under the null hypothesis that the order of arrival of the forecast revisions does not matter because there is no difference in the earnings information flow for one portfolio relative to the other. To compute the distribution of test statistics under the null, I randomly scramble the order of the forecast revision pairs (i.e., one forecast revision for each portfolio for each time increment), recalculate the *ΔEIFT* test statistic, repeat the process 1,000 times, and count the number of times the magnitude (i.e., absolute value) of the outcome is equal to or greater than the magnitude of my actual test statistic. This process compares my actual test statistic to the distribution of the test statistic under the null that the order of forecast revisions does not matter.

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 6
Regression Analyses of Earnings Information Flow Timeliness on the Direction and Magnitude of the Earnings News

Dependent Variable: Earnings Information Flow Timeliness (EIFT)

	(1)		(2)		(3)			
					ABSFE	*GOOD_NEWS*		
	Coef.	*t-stat*	Coef.	*t-stat*	*Decile*	*Coeff.*	*t-stat*	Adj. R. Sq.
Primary Variables								
GOOD_NEWS (GN)	-25.4951	*-27.46* ***	-40.9350	*-23.18* ***	1	*-41.03*	*-15.39*	0.2672
*GN * ABSFE*			3.4952	*2.63* ***	2	*-34.82*	*-15.20*	0.2663
*BN * ABSFE*			-27.8562	*-14.99* ***	3	*-31.01*	*-13.52*	0.2962
Control Variables					4	*-31.03*	*-12.18*	0.2728
DISPERSION	8.2301	*7.75* ***	14.0194	*11.45* ***	5	*-24.82*	*-10.66*	0.2527
FOLLOWING	2.2345	*2.20* **	1.7102	*1.72* *	6	*-24.77*	*-11.89*	0.2391
Q4	-4.4312	*-6.86* ***	-3.8991	*-6.10* ***	7	*-22.58*	*-12.37*	0.2646
MTB	8.1687	*7.74* ***	4.9324	*4.51* ***	8	*-17.88*	*-9.94*	0.2130
PRQ_EALAG	-0.2533	*-5.58* ***	-0.2416	*-5.34* ***	9	*-17.09*	*-8.89*	0.2230
*SS * IND_EIFT*	0.0485	*5.96* ***	0.0545	*6.57* ***	10	*-11.08*	*-7.23*	0.1896
*OS * IND_EIFT*	-0.0373	*-6.01* ***	-0.0386	*-6.27* ***				
NO_IND_NEWS	1.3683	*2.31* **	1.3797	*2.35* **				
Fixed Effects	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Fixed Effects = Firm, Calendar Qtr*			
Clustered Standard Errors	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Clustered Standard Errors by Firm and Calendar Qtr*			
EIFT Winsorization/Truncation	*1% Winsorization*		*1% Winsorization*		*Controls = DISPERSION, FOLLOWING, Q4. MTB,*			
Adj. R-Square	*0.180*		*0.198*		*PRQ_EALAG, SS*IND_EIFT, OS*IND_EIFT,*			
N	*54,017*		*54,017*		*NO_IND_NEWS*			

Notes: This table presents the results of a series of regression analyses to examine how the direction and magnitude of the earnings news influence the timeliness of the earnings information flow. Column (1) of the table estimates a regression to examine the direction of the news; column (2) examines both the direction and the magnitude of the earnings news; and column (3) estimates a series of ten regressions to explore how the coefficient on an indicator variable for the direction of the news changes across deciles of earnings news magnitude. Each regression includes a series of controls for the analyst forecasting environment.

GOOD_NEWS/GN (*BN*) is an indicator variable set to one if the forecast error for the firm is positive (negative). *ABSFE* is the scaled decile rank of the forecast error scaled by price at the beginning of the period. *SS* (*OS*) are indicator variables set to one if the forecast error for the firm is the same sign (opposite sign) as the forecast error for the industry. I define all other variables in Appendix A. All continuous control variables are calculated as scaled decile ranks (ranging between 0 and 1) on an annual basis.

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 7
Regression Analyses that Exploit Hurricane Katrina to Distinguish Between Differential Earnings Information Flow and Differential Timing of Shocks to Earnings

Dependent Variable: Earnings Flow Timeliness (EIFT)

	(1)		(2)	
	Coef.	*t-stat*	Coef.	*t-stat*
Primary Variables				
GOOD_NEWS (GN)	-11.9568	*-2.89* ***	-36.6989	*-5.23* ***
*GN * ABSFE*			21.8927	*2.44* **
*BN * ABSFE*			-27.4306	*-3.02* ***
Control Variables				
DISPERSION	6.8926	*1.03*	6.7169	*0.92*
FOLLOWING	14.9987	*2.17* **	15.2866	*2.11* **
Q4	-19.4336	*-2.70* ***	-20.1847	*-2.79* ***
MTB	13.3766	*1.97* **	12.4786	*1.84* *
PRQ_EALAG	-1.2813	*-2.93* ***	-1.2839	*-2.98* ***
Fixed Effects	*Industry*		*Industry*	
Clustered Standard Errors	*No*		*No*	
EIFT Winsorization/Truncation	*1% Winsorization*		*1% Winsorization*	
Adj. R-Square	*0.161*		*0.186*	
N	*570*		*570*	

Notes: This table presents the results of a series of regression analyses that exploit Hurricane Katrina to distinguish between differential earnings information flow and differential timing of shocks to earnings. Column (1) of the table estimates a regression to examine the direction of the news, column (2) examines both the direction and the magnitude of the earnings news, and column (3) estimates a series of five regressions examining the direction of the news within each quintile of earnings news magnitude. Each regression includes a series of controls for the analyst forecasting environment.

GOOD_NEWS/GN (*BN*) is an indicator variable set to one if the forecast error for the firm is positive (negative). *ABSFE* is the scaled quintile rank of the forecast error scaled by price at the beginning of the period. I define all other variables in Appendix A. All continuous control variables are calculated as scaled quintile ranks (ranging between 0 and 1).
***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 8
Regression Analyses to Examine Which Managerial Incentives Influence the Relative Timeliness of Good Versus Bad News

Dependent Variable: Earnings Information Flow Timeliness (EIFT)				
		Coef.	*t-stat*	
GOOD_NEWS (GN)		-57.2462	*-18.76*	***
*GN * ABSFE*		9.8086	*5.79*	***
*BN * ABSFE*		-34.6527	*-16.47*	***
GN*LITIG_MON				
*GN*LITRISK*	(-)	-6.6654	*-5.59*	***
*GN*INST_OWN%*	(-)	-6.3986	*-4.29*	***
*GN*SHORT_INT%*	(-)	-2.4966	*-1.71*	*
GN*INCENT				
*GN*INSIDER_SALES*	(+)	9.3238	*6.32*	***
*GN*INSIDER_OWN%*	(+)	-0.4796	*-0.33*	
*GN*OSCORE*	(+)	1.3799	*1.08*	
*GN*SALE_GRQ*	(+)	11.1174	*6.69*	***
*GN*PR12_RET*	(+)	16.9523	*8.57*	***
*GN*ABS_ACC*	(+)	-0.8066	*-0.62*	
*GN*CAP_INTEN*	(+)	4.3168	*3.04*	***
*GN*STDRET*	(+)	-6.2026	*-4.02*	***
*GN*PR_FE*	(+)	-3.5860	*-1.93*	*
LITIG_MON				
LITRISK	(+)	10.2790	*10.29*	***
INST_OWN%	(+)	4.3697	*4.07*	***
SHORT_INT%	(+)	1.2656	*1.22*	
INCENT				
INSIDER_SALES	(-)	-4.1133	*-4.32*	***
INSIDER_OWN%	(-)	0.1167	*0.07*	
OSCORE	(-)	-1.5310	*-1.76*	*
SALE_GRQ	(-)	-4.4000	*-4.19*	***
PR12_RET	(-)	-7.8906	*-6.57*	***
ABS_ACC	(-)	-0.4286	*-0.52*	
CAP_INTEN	(-)	-2.8398	*-1.97*	**
STDRET	(-)	1.3910	*1.16*	
PR_FE	(-)	2.6984	*2.19*	**
Other Control Variables	*DISPERSION, FOLLOWING, ABS_FE, Q4, MTB, PRQ_EALAG, SS*IND_EIFT, OS*IND_EIFT, NO_IND_NEWS*			
Fixed Effects		*Firm, Calendar Qtr*		
Clustered Standard Errors		*Firm, Calendar Qtr*		
EIFT Winsorization/Truncation		*1% Winsorization*		
Adj. R-Square		*0.233*		
N		*43,031*		

Notes: This table presents the results of a series of regression analyses to examine which managerial incentives influence the relative timeliness of good versus bad news.

GOOD_NEWS/GN (*BN*) is an indicator variable set to one if the forecast error for the firm is positive (negative). *ABSFE* is the scaled decile rank of the forecast error, scaled by price at the beginning of the period. *LITIG_MON* is a vector of scaled tercile variables (on an annual basis) to reflect litigation risk and the extent of outside monitoring. *INCENT* is a vector of scaled tercile variables (on an annual basis) to reflect capital market incentives. I define each of the variables (and provide rationale for the predictions) in Appendix A. All other variables are as defined in table 6.

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The coefficient estimates for the control variables, fixed effects, and the intercept are not tabulated for brevity.

Table 9

Association Tests between Earnings Information Flow Timeliness and Observable Disclosure Variables

Dependent Variable: Earnings Information Flow Timeliness (EIFT)	(1)		(2)	
	Coef.	*t-stat*	Coef.	*t-stat*
Proxy Validation Variables				
PD1_MF	7.6211	*9.34* ***	9.6075	*14.69* ***
PD2_MF	7.3535	*6.17* ***	9.9630	*8.76* ***
PD3_MF	-1.2576	*-1.11*	0.1581	*0.14*
PD4_MF	-7.9032	*-7.95* ***	-5.5120	*-6.43* ***
LN_PD1_8K	1.7988	*3.91* ***	1.7382	*4.78* ***
LN_PD2_8K	0.5564	*1.09*	0.7829	*1.71*
LN_PD3_8K	-0.8511	*-2.18* **	-1.2076	*-3.23* ***
LN_PD4_8K	-1.6661	*-3.48* ***	-2.0883	*-5.61* ***
Other Control Variables	*DISPERSION, FOLLOWING, ABS_FE, Q4, MTB, PRQ_EALAG, SS*IND_EIFT, OS*IND_EIFT, NO_IND_NEWS*			
Fixed Effects	*Firm, Calendar Qtr*		*Industry, Calendar Qtr*	
Clustered Standard Errors	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*	
EIFT Winsorization/Truncation	*1% Winsorization*		*1% Winsorization*	
Adj. R-Square	*0.106*		*0.080*	
N	*54,017*		*54,017*	

Notes: This table presents regression analyses to examine the association between my earnings information flow timeliness measure and the timing of observable disclosures. To do so, I follow Anilowksi et al. (2007) and divide each fiscal quarter into four subperiods: (i)the period from the end of the previous fiscal quarter to 50 calendar days before the end of the fiscal quarter; (ii)the period from 50 days before the end of the fiscal quarter to 25 days before the end of that quarter; (iii)the period from 25 days before the end of the fiscal quarter to the end of that quarter; and (iv)the period from the end of the fiscal quarter to the earnings announcement date. I then examine how observable firm disclosures (management forecasts and 8-K filings) within each subperiod are associated my *EIFT* measure.

PD1_MF (*PD2_MF, PD3_MF, PD4_MF*) is an indicator variable set to one if the firm discloses a management forecast in subperiod 1 (subperiod 2, subperiod 3, subperiod 4), zero otherwise. *LN_PD1_8k (LN_PD2_8k, LN_PD3_8k, LN_PD4_8k)* is the natural log of one plus the number of days in which the firm issued an 8-K filing in subperiod 1 (subperiod 2, subperiod 3, subperiod 4). I define each of the other variables in Appendix A. All continuous control variables are calculated as scaled decile ranks (ranging between 0 and 1) on an annual basis. ***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 10
Change in Earnings Information Flow in Response to Management Forecast Disclosures

Bad News (MF revision is 0 to 25 percent of total FE)			
tday	N Obs	Mean	Median
-2	548	23%	0%
-1	548	23%	0%
0	548	24%	0%
1	548	28%	6%
2	548	37%	20%
3	548	38%	20%
4	548	39%	21%
5	548	39%	21%
tday 5 - tday-2		**16%**	**21%**
p-value		(0.00)	(0.00)

Good News (MF revision is 0 to 25 percent of total FE)			
tday	N Obs	Mean	Median
-2	1,211	2%	0%
-1	1,211	3%	0%
0	1,211	3%	0%
1	1,211	8%	0%
2	1,211	20%	18%
3	1,211	21%	20%
4	1,211	21%	20%
5	1,211	21%	20%
tday 5 - tday-2		**19%**	**20%**
p-value		(0.00)	(0.00)

Bad News (MF revision is 25 to 50 percent of total FE)			
tday	N Obs	Mean	Median
-2	744	19%	0%
-1	744	19%	0%
0	744	20%	0%
1	744	29%	18%
2	744	51%	43%
3	744	53%	44%
4	744	54%	44%
5	744	54%	44%
tday 5 - tday-2		**35%**	**44%**
p-value		(0.00)	(0.00)

Good News (MF revision is 25 to 50 percent of total FE)			
tday	N Obs	Mean	Median
-2	1,315	2%	0%
-1	1,315	2%	0%
0	1,315	2%	0%
1	1,315	12%	0%
2	1,315	37%	39%
3	1,315	40%	40%
4	1,315	40%	40%
5	1,315	41%	40%
tday 5 - tday-2		**38%**	**40%**
p-value		(0.00)	(0.00)

Bad News (MF revision is 50 to 75 percent of total FE)			
tday	N Obs	Mean	Median
-2	818	17%	2%
-1	818	17%	2%
0	818	18%	4%
1	818	31%	25%
2	818	67%	67%
3	818	71%	67%
4	818	72%	69%
5	818	72%	70%
tday 5 - tday-2		**56%**	**68%**
p-value		(0.00)	(0.00)

Good News (MF revision is 50 to 75 percent of total FE)			
tday	N Obs	Mean	Median
-2	698	2%	0%
-1	698	2%	0%
0	698	2%	0%
1	698	14%	0%
2	698	55%	60%
3	698	59%	62%
4	698	60%	63%
5	698	60%	63%
tday 5 - tday-2		**58%**	**63%**
p-value		(0.00)	(0.00)

Bad News (MF revision is 75 to 100 percent of total FE)			
tday	N Obs	Mean	Median
-2	1057	8%	0%
-1	1057	8%	0%
0	1057	9%	0%
1	1057	28%	14%
2	1057	81%	88%
3	1057	87%	92%
4	1057	88%	93%
5	1057	88%	93%
tday 5 - tday-2		**81%**	**93%**
p-value		(0.00)	(0.00)

Good News (MF revision is 75 to 100 percent of total FE)			
tday	N Obs	Mean	Median
-2	349	-1%	0%
-1	349	-1%	0%
0	349	0%	0%
1	349	16%	0%
2	349	64%	75%
3	349	69%	80%
4	349	70%	81%
5	349	71%	81%
tday 5 - tday-2		**71%**	**81%**
p-value		(0.00)	(0.00)

Notes: This table examines the change in earnings information flow surrounding the release of management forecasts. I examine eight partitions based on the direction of the overall news for the quarter and the magnitude of the revision suggested by the management forecast.

To perform this analysis, I calculate the daily ratio FR_m/FE for each firm-quarter on the eight trading days surrounding the release of a management forecast (tday=0), where FR_m is the forecast revision on trading day m (calculated as the difference between the consensus forecast at m and the consensus forecast at the beginning of the quarter) and FE is the forecast error for the full quarter calculated by taking the difference between the actual earnings per share and the consensus forecast at the beginning of the period). I then provide the mean and median of each partition on a daily basis.

Table 11
Regression Analyses to Examine whether the relation between Earnings Information Flow Timeliness and the Direction and Magnitude of the Earnings News Differs Across SEO and non-SEO Quarters

Dependent Variable: Earnings Information Flow Timeliness (EIFT)

	(1)		(2)		(3)	
			UNAFFILIATED (SEO=0)		*AFFILIATED (SEO=1)*	
	Coef.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Primary Variables						
GOOD_NEWS	-41.5260	*-24.00* ***	-41.3873	*-24.15* ***	-37.5969	*-9.24* ***
*GN * ABSFE*	3.1358	*2.38* **	2.9214	*1.97* **	6.0739	*1.57*
*BN * ABSFE*	-27.6487	*-14.94* ***	-27.2157	*-14.63* ***	-31.0553	*-5.77* ***
*GN * SEO*	3.0278	*3.71* ***				
*BN * SEO*	-3.4131	*-3.90* ***				
Control Variables						
DISPERSION	14.0163	*11.35* ***	13.3831	*9.13* ***	20.0960	*5.20* ***
FOLLOWING	1.7823	*1.79* *	2.7088	*2.44* **	-5.3301	*-1.56*
Q4	-3.8976	*-6.10* ***	-3.9058	*-6.20* ***	-4.1597	*-1.34*
MTB	4.9046	*4.50* ***	4.3036	*3.34* ***	6.3244	*1.73* *
PRQ_EALAG	-0.2392	*-5.25* ***	-0.2365	*-5.07* ***	-0.1387	*-1.05*
*SS * IND_EIFT*	0.0544	*6.62* ***	0.0523	*6.60* ***	0.0737	*3.78* ***
*OS * IND_EIFT*	-0.0384	*-6.23* ***	-0.0395	*-5.84* ***	-0.0307	*-2.02* **
NO_IND_NEWS	1.3669	*2.34* **	1.4515	*2.11* **	1.5024	*0.84*
Fixed Effects	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Firm, Calendar Qtr*	
Clustered Standard Errors	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Firm, Calendar Qtr*	
EIFT Winsorization/Truncation	*1% Winsorization*		*1% Winsorization*		*1% Winsorization*	
Adj. R-Square	*0.199*		*0.210*		*0.117*	
N	*54,017*		*46,721*		*7,296*	

Notes: This table presents the results of a series of regression analyses to examine whether the relation between Earnings Information Flow Timeliness and the direction and magnitude of the earnings news differs across Seasoned Equity Offering (*SEO*) and *non-SEO* quarters. Column (1) begins with the specification in equation (3) and incorporates a *SEO* indicator variable interacted with good news and bad news. Columns (2) and (3) estimate equation (3) separately for observations where *SEO* is set to zero ("unaffiliated") and for those where *SEO* is set to one ("affiliated"). I set *SEO* to one for any firm quarter containing a seasoned equity offering or for any firm quarter where a seasoned equity offering has occurred within the past year for the firm. All other variables are as defined previously and in Appendix A. I use scaled decile ranks (ranging between 0 and 1) for all continuous control variables.

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 12
Regression Analyses Partitioned Across Management Forecast and Non-Management Forecast Quarters

Dependent Variable: Earnings Information Flow Timeliness (EIFT)

	(1)		(2)	
	Management Guidance (MF=1)		*No Management Guidance (MF=0)*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*
Primary Variables				
GOOD_NEWS	-55.3471	*-22.99* ***	-36.1347	*-19.01* ***
*GN * ABSFE*	7.2748	*2.96* ***	1.2840	*0.84*
*BN * ABSFE*	-26.9344	*-12.85* ***	-27.0573	*-13.04* ***
Control Variables				
DISPERSION	7.8124	*3.07* ***	17.0271	*12.33* ***
FOLLOWING	1.4060	*0.78*	0.6155	*0.50*
Q4	-2.7160	*-2.38* **	-4.6686	*-5.31* ***
MTB	4.1931	*1.63*	5.2477	*4.45* ***
PRQ_EALAG	-0.3300	*-3.91* ***	-0.2011	*-4.00* ***
*SS * IND_EIFT*	0.0237	*2.00* **	0.0609	*6.55* ***
*OS * IND_EIFT*	-0.0335	*-2.55* **	-0.0379	*-5.51* ***
NO_IND_NEWS	1.4608	*1.23*	1.3515	*2.06* **
Fixed Effects	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*	
Clustered Standard Errors	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*	
EIFT Winsorization/Truncation	*1% Winsorization*		*1% Winsorization*	
Adj. R-Square	*0.302*		*0.167*	
N	*11,912*		*42,105*	

Notes: This table presents the results of equation (3) separately for management guidance and no management guidance firm quarters. Column (1) presents the results for the subset of firm quarters that contain explicit management guidance according to I/B/E/S and column (2) presents the results for the subset of firm quarters with no explicit guidance. All variables are as defined previously (and in Appendix A).

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 13
Regression Analyses Partitioned Across the Extent of Earnings Management (Abnormal Accruals)

Dependent Variable: Earnings Information Flow Timeliness (EIFT)								
	Include Abnormal Accrual Controls		***Partition By Signed Abnormal Accrual Tercile***					
			1		**2**		**3**	
	Coef.	*t-stat*	Coef.	*t-stat*	Coef.	*t-stat*	Coef.	*t-stat*
Primary Variables								
GOOD_NEWS	-40.1576	*-20.98* ***	-41.7061	*-17.99* ***	-38.9811	*-17.64* ***	-44.1569	*-18.51* ***
*GN * ABSFE*	3.9119	*2.91* ***	3.1228	*1.21*	1.4130	*0.61*	6.7497	*2.56* **
*BN * ABSFE*	-27.7939	*-14.55* ***	-30.3376	*-10.97* ***	-28.6402	*-10.00* ***	-24.7991	*-9.07* ***
*GN * ABACC*	-0.8889	*-1.33*						
*BN * ABACC*	1.3655	*1.97* **						
Control Variables								
DISPERSION	14.0543	*12.13* ***	14.4231	*6.68* ***	15.4820	*7.21* ***	13.5721	*6.56* ***
FOLLOWING	1.5454	*1.49*	1.0076	*0.54*	1.7250	*1.14*	1.2306	*0.72*
Q4	-3.9683	*-6.18* ***	-3.3522	*-2.93* ***	-1.7855	*-1.11*	-6.4339	*-5.42* ***
MTB	4.8409	*4.13* ***	2.6231	*1.12*	5.1313	*2.14* **	4.2302	*2.15* **
PRQ_EALAG	-0.2374	*-5.14* ***	-0.3610	*-4.59* ***	-0.1651	*-1.83* *	-0.2635	*-3.69* ***
*SS * IND_EIFT*	0.0514	*6.08* ***	0.0574	*5.12* ***	0.0633	*4.71* ***	0.0407	*3.24* ***
*OS * IND_EIFT*	-0.0380	*-5.93* ***	-0.0484	*-4.35* ***	-0.0304	*-2.42* **	-0.0240	*-2.14* **
NO_IND_NEWS	1.4311	*2.40* **	0.7634	*0.66*	2.1713	*1.83* *	1.4012	*1.06*
Fixed Effects	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Firm, Calendar Qtr*	
Clustered Standard Errors	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Firm, Calendar Qtr*	
EIFT Winsorization/Truncation	*1% Winsorization*		*1% Winsorization*		*1% Winsorization*		*1% Winsorization*	
Adj. R-Square	*0.198*		*0.195*		*0.206*		*0.197*	
N	*50,978*		*16,980*		*17,005*		*16,993*	

Notes: This table presents the results of equation (3), while controlling for or partitioning by the extent of earnings management. This table uses signed abnormal accruals as its proxy for earnings management. Specifically, the residual from a performance-matched modified Jones model (as in Kothari et al., 2005) is the proxy for abnormal accruals ("*ABACC*"). Column (1) includes abnormal accrual controls, interacted with good and bad news. Columns (2) through (4) estimate equation (3) separately for each tercile of signed abnormal accrual. All other variables are as defined previously (and in Appendix A).

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 14
Regression Analyses Excluding Meet-or-Beat Observations

Dependent Variable: Earnings Information Flow Timeliness (EIFT)		
	MBE = 0	
	Coef.	*t-stat*
Primary Variables		
GOOD_NEWS	-42.5510	*-19.98* ***
*GN * ABSFE*	13.3719	*8.75* ***
*BN * ABSFE*	-21.0974	*-9.14* ***
Control Variables		
DISPERSION	12.4864	*9.18* ***
FOLLOWING	2.9294	*2.61* ***
Q4	-4.8386	*-6.33* ***
MTB	6.7616	*5.23* ***
PRQ_EALAG	-0.1956	*-3.90* ***
*SS * IND_EIFT*	0.0639	*6.51* ***
*OS * IND_EIFT*	-0.0380	*-6.22* ***
NO_IND_NEWS	1.3647	*1.93* *
Fixed Effects	*Firm, Calendar Qtr*	
Clustered Standard Errors	*Firm, Calendar Qtr*	
EIFT Winsorization/Truncation	*1% Winsorization*	
Adj. R-Square	*0.188*	
N	*46,053*	

Notes: This table presents the results of equation (3), excluding meet-or-beat observations (i.e., those with non-negative earnings surprises less than $0.02). All other variables are as defined previously (and in Appendix A).

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 15

Regression Analyses Controlling For Expectations Management (Walk-Down)

Dependent Variable: Earnings Information Flow Timeliness (EIFT)

	(1)			(2)			
					GOOD_NEWS		
	Coef.	t-stat		ABSFE Decile	Coeff.	t-stat	Adj. R. Sq.
Primary Variables							
GOOD_NEWS	-18.8255	*-13.99*	***	1	*-18.27*	*-8.39*	0.3000
*GN * ABSFE*	9.4375	*7.04*	***	2	*-16.41*	*-8.67*	0.2966
*BN * ABSFE*	-9.0807	*-6.56*	***	3	*-12.90*	*-6.27*	0.3078
WD_SWITCH	56.8168	*47.08*	***	4	*-14.70*	*-6.76*	0.2923
Control Variables				5	*-12.81*	*-6.74*	0.2888
DISPERSION	4.3701	*4.10*	***	6	*-14.57*	*-8.48*	0.2533
FOLLOWING	2.4562	*3.06*	***	7	*-11.73*	*-6.38*	0.2598
Q4	-4.1459	*-6.62*	***	8	*-9.69*	*-6.08*	0.2444
MTB	5.1386	*5.05*	***	9	*-10.64*	*-6.67*	0.2487
PRQ_EALAG	-0.2780	*-7.49*	***	10	*-6.70*	*-5.29*	0.2516
*SS * IND_EIFT*	0.0372	*6.24*	***				
*OS * IND_EIFT*	-0.0313	*-5.63*	***	*Excludes all firm quarters that switched forecast error sign*			
NO_IND_NEWS	0.7068	*1.34*		*(i.e., from good to bad or from bad to good); n=45,672*			
Fixed Effects	*Firm, Calendar Qtr*			*Fixed Effects = Firm, Calendar Qtr*			
Clustered Standard Errors	*Firm, Calendar Qtr*			*Clustered Standard Errors by Firm and Calendar Qtr*			
EIFT Winsorization/Truncation	*1% Winsorization*			*Controls = DISPERSION, FOLLOWING, Q4. MTB,*			
Adj. R-Square	*0.377*			*PRQ_EALAG, SS*IND_EIFT, OS*IND_EIFT,*			
N	*54,017*			*NO_IND_NEWS*			
				N=45672			

Notes: This table presents the results of equation (3), controlling for expectations management (i.e., walk down behavior). Specifically, in column (1), I control for expectations management with an indicator variable (*WD_SWITCH*) set to one for observations that switched from bad news at the beginning of the quarter to good news at the end of the quarter. In column (2), I estimate equation (3) for each *ABSFE* decile, excluding observations that switched surprise signs (in either direction) from the beginning to the end of the quarter. All other variables are as defined previously (and in Appendix A).

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 16
Regression Analyses Partitioned By Prior Quarter's Earnings News

Dependent Variable: Earnings Information Flow Timeliness (EIFT)	(1)			(2)			(3)			(4)		
	SMALL GOOD NEWS			*LARGE GOOD NEWS*			*SMALL BAD NEWS*			*LARGE BAD NEWS*		
	Coef.	*t-stat*		*Coeff.*	*t-stat*		*Coeff.*	*t-stat*		*Coeff.*	*t-stat*	
Primary Variables												
GOOD_NEWS	-35.7783	*-15.70*	***	-25.6884	*-8.59*	***	-58.4037	*-19.89*	***	-76.6014	*-14.08*	***
*GN * ABSFE*	1.2847	*0.52*		0.9145	*0.40*		2.1700	*0.40*		5.4094	*1.04*	
*BN * ABSFE*	-29.4006	*-10.54*	***	-24.2069	*-8.81*	***	-43.7656	*-11.54*	***	-50.1497	*-11.80*	***
Control Variables												
DISPERSION	10.0738	*4.84*	***	12.3778	*5.12*	***	15.9626	*4.74*	***	18.7190	*6.87*	***
FOLLOWING	-1.9121	*-0.94*		1.1439	*0.55*		-2.2176	*-0.72*		7.9696	*3.05*	***
Q4	-4.7124	*-3.88*	***	-2.8011	*-2.29*	**	-3.5754	*-1.67*	*	-4.8069	*-2.40*	**
MTB	2.7038	*1.15*		5.3400	*2.30*	**	-5.0178	*-1.33*		4.6906	*1.52*	
PRQ_EALAG	-0.0519	*-0.69*		-0.3406	*-4.52*	***	-0.1124	*-0.91*		-0.3850	*-3.20*	***
*SS * IND_EIFT*	0.0582	*4.75*	***	0.0692	*4.60*	***	0.0534	*3.39*	***	0.0361	*2.47*	**
*OS * IND_EIFT*	-0.0390	*-3.73*	***	-0.0312	*-3.24*	***	-0.0145	*-0.74*		-0.0538	*-2.77*	***
NO_IND_NEWS	2.2158	*1.92*	*	2.3982	*2.22*	**	-0.9943	*-0.52*		1.0850	*0.56*	
Fixed Effects	*Firm, Calendar Qtr*			*Firm, Calendar Qtr*			*Firm, Calendar Qtr*			*Firm, Calendar Qtr*		
Clustered Standard Errors	*Firm, Calendar Qtr*			*Firm, Calendar Qtr*			*Firm, Calendar Qtr*			*Firm, Calendar Qtr*		
EIFT Winsorization/Truncation	*1% Winsorization*			*1% Winsorization*			*1% Winsorization*			*1% Winsorization*		
Adj. R-Square	*0.214*			*0.120*			*0.322*			*0.290*		
N	*15,159*			*16,182*			*8,502*			*10,893*		

Notes: This table presents the results of equation (3), partitioned by the prior quarter's earnings news. Specifically, I partition my sample into four groups based on the direction and magnitude of the prior quarter's earnings surprise (i.e., small-good, large-good, small-bad, large-bad) and re-estimate equation (3) for each subgroup. "Small" and "large" are based on median splits. Earnings surprise is defined as the difference between the actual I/B/E/S earnings and the consensus analyst forecast at the beginning of the current quarter. All other variables are as defined previously (and in Appendix A).

***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity.

Table 17
Regression Analyses to Compare Relative Importance of Economy-, Industry-, and Firm-News in Explaining Earnings Information Flow Timeliness

Panel A: Pooled Regression Specification

Dependent Variable: Earnings Information Flow Timeliness (EIFT)

	(1) Economy News		(2) Industry News		(3) Firm News		(4) Comprehensive	
	Coef.	*t-stat*	Coef.	*t-stat*	Coef.	*t-stat*	Coef.	*t-stat*
Primary Variables								
*SS * AGG_EIFT*	0.0624	*2.42* **					0.0125	*0.76*
*OS * AGG_EIFT*	-0.0067	*-0.28*					-0.0074	*-0.48*
No_AGG_News	2.6638	*2.47* **					1.0641	*0.73*
*SS * IND_EIFT*			0.1191	*8.15* ***			0.0564	*3.55* ***
*OS * IND_EIFT*			-0.0729	*-6.44* ***			-0.0335	*-2.32* **
No_IND_News			2.8048	*3.81* ***			1.8193	*2.96* ***
GOOD_NEWS					-42.7847	*-21.32* ***	-40.7631	*-23.18* ***
*GN * ABSFE*					4.6525	*3.44* ***	3.5885	*2.67* ***
*BN * ABSFE*					-26.7440	*-15.03* ***	-28.0026	*-14.80* ***
Control Variables								
DISPERSION	14.4271	*13.55* ***	13.2291	*12.40* ***	14.2296	*11.74* ***	14.4620	*11.68* ***
FOLLOWING	3.6271	*2.88* ***	2.9445	*2.36* ***	0.5104	*0.49*	0.3896	*0.38*
Q4	-4.4409	*-6.03* ***	-4.4170	*-6.02* ***	-4.5924	*-6.14* ***	-4.5055	*-6.19* ***
MTB	6.0515	*5.13* ***	6.4944	*5.39* ***	5.3309	*4.60* ***	5.3078	*4.71* ***
PRQ_EALAG	-0.1155	*-2.26* **	-0.1366	*-2.94* ***	-0.2440	*-5.02* ***	-0.2547	*-5.33* ***
Fixed Effects	*Firm*		*Firm*		*Firm*		*Firm*	
Clustered Standard Errors	*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Firm, Calendar Qtr*		*Firm, Calendar Qtr*	
EIFT Winsorization/Truncation	*1% Winsorization*		*1% Winsorization*		*1% Winsorization*		*1% Winsorization*	
Adj. R-Square	*0.076*		*0.098*		*0.189*		*0.195*	
N	*54,017*		*54,017*		*54,017*		*54,017*	

Table 17 (Continued)

Panel B: Vuong Tests

P-Values From Vuong Tests of Differences in Explanatory Power		
	Industry News	Economy News
Firm News	0.000	0.000
Industry News		0.000

Panel C: Distribution of R-Squares From Firm-Specific Regressions

R-Square Distributions

	Mean	*Min*	*Q1*	*Median*	*Q3*	*Max*	*Std Dev*
Economy News	0.18	0.00	0.06	0.13	0.24	0.95	0.15
Industry News	0.21	0.00	0.08	0.17	0.30	0.93	0.17
Firm News	0.32	0.00	0.15	0.29	0.45	0.99	0.21

	P-Value
Test Firm News > Economy News	0.00
Test Firm News > Industry News	0.00
Test Industry News > Economy News	0.00

Adjusted R-Square Distributions

	Mean	*Min*	*Q1*	*Median*	*Q3*	*Max*	*Std Dev*
Economy News	0.01	-0.49	-0.10	-0.02	0.09	0.94	0.18
Industry News	0.05	-0.45	-0.08	0.02	0.15	0.93	0.19
Firm News	0.18	-0.48	0.00	0.15	0.35	0.99	0.25

	P-Value
Test Firm News > Economy News	0.00
Test Firm News > Industry News	0.00
Test Industry News > Economy News	0.00

Notes: This table presents the results of regression analyses to compare the relative importance of economy-, industry-, and firm-news in explaining earnings information flow timeliness. Panel A presents the results from a pooled analysis; Panel B presents the p-values from Vuong (1989) tests of the differences in explanatory power across the three models in columns (1), (2), and (3) of Panel A; Panel C presents the r-square distributions for regressions estimated by firm.

SS and *OS* are indicator variables for same sign and opposite sign, respectively (e.g., if the forecast error for a firm-quarter is positive and the aggregate, or industry, forecast error is also positive then *SS* would be set to one and *OS* would be set to zero). *No_AGG_News* (*No_IND_News*) are indicator variables set to one if the aggregate (industry) forecast error for the quarter is less than 2 percent. AGG_EIFT is calculated in similar fashion to IND_EIFT, except using economy-wide earnings estimates rather than industry-wide. I define all other variables in Appendix A. All continuous control variables are calculated as scaled decile ranks (ranging between 0 and 1) on an annual basis. The firm-specific regressions in Panel C exclude control variables and require at least 10 observations per firm. ***/**/* represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Fixed effects are not tabulated for brevity. P-values in Panel C are based on Kolmogorov-Smirnov tests.

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EDUCATION AND PROFESSIONAL CERTIFICATION

Ph.D.	Accounting • Indiana University, Kelley School of Business	2015
M.S.	Accounting • University of Illinois at Chicago	2008
B.B.A.	Accounting • University of Michigan, Ross School of Business	2002

Certified Public Accountant (Illinois)

Certified Fraud Examiner *(Inactive)*

RESEARCH

Research Interests: Financial accounting and the capital markets: how economic forces shape information flows and financial reporting; information intermediaries; litigation.

Working Papers:

- "The Flow of Earnings Information to the Market"
  - Revising for Second Submission to *Journal of Accounting and Economics*.
  - Based on dissertation at Indiana University
  - Committee: Teri Yohn (chair), Daniel Beneish, Brian Miller, Jim Wahlen, and Bob Jennings
- "Understanding the relation between accruals and volatility: A real options-based investment approach" (with Salman Arif and Teri Yohn)
  - Revising for Fourth Submission to *Journal of Accounting and Economics*.
  - Accepted to the 2013 Conference on Financial Economics and Accounting.
  - Accepted to the 2013 Midwest Accounting Conference.
  - Accepted to the 2014 Annual Congress of the European Accounting Association.
  - Accepted to the 2014 American Accounting Association Annual Meeting.
- "What is the perceived value of audited disclosures to equity investors?" (with Joe Schroeder and Teri Yohn)
  - Revising for Second Submission to *Contemporary Accounting Research*.
  - Accepted to the 2014 Utah Winter Accounting Conference.
  - Accepted to the 2014 International Symposium on Audit Research.
  - Accepted to the 2014 American Accounting Association Annual Meeting.
- "Operating Earnings Disaggregation and Abnormal Investor Disagreement around Earnings Announcements" (with Eric Holzman, Joe Schroeder, and Teri Yohn)
- "Turning a Blind Eye to High Performing Cheaters: Evidence from the NCAA" (with Brian Miller and Matthew Semadeni)

Work in Progress:

- "Releasing Earnings Concurrently with SEC Periodic Filings: An Examination of the Determinants and Consequences" (with Salman Arif, Joe Schroeder, and Teri Yohn)
- "Analyst Target Prices and the Inclusion of Firm-Specific Risk"
- "Shareholder Litigation, Conservatism, and Special Charges"

INVITED WORKSHOP AND CONFERENCE PRESENTATIONS

- The Pennsylvania State University, 2015
- Boston University, 2015
- New York University, 2015
- University of Utah, 2015
- University of Colorado, 2015
- Temple University, 2015
- University of Notre Dame, 2015
- University of Rochester, 2015
- American Accounting Association Annual Meeting, 2014

CONFERENCE PARTICIPATION

- University of Illinois at Chicago Accounting Research Conference (2014, 2015)
- University of Texas at Austin McCombs Accounting Research Conference (2014)
- AAA Annual Meeting (2014)
- AAA FARS Mid-Year Meeting (2014)
- AAA Doctoral Consortium, Lake Tahoe (2012)
- Financial Accounting Standard Board's Doctoral Student Program (2012)
- Conference on Financial Economics and Accounting (2011, 2013)
- Midwest Summer Accounting Conference (2011, 2013, 2014)

ACADEMIC EXPERIENCE

University of Colorado (August 2015-December 2015), Acting Assistant Professor

- Principles of Accounting and Finance (Fall 2015)

Indiana University (2011-2014), Instructor

- Foundations of Accounting (Summer 2014)
  - Avg. Instructor Rating 6.6 / 7.0
- Instructor, Introduction to Financial Accounting (Summer 2013)
  - Avg. Instructor Rating 6.6 / 7.0
- Instructor, Introduction to Financial Accounting (Summer 2011)
  - Avg. Instructor Rating 6.1 / 7.0
- SAS Programming Course (Spring 2013, Spring 2014)
  - Developed and taught a short SAS course as a component of the Capital Markets Doctoral Seminar (taught by Teri Yohn).

PROFESSIONAL EXPERIENCE

- The Kenrich Group, Manager/Consultant – Litigation Consulting (2005-2010)
  - Analyzed and researched accounting and economic issues to assess their impact on contractual obligations and financial commitments underlying corporate disputes.
  - Calculated and quantified corporate damages using techniques such as increased cost analysis, critical path schedule analysis, productivity analysis, lost profit analysis and other forensic accounting analysis.

- Standard Federal Bank, Credit Analyst – Commercial Banking (2002-2004)
  - Assessed the credit-worthiness of prospective clients through the evaluation of financial statements and the application of ratio analysis.

HONORS

- Panschar Undergraduate Teaching Award Nominee (2014)
- AAA/Deloitte/J. Michael Cook Doctoral Consortium Fellow (2012)
- Invited participant at the FASB Doctoral Student Program (2012)
- Dean's Doctoral Fellowship, Indiana University
- Devault Fellowship, Indiana University